SCIENTIFIC OASIS

Journal of Operations Intelligence

Journal homepage: www.jopi-journal.org
eISSN: 3009-4267

# Measurement Method for Food Supply Chain Security Level from the Perspective of Resilience

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**ARTICLE INFO**

***Article history:***
Received 22 February 2025
Received in revised form 17 April 2025
Accepted 23 May 2025
Available online 28 May 2025

***Keywords:***
Food Supply Chain Resilience; MCDM; Fuzzy set; MABAC.

**ABSTRACT**

The resilience of China's food supply chain is of significant importance for ensuring national food security and maintaining social stability, and there is a close connection between supply chain resilience and safety levels, which can be considered integrated to some extent. To quantitatively measure the safety level of the food supply chain, this study explores the measurement of food supply chain safety based on an improved MABAC model. First, content mining is used to collect and analyze literature, identifying resilience risk factors and relevant evaluation indicators in the food supply chain. Second, T-spherical fuzzy sets are employed to convert expert evaluation language, and expert weights are determined through score functions to establish a weighted evaluation matrix. Finally, the entropy method is used to calculate indicator weights, combined with the MABAC method for risk ranking to derive the final results. The findings indicate that emergencies, the economy, and the market are the primary risk factors affecting the resilience of the food supply chain. The conclusion emphasizes the need to focus on controlling emergencies, guiding economic and market development directions, preparing risk prevention plans in advance, reducing the probability of unexpected events and their severity, and enhancing supply chain resilience and safety levels.

## 1. Introduction

Food security is of paramount national importance, and serves as an essential foundation for economic development, social stability, and national security. The 2025 Central Document No. 1 proposes to continuously enhance the supply guarantee capacity of important agricultural products such as grain, improve the coordination mechanism between agricultural product trade and production, take domestic stable production and supply guarantee as the foundation, strengthen the balance between supply and demand of agricultural products and the monitoring and early warning of the entire chain, accurately identify supply and demand gaps and regulatory focus points, optimize the layout of import sources, and dynamically adjust the scale and pace of imports. Balancing market

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https://doi.org/10.31181/jopi31202557

supply and price stability, coordinating and smoothing the domestic and international dual circulation at a higher level, protecting the interests of farmers and their enthusiasm for growing grain, and consolidating the bottom line of food security through opening up. Against the background of economic globalization, China's dependence on foreign grain imports is high, which is closely related to the international situation. To ensure national food security, enhance the stability of the food supply chain and reduce risks in the food supply chain, the Seventh Meeting of the Standing Committee of the 14th National People's Congress passed the "Grain Security Guarantee Law of the People's Republic of China" on December 29, 2023. The 2023 Central Document No. 1 emphasizes the imperative to "resolutely safeguard national food security" and "accelerate the building of a strong agricultural nation," underscoring that food security constitutes a critical pillar of national welfare and people's livelihood. To ensure an effective food supply and maintain fundamental price stability, it is essential to enhance the resilience of the food supply chain, continuously strengthening its stability, security, adaptability, and coordination. The 20th National Congress of the Communist Party of China clearly points out that China needs to make concerted efforts to comprehensively enhance the resilience and security of industrial chains and supply chains. In a report to the 20th National Congress of the Communist Party of China, General Secretary Xi Jinping mentioned the security of industrial chains and supply chains twice. The first time was in the part of "Accelerating the Building of a New Development Pattern and Focusing on Promoting High-quality Development," where it was stated that efforts should be made to enhance the resilience and security level of industrial chains and supply chains； For the second time, in the section on "Promoting the Modernization of the National Security System and Capacity and Resolutely Safeguarding National Security" where it was stated that efforts should be made to enhance the resilience and security level of industrial and supply chains. Therefore, enhancing the resilience of China's food supply chain, strengthening the stability of the grain supply, and identifying and preventing the risk of chain breaks at each link of the grain supply chain has become an important topic in China's food security research.

The food supply chain is a complex network connecting various links of grain production, processing, circulation, and consumption, and its stability and resilience are directly related to the maintenance of food security. In addition, compared to the supply chains of general industrial products, the grain supply chain has obvious weaknesses in all aspects. The structural defects of the food supply chain make it extremely vulnerable to interference from the complexity of the supply chain's external environment, the instability of the implementation process, and the uncertainties of internal links. As a result, it significantly affects the safety and stability of the grain supply. Many interfering factors are intertwined, forming numerous obstacles that enhance the stability and resilience of the food supply chain. From the perspective of natural factors, climate change-induced extreme weather events—including torrential rains, droughts, and hurricanes—are undermining the very foundation of agricultural production with unprecedented frequency and intensity, resulting in reduced crop yields or even complete harvest failures [1]. From an economic perspective, market fluctuations, including significant ups and downs in grain prices, instability in energy prices, and changes in exchange rates, have a significant impact on the costs and revenues of various links in the grain supply chain. This, in turn, disrupts the orderly operation of supply chains [2]. From a social perspective, population growth and structural changes have brought about profound transformations in the grain demand structure, imposing higher requirements on the responsiveness of the supply chain. Moreover, social conflicts and instabilities, whether local wars or social unrest, have the potential to damage facilities related to grain production and circulation, plunging the supply chain into paralysis. In the field of technology, although innovation provides an opportunity to enhance the efficiency of the supply chain, imbalances in technology application, data security issues, and the risk of technical failures also pose new challenges to the stability and resilience of the food supply chain [3]. This means that resilience of the food supply chain is disrupted by multiple factors.

Under the complex and volatile realistic background and the immature theoretical background, this study integrates the resilience concept in the field of system security with the risk analysis theory to carry out risk identification in the grain supply chain and expand the existing theoretical and methodological system of supply chain risk analysis. Based on risk identification, a dynamic risk assessment method for the food supply chain, from the perspective of resilience, was developed by combining multi-attribute decision-making methods. The aim is to provide new methods and perspectives for research in this field, enrich and develop the dynamic risk assessment mechanism and research method system of the grain supply chain, improve the resilience and security level of the food supply chain, and contribute new methods and new ideas to ensure national food security.

### *1.1 Research Status*

#### *1.1.1 Research status of resilience in the food supply chain*

In recent years, influenced by domestic and international circumstances, risks in the food supply chain have increased significantly, exacerbating the challenges in grain market utilization. Thus, enhancing the resilience of the grain supply chain and stabilizing its operations has become a pressing issue that demands urgent solutions. Consequently, research on this topic has substantial practical significance. Based on the existing literature, relevant studies have primarily focused on three key dimensions: first, the structural composition of food supply chains. Dong and Wang [4] applied the theory of the supply chain control tower to expound on the basic structure of the grain supply chain. They empowered the digital development of the supply chain from three aspects: management digitalization, information transparency, and flexible decision-making, achieving prevention in advance, control during the process, and traceability after the event [4]. Yin [5] employed a multiple regression model to conduct in-depth research on the supply chain from various links such as grain production and sales, and tested the model to further analyze the factors involved in the construction of the food supply chain. Second, these factors influence the food supply chain. After a series of studies, Yin [5] found that the grain supply chain is mainly affected by the output and sales volume of grain. Third, risk analysis of the grain supply chain. According to the existing literature, Hu, Y. and Huang [6] believe that supply chain risks refer to the uncertain factors and unexpected events that affect the safe operation of the supply chain, prevent it from achieving the expected goals, and lead to the disintegration of the supply chain. Ding and Xu [7] pointed out that the upstream and downstream links of the supply chain are very closely connected. Any problem in the middle link may lead to the interruption of the supply chain operation. Therefore, it is extremely important to combat risks in the food supply chain and ensure food security.

