


## Article

# Early Warning for Manufacturing Supply Chain Resilience Based on Improved Grey Prediction Model

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**Abstract:** In a dynamic, uncertain environment, increased supply chain resilience can improve business quality. Predicting changes in enterprise supply chain resilience can help enterprises adjust their operational strategy timeously and reduce the risk of supply and demand interruption. First, a comprehensive resilience assessment framework for manufacturing enterprises was constructed from the perspective of the supply chain, and an improved technique for order of preference by similarity to the ideal solution (TOPSIS) method was used to quantify the resilience level. Considering that the resilience index is easily affected by uncertain factors, and this produces large fluctuations, the buffer operator and metabolism idea are introduced to improve the grey prediction model. This improvement can realize dynamic tracking of the enterprise resilience index and evaluate changes in the enterprise resilience level. Finally, through the analysis of the supply chain data of a famous electronic manufacturing enterprise in China over a two-and-a-half-year period, the results show that the improved TOPSIS method and the improved grey prediction model are effective in improving the supply chain resilience of manufacturing enterprises. This study provides a reference method for manufacturing enterprises to improve their supply chain resilience.

**Keywords:** manufacturing enterprise; supply chain resilience; TOPSIS; grey prediction model; early warning



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## 1. Introduction

High-quality development of the manufacturing industry plays an important role in promoting regional economic development and improving regional core competitiveness [1]. However, increasingly fierce international competition and a complex business environment make the supply chain of the manufacturing industry vulnerable to many uncertain factors. Natural disasters, political instability, public emergencies, and wars have a destructive impact on the production and operation of supply chain node enterprises [2]. Decision-makers attempt to reduce the impact of uncertain events through traditional risk management methods, such as interpretive structural models and event trees [3]. However, owing to the sudden occurrence and uncertainty of events, enterprises typically find it challenging to account for all risk events and respond in a timely manner. Without a proactive and comprehensive approach to improve the anti-risk capability of the system [4], enterprises will easily encounter difficulties, such as operational interruptions, which will affect the entire manufacturing supply chain.

In recent years, research on supply chain resilience and sustainability has received increasing attention. Resilience stresses a system's ability to adapt to uncertain environments, respond quickly to sudden risks, and recover quickly after the occurrence of risks [5]. Having a high level of resilience can help companies achieve higher-quality operations and sustainability in an uncertain environment. Sustainability is defined as the management of materials, information, and capital flow in a system from the three dimensions of economy, environment, and society, to achieve sustainable development of the system [6]. Regarding the relationship between resilience and sustainability, Zavala-Alcivar et al. [7] believe that

if a supply chain wants to meet the requirements of sustainability, its operational process must be resilient, and this resilience management will also affect the sustainability of the supply chain. Therefore, resilience management through quantitative and integrated analyses can effectively help supply chains improve sustainability.

Similar to research on risk management, the multi-attribute decision-making method (MCDM) can be used to measure the resilience level of enterprises during the operation process. Pournader et al. [8] constructed a supply chain risk resilience assessment model using data envelopment analysis (DEA) and fuzzy set theory. Pei et al. [9] used grey correlation analysis and a back propagation neural network to evaluate the safety of production resilience by considering the influence of recovery, self-organizing, and learning resilience to improve the safety production resilience of enterprises. However, these multi-attribute decision-making methods are easily restricted by the sample size and indicators, and their application scenarios are limited. TOPSIS can overcome these shortcomings and is suitable for comprehensive evaluation under various scenarios. The traditional technique for order of a preference by similarity to the ideal solution (TOPSIS) method cannot solve the problems of linear correlation among the indicators, and the setting of index weights is not acceptable. Therefore, researchers have improved the method from two different directions: one is to improve the distance formula, and the other is to combine the determination method of weights to make the evaluation results more scientific. Liu et al. [10] proposed a toughness evaluation model, MTS-GRA-TOPSIS, based on the weighted Mahalanobis distance and grey relational TOPSIS, aimed at the resilience of agricultural water and soil resources in the face of various disasters. Tadic et al. [11] combined the fuzzy analytic hierarchy process (FAHP) and the TOPSIS method to evaluate the factors influencing the organizational resilience of small and medium enterprises. Mohammed et al. [12] proposed the concept of green resilience and evaluated the resilience of a supply network by constructing a fuzzy multi-objective programming model (GR-FMOPM) combined with the FAHP and TOPSIS methods. In the quantification process of resilience, the linear correlation between resilience indicators was weak, but different indicator weights had a significant impact on the evaluation results. Therefore, by combining the FAHP to set the weights, the evaluation results can be made more convincing.

In addition, it is important to prevent supply chain disruptions and improve system resilience by improving the early warning capability of enterprises [13]. In an uncertain environment, supply chain resilience typically remains unstable for long periods. With knowledge of early warning signs, companies can make timely strategic changes and reduce the likelihood of disruptions. It is difficult to achieve accurate predictions using conventional quantitative analysis methods in uncertain environments, and the indicators related to enterprise resilience are greatly affected by recent events. Grey system theory has higher accuracy in predicting small samples of uncertain information [14]; therefore, it has been widely used. Traditional grey prediction methods require smooth data series. Therefore, the performance of the traditional prediction methods for series data with fluctuating characteristics is poor. To solve this problem, some scholars have introduced a method of weakening the buffer operator to modify the original sequence, so that the modified sequence is relatively smooth. Rajesh [15] analyzed enterprise resilience from the aspects of flexibility, responsiveness, and production efficiency, and used the improved grey forecasting model to measure resilience. According to the five evaluation dimensions of retail resilience, the grey model is used to predict resilience, and the Markov model based on movement probability is used to modify the prediction results, which can effectively help managers improve their decision-making abilities [16]. In addition, some scholars have introduced a metabolism theory into grey prediction to improve the accuracy of short-term prediction through iterative updating [17]. However, the advantages of these two methods have not been combined to improve the grey prediction model for improving the accuracy of short-term predictions of volatility series.

