

An integrated T-spherical fuzzy GLDS method for evaluating resiliency in the food supply chain

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ARTICLE INFO

Article history:

Received 1 September 2024
Received in revised form 10 January 2025
Accepted 4 March 2025
Available online 4 March 2025

Keywords:

Food Supply Chain(FSC); T-spherical fuzzy set; GLDS method; PWA operator; the entropy measure

ABSTRACT

A resilient food supply chain is vital for maintaining the stability and efficiency of food distribution systems. This study introduces a novel approach that integrates a T-spherical fuzzy set with the Group Linear Distance System (GLDS) method to evaluate resiliency in the food supply chain. The T-spherical fuzzy set is utilized to handle the food supply chain's uncertainties and vagueness in assessing resiliency factors, such as farmers, processors, wholesalers, supermarkets, and small retailers. The TSF-GLDS method is integrated with the PWA operator and using entropy measurement, the significance weights of these factors are determined and the resiliency index is calculated. The approach provides a comprehensive and reliable tool for decision-makers to assess and enhance the resiliency of food supply chains. This article verifies the constructed method's validity and practicality through examples. The results demonstrate its ability to quantitatively measure the degree of resiliency and provide insights for optimizing food supply chain operations. To summarize, this integrated approach contributes to the better understanding and managing resiliency in food supply chains, ultimately leading to more robust and reliable systems.

1. Introduction

Food, as the most basic consumer goods, has always been the focus object of governments to protect. What's more, food supply safety affects the stability of nation and society. However, compared with the general industrial supply chain, the FSC has obvious weaknesses in every link, and the structural defects of the FSC make it extremely vulnerable to the interference of complex external environment and internal risks, which seriously affects the security and steadiness of grain supply. The 2023 Global Food Crises Report from the Global Network Against Food Crises (GNAFC) accentuates that hunger is exacerbated not only by conflict and extreme weather events but also by the economic repercussions of COVID-19 and the ripple effects of the crisis in Ukraine. While conflict and extreme weather events continue to cause severe food insecurity and malnutrition, the economic impact of COVID-19 and the knock-on effects of the crisis in Ukraine are also major contributors to hunger, according to the 2023 Global Food Crises Report released by the GNAFC. The

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<https://doi.org/10.59543/comdem.v2i.13877>

complexity and variability of the global situation increase the risks and uncertainties of the FSC system. How to systematically study the resiliency in FSC has important theoretical and practical significance. Therefore, many scholars do research related to FSC in order to enhance the stability of the FSC. Blessley and Mudambi [1] comprehensively elaborated on the three stages of a resilient food bank supply chain: prediction, adaptation and response, as well as recovery and learning. Gomez and Grady [2] concluded that resilience and sustainability of supply chains can coexist by studying the interaction between food supply environmental impacts and resilience in US cities [3]. Yazdani et al. [4] investigated the agricultural FSCM of Andalusia Province of Spain and indicated that supermarkets and wholesalers are determined to be the most resilient players in the FSCM of Andalusia Province of Spain. At present, globalization has made the supply chain more complex. Climate change has increased the frequency and intensity of extreme weather [5]. The COVID-19 has further exposed the vulnerability of the supply chain. Any node interruption may affect the entire system [6]. Studying resilience helps the supply chain adapt to these changes to cope with similar crises in the future [7]. However, there is no one researching how to evaluate the resiliency in the development of the FSC, so an evaluation framework is developed to enhance the resiliency level of FSC by the current study.

Because of the complexity of FSC, the decision data cannot extremely grasp the key points of resiliency in various segments of FSC. Therefore, various techniques are utilized to represent uncertain data so that the features of resiliency can be captured fully. Among these techniques, fuzzy sets are widely regarded as the most popular way to process uncertain decision information for identifying and evaluating resiliency, such as the “Hesitant fuzzy set (HFS)” [8], the “Fermatean fuzzy set (FFS)” [9], the “Pythagorean fuzzy set (PFS)”, and the “intuitionistic fuzzy set (IFS)”. Owing to the complicity and non-determinacy of real-world issues, these approaches are limited in dealing with complex and unpredictable information. Compared to the methods above, the TSFS is a more flexible technique to convey comprehensive uncertainty involved in experts’ information. In the procedure of evaluating the pharmaceutical enterprises, Liu et al. [10] applied TSFS to process evaluation information. Wang et al. [11] introduced a hybrid structure of TSFS to handle uncertain assessment information. Garg et al. [12] used a mixed TSFS to tackle the fuzzy and uncertain information. The TSFS is applied to handle the information fusion during the precise information process by Nazeer et al [13]. Moreover, the TSFS has been widely utilized in diverse fields because of its capacity to encompass the precision, constraint, and inaccuracy of uncertain information. For example, T-spherical fuzzy has been used to evaluate digital transformation solutions and support their selection in entrepreneurial small and medium-sized enterprises [14]. Using T-Spherical Fuzzy Decision Testing and DEMATEL to evaluate alternative social banking systems (interest free) [15]. What’s more, T-spherical fuzzy is also used to analyze issues related to smart grids in uncertain environment [16]. And it has also begun to be applied in the medical field. A new machine learning model for ASD diagnosis based on computational intelligence has been developed [17]. As a result, we implement the TSFS for handling the information provided by professionals.