Ultimately, enhancing the resilience of industrial and supply chains is important for improving the level of risk resistance and security. Scholars at home and abroad have conducted a series of studies focusing on the connotations of the resilience and security level of industrial and supply chains [8-12]. Zeng [13] expounded on the content and correlation of the two concepts of resilience and security level of the industrial chain and supply chain from both dynamic and static perspectives. Shi and Lu [14] believe that the resilience of industrial and supply chains refers to their ability to respond to internal and external shocks, while the security level of industrial and supply chains refers to a country's control over each link in the industrial and supply chains. Guo and Xu [15] believe that the resilience of industrial and supply chains can be defined as the ability of industrial chains to cope with internal and external shocks. These studies provide suggestions for the conceptual determination and scope division of supply chain resilience and security. Before defining the concept, supply chain resilience and security levels have objectively existed in various fields, as there is a supporting supply chain behind each product and service [16]. With the development of the market and increasing emphasis on the supply chain, levels of supply chain resilience and security have been proposed and defined. In foreign journals, some scholars have linked supply chain resilience with digital development to study the resilience of digital supply chains in the current context [17]， A large proportion of scholars still conduct research on emergencies and supply chain resilience issues in various industries [18]. These studies offer suggestions on the conceptual definition of resilience and safety levels, but few studies have explored how to quantitatively analyze and assess safety levels and resilience. Therefore, this study conducts research on a measurement method for the security level of the grain supply chain based on fuzzy numbers and the MABAC method.

### *1.1.2 Research status of MABAC method*

The Multi-Attribute Border Approximation Area Comparison (MABAC) method comprehensively evaluates the advantages and disadvantages of the scheme by comparing the distances of the scheme from the ideal solution and the negative ideal solution under each attribute. This provides a scientific basis for complex decision-making problems. The MABAC method was proposed by Pamučar and Ćirović [19]. Its core lies in constructing an approximate boundary region of attribute values and determining the ranking of schemes by calculating the distance from each scheme to the boundary region[19]. As an effective multiattribute decision-making method, the MABAC method has been widely applied and studied in multiple fields in recent years. For example, in the problem of supplier selection, Chattopadhyay, Das, and Chakraborty [20] introduced the MABAC method combined with rough numbers to select suppliers in the steel industry. By comprehensively considering multiple attributes, such as the product quality, delivery time, and price of the suppliers, the best one was screened out from numerous candidate suppliers, effectively reducing the procurement cost and ensuring the stable operation of the supply chain [20]. Đoković and Doljanica [21] applied the MABAC method to investment decisions, weighing factors such as project investment costs, environmental impacts, and efficiency, providing decision support for the rational allocation of resources, and selecting high-potential investment projects. In terms of the selection of medical plans, Chen et al.[22] developed a hybrid heterogeneous framework using methods such as MABAC to evaluate the disposal mode of emergency medical waste (EMW), providing more comprehensive and accurate decision support for the disposal of medical waste.

Furthermore, hybrid multiattribute decision-making methods have received extensive attention in recent years. Compared with the single decision-making method, the hybrid decision-making method can integrate the advantages of various methods and compensate for each other's deficiencies, thereby obtaining a more reasonable ranking of alternative schemes. For example, Liu and Zhang established a MABAC method that extends to the Normal oscillation-Hesitant Fuzzy Set (NMHFZ) to handle complex fuzzy information and applied it to the selection of cold chains, thereby obtaining stable results for multi-attribute decision-making [23]. Büyüközkan et al.[24] utilized the indecisive and ambiguous language MABAC to select the best health tourism strategy. Pamučar et al.[25] used multi-attribute boundary approximate area comparison based on D number (MABAC-D) during the management of medical waste to evaluate and select infectious waste treatment facilities. In order to handle complex and uncertain decision-making problems in multi-attribute group decision-making, Guo [26] adopted methods such as the exponential TODIM (ExpTODIM) and MABAC to evaluate the college English teaching quality of MOOC. Deveci et al. [27]proposed a new fuzzy hybrid model, which combines the multi-attribute boundary approximate area comparison (MABAC) model based on Type 2 neutron fuzzy number (T2NN) for the selection of offshore wind farms in the United States. Tan et al. [28] developed a hybrid MABAC method with Fermatean fuzzy sets and applied this new method to the field of venture capital evaluation. Therefore, this study investigates the multi-attribute group decision-making problem based on the MABAC method in a hesitant fuzzy language environment and further optimizes the MABAC method in a hesitant fuzzy language environment to solve the ranking problem of risk factors for resilient subjects in the grain supply chain.

### *1.2 Identification of Risk Factors in the Food Supply Chain from the Perspective of Resilience*

As a new form of communication, Internet new media has an advantage that traditional media cannot compare with. The new media of the Internet have the unique advantages of diversified dissemination, interactivity, rapidity, wide coverage, globality, and openness. Therefore, this study attempts to use web crawler tools to crawl information related to the grain supply chain from new media platforms on the Internet, conduct word frequency analysis on the crawled content, extract keywords, and select phrases that meet the conditions from keywords as risk factors. To obtain a higher correlation and interactivity between the final obtained risk factors and the grain supply chain, this study adopts a multi-layer screening method in the process of word frequency statistics. Firstly, the first-level risk factor indicators are obtained through the initial statistics and screening. Then, the keywords of the second-level risk factors are selected based on the meaning of each first-level risk factor indicator. This multi-layer screening method can improve the accuracy of information acquisition. A schematic diagram of the identification process for the risk factors in this grain supply chain is shown in Figure 1.