Abundant research has been conducted on the measurement, evaluation, and prediction of enterprise resilience in many industries. However, measuring the supply chain

resilience of manufacturing enterprises and building a practical resilience early warning system requires further study. This study focuses on two aspects. First, based on relevant research and the investigation of manufacturing enterprises, an evaluation index system framework of supply chain resilience of manufacturing enterprises was constructed, and the resilience level was quantified. Second, by introducing a buffer operator and metabolism idea into grey theory, the supply chain resilience of manufacturing enterprises was dynamically predicted, and a resilience early warning system was constructed. By collecting the operational data of a large electronics manufacturing enterprise in China for two and a half years during the COVID-19 pandemic, this study monitored the resilience level, effectively helping enterprises adjust their production and operation strategies in a timely manner and improve their early warning capabilities.

## 2. Evaluation Index System of Supply Chain Resilience

### 2.1. Analysis of Indexes Affecting Resilience

Resilience can be measured using various methods. Existing studies on resilience evaluation are multifaceted, including collaboration, visibility, security redundancy, market location, and partnership [18]. For manufacturing companies, supply chain resilience is crucial for high-quality development. Supply chain resilience refers to the supply chain's ability to prevent and respond to uncertain events, recover from disruptions, and maintain normal operational levels [5]. Therefore, when analyzing indicators of supply chain resilience, researchers primarily analyze the factors affecting resilience according to three factors: responsiveness, adaptability, and resilience [19]. Hosseini and Barker [20] drew on the ideas of Vugrin et al. [19] and used a Bayesian network model to evaluate the resilience of different suppliers in terms of absorption, adaptation, and resilience. Kazemian et al. [21] selected eight factors affecting supply chain resilience from three dimensions: supply network size, density, and proportion of suppliers.

Therefore, on the basis of our literature review and enterprise investigation, this study focuses on the perspective of the manufacturing enterprise supply chain and analyzes the indicators affecting the resilience level from three dimensions: responsiveness, adaptability, and resilience itself. These three dimensions target the stages before, during, and after the occurrence of uncertain events. Table 1 shows the current research on resilience dimensions and indicators selection.

**Table 1.** The current research on resilience dimensions and indicators selection.

Literature	Dimensions			Resilience Indicators
	Responsiveness	Adaptability	Recovery	
[4]	✓		✓	Supply chain (re)engineering, collaboration, agility, risk awareness/knowledge management
[18]		✓	✓	Agility, collaboration, information-sharing, awareness, visibility, flexibility, redundancy, market position
[19]	✓	✓	✓	Flexibility, redundancy, robustness, disruptive event, recovery effort
[20]	✓	✓	✓	Lead time, surplus inventory, backup supplier, physical protection, rerouting, technical resources, budget resources
[21]	✓	✓	✓	Supply network size, density, proportion of suppliers, overall clustering, flow complexity, centralization
[22]	✓		✓	Disaster preparation, flexibility, redundancy, visibility, collaboration, recovery time, cost, absorption of disruption
[23]	✓			Lead time, capacity buffers, inventory, risk sharing, rapid configuration, flexible, demand visibility
[24]		✓	✓	Volume, delivery, production, robustness, re-configuration, relationship, logistics
[25]	✓	✓	✓	Flexibility, decentralization, capacity reservations, risk mitigation inventory, lead time, backup suppliers
[26]		✓	✓	Surplus inventory, location separation, backup supplier, robustness, reliability
[27]			✓	Supply chain structure reconfiguration

- (1) **Responsiveness.** Responsiveness refers to an enterprise's ability to perceive and predict the risks of external information in the operational process [22]. Agility and collaboration are key indicators that affect supply chain responsiveness. Agility requires enterprises to respond quickly to market demand or supply changes and to help them deal with uncertain risks in a timely manner [23,28]. Among these factors, an extended delivery lead time and slow order response speed indicate that the enterprise has a poor perception of production, demand, and other information. Collaborative capability emphasizes that enterprises and partners reduce uncertain risks and improve service levels through information-sharing and the application of information technology [4]. Reduced information-sharing, limited timely delivery of materials, and a qualified rate of material supply indicates that the production and delivery capacity of the cooperative enterprise cannot meet the requirements, or the organization and management of the production process cannot keep up with the requirements of the enterprise operation, and it is difficult for the enterprise to respond quickly to uncertain events.
- (2) **Adaptability.** Adaptability enables enterprises to maintain stable production and operation during emergencies and reduces the possibility of interruption risk, which can be reflected by two indicators: flexibility and security redundancy. Enterprise flexibility refers to the ability to quickly adjust production and operational plans according to demand and environmental conditions during emergencies [24]. The safety redundancy index reflects the strategic use of excess reserve resources by enterprises to improve their ability to cope with sudden risks [25].
- (3) **Recovery.** Recovery refers to the supply chain's ability to quickly return to normal operations after the occurrence of disruption risk [26]. Emergency response capability refers to the establishment of an emergency mechanism by means of resource reallocation and information monitoring after an operational interruption to improve recovery capability [27]. The emergency capacity of an enterprise includes standby suppliers, on-time delivery of finished products, and a qualified rate of finished products. The higher these indicators, the higher the production and operation efficiency of an enterprise and the faster it can return to normal production and operation after interruption. In addition, logistics support can guarantee the transportation and distribution of goods under interrupted conditions.