In addition, assessing resiliency also requires consideration of multiple indicators and options. Thus, it can be regarded as a decision-making issue with multiple criteria. Numerous MCDM techniques have been proposed by many scholars, such as the TOPSIS method [18, 19], TODIM method [20], and the VIKOR method [21]. The TOPSIS method and VIKOR method’s core concept is to select the compromise solution that approaches the ideal solution [22, 23]. However, these methods ignored something important, which leads to deviations from the evaluation results. The traditional TOPSIS method fails to capture the interrelationship between alternative and ideal solutions which leads to the inaccuracy and subjectivity of the results increasing. The classical VIKOR method is a compromising method with priorities, but it ignores the ranking between individual and

collective. Moreover, the TODIM method doesn't the issue of normalization and has poor adaptability[24]. Compared to the aforementioned MCDM techniques, the GLDS method is worth noting because it can improve the shortcomings existing in the above methods. In addition, it can more effectively model individual risk attitudes and the group during the prioritization. Therefore, the GLDS method is widely applied to tackle alternative priority problems. For instance, a hybrid GLDS method is introduced to evaluate the bus company in the field of Public transportation by Wang et al. [25]. In order to sort out the choice of social capital in public-private-partnership projects, Liu et al. [26] suggested a strategy. A novel approach was introduced that integrates the q-rung orthopair fuzzy entropy with the GLDS method. Liao et al. [27] originated a new hybrid GLDS way to address the MAGDM issue. So as to assess the agriculture supply chain risks, a comprehensive GLDS method is applied by Zhai et al. [28]. Thus, the GLDS method is extremely feasible to select as the technique of prioritizing alternatives.

Thus, we put forward a hybrid model for the resiliency of FSC by combining the GLDS method and TSFS. In this model, the TSFS is applied to deal with the uncertain assessment information from different specialists. Next, the PWA operator is used to integrate information by considering the interrelationships among various experts. What's more, the entropy measure for TSFS is introduced as a weighting technique to determine the significance of every criterion. Finally, utilizing the GLDS technique for prioritizing the resiliency of the FSC is beneficial to promoting the implementation of a resilient FSC.

In conclusion, the primary findings of this paper can be outlined below:

(i) The information integration technique considers differences in information provided by various experts while building a group evaluation information matrix. To determine the weight of specialists, we introduce an optimization weighting method in the process of integrating expert information. What's more, it also involves the application of TSFS to deal with the evaluation information, which is independently hesitant, inconsistent, and uncertain.

(ii) A new hybrid GLDS model is constructed to prioritize the resiliency in FSC. The TSF-GLDS method provides a new solution for measuring the food supply chain's security level. According to the sorted literature, this method is the first to appear, and it ensures reliable and understandable prioritization of alternatives.

The remaining portion of this document is constructed in the following form. This part shows a literature review on methods for prioritizing alternatives and developing the GLDS approach. Section 2 has a concise overview of TSFS. Section 3 introduces the extended GLDS approach for evaluating resiliency on the basis of FSC. In Section 4, there is a numerical example that demonstrates the measurement of the resilience of FSC. The conclusion part of this article entails summarizing the findings and outlining the areas for future research.