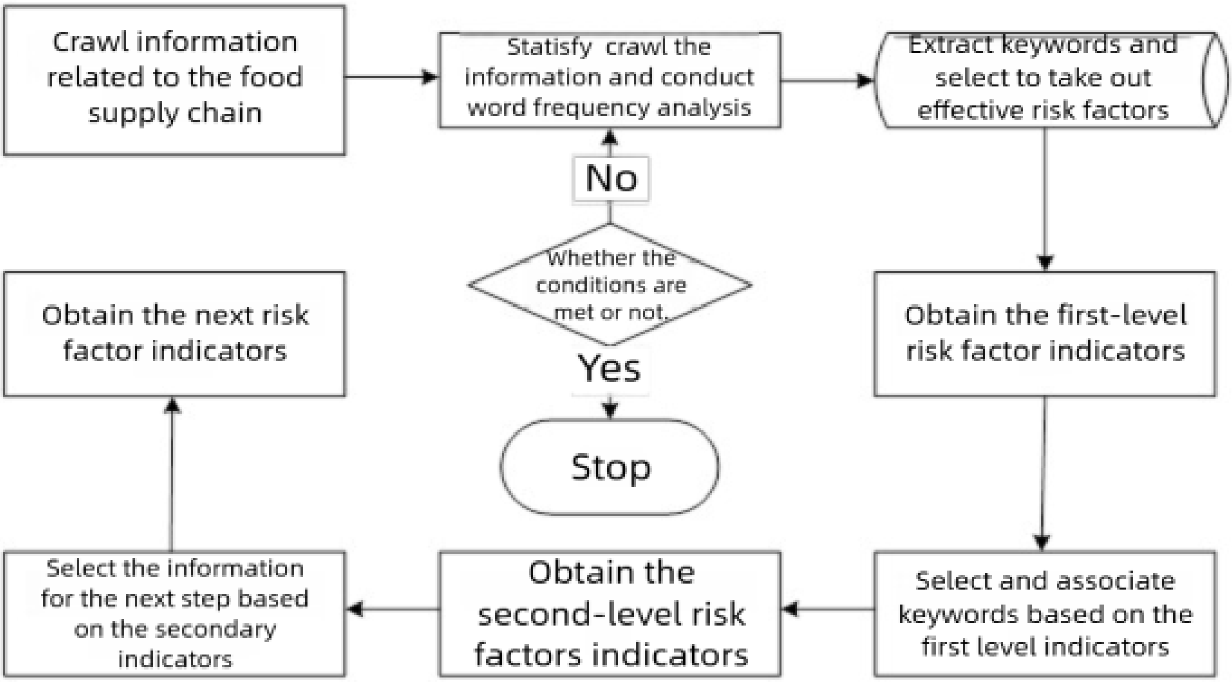


**Fig. 1.** Identification of risk factors

## 2. Methodology

The essence of the research on measuring the security level of the food supply chain is to enhance the resilience of the grain supply chain. In view of the complex characteristics, such as China's large population and the volatile international situation, the improved MABAC method was selected, and resilience was taken as the background for measuring the security level of the food supply chain to construct a risk assessment model.

### *2.1 Analysis Steps*

This section introduces the process of risk factor assessment using the integrated T-domain fuzzy MABAC method based on the WPA and Bonferroni mean operators after determining the risk factors. A flowchart is shown in Figure 2.

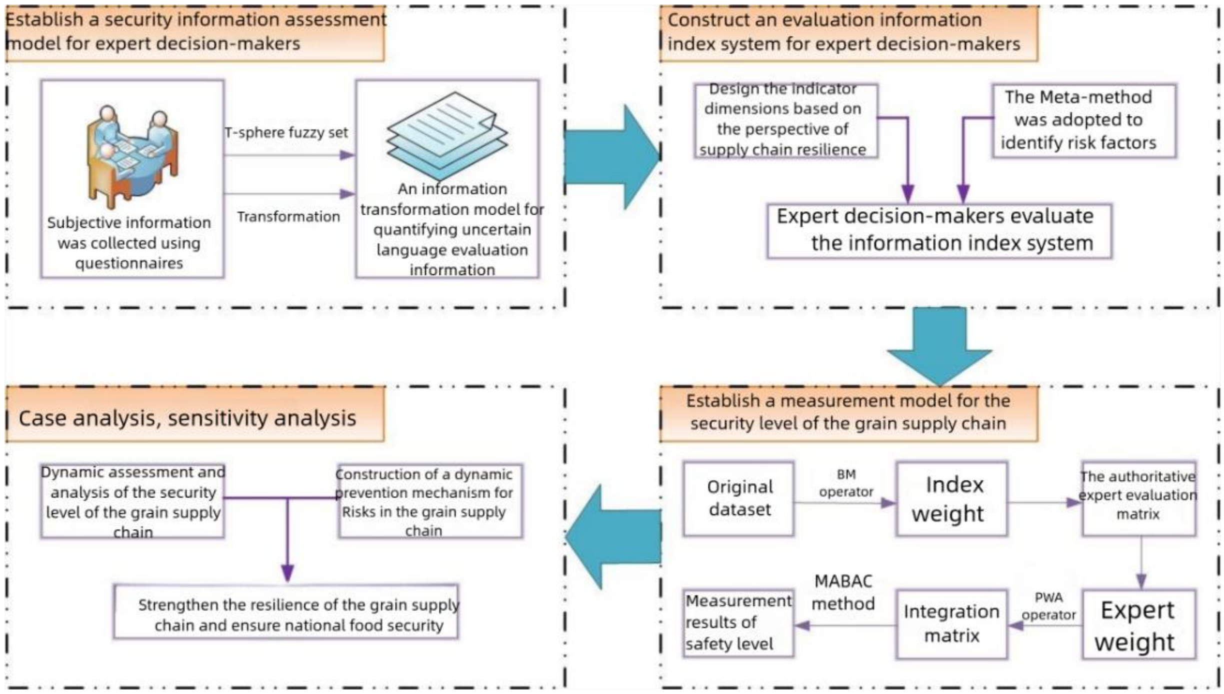


**Fig. 2.** Research method and process

### *2.1.1 Acquisition of risk assessment information*

As mentioned in the first part, risk analysis of the food supply chain based on MABAC can be regarded as an MCDM problem. In this case, we consider the risk analysis problem of the grain supply chain based on MABAC as the MCDM problem, in which we must handle the uncertain fuzziness and random language in the context during the risk assessment process of the grain supply chain. Therefore, we assume that $H_i = \{H_1, H_2, H_3, ..., H_m\}$ is a set of food supply chain risks and $c_j = \{c_1, c_2, c_3, ..., c_n\}$ is a set of risk parameters, among which the initial food supply chain risk assessment information $L^\tau = \left[l_{ij}^\tau\right]_{m\times n}$ is expressed in language terms. Suppose $w = (w_1, w_2, w_3, ..., w_n)^T$ is the weight vector of the risk parameters, where $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j = 1$.Furthermore, we assume that a group of decision-makers $e^\tau\left(\tau = 1,2,3,...,t\right)$ need to use language terms to provide risk assessment information on hazard factors in the food supply chain under risk factors. Then, $\omega = \left\{\omega_{ij}^1, \omega_{ij}^2, \omega_{ij}^3, ..., \omega_{ij}^t\right\}$ represents the importance of decision-maker $\tau$ ,which meets the following conditions: $\omega_{ij}^\tau \in [0,1]$ and $\sum_{\tau=1}^{t} \omega_{ij}^\tau = 1$ .Ultimately, this model can be used to convert language terms related to risk assessment information. This stage includes the following two steps:

Step 1: Use the risk parameters of FMEA to identify potential hazards in the food supply chain

The essence of this sub-step is to identify all potential hazards in the food supply chain from the three risk parameters. The three risk parameters in FMEA are occurrence (O), severity (S), and detectivity (D). The decision-makers' group is composed of various experts $e^\tau\left(\tau = 1,2,3,...,t\right)$ with relevant professional knowledge, experience, knowledge and background, etc. Participation is an important basis for this step.