## 2.2. Construction of Resilience Evaluation Index System

Based on the aforementioned analysis and discussion, we conducted field interviews to investigate a large electronics manufacturing enterprise. Based on a detailed understanding of the actual business process of the enterprise, several rounds of interviews were conducted with the relevant directors of the supply chain department of the enterprise. The departments interviewed include planning, production, storage, etc., and these were chosen mainly to understand the main factors affecting the resilience of the company's supply chain and the corresponding adjustment strategies in the case of external interference. Subsequently, we also made a return visit to build and continuously optimize the evaluation hierarchy of the supply chain resilience of manufacturing enterprises. Finally, we obtained a hierarchical model of supply chain resilience evaluation, as shown in Figure 1. The construction of the three hierarchical models is beneficial for the quantification of indicators and the evaluation of resilience. These indicators can not only comprehensively reflect the current level of enterprise supply chain resilience but also analyze the changing trend of enterprise resilience through the real-time collection of enterprise operation data series at different moments of prediction.

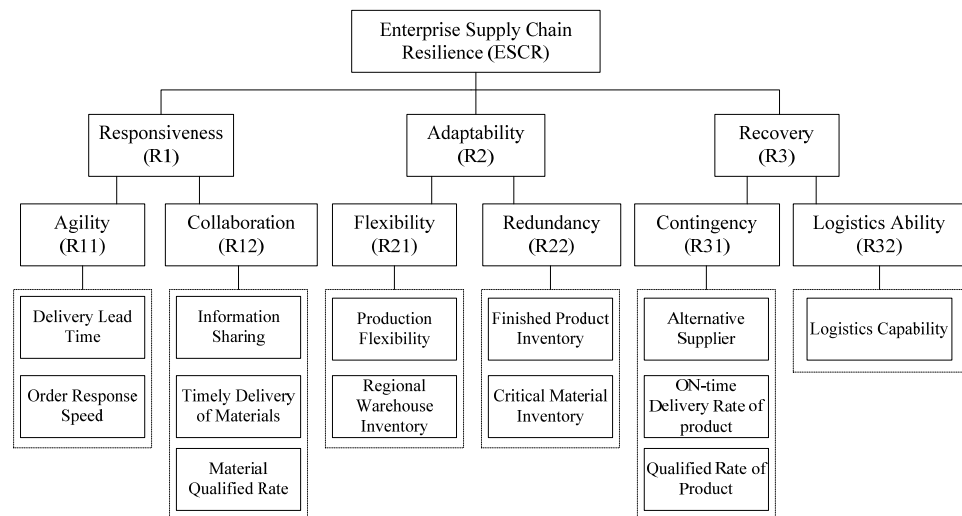


Figure 1. The hierarchical model of enterprise supply chain resilience evaluation.

### 3. Evaluation and Prediction of Supply Chain Resilience

#### 3.1. Evaluation of Supply Chain Resilience

The evaluation of supply chain resilience requires comprehensive quantification of the indicators of each dimension. Combined with related research, we used FAHP and an improved TOPSIS to quantify the resilience level of the supply chain. Suppose that the data of  $j$  ( $j = 1, 2, \dots, n$ ) resilience evaluation indicators of an enterprise at  $i$  ( $i = 1, 2, \dots, m$ ) decision points are collected. First, the weights of the evaluation indicators are determined.

##### 3.1.1. Determination of the Indicator Weight

In view of the shortcomings of the traditional analytic hierarchy process (AHP) method, this study extends the AHP method to a fuzzy environment by referring to the research of Jiet et al. [29]. The FAHP method was used to construct a fuzzy consistency matrix to eliminate the consistency problem of experts in the process of weight assignment and make weight allocation more reasonable. The calculation steps of the FAHP method are as follows:

Step 1: According to the hierarchical structure of the evaluation index system of supply chain resilience, the evaluation factor sets at different levels were established, including three first-level indicators, six second-level indicators, and thirteen third-level indicators.

Step 2: Referring to the five-scale method [30] (as shown in Table 2), the importance degree  $a_{ij}$  ( $i, j = 1, 2, \dots, n$ ) between the two indicators is compared using expert scoring, and the fuzzy complementary judgment matrix  $A_{n \times n}$  is constructed.

Table 2. The five-scale method.

Intensity of Importance	Definition
0.5	The factor $i$ is equally as important as factor $j$
0.6	The factor $i$ is slightly more important than factor $j$
0.7	The factor $i$ is obviously more important than factor $j$
0.8	The factor $i$ is substantially more important than factor $j$
0.9	The factor $i$ is tremendously more important than factor $j$
Reciprocal	The factor $i$ is compared with factor $j$ as $a_{ij}$ . Then, comparison between factors $j$ and $i$ is $a_{ji} = 1 - a_{ij}$ , $a_{ii} = 0.5$

Step 3: By summing each row of the fuzzy complementary judgment matrix  $A_{n \times n}$ , we obtain:

$$r_i = \sum_{j=1}^n a_{ij} \quad (i = 1, 2, \dots, n) \tag{1}$$

$$r_{ij} = \frac{r_i - r_j}{2(n-1)} + 0.5 \quad (2)$$

and the fuzzy consistency matrix  $R_{n \times n}$  is obtained.

Step 4: By normalizing the fuzzy consistency matrix, the weight  $W = (\omega_1, \omega_2, \dots, \omega_n)$  of each resilience indicator was obtained. The normalization formula is as follows:

$$\omega_i = \frac{\sum_{j=1}^n r_{ij} - 1 + \frac{n}{2}}{n(n-1)} \quad (i = 1, 2, \dots, n) \quad (3)$$

among them,  $\sum_{i=1}^n \omega_i = 1$ ,  $\omega_i \geq 0$  ( $i = 1, 2, \dots, n$ ).

Step 5: The characteristic matrix  $W_{n \times n}^*(w_{ij})$  of  $A_{n \times n}$  is constructed and the compatibility index of the matrix is calculated as follows:

$$w_{ij} = \frac{w_i}{w_i + w_j} \quad (4)$$

$$I(A, W^*) = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n |a_{ij} + w_{ij} - 1| \quad (5)$$

If  $I(A, W^*) < 0.1$ , it passes the consistency test.