2. Preliminaries

2.1 T-Spherical fuzzy set

Definition 1: Let X be a nonempty fixed set, then a TSFS \mathfrak{S}^q on X can be expressed as follows:

$$\tilde{\mathfrak{S}} = \left\{ \left\langle x, \left(\mu_{\tilde{\mathfrak{S}}}^q(x), \nu_{\tilde{\mathfrak{S}}}^q(x), \pi_{\tilde{\mathfrak{S}}}^q(x) \right) \right\rangle \mid x \in X \right\} \quad (1)$$

Where $\mu_{\tilde{\mathfrak{S}}}^q(x): X \rightarrow [0,1]$, $\nu_{\tilde{\mathfrak{S}}}^q(x): X \rightarrow [0,1]$ and $\pi_{\tilde{\mathfrak{S}}}^q(x): X \rightarrow [0,1]$ denote the degree of membership, degree of abstinence, and degree of non-membership of x to X , respectively, which satisfy every condition $x \in X : 0 \leq \mu_{\tilde{\mathfrak{S}}}^q(x) + \nu_{\tilde{\mathfrak{S}}}^q(x) + \pi_{\tilde{\mathfrak{S}}}^q(x) \leq 1, q \geq 1$. The triplet $\langle \mu, \nu, \pi \rangle$ is called a T-spherical fuzzy

number (T-SFN) for simplicity.

Definition 2: [29] Suppose that the sets $\mathfrak{S}_1^q = [\mu_{\mathfrak{S}_1^q}, \nu_{\mathfrak{S}_1^q}, \pi_{\mathfrak{S}_1^q}]$ and $\mathfrak{S}_2^q = [\mu_{\mathfrak{S}_2^q}, \nu_{\mathfrak{S}_2^q}, \pi_{\mathfrak{S}_2^q}]$ are two T-SFNs; then the operation rules between \mathfrak{S}_1^q and \mathfrak{S}_2^q are expressed as follows:

① Addition of \mathfrak{S}_1^q and \mathfrak{S}_2^q

$$\mathfrak{S}_1^q + \mathfrak{S}_2^q = \left\langle \left(1 - \left(1 - \mu_{\mathfrak{S}_1^q}^q\right)\left(1 - \mu_{\mathfrak{S}_2^q}^q\right)\right)^{1/q}, \left(\left(1 - \mu_{\mathfrak{S}_1^q}^q\right)\left(1 - \mu_{\mathfrak{S}_2^q}^q\right) - \left(1 - \mu_{\mathfrak{S}_1^q}^q - \nu_{\mathfrak{S}_1^q}^q\right)\left(1 - \mu_{\mathfrak{S}_2^q}^q - \nu_{\mathfrak{S}_2^q}^q\right)\right)^{1/q}, \right. \\ \left. \left(\left(1 - \mu_{\mathfrak{S}_1^q}^q - \nu_{\mathfrak{S}_1^q}^q\right)\left(1 - \mu_{\mathfrak{S}_2^q}^q - \nu_{\mathfrak{S}_2^q}^q\right) - \left(1 - \mu_{\mathfrak{S}_1^q}^q - \nu_{\mathfrak{S}_1^q}^q - \pi_{\mathfrak{S}_1^q}^q\right)\left(1 - \mu_{\mathfrak{S}_2^q}^q - \nu_{\mathfrak{S}_2^q}^q - \pi_{\mathfrak{S}_2^q}^q\right)\right)^{1/q} \right\rangle \quad (2)$$

② Multiplication of \mathfrak{S}_1^q and \mathfrak{S}_2^q

$$\mathfrak{S}_1^q \otimes \mathfrak{S}_2^q = \left\langle \left(\left(1 - \pi_{\mathfrak{S}_1^q}^q - \nu_{\mathfrak{S}_1^q}^q\right)\left(1 - \pi_{\mathfrak{S}_2^q}^q - \nu_{\mathfrak{S}_2^q}^q\right) - \left(1 - \pi_{\mathfrak{S}_1^q}^q - \nu_{\mathfrak{S}_1^q}^q - \mu_{\mathfrak{S}_1^q}^q\right)\left(1 - \pi_{\mathfrak{S}_2^q}^q - \nu_{\mathfrak{S}_2^q}^q - \mu_{\mathfrak{S}_2^q}^q\right)\right)^{1/q}, \right. \\ \left. \left(\left(1 - \pi_{\mathfrak{S}_1^q}^q\right)\left(1 - \pi_{\mathfrak{S}_2^q}^q\right) - \left(1 - \pi_{\mathfrak{S}_1^q}^q - \nu_{\mathfrak{S}_1^q}^q\right)\left(1 - \pi_{\mathfrak{S}_2^q}^q - \nu_{\mathfrak{S}_2^q}^q\right)\right)^{1/q}, \left(1 - \left(1 - \pi_{\mathfrak{S}_1^q}^q\right)\left(1 - \pi_{\mathfrak{S}_2^q}^q\right)\right)^{1/q} \right\rangle \quad (3)$$