Step 2: Convert the language terms related to the risk assessment information

Based on the language risk assessment information $L^{\tau}=\left[l_{ij}^{\tau}\right]_{m\times n}$ from different decision-makers, this model is used to convert these language variables into measurable risk rating scores. The final result can be expressed as $S^{\tau}=\left[y_{ij}^{\tau}\right]_{m\times n}$, and its form is as follows:

$$S_{ij}^{\tau}=\left[y_{ij}^{\tau}\right]_{m\times n}=\begin{bmatrix}\left(\mu_{11}^{\tau},\nu_{11}^{\tau},\pi_{11}^{\tau}\right) & \cdots & \cdots & \left(\mu_{1n}^{\tau},\nu_{1n}^{\tau},\pi_{1n}^{\tau}\right)\\ \vdots & & & \vdots\\ \vdots & & & \vdots\\ \left(\mu_{m1}^{\tau},\nu_{m1}^{\tau},\pi_{m1}^{\tau}\right) & \cdots & \cdots & \left(\mu_{mn}^{\tau},\nu_{mn}^{\tau},\pi_{mn}^{\tau}\right)\end{bmatrix} \tag{1}$$

*2.1.2 Integration of risk assessment information*

During the process of prioritizing risks, a group of decision-makers with different experiences and knowledge provides risk-rating information. Therefore, there are deviations in the risk rating information provided by these decision makers. Therefore, we introduced the WPA operator to handle this issue, as the WPA operator can reveal the impact of information bias on the risk assessment results. In addition, in the process of risk ranking, the existing calculation methods for decision-maker weight vectors seldom consider consistency. Furthermore, a high degree of consistency indicates that the risk rating results are supported by the majority of decision-makers. In this case, a distance-based similarity measurement method for maximizing the consistency of population decisions is proposed to determine the weight vectors of decision makers in an appropriate manner. Finally, in this subsection, we use the distance-based similarity measurement method to calculate the weight vectors of experts in the process of risk assessment information fusion through the WPA operator.

Step 1：Calculation of expert weight vectors based on distance similarity measure

In the risk assessment process of MABAC, the significance of each expert decision maker is predetermined, but the initial significance of expert decision makers should be unknown. Considering consistency, the importance of decision-makers providing information in a group is quite different from that of the information provided by most experts and should be given a rather small proportion. Therefore, we introduced a distance-based similarity measure to solve for the weight vector of each expert. Suppose that $l_{ij}^{\tau}=\left(\mu_{ij}^{\tau},\nu_{ij}^{\tau},\pi_{ij}^{\tau}\right)$ is the risk score derived based on the language risk assessment information of the $i$ food supply chain hazard under the $j$ risk parameter provided by the decision-maker. Finally, the average value of the risk assessment values can be defined as follows:

$$\bar{l}_{ij}=\left(\overline{\mu}_{ij}^{\tau},\overline{\nu}_{ij}^{\tau},\overline{\pi}_{ij}^{\tau}\right)=\frac{1}{t}\left(l_{ij}^{1}+l_{ij}^{2}+\cdots+l_{ij}^{t}\right) \tag{2}$$

Based on the distance-based similarity measurement mentioned in it, we calculate the similarity degree between $l_{ij}^{\tau}$ and $\bar{l}_{ij}$ as follows:

$$S\left(l_{ij}^{\tau},\overline{l_{ij}}\right)=1-\frac{d\left(l_{ij}^{\tau},\overline{l_{ij}}\right)}{\sum_{\tau=1}^{t}d\left(l_{ij}^{\tau},\overline{l_{ij}}\right)} \tag{3}$$

Among them, $d\left(l_{ij}^{\tau},\overline{l_{ij}}\right)$ is the distance between $l_{ij}^{\tau}$ and $\bar{l}_{ij}$, which can be calculated using the Euclidean distance equation, as shown in Equation (4).And $b_1=\langle\mu_1,\nu_1,\pi_1\rangle$, $b_2=\langle\mu_2,\nu_2,\pi_2\rangle$, $q=2$。

$$d\left(b_1,b_2\right)=\left(\left|\mu_1^q-\mu_2^q\right|^2+\left|\nu_1^q-\nu_2^q\right|^2+\left|\pi_1^q-\pi_2^q\right|^2\right)^{\frac{1}{2}} \tag{4}$$

Next, we calculate the ideal similarity measures of regularity and negativity as follows:

$$S^+\left(l_{ij}^{\tau},\overline{l_{ij}}\right)=\left[x_{ij}^+\right]_{m\times n},x_{ij}^+=\frac{1}{t}\sum_{\tau=1}^{t}S\left(l_{ij}^{\tau},\overline{l_{ij}}\right) \tag{5}$$

$$S^-\left(l_{ij}^{\tau},\overline{l_{ij}}\right)=\left[x_{ij}^-\right]_{m\times n},x_{ij}^-=\min_{1\le\tau\le t}\left(S\left(l_{ij}^{\tau},\overline{l_{ij}}\right)\right) \tag{6}$$

Ultimately, the weight vector $\omega_{\tau}$ of the $\tau$th decision-maker can be defined as follows:

$$\omega_{\tau}=\frac{\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(S\left(l_{ij}^{\tau},\overline{l_{ij}}\right)-S^-\left(l_{ij}^{\tau},\overline{l_{ij}}\right)\right)^2}}{\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(S\left(l_{ij}^{\tau},\overline{l_{ij}}\right)-S^+\left(l_{ij}^{\tau},\overline{l_{ij}}\right)\right)^2}+\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(S\left(l_{ij}^{\tau},\overline{l_{ij}}\right)-S^-\left(l_{ij}^{\tau},\overline{l_{ij}}\right)\right)^2}} \tag{7}$$

Step 2：Integrate information by applying the WPA operator

Definition 1: Suppose $y_{ij}^{\tau}=\left[\mu_{ij}^{\tau},\nu_{ij}^{\tau},\pi_{ij}^{\tau}\right]$ is the relevant triplet language risk rating score for the $i$th food supply chain hazard under the $j$th risk parameter provided by decision-maker $e^{\tau}$. Therefore, the interval triplet language WPA operator used for risk information integration can be defined as follows:

$$y_{ij}=WPA-\left(y_{ij}^{1},y_{ij}^{2},\cdots,y_{ij}^{t}\right)=\sum_{\tau=1}^{t}\frac{\omega_{\tau}\left(1+f\left(y_{ij}^{\tau}\right)\right)}{\sum_{\tau=1}^{t}\omega_{\tau}\left(1+f\left(y_{ij}^{\tau}\right)\right)}\cdot y_{ij}^{\tau}, \tag{8}$$

Among them, $f\left(y_{ij}^{\tau}\right)$ is defined as

$$f\left(y_{ij}^{\tau}\right)=\sum_{\tau'=1,\tau\ne\tau'}^{t}Sup\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right), \tag{9}$$

Among them, the support function $Sup\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right)$ represents the support degree from $y_{ij}^{\tau'}$ to $y_{ij}^{\tau}$, and this support function must meet the following restrictive requirements:

①$Sup\left(\tilde{y}_{ij}^{\tau},\tilde{y}_{ij}^{\tau'}\right)\in[0,1]$

②$Sup\left(\tilde{y}_{ij}^{\tau},\tilde{y}_{ij}^{\tau'}\right)=Sup\left(\tilde{y}_{ij}^{\tau},\tilde{y}_{ij}^{\tau'}\right)$

③$Sup\left(\tilde{y}_{ij}^{\tau},\tilde{y}_{ij}^{\tau'}\right)\ge Sup\left(\tilde{y}_{ij}^{\tau},\tilde{y}_{ij}^{\tau'}\right),if\left|\tilde{y}_{ij}^{\tau}-\tilde{y}_{ij}^{\tau'}\right|<\left|\tilde{y}_{ij}^{\tau}-\tilde{y}_{ij}^{\tau'}\right|$

In this case, we introduced a similarity measure based on the distance between the risk scores of triplet languages to calculate the support function. The support function based on similarity measurement can be derived using the following equation:

$$Sup\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right)=S\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right)=1-d\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right) \tag{10}$$

Among them, $Sup\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right)$ is a distance-based support function, and $d\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right)$ represents the distance between $y_{ij}^{\tau'}$ and $y_{ij}^{\tau}$, which can be expressed as:

$$d\left(y_{ij}^{\tau},y_{ij}^{\tau'}\right)=\left[\left|\mu_{ij}^{\tau2}-\mu_{ij}^{\tau'2}\right|^2-\left|\nu_{ij}^{\tau2}-\nu_{ij}^{\tau'2}\right|^2\left|\pi_{ij}^{\tau2}-\pi_{ij}^{\tau'2}\right|^2\right]^{\frac{1}{2}} \tag{11}$$

### *2.1.3 Calculation of risk priority ranking*

When applying the MABAC method for risk ranking, it is necessary to first generate the weighted T-interval risk matrix and then calculate the score of each risk factor in the grain supply chain more accurately. Therefore, this section includes two sections: the calculation of index weights and the risk priority ranking based on the MABAC method of the T-spherical fuzzy set.