### 3.1.2. Quantification of Resilience Level Based on Improved TOPSIS

TOPSIS is a ranking method for approximating ideal points in multi-objective decision analysis. This method quantifies the evaluation object by determining the Euclidean distance between each solution and the positive/negative ideal solution and has been widely used in manufacturing, medicine, risk management, and other fields with good evaluation effects [31]. The determination of a positive/negative ideal solution often depends on the optimal and the worst values of each index. As a result, the overall resilience level of the target cannot be evaluated in a more accurate way, owing to the influence of the current data characteristics during normalization. However, the evaluation results can be made more convincing by optimizing and adjusting the positive and negative ideal solutions [32,33]. Considering that the indicators in the actual operation process of enterprises often cannot reach the ideal state, the model is improved by setting the optimal value and worst value by experts based on the investigation of enterprises so that the model can better reflect the current resilience level of enterprise operations.

The specific steps to improve the TOPSIS method are as follows:

Step 1: Determine the optimal and worst solution sets of the index according to the industry standards and expert opinions, denoted as follows:

$$A = [y_1^+, y_2^+, \dots, y_j^+] \quad (6)$$

$$B = [y_1^-, y_2^-, \dots, y_j^-] \quad (7)$$

where  $j = 1, 2, \dots, n$ . For the negative index, the optimal solution is smaller than the worst solution.

Step 2: Normalize the initial evaluation matrix  $P_{m \times n}(p_{ij})$  to obtain the feature matrix  $N_{m \times n}(n_{ij})$ :

$$n_{ij} = \frac{p_{ij} - y_j^-}{y_j^+ - y_j^-} \quad (8)$$

where  $p_{ij}$  is the value of index  $j$  of the enterprise at time  $i$ .

Step 3: Using the index weight matrix  $W_{n \times n}$  obtained using the FAHP method, the weighted feature matrix  $V_{m \times n}(v_{ij})$  is calculated as follows:

$$V_{m \times n} = N_{m \times n} \times W_{n \times n} \quad (9)$$



Step 4: Calculate the Euclidean distance between each index and the positive and negative ideal solutions for decision time  $i$ :

$$d_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - V_j^+)^2} \quad (10)$$

$$d_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - V_j^-)^2} \quad (11)$$

where  $i = 1, 2, \dots, m$ , and  $V_j^+$  and  $V_j^-$  are the maximum and minimum values of each column of the characteristic matrix  $V_{m \times n}$ , respectively.

Step 5: Score the resilience level of the enterprise at decision time  $i$  and obtain its value:

$$c_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (12)$$

where  $0 \leq c_i \leq 1$ . The higher  $c_i$  is, the stronger the resilience of the enterprise at time  $i$ .

### 3.2. Prediction of Resilience Indicators Based on Improved Grey Prediction Method

The resilience of enterprises is relatively stable from a macro perspective, whereas from a micro perspective, the resilience of enterprises is more prone to fluctuations caused by unconventional factors, and distant historical data have a reduced impact on the future state. Therefore, traditional forecasting methods such as neural networks and support vector machines, which rely on a large amount of historical data to predict the future state, are seldom accurate. The grey prediction method with uncertain information and a small sample can predict the future state according to limited grey information [34].

The enterprise resilience index is disturbed by uncertain factors, which usually produce a fast or slow evolution trend, whereas the prediction accuracy of the grey forecasting method for non-smooth series is not high. Therefore, by introducing a buffer operator [15] to modify the original sequence, a sequence with random fluctuation characteristics can be predicted and the prediction accuracy can be greatly improved. The improved grey prediction method includes the following five steps:

(1) Stepwise ratio checkout was used to analyze the feasibility of the model.

The time series of the resilience index  $r$  is given as follows:

$$X = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \quad (13)$$

where  $x^{(0)}(i) > 0$  ( $i = 1, 2, \dots, n$ ), and  $n$  denotes the number of prediction samples. To judge whether the grey prediction method can be used for sequence data by calculating the stage ratio:

$$\sigma(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)} \quad (14)$$

where  $k = 1, 2, \dots, n$ . For  $\forall k$ , if  $\sigma(k) \in (e^{\frac{-2}{n+1}}, e^{\frac{2}{n+1}})$ , it passes a stepwise ratio checkout.

(2) Weakening the buffer operator  $D$ .

If the index sequence fails to pass the stepwise ratio checkout, the average weakening buffer operator  $D$  (AWBO) is introduced to correct the original sequence. Let us set  $XD = (x^{(0)}(1)d, x^{(0)}(2)d, \dots, x^{(0)}(n)d)$ , where

$$x^{(0)}(k)d = \frac{1}{n+k-1} (x^{(0)}(k) + x^{(0)}(k+1) + \dots + x^{(0)}(n)) \quad (15)$$

and  $k = 1, 2, \dots, n$ . The corrected sequence  $\tilde{X} = (\tilde{x}^{(0)}(1), \tilde{x}^{(0)}(2), \dots, \tilde{x}^{(0)}(n))$  can be obtained, and Step (1) can be repeated for verification. If verified, we proceed to Step (3).

(3) Establishment of GM(1,1) model.