③ Multiplication of a crisp value λ

Let the set $\mathfrak{S}^q = [\mu_{\mathfrak{S}^q}, \nu_{\mathfrak{S}^q}, \pi_{\mathfrak{S}^q}]$ be an T-SFN; then the multiplication of a crisp value λ with \mathfrak{S}^q is defined as below.

$$\lambda \mathfrak{S}^q = \left\langle \left(1 - \left(1 - \mu_{\mathfrak{S}^q}^q\right)^\lambda\right)^{1/q}, \left(\left(1 - \mu_{\mathfrak{S}^q}^q\right)^\lambda - \left(1 - \mu_{\mathfrak{S}^q}^q - \nu_{\mathfrak{S}^q}^q\right)^\lambda\right)^{1/q}, \left(\left(1 - \mu_{\mathfrak{S}^q}^q - \nu_{\mathfrak{S}^q}^q\right)^\lambda - \left(1 - \mu_{\mathfrak{S}^q}^q - \nu_{\mathfrak{S}^q}^q - \pi_{\mathfrak{S}^q}^q\right)^\lambda\right)^{1/q} \right\rangle \quad (4)$$

④ Exponent ($\lambda > 0$) of T-SFN

Assume that the set $\mathfrak{S}^q = [\mu_{\mathfrak{S}^q}, \nu_{\mathfrak{S}^q}, \pi_{\mathfrak{S}^q}]$ is an T-SFN, then the exponent ($\lambda > 0$) of the set \mathfrak{S}^q is denoted as follows:

$$\mathfrak{S}^{\lambda q} = \left\langle \left(\left(1 - \pi_{\mathfrak{S}^q}^q - \nu_{\mathfrak{S}^q}^q\right)^\lambda - \left(1 - \pi_{\mathfrak{S}^q}^q - \nu_{\mathfrak{S}^q}^q - \mu_{\mathfrak{S}^q}^q\right)^\lambda\right)^{1/q}, \left(\left(1 - \pi_{\mathfrak{S}^q}^q\right)^\lambda - \left(1 - \pi_{\mathfrak{S}^q}^q - \nu_{\mathfrak{S}^q}^q\right)^\lambda\right)^{1/q}, \left(1 - \left(1 - \pi_{\mathfrak{S}^q}^q\right)^\lambda\right)^{1/q} \right\rangle \quad (5)$$

Definition 3. [30] For any TSFN $\mathfrak{S} = (\mu_x, \nu_x, \pi_x), q \geq 1$, the score and accuracy functions can be defined in the following:

$$F(\mathfrak{S}) = \frac{(1 + \mu_x^q + \nu_x^q + \pi_x^q)}{2}, F(\mathfrak{S}) \in [0, 1] \quad (6)$$

$$T(\mathfrak{S}) = \mu_x^q + \nu_x^q + \pi_x^q, T(\mathfrak{S}) \in [0, 1] \quad (7)$$

Next, the rules for comparing TSFNs are presented below:

1. If $F(S_1) < F(S_2)$, then $(S_1) < (S_2)$;
2. If $F(S_1) = F(S_2)$, then
 - If $T(\mathfrak{S}_1) < T(\mathfrak{S}_2)$, then $\mathfrak{S}_1 < \mathfrak{S}_2$;
 - If $T(\mathfrak{S}_1) = T(\mathfrak{S}_2)$, then $\mathfrak{S}_1 = \mathfrak{S}_2$.

Definition 4. [31] Let $b_1 = \langle \mu_1, \nu_1, \pi_1 \rangle$ and $b_2 = \langle \mu_2, \nu_2, \pi_2 \rangle$ represent two T-SFNs, the Euclidean distance between them can be defined as follows:

$$d(b_1, b_2) = \left(\left| \mu_1^q - \mu_2^q \right|^2 + \left| \nu_1^q - \nu_2^q \right|^2 + \left| \pi_1^q - \pi_2^q \right|^2 \right)^{\frac{1}{2}} \quad (8)$$