Step 1： Calculation of index weights

We defined the optimistic and pessimistic risk scores for each risk parameter.

$$K = \begin{cases} K^{+} = \left(k_1^{+}, k_2^{+}, \ldots, k_n^{+}\right) \\ K^{-} = \left(k_1^{-}, k_2^{-}, \ldots, k_n^{-}\right) \end{cases} \tag{12}$$

Among them, elements $k_j^{+}$ and $k_j^{-}$ are defined as:

$$k_j^{+} = \begin{cases} \max\limits_i y_{ij}^{\tau}, & if\ j \le g \\ \min\limits_i y_{ij}^{\tau}, & if\ j > g \end{cases} \tag{13}$$

$$k_j^{-} = \begin{cases} \min\limits_i y_{ij}^{\tau}, & if\ j \le g \\ \max\limits_i y_{ij}^{\tau}, & if\ j > g \end{cases} \tag{14}$$

Among them, $g$ represents the revenue standard number, and $j = g+1, g+2, \ldots, n$ is used as the cost standard number.

Calculate the distance between each risk parameter and the optimistic and pessimistic risk scores.

By defining the distances between the parameters in the T-spherical fuzzy set, the distances between each risk parameter and the optimistic and pessimistic risk scores can be calculated as follows:

$$d_j^{+} = \sum\nolimits_{i=1}^{m} d\left|y_{ij}^{\tau}, k_j^{+}\right| \tag{15}$$

$$d_j^{-} = \sum\nolimits_{i=1}^{m} d\left|y_{ij}^{\tau}, k_j^{-}\right| \tag{16}$$

Among them, the distance equations between $y_{ij}^{\tau}$ and $k_j^{+}$, $y_{ij}^{\tau}$ and $k_j^{-}$ are calculated using the Euclidean distance equation, that is, Equation (4), where $q = 2$ .

Determining discrete values of each risk parameter. If the discrete value of the risk parameter is large, the risk parameter becomes more important. The dispersion value of each risk parameter $c_j\left(j = 1, 2, \ldots, n\right)$ can be expressed as follows:

$$w_j = \frac{d_j^{+}}{\left(d_j^{+} + d_j^{-}\right)} \tag{17}$$

Step 2: Risk priority ranking based on the MABAC method for T-spherical fuzzy sets.

Generate a weighted T-interval risk matrix.

$$R = \left[r_{ij}\right]_{m \times n} \tag{18}$$

Among them, $r_{ij} = w_j y_{ij}$ , in this equation, $w_j$ are the weights of the risk parameters, and $r_{ij}$ is the T-spherical fuzzy set.

Calculate the boundary approximate area vector $\left(r_j\right)_{1 \times n}$ for each risk parameter. The $r_j$ elements are calculated as follows:

$$r_j = \left( \overset{m}{\underset{i=1}{\otimes}} r_{ij} \right)^{\frac{1}{m}} \tag{19}$$

Determine the distance measurement matrix.

$$D_{ij} = \begin{cases} d\left(r_{ij}, r_j\right), r_{ij} > r_j \\ 0, r_{ij} = r_j \\ -d\left(r_{ij}, r_j\right), r_{ij} < r_j \end{cases} \tag{20}$$

Among them, $d\left(r_{ij}, r_j\right)$ represents the distance between $r_{ij}$ and $r_j$ , which can be calculated like Equation (4).

The geometric Bonferroni mean (GBM) operator is used to calculate the score of risk for each occupation.

$$RS_i = \frac{1}{\rho+\delta}\left[\prod_{\substack{j,j'=1 \\ j\neq j'}}^{n}\left(\rho D_{ij} \oplus \delta D_{ij}'\right)\right]^{\frac{1}{n(n-1)}} \tag{21}$$

## 3. Results

### *3.1 Application of the Method*

In this section, taking the grain supply chain as an example, web crawlers and content mining techniques are applied to identify the risks of the grain supply chain, and the T-spherical fuzzy MABAC method is used to analyze the risks of the food supply chain.

#### *3.1.1 Identification of risk factors*

First, we used the Web Scraper Web crawler software to crawl the relevant content of the risks in the grain supply chain on Weibo. Among numerous online new media platforms, as far as the investigation is known, Weibo has existed for a long time and covers a wide range of subjects. Many of its viewpoints largely conform to the multi-angle characteristics of this study. Therefore, this article takes Weibo as the platform for capturing the initial information. Then, we cleaned the initial crawled data and screened out the data we needed around the theme of risks in the grain supply chain. Subsequently, we used ROST CM software to perform word segmentation on the data and then conducted word frequency analysis. The results of the word frequency analysis are shown in Figure 3. After extracting the keywords, the primary risk factor indicators were obtained. Finally, the keywords were statistically analyzed and a secondary manual screening was conducted to screen out the high-frequency words, thereby extracting the secondary risk factor indicators. After a series of operations, this paper identified ten high-frequency risk factors, namely agriculture, economy, energy, industrial chain, emergencies, market, government, famine, climate, and environment, and conducted a risk analysis on these ten risk hazard factors. The analytical process is described in detail in the next subsection.

#### *3.1.2 Transformation of risk information*

According to the above, this paper uses $Rfi(i = 1,2, \ldots 10)$ to represent ten risk factors including agriculture, economy, energy, industrial chain, emergencies, market, government, famine, climate and environment, as shown in Table 1. In this case, the T-spherical fuzzy MABAC method was introduced to evaluate and prioritize the risks of the food supply chain. First, three experts with excellent relevant professional knowledge were invited. Then, we used the T-spherical fuzzy corresponding linguistic scale given in Table 2 to assess the risks of these ten risk factors from three risk parameters.