The modified sequence  $\tilde{X}$  is accumulated once (1-AGO) to generate the sequence:

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)) \quad (16)$$

where  $x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i)$ . Let  $Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), \dots, z^{(1)}(n))$  be the background value of  $X^{(1)}$ , where

$$z^{(1)}(k) = \frac{1}{2}(x^{(1)}(k) + x^{(1)}(k-1)) \quad (17)$$

Then, the whitening differential equation of GM(1,1) is:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = \mu \quad (18)$$

where  $a$  is the grey number for development and  $\mu$  is the grey number for endogenous control. This simplifies to:

$$\tilde{x}^{(0)}(k) = \mu - az^{(1)}(k) \quad (19)$$

The leastsquares method is used to estimate the equation parameters, and the parameters  $a$  and  $\mu$  to be estimated satisfy:

$$\hat{u} = (a, \mu)^T = (B^T B)^{-1} B^T M \quad (20)$$

where:

$$B = \begin{bmatrix} -z^{(1)}(2) & -z^{(1)}(3) & \dots & -z^{(1)}(n) \\ 1 & 1 & \dots & 1 \end{bmatrix}^T \quad (21)$$

$$M = [x^{(0)}(2) \quad x^{(0)}(3) \quad \dots \quad x^{(0)}(n)]^T \quad (22)$$

To solve the parameters, we use  $x^{(1)}(0) = x^{(0)}(1)$ , and the time response sequence of the grey differential equation can be obtained as follows:

$$x^{(1)}(k+1) = \left[ x^{(0)}(1) - \frac{\mu}{a} \right] e^{-ak} + \frac{\mu}{a} \quad (23)$$

where  $k = 1, 2, \dots, n-1$ . A cumulative reduction (IAGO) operation was performed on the obtained sequence to obtain the final prediction result as follows:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = \left[ x^{(0)}(1) - \frac{\mu}{a} \right] (1 - e^a) e^{-ak} \quad (24)$$

where  $k = 1, 2, \dots, n$ .

(4) Metabolism model for grey prediction.

The traditional grey model is based on past static data at time  $t$  for prediction; however, in an uncertain environment, new grey information will be added to the prediction system. As time passes, the older the data, the less information it contains, and the error accumulates when grey theory is used for prediction. The metabolism model can add the idea of a real-time dynamic update of information to the grey prediction to realize a dynamic prediction of the sequence, effectively reducing the prediction error [35].

If  $n$  original data are required for the prediction, the metabolism model selects the data in the time range  $t$  to predict the data at time  $t+1$  and then removes the oldest data  $x^{(0)}(1)$ , and adds the new data  $x^{(0)}(t+1)$ . Considering this, as the original series  $X^{(0)} = [x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(t+1)]$ , where  $t = 1, 2, \dots, n-1$ , a new prediction model is



obtained. Step (3) is repeated to achieve the desired metabolism. By constantly updating the data series and dynamically predicting the data at time  $t + 1$ , a new prediction series was obtained. When  $t + 1 = n$ , the predicted data  $\hat{x}^{(0)}(n + 1)$  are added to the original sequence, and the subsequent data are predicted. Therefore, the decision-maker can obtain the predicted value of the development trend according to existing information to help the enterprise make timely strategy adjustments.

(5) Model verification.

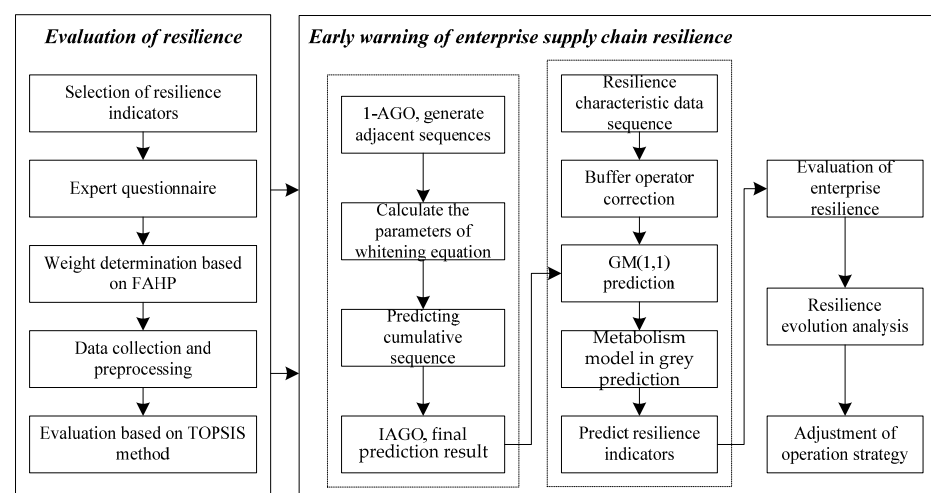
Because the model requires multiple iterations, we selected the mean absolute percentage error (MAPE) to check the validity of the model:

$$\text{MAPE} = \frac{1}{n} \sum_{i=t}^n \left| \frac{\hat{x}_i - x_i}{x_i} \right| \times 100\% \quad (25)$$

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

### 3.3. Resilience Early Warning Process Based on TOPSIS-Grey Prediction

To quantify the resilience level of enterprise supply chains more accurately, this study proposes an improved FAHP-TOPSIS method that includes the processes of resilience indicators selection, designing an expert questionnaire, and TOPSIS evaluation. This study also used buffer operators for sequence correction, one-accumulation generation operation (1-AGO), predicted cumulative sequence, and inverse accumulated generation operation (IAGO) in order to construct an improved grey prediction method to predict the resilience characteristics of future times to achieve a better prediction effect. The method was combined with the improved grey prediction method to describe the resilience characteristics of future times to achieve a better prediction effect. By further analyzing the evolution of an enterprise's supply chain resilience at different times, the enterprise's resilience early warning ability is realized, and the supply chain interruption risk is reduced. The entire enterprise supply chain resilience warning process is illustrated in Figure 2.



**Figure 2.** Early warning process of enterprise supply chain resilience.

## 4. Numerical Calculation and Analysis

### 4.1. Background and Data Description

As an example, a numerical calculation process was tested in a large electronic manufacturing enterprise in China. The company is a leading manufacturer of security products worldwide. However, in recent years, owing to the rapidly changing external environment, especially the impact of international supply chain disruptions and the COVID-19 pandemic, the daily operation of companies has encountered great challenges. The company

urgently needs to establish an early warning mechanism for supply chain resilience, which can track and predict the changes in the company's supply chain resilience indicators in real time, help decision-makers adjust the enterprise operation strategy in time, and reduce the risk of supply or production interruption.