3. The proposed methodology

We introduce an optimization weighting method to determine the weight of specialists, and based on this, score the influencing factors to determine the main influencing factors. The specific process is shown in Fig. 1. A set of alternatives is regarded as $H = \{h_i | i = 1, 2, \dots, m\}$ and a set of parameters is denoted as $\square = \{q_j | j = 1, 2, \dots, n\}$. To begin, $E = \{e^\lambda | \lambda = 1, 2, \dots, t\}$ is on behalf of the group of experts who provided the raw evaluation scoring information associated with the i th alternative under the j th parameter. Next, let $\aleph = \{\varpi_\lambda | \lambda = 1, 2, \dots, t\}$ be the important degrees of each specialist in the group, and it should meet the requirement of $\sum_{\lambda=1}^t \varpi_\lambda = 1$ and $0 \leq \varpi_\lambda \leq 1$. Next, the parameter set's weight vector is shown as meeting the conditions $\aleph = (\omega_1, \omega_2, \dots, \omega_n)^T$. It also satisfies $\sum_{j=1}^n \omega_j = 1$ and $0 \leq \omega_j \leq 1$.

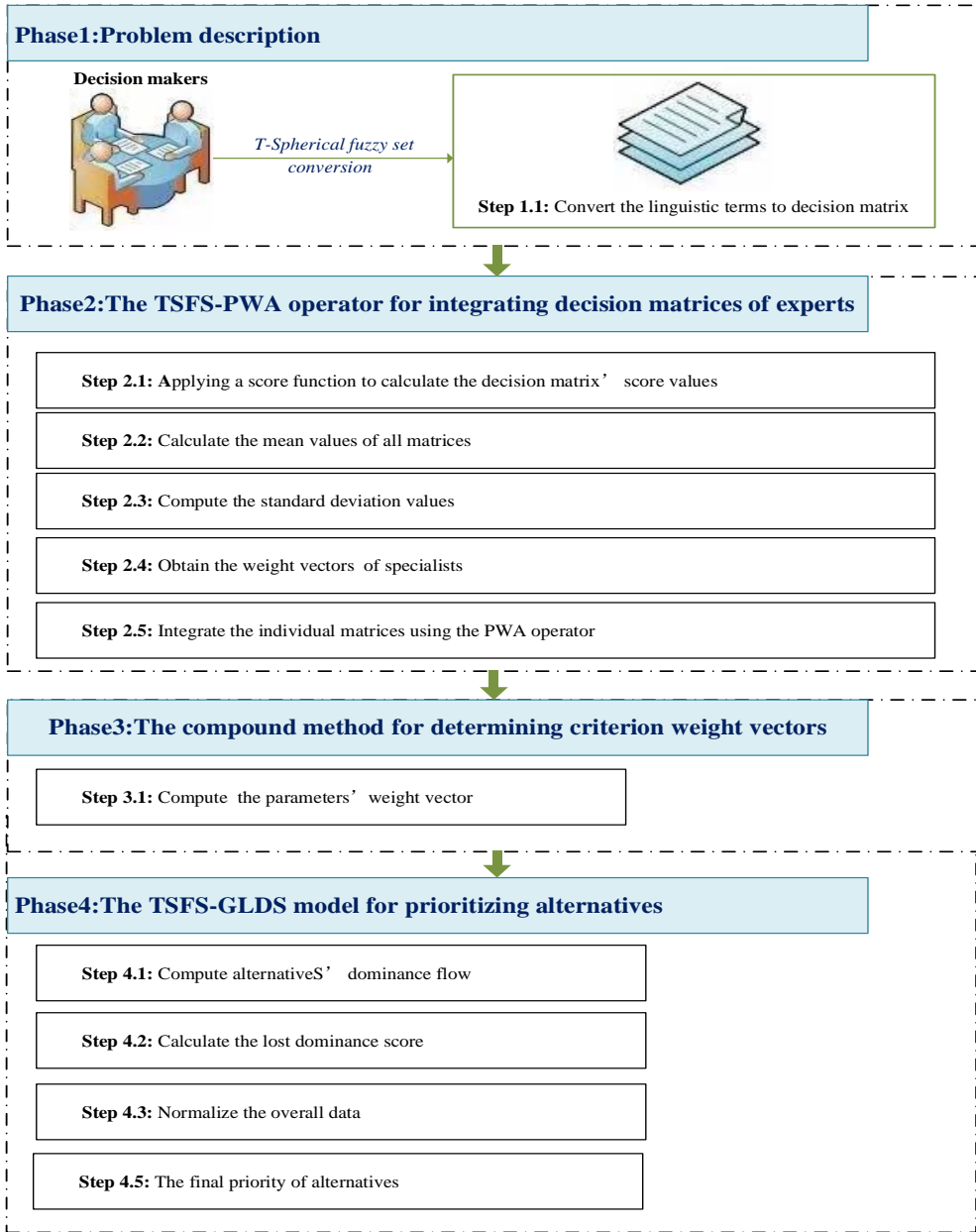


Fig. 1. The flow chart of the constructed approach

At first, we construct the first step to deal with the initial language information in the framework of prioritizing the alternatives and it is shown as follows.