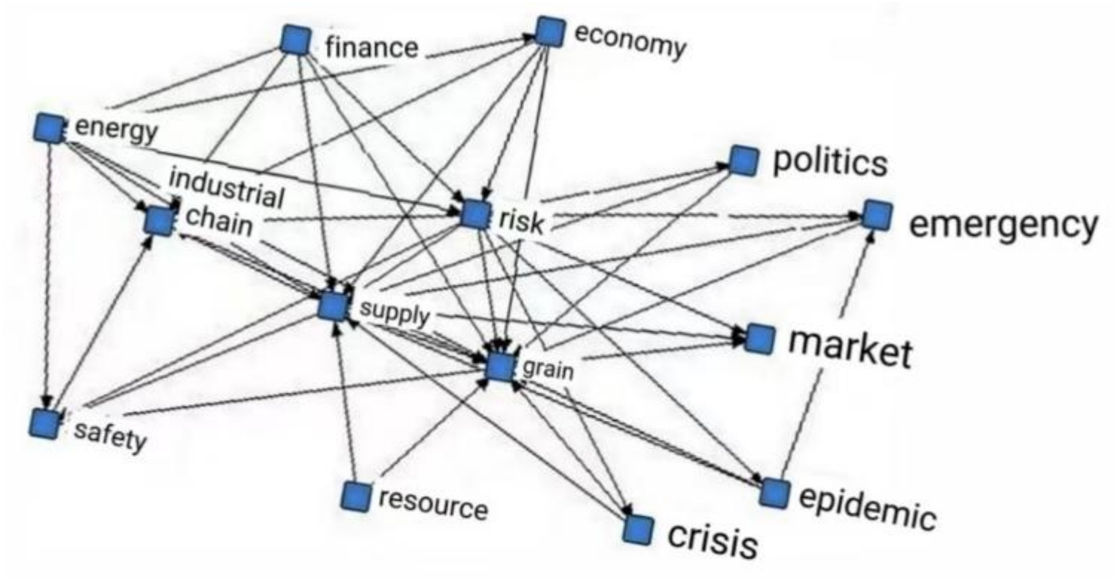


**Fig. 3.** Word frequency analysis result

**Table 1**
Risk Factors

| Serial number | Risk factor |
|---|---|
| $Rf_1$ | Agriculture |
| $Rf_2$ | Economy |
| $Rf_3$ | Energy |
| $Rf_4$ | Industrial chain |
| $Rf_5$ | Emergency |
| $Rf_6$ | Market |
| $Rf_7$ | Government |
| $Rf_8$ | Famine |
| $Rf_9$ | Climate |

**Table 2**
Language scaling

| Language scaling | T-SFN |
|---|---|
| VL | (0.85,0.15,0.10) |
| L | (0.75,0.25,0.20) |
| M | (0.55,0.50,0.25) |
| H | (0.25,0.75,0.20) |
| VH | (0.15,0.85,0.10) |

The risk assessment linguistic variables provided by experts are shown in Table 3. Finally, the T-spherical fuzzy MABAC method is applied to calculate the risk priority of the ten risk factors in the grain supply chain and rank all the risk factors in terms of priority. The specific calculation and ranking process of the risk factor priority is presented in this section.

**Table 3**
The language risk assessment level of experts

| Risk factors | E1 | | | E2 | | | E3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | O | S | D | O | S | D | O | S | D |
| Rf1 | L | VH | M | H | VH | M | L | VH | M |
| Rf2 | H | VH | VL | H | VH | M | H | VH | M |
| Rf3 | L | VH | VL | H | VH | VL | L | VH | VL |
| Rf4 | H | H | VL | H | VH | H | M | H | VL |
| Rf5 | H | VH | VH | H | VH | VH | VH | VH | VH |
| Rf6 | H | VH | M | H | VH | M | H | VH | M |
| Rf7 | L | H | M | H | H | M | VL | H | L |
| Rf8 | H | VH | M | H | VH | M | M | H | H |
| Rf9 | L | VH | H | L | VH | H | L | VH | H |
| Rf10 | H | H | VL | H | H | VL | H | H | VL |

### *3.1.3 Integration of risk assessment information*

First, through the language scale related to the T-SFN, the language risk assessment information given by each expert is converted into a digital risk assessment information matrix. The risk assessment matrices for each expert are listed in Tables 4-6.

**Table 4**
The fuzzy risk assessment matrix from Expert 1

| Risk factors | O | S | D |
|---|---|---|---|
| | ($\mu$, $v$, $\pi$) | ($\mu$, $v$, $\pi$) | ($\mu$, $v$, $\pi$) |
| $Rf_1$ | (0.75,0.25,0.20) | (0.15,0.85,0.10) | (0.75,0.25,0.20) |
| $Rf_2$ | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.75,0.25,0.20) |
| $Rf_3$ | (0.75,0.25,0.20) | (0.15,0.85,0.10) | (0.75,0.25,0.20) |
| $Rf_4$ | (0.25,0.75,0.20) | (0.25,0.75,0.20) | (0.75,0.25,0.20) |
| $Rf_5$ | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.75,0.25,0.20) |
| $Rf_6$ | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.75,0.25,0.20) |
| $Rf_7$ | (0.75,0.25,0.20) | (0.25,0.75,0.20) | (0.75,0.25,0.20) |
| $Rf_8$ | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.75,0.25,0.20) |
| $Rf_9$ | (0.75,0.25,0.20) | (0.15,0.85,0.10) | (0.75,0.25,0.20) |
| $Rf_{10}$ | (0.25,0.75,0.20) | (0.25,0.75,0.20) | (0.75,0.25,0.20) |

**Table 5**
The fuzzy risk assessment matrix from Expert 2

| Risk factors | O | S | D |
|---|---|---|---|
| | ($\mu$, $v$, $\pi$) | ($\mu$, $v$, $\pi$) | ($\mu$, $v$, $\pi$) |
| Rf1 | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.55,0.50,0.25) |
| Rf2 | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.55,0.50,0.25) |
| Rf3 | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.85,0.15,0.10) |
| Rf4 | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.25,0.75,0.20) |
| Rf5 | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.15,0.85,0.10) |
| Rf6 | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.55,0.50,0.25) |
| Rf7 | (0.25,0.75,0.20) | (0.25,0.75,0.20) | (0.55,0.50,0.25) |
| Rf8 | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.55,0.50,0.25) |
| Rf9 | (0.75,0.25,0.20) | (0.15,0.85,0.10) | (0.25,0.75,0.20) |
| Rf10 | (0.25,0.75,0.20) | (0.25,0.75,0.20) | (0.85,0.15,0.10) |

**Table 6**
The fuzzy risk assessment matrix from Expert 3

| Risk factors | O | S | D |
|---|---|---|---|
| | ($\mu$, $v$, $\pi$) | ($\mu$, $v$, $\pi$) | ($\mu$, $v$, $\pi$) |
| $Rf_1$ | (0.75,0.25,0.20) | (0.15,0.85,0.10) | (0.55,0.50,0.25) |
| $Rf_2$ | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.55,0.50,0.25) |
| $Rf_3$ | (0.75,0.25,0.20) | (0.15,0.85,0.10) | (0.85,0.15,0.10) |
| $Rf_4$ | (0.55,0.50,0.25) | (0.25,0.75,0.20) | (0.85,0.15,0.10) |
| $Rf_5$ | (0.15,0.85,0.10) | (0.15,0.85,0.10) | (0.15,0.85,0.10) |
| $Rf_6$ | (0.25,0.75,0.20) | (0.15,0.85,0.10) | (0.55,0.50,0.25) |
| $Rf_7$ | (0.85,0.15,0.10) | (0.25,0.75,0.20) | (0.75,0.25,0.20) |
| $Rf_8$ | (0.55,0.50,0.25) | (0.25,0.75,0.20) | (0.25,0.75,0.20) |
| $Rf_9$ | (0.75,0.25,0.20) | (0.15,0.85,0.10) | (0.25,0.75,0.20) |
| $Rf_{10}$ | (0.25,0.75,0.20) | (0.25,0.75,0.20) | (0.85,0.15,0.10) |

The WPA operator is then used to aggregate the risk information matrices of the experts. To apply the WPA operator, we must calculate the weight vector of each expert using Equations (2)- (7). The specific calculation process of each expert's weight vector is as follows.