In the course of interviewing the directors of the supply chain-related departments of the electronics manufacturing enterprise studied, we learned in detail about the availability of data on resilience indicators and the substitutability of the related indicators. All available and alternative indicator data were exported from the ERP system (SAP) used by the enterprise. Owing to the complexity of the company's business process and product line, we selected a typical product line of the company and collected 13 resilience indicator data points from 30 monthly time nodes from January 2020 to June 2022. Considering the characteristics of the industry and the actual operation of the company, some resilience evaluation indicators were replaced by relevant indicators. For example, the order response speed is replaced by the 24 h order response ratio, and the on-time material delivery ratio is replaced by the material pickup achievement ratio. In addition, the optimal and worst solutions of each index are determined according to experts' understanding of the industry and its competitors. The relevant data were preprocessed by normalization.

#### 4.2. Quantification of Resilience Indicators

Because of the complexity of the three-level hierarchy, ignoring second-level indicators does not affect the results or presentation of the research. Therefore, this study simplifies the hierarchy of the evaluation index for enterprise supply chain resilience. Simultaneously, by comparing the importance of resilience indicators under the different dimensions according to the scoring rules given in Table 2, the expert questionnaire was designed and distributed to an expert group composed of 20 people. The expert group consisted of senior management of the supply chain department of the enterprise and professors from several local universities in the supply chain field, and a total of 18 valid questionnaires were collected. The FAHP method was used to calculate the weight of each index, all of which passed the consistency check, as presented in Table 3.

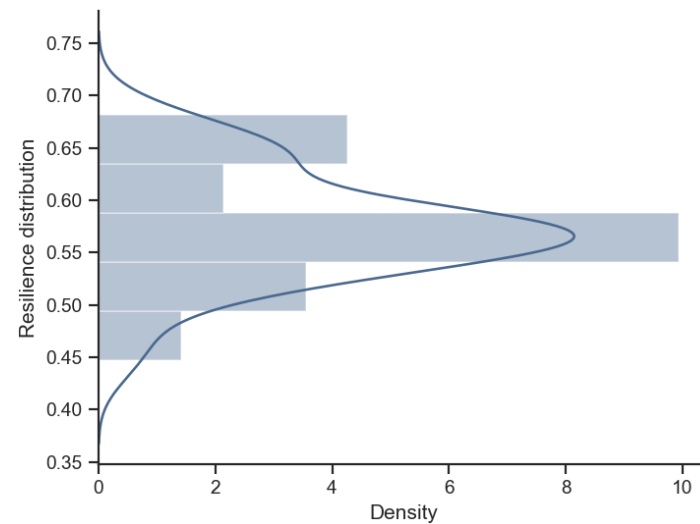
**Table 3.** Resilience indicator weight.

The First Layer		The Second Layer		
Dimension	Local Weights	Resilience Indicator	Local Weights	Global Weights
Responsiveness	0.5102	Delivery lead time	0.2641	0.1348
		Order response speed	0.2513	0.1282
		Information sharing	0.1601	0.0817
		Timely delivery of materials	0.1662	0.0848
		Material qualified rate	0.1583	0.0808
Adaptability	0.2537	Production flexibility	0.2583	0.0655
		Regional warehouse inventory	0.2509	0.0636
		Finished product inventory	0.2417	0.0613
		Critical material inventory	0.2491	0.0632
Recovery	0.2361	Alternative suppliers	0.2537	0.0599
		Qualified rate of product	0.2500	0.0590
		On-time delivery of product	0.2592	0.0612
		Logistics capability	0.2371	0.0560

Different industries place varying emphasis on the dimensions of resilience. According to the weight calculation results above, the responsiveness of manufacturing supply chain resilience occupies a large weight in the three dimensions, which is consistent with Rajesh's [15] conclusion in that responsiveness is the primary demand for gaining market share and achieving sustainable competitiveness. At the same time, Rajesh [36] evaluated the resilience level of manufacturing supply chain, and concluded that attributes such as demand risk, response speed, and information-sharing made significant contributions

to supply chain resilience, which required special attention. These results also verify the above weight calculation results.

Thus, a weight coefficient matrix  $W$  was constructed, and the quantitative value of the company's supply chain resilience was calculated using the improved TOPSIS method. The resilience distribution of the companies from 2020 to 2022 is shown in Figure 3.



**Figure 3.** Distribution of the company's supply chain resilience from 2020 to 2022.

As shown in Figure 3, the company's supply chain resilience value is distributed between 0.45 and 0.70 from 2020 to 2022, with the majority greater than 0.5. However, the overall performance of the company's supply chain resilience is not strong enough, and there are many time nodes with a resilience distribution between 0.55 and 0.60, accounting for 1/3 of the total sample number. Reflecting the double pressure of international supply chain interruption and the pandemic over the past two years, the influence of uncertain factors creates room for improvement in the company's supply chain resilience.

#### 4.3. Grey Prediction of Resilience Indicators

Some resilience indicators were relatively stable over time, whereas others were not. Therefore, we must select supply chain resilience indicators that are susceptible to external factors and predict future changes based on historical data from the past two years. According to the characteristics of the industry and the actual circumstances of the company, seven unstable forecasting indicators were selected, with a forecast period of three months. The selected resilience indicators and the corresponding original data are listed in Table 4.

**Table 4.** Original data for selected resilience indicators.

Time	Order Response Speed	Timely Delivery of Materials	Actual Production Capacity	Finished Product Inventory	Critical Material Inventory	On-Time Delivery of Product	Logistics Capability
2020/01	0.915	0.7009	2869	3981	253264	0.910	2786
2020/02	0.900	0.2091	758	5496	161576	0.810	1435
2020/03	0.900	0.6790	3070	2655	150364	0.848	2098
2020/04	0.920	0.9050	4473	2933	21980	0.824	2373
2020/05	0.925	0.8497	5558	2880	200357	0.871	2543
2020/06	0.920	0.8709	5611	2681	182800	0.921	2539

Through the analysis of the original data series, it was found that the original data belong to the non-smooth series, which is impacted by external factors, the fluctuation range of the data is large, and the model cannot pass the stepwise ratio checkout. After

introducing the weakening buffer operator to correct the original data sequence, it smoothly passed the stepwise ratio checkout. The traditional GM(1,1), AWBO buffer operator modified GM(1,1), and metabolism model modified GM(1,1) models were used to predict the seven selected resilience indicators. The metabolic cycle  $t$  was set to 6 months, and the MAPE was used to check the accuracy of the prediction model. The prediction results are listed in Table 5.

**Table 5.** Comparison of prediction errors for each model (%).

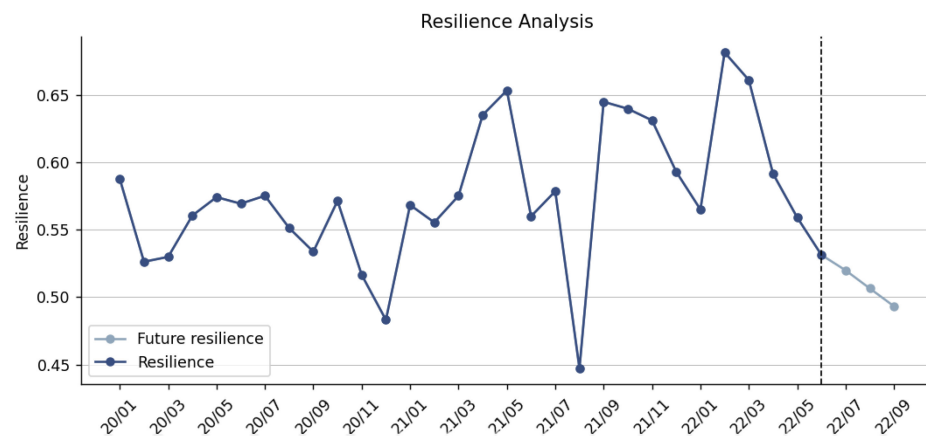
Indicators	Traditional GM(1,1)	AWBO Buffer Operator Modified GM(1,1)	Metabolic Method Modified GM(1,1)
Order response speed	3.06	1.00	0.81
Timely delivery of materials	10.16	3.26	2.33
Actual production capacity	31.19	4.69	5.39
Finished product inventory	19.44	6.47	4.10
Critical material inventory	47.71	6.70	3.64
On-time delivery of product	16.22	4.60	3.18
Logistics capability	38.62	10.36	6.26
MAPE	23.77	5.30	3.67

By comparing the average MAPE of the prediction results of the seven resilience indicators using the different grey prediction methods, it can be observed that the traditional grey prediction method has a poor prediction effect on the non-smooth data series because of the volatility of the original series. However, the AWBO buffer operator can be used to improve the highly volatile indicator values according to the rules of the series information, which makes the modified original data series relatively smooth and reduces the prediction error to a certain extent. In addition, by using metabolism theory to predict the modified series, it can dynamically eliminate older data, so that the prediction results are greatly influenced by the more recent time series. This increased the accuracy of the prediction result, and the average error of the model prediction was reduced from 23.77% to 3.67%. For the prediction of resilience indicators of manufacturing enterprises in uncertain environments, the improved grey prediction method is significantly better than the traditional method, particularly for short-term prediction with high accuracy.

#### 4.4. Evolutionary Analysis of Resilience Indicators

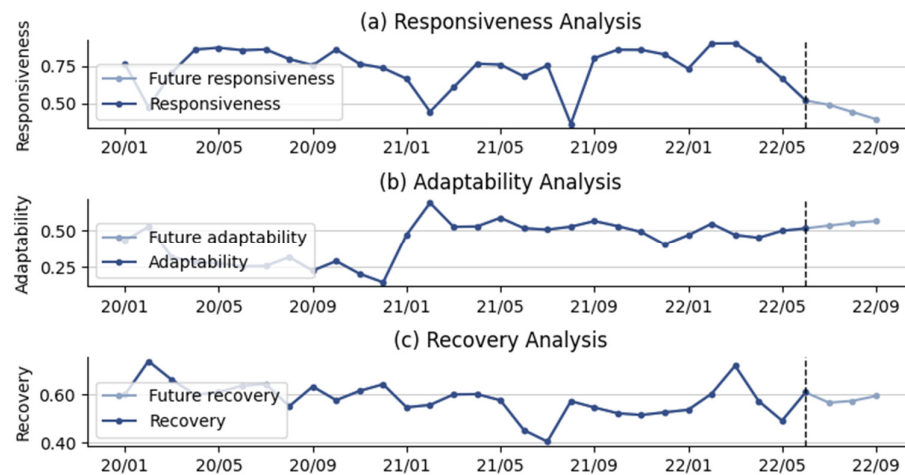
By analyzing the real evolution of data trends, enterprises can use the information gained to adopt change strategies and make decision-makers pay more attention to indicators with negative evolution paths [15,16]. To further analyze the future evolution trend of resilience indicators, this study predicts the resilience indicators from July to September 2022 based on the improved grey prediction model of metabolism and quantifies the future supply chain resilience of the company. The evolution of supply chain resilience from January 2020 is illustrated in Figure 4.

As shown in Figure 4, a company's resilience is unstable due to uncertain factors such as technological competition between countries, economic fluctuations, and epidemic prevention and control, and resilience changes significantly at certain times. For example, the company's supply chain resilience reached its lowest point in August 2021, which was mainly influenced by government demand within the security industry. However, overall, the company's supply chain resilience showed an upward trend after the introduction of the supply chain resilience warning mechanism. For example, in March 2022, corporate resilience reached a record high, indicating that policymakers could effectively improve resilience and the ability to cope with uncertain risks through operational strategy adjustments.