Step 1：The average value of the risk assessment value is calculated using Equation (2). This part takes the assessment information regarding Rf1 given by Expert 1 under the risk parameter O as an example.

Step 2： In order to calculate the similarity degree between $l_{11}^{1}$ and $\bar{l}_{11}$, the Euclidean distance Equation (4) is first applied to calculate the distance between $l_{ij}^{\tau}$ and $\bar{l}_{ij}$, and it can be obtained

$$d\left(l_{11}^{1},\overline{l_{11}}\right)=\left(\left|0.75^{2}-0.583^{2}\right|^{2}+\left|0.25^{2}-0.417^{2}\right|^{2}+\left|0.20^{2}-0.200^{2}\right|^{2}\right)^{\frac{1}{2}}=0.248$$

Next, Equations (3), (5), and (6) can be applied to calculate the similarity degree between $l_{11}^{1}$ and $\bar{l}_{11}$, obtaining the ideal similarity measures of regularity and negativity.

$S\left(l_{11}^{1},\overline{l_{11}}\right)=0.745$，

$S^{+}\left(l_{11}^{1},\overline{l_{11}}\right)=\frac{1}{3}\sum_{\tau=1}^{3}S\left(l_{11}^{\tau},\overline{l_{11}}\right)=0.667$ and $S^{-}\left(l_{11}^{1},\overline{l_{11}}\right)=\min_{1\le\tau\le3}\left(S\left(l_{11}^{\tau},\overline{l_{i11}}\right)\right)=0.510$ .

Step 3：After calculating all the data, Equation (7) was applied to calculate the weights of the three experts as $\{\omega_1,\omega_2,\omega_3\}=\{0.808,0.694,0.618\}$ .

Next, after knowing the weight vectors of each expert, we can use Equations (8) to (11) and apply the WPA operator to integrate the risk assessment information. Then, we can obtain the language risk rating score of the $i$th occupational hazard under the risk parameters provided by the decision-makers, as shown in Table 7.

**Table 7**
Information integration matrix

| O | S | D |
|---|---|---|
| （0.277,0.437,0.200） | （0.150,0.850,0.100） | （0.550,0.500,0.250） |
| （0.250,0.750,0.200） | （0.150,0.850,0.100） | （0.644,0.390,0.203） |
| （0.601,0.399,0.200） | （0.150,0.850,0.100） | （0.850,0.150,0.100） |
| （0.319,0.693,0.215） | （0.213,0.787,0.163） | （0.688,0.312,0.127） |
| （0.225,0.775,0.174） | （0.150,0.850,0.100） | （0.150,0.850,0.100） |
| （0.250,0.750,0.200） | （0.150,0.850,0.100） | （0.550,0.500,0.250） |

**Table 7**
Continued

| O | S | D |
|---|---|---|
| (0.628,0.372,0.176) | (0.250,0.750,0.200) | (0.597,0.441,0.238) |
| (0.319,0.693,0.211) | (0.175,0.825,0.125) | (0.481,0.557,0.239) |
| (0.750,0.250,0.200) | (0.150,0.850,0.100) | (0.250,0.750,0.200) |
| (0.250,0.750,0.200) | (0.250,0.750,0.200) | (0.850,0.150,0.100) |

### *3.1.4 Weighted risk matrix*

More importantly, if we want to obtain the weighted T-spherical risk matrix, we first need to calculate the weight vector of each risk parameter. In order to obtain the optimistic and pessimistic risk scores of each risk parameter, the score function values of each influencing factor under the risk factors were calculated using Definition 1, as shown in Table 8.

Definition 1. According to T-SFSs $S=\left(\mu_x,\nu_x,\pi_x\right),q\geq 1$,then, the definition of the score function is as follows:

$$F\left(S\right)=\frac{\left(1+\mu_x^q+\nu_x^q+\pi_x^q\right)}{2},F\left(S\right)\in\left[0,1\right] \quad (22)$$

$$T\left(S\right)=\mu_x^q+\nu_x^q+\pi_x^q,T\left(S\right)\in\left[0,1\right] \quad (23)$$

In order to explain the potential relationship between T-SFSs, the following rules were formulated:

1.If $F\left(S_1\right)<F\left(S_2\right)$, then $\left(S_1\right)<\left(S_2\right)$;

2.If $F\left(S_1\right)=F\left(S_2\right)$, then

(1). If $T\left(S_1\right)<T\left(S_2\right)$, then $S_1<S_2$;

(2). If $T\left(S_1\right)=T\left(S_2\right)$, then $S_1=S_2$.

**Table 8**
Score function value

| O | S | D |
|---|---|---|
| (0.203, 0.319,0.146) | (0.067,0.380,0.045) | (0.291,0.265,0.132) |
| (0.183,0.548,0.146) | (0.067,0.380,0.045) | (0.341,0.207,0.107) |
| (0.439,0.292,0.146) | (0.067,0.380,0.045) | (0.450,0.079,0.053) |
| (0.233,0.506,0.157) | (0.095,0.352,0.073) | (0.364,0.165,0.067) |
| (0.165,0.566,0.127) | (0.067,0.380,0.045) | (0.079,0.450,0.053) |
| (0.183,0.548,0.146) | (0.067,0.380,0.045) | (0.291,0.265,0.132) |
| (0.459,0.272, 0.129) | (0.112,0.335,0.089) | (0.316,0.233,0.126) |
| (0.233,0.506,0.155) | (0.078,0.369,0.056) | (0.255,0.295,0.126) |
| (0.548,0.183,0.146) | (0.067,0.380,0.045) | (0.132,0.397,0.106) |
| (0.183,0.548,0.146) | (0.112,0.335,0.089) | (0.450,0.079,0.053) |

Therefore, the optimistic and pessimistic risk scores for each risk parameter are $K^+=\left[0.841,0.878,0.878\right]$and $K^-=\left[0.654,0.833,0.793\right]$ , then apply it to calculate the distance between each risk parameter and the optimistic and pessimistic risk scores

$d_j^+=\sum_{i=1}^{10}d\left|y_{ij}-k_j^+\right|=\left[0.332,0.141,0.499\right]$ $d_j^-=\sum_{i=1}^{10}d\left|y_{ij}-k_j^-\right|=\left[0.390,0.829,0.318\right]$.

The discrete values of the risk parameter O can be calculated as follows：$w_1 = \frac{d_1^+}{\left(d_1^+ + d_1^-\right)} = \frac{0.332}{0.332 + 0.390} = 0.460$

In the same way, the discrete values of the risk parameters S and D are calculated, and the result is: $w_2 = 0.145, w_3 = 0.611$ 。Finally, the weighted T-sphere risk matrix can be expressed as Table 9.