**Figure 4.** The evolution trend of enterprise supply chain resilience.

From a recent perspective, the company's resilience value is declining relatively rapidly after March 2022. This is because of further international policy sanctions and the interference and influence of domestic epidemic prevention and control strategies, which have affected the supply chain of key materials, capacity support, and sales to varying degrees. According to the prediction of resilience indicator data from July to September, if the company continues to develop according to the existing operational strategy, the resilience of the supply chain will be further reduced, which can easily lead to risk. Accordingly, the decision-maker should implement the operation strategy with a relatively large-scale adjustment in time. Therefore, we further analyzed the reasons for the continuous decline in supply chain resilience from three dimensions: responsiveness, adaptability, and recovery, and the results are shown in Figure 5.



**Figure 5.** The evolution trend of each dimension of enterprise supply chain resilience.

From the evolution trend of the three dimensions in Figure 5, it can be seen that responsiveness is the main factor affecting changes in company resilience. Therefore, enhancing the perception of the external environment and improving early warning ability can effectively improve a company's supply chain resilience. In addition, the adaptability performance was relatively stable. The company began to adjust its inventory strategy at the beginning of 2021 to buffer supply chain risks through high inventory, greatly improving its adaptive capacity. Figure 5b shows the changing trend of the adaptive capacity. By comparing Figures 4 and 5c, it can be seen that when the company's supply chain resilience begins to decrease, the level of recovery is often higher because the company's recovery ability is in play after the occurrence of risks.

In the next three months, although the company's ability to adapt and recover gradually improved, the impact of reduced responsiveness capacity also reduced supply chain

resilience. At this time, the decision-makers of the company should focus on improving the response speed to changes in the external environment and adjust the operation strategy, for example, by improving the processing speed for orders, improving the degree of information sharing with suppliers, and improving the quality of materials and services of suppliers.

The aforementioned prediction results and strategy suggestions were also verified in follow-up enterprise visits. In the most recent return visit (26 September 2022), the company's supply chain director gave feedback that due to the impact of epidemic prevention and control and international sanctions, the company is facing a trend of declining response speed on the supply and demand side of the supply chain. It was also noted that it is also actively changing through strategy adjustment. This further confirmed the feasibility and practicability of this study.

Cantini et al. [37] proposed a decision support system to help managers and practitioners design and configure the spare parts supply chain to determine whether it is necessary to switch from conventional manufacturing technology to additive manufacturing technology. Similarly, the application of supply chain resilience early warning also needs the support of a decision support system. As part of the intelligent factory construction project, the company's supply chain resilience early warning system will continue to improve, deploy, and play an important role on the basis of further verification. A prototype system currently under testing includes a data mid-end, a library of evaluation and prediction algorithms, and applications that support the mobile side. Collecting, analyzing, and predicting the comprehensive supply chain resilience indicators' data can provide early warning and decision support basis for the company's supply chain managers, practitioners, and other decision-makers in real time. This means that intelligent factories will become smarter and more stable in the uncertain environment.

## 5. Conclusions

Resilience theory is an important supplement to traditional risk management and can be used to help enterprises identify potential supply chain risks in a timely manner. A quantitative calculation of enterprise supply chain resilience was performed by constructing an evaluation index system of supply chain resilience for manufacturing enterprises. Compared with relevant studies, this study not only evaluates the supply chain resilience of manufacturing enterprises and predicts the future resilience of enterprises based on historical data related to resilience, but also analyzes the resilience level and the evolution process of each resilience index across various dimensions. By constructing an early warning mechanism of supply chain resilience for manufacturing enterprises, the change in resilience and its causes can be grasped in real time, which provides a basis for decision-makers to adjust operational strategies timeously to improve the ability of enterprises to respond to market or environmental changes and reduce the risk of supply chain interruption.

Through the analysis of the actual operational data of a large electronic manufacturing enterprise, the results show that the enterprise is affected by many uncertain factors from 2020 to 2022, resulting in significant fluctuations in the supply chain resilience (the distribution of resilience value is between 0.4 and 0.7), indicating that there is considerable room for improvement in the supply chain resilience of the company. The numerical results also demonstrate that the proposed improved FAHP-TOPSIS method can accurately measure and reflect the supply chain resilience level during the enterprise operation process. The grey prediction method based on the AWBO buffer operator and metabolism model can better solve the problem of data fluctuation; therefore, it can be applied to the prediction of resilience indicator data.

This study enriches the application of the grey prediction method in the field of enterprise supply chain resilience and provides methods for relevant manufacturing enterprises to establish an early warning mechanism of supply chain resilience, maintain a high level of operational resilience, and reduce the risk of disruption. However, this study has some shortcomings. Owing to the difficulty of obtaining some data, some indicators such as



visibility and risk prediction must be discarded while constructing the resilience evaluation system. This makes the evaluation of the supply chain resilience of manufacturing enterprises insufficiently comprehensive. Future research should consider two aspects. Resilience warnings in an uncertain environment can be studied from the perspective of general manufacturing companies rather than electronic manufacturing companies. Additionally, the interaction between risk and resilience under external disturbances can be explored by combining the relevant research on risk management.

Additive manufacturing is a disruptive digital technology in Industrial 4.0 technology, and it is also regarded as the next revolution in the field of spare parts [37]. Related research shows that the use of additive manufacturing will affect the resilience of the supply chain by affecting the state and structural dynamics of the supply chain [38]. As a large electronic manufacturing company, supply chain managers are also actively considering how to introduce the decision-making problem of additive manufacturing, in order to further effectively solve the impact of procurement interruption of some key spare parts, especially structural components, on the resilience of their supply chain. This is another important and interesting research direction for the future.

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