**Table 9**
Weighted T-ball risk matrix

| O | S | D |
|---|---|---|
| （0.654,0.878,0.808） | （0.179,0.000,0.070） | （0.144,0.097,0.011） |
| （0.833,0.878,0.804） | （0.000,0.000,0.074） | （0.035,0.097,0.007） |
| （0.780,0.878,0.878） | （0.053,0.000,0.000） | （0.018,0.097,0.081） |
| （0.814,0.846,0.793） | （0.019,0.032,0.085） | （0.016,0.065,0.004） |
| （0.841,0.878,0.878） | （0.008,0.000,0.000） | （0.043,0.097,0.081） |
| （0.833,0.878,0.808） | （0.000,0.000,0.070） | （0.035,0.097,0.011） |
| （0.782,0.616,0.828） | （0.051,0.046,0.074） | （0.016,0.052,0.007） |
| （0.813,0.778,0.878） | （0.020,0.014,0.078） | （0.015,0.083,0.003） |
| （0.833,0.563,0.893） | （0.000,0.000,0.046） | （0.035,0.097,0.036） |
| （0.833,0.833,0.833） | （0.000,0.046,0.000） | （0.035,0.052,0.081） |

### *3.1.5 Risk priority calculation and ranking*

Based on this matrix, the distance-based measure matrix can be calculated through Equations (19) and (20). Finally, using the BM operator, the risk score of each risk factor is calculated through Equation (21). Therefore, the final risk ranking results are shown in Table 10 as follows.

**Table 10**
Sorting result

| Risk factors | RS | Sorting |
|---|---|---|
| Rf1 | 0.248 | 8 |
| Rf2 | 0.308 | 2 |
| Rf3 | 0.270 | 6 |
| Rf4 | 0.291 | 4 |
| Rf5 | 0.323 | 1 |
| Rf6 | 0.293 | 3 |
| Rf7 | 0.214 | 10 |
| Rf8 | 0.260 | 7 |
| Rf9 | 0.271 | 5 |
| Rf10 | 0.238 | 9 |

As shown in Table 10, the final risk priority ranking of the ten risk factors in the grain supply chain is determined by the value of, and the ranking results are Rf5, Rf2, Rf6, Rf4, Rf9, Rf3, Rf8, Rf1, Rf10, and Rf7.

After obtaining the ranking results of the risk factors faced by the grain supply chain, the risk factors at the top of the ranking often indicate a lower safety level with more potential safety hazards and uncertainties.

### *3.2 Implications for Enhancing the Resilience of the Food Supply Chain*

#### *3.2.1. Strengthen emergency prevention and control measures*

Establish and improve a regular mechanism for preventing and controlling emergencies and strictly implement epidemic prevention policies in all links of grain production, processing, transportation, and storage, such as regular nucleic acid testing for employees and disinfection of workplaces. Strengthen international cooperation, jointly respond to global public health emergencies, share experiences and information on the prevention and control of emergencies, and reduce the risk of the spread of emergencies in the international food supply chain.

#### *3.2.2 Promote steady economic development*

The government has introduced special support policies for the grain industry, such as tax incentives and financial subsidies, to reduce the operating costs of grain enterprises and enhance their economic strength. Increasing investment in the infrastructure construction of the grain industry, improving storage and logistics conditions, enhancing the overall efficiency of the supply chain, and ensuring stable operation amidst economic fluctuations.

#### *3.2.3 Strengthen market monitoring and regulation*

Build a comprehensive market monitoring system to grasp real-time information such as grain price trends, inventory changes, and import and export dynamics, and conduct market analysis and prediction using big data, artificial intelligence, and other technologies. Based on market conditions, measures such as the release of reserve grain and the regulation of imports and exports to stabilize the supply, demand, and prices of the grain market and prevent significant market fluctuations.

#### *3.2.4 Optimize the supply chain management strategy*

Make full use of scientific methods such as T-spherical fuzzy sets, PWA operators, and MABAC models to accurately identify, quantitatively evaluate, and rank risks in the grain supply chain. Based on the evaluation results, the supply chain layout should be optimized in a targeted manner, the grain production areas should be rationally planned to reduce the dependence on a single production area, the transportation routes should be optimized to improve the efficiency and flexibility of logistics distribution, and a multi-level warehousing system should be established to ensure the safety of grain reserves and the convenience of grain allocation and transportation.

#### *3.2.5 Continuous Refinement of the Evaluation Indicator System*

Through content mining, extensive research literature and practical cases related to domestic and international grain supply chains are collected. New risk elements and evaluation indicators are analyzed and refined, and the risk evaluation index system for the resilience of the grain supply chain is constantly updated and improved. Regularly review and verify the indicator system to ensure its scientific, accuracy, and timeliness, thereby providing a reliable basis for the risk assessment of the food supply chain.

## 4.Conclusion and Prospect

### *4.1 Research Conclusions*

As a necessity for people's daily lives, grain has always been an object of key protection in various countries. The efficiency and security of a supply chain are closely related to the stability of a country and society. However, against the backdrop of financial crises and unexpected incidents, the grain supply chain is highly vulnerable to interference from external environments and internal risks, leading to turmoil in the global grain market and posing challenges to national food security.

Therefore, it is of the utmost importance to conduct an analysis and prevention of risks within the grain supply chain. This study aims to analyze the risks in the operation of the grain supply chain against the backdrop of unexpected incidents. Through a literature review and extensive data retrieval, this research identifies and forecasts the risk factors in the process of analyzing the risks of the grain supply chain. First, the risk factors related to the grain supply chain were obtained using the crawler software Web Scraper. Then, the initial crawled data were cleaned to screen out the required data. Subsequently, word frequency analysis was conducted using ROST CM software to screen for risk factor indicators. Then, the integrated T-domain fuzzy MABAC method based on the WPA operator and Bonferroni mean operator was used for risk factor assessment. During the assessment process, we introduced a distance-based similarity measure to solve for the weight vector of each expert. Finally, the results of the risk assessment were obtained as follows: emergencies constitute the primary factor influencing risks in China's grain supply chain, which underscores the imperative to enhance predictive and analytical capabilities for unexpected events during supply chain operations. This necessitates substantial improvements in the development of information infrastructure for grain supply chains as well as the establishment of a comprehensive disaster risk management system. Such measures will provide effective solutions for future risk management, thereby reducing the risk exposure level of grain supply chain systems and strengthening the supply chain resilience.

### *4.2 Limitations and future directions*

Owing to the limited available data, continuous changes, and strong complexity of things, the ranking results of this study inevitably have a defect in timeliness. The original data matrix is obtained by determining the scale of the different influencing factors through expert scoring. The data therein are based on the personal experience of experts, and the data samples are limited. Therefore, there may be certain deviations and subjectivity in the analysis of the results. Hence, this study had certain limitations.

Stability of the grain supply chain is key to ensuring food security. In subsequent research, if we aim to effectively enhance the resilience and stability of the grain supply chain, it is necessary to broaden the perspective by considering its influencing factors. In the quantitative research stage, the sample size should be expanded to improve the accuracy of the research results, precisely identify the key factors influencing resilience, and propose effective suggestions accordingly.

## Author Contributions

Conceptualization, Y.S., X.Y. and C.S.; methodology, Y.S., X.Y. and C.S.; software, Y.S.; validation, X.Y. and C.S.; formal analysis, X.Y. and C.S.; investigation, Y.S., X.Y. and C.S.; writing—original draft preparation, Y.S., X.Y. and C.S.; writing—review and editing, Y.S., X.Y. and C.S.; visualization, X.Y. and C.S.; supervision, Y.S., X.Y. and C.S. All authors have read and agreed to the published version of the manuscript.

## Funding

This research received no external funding.

## Conflicts of Interest

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

## Data Availability Statement
The datasets generated during and/or analyzed during the current study is available from the corresponding author on reasonable request.

## Acknowledgement
This research was not funded by any grant.

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