Step 1.1 Convert the linguistic terms to a decision matrix

According to the circumstance of the issue definition, a TSFSs-based decision matrix can be obtained by converting the qualitative decision information $X_L^\lambda = [x_{ijL}^\lambda]_{m \times n}$ from the λ^{th} expert, and the result is revealed as follows:

$$X^\lambda = \begin{matrix} h_1 \\ h_2 \\ \vdots \\ h_m \end{matrix} \begin{pmatrix} x_{11}^\lambda & x_{12}^\lambda & \cdots & x_{1n}^\lambda \\ x_{21}^\lambda & x_{22}^\lambda & \cdots & x_{2n}^\lambda \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1}^\lambda & x_{m2}^\lambda & \cdots & x_{mn}^\lambda \end{pmatrix}_{m \times n} \quad (9)$$

where the element x_{ij}^λ is represented as $x_{ij}^\lambda = (\alpha_{ij}^\lambda, \beta_{ij}^\lambda, \gamma_{ij}^\lambda), \lambda = 1, 2, \dots, t$.

3.1 The TSFS-PWA operator for integrating decision matrices of experts

We initially define the PWA operator under the background of TSFSs to integrate the decision data of specialists here. After that, a majorization model on the basis of deviation is introduced to measure the weight vectors of every specialist in the TSFS setting. This hybrid method of integrating the specialists' decision matrices is put forward in the following process.

Step 2.1 Determine the decision matrix's ratings $X^\lambda = [x_{ij}^\lambda]_{m \times n}$ using the score function with the following formula.

$$\varphi_{ij}^\lambda = F(x_{ij}^\lambda) = \frac{(1 + \alpha_{ij}^\lambda + \beta_{ij}^\lambda + \gamma_{ij}^\lambda)}{2}, F(x_{ij}^\lambda) \in [0, 1] \quad (10)$$

In which, $\varphi_{ij}^\lambda (i = 1, 2, \dots, m; j = 1, 2, \dots, n; \lambda = 1, 2, \dots, t)$ is the element of the decision matrix $S_{ij}^\lambda = [\varphi_{ij}^\lambda]_{m \times n}$ based on the score values.

Step 2.2 Calculate the mean values of all matrices $S_{ij}^\lambda = [\varphi_{ij}^\lambda]_{m \times n} (\lambda = 1, 2, \dots, t)$, and it is shown as follows:

$$\bar{\varphi}_{ij} = \frac{1}{t} \sum_{\lambda=1}^t \varphi_{ij}^\lambda \quad (11)$$

where $\bar{\varphi}_{ij}$ is the element of the matrix $\bar{S} = [\bar{\varphi}_{ij}]_{m \times n}$.

Step 2.3 Compute the standard deviation values $\theta = [\xi_\lambda]_{1 \times t}$, where

$$\xi_\lambda = \sqrt{\frac{1}{m \times n} \sum_{i=1}^m \sum_{j=1}^n (\varphi_{ij}^\lambda - \bar{\varphi}_{ij})^2} \quad (12)$$

Step 2.4 Obtain the weight vectors $\varpi_\lambda (\lambda = 1, 2, \dots, t)$ of specialists using the formula as follows:

$$\varpi_\lambda = \frac{\xi_\lambda}{\sum_{\lambda=1}^t \xi_\lambda} \quad (13)$$

where $\varpi_\lambda \in [0,1]$ and $\sum_{\lambda=1}^t \varpi_\lambda = 1$.

Step 2.5 Integrate the individual matrices using the PWA operator

Suppose that $x_{ij}^\lambda = (\alpha_{ij}^\lambda, \beta_{ij}^\lambda, \gamma_{ij}^\lambda), \lambda = 1, 2, \dots, t$ is the relevant triplet risk rating score of the λ th expert for the i th hazard under j th risk parameters. This step is proposed to integrate the decision matrices $X_L^\lambda = [x_{ijL}^\lambda]_{m \times n}$ of all experts by the PWA operator. Consequently, the triplet linguistic PWA operator for risk information integration can be defined as follows:

$$x_{ij} = PWA_{TSFS} - (x_{ij}^1, x_{ij}^2, \dots, x_{ij}^t) = \sum_{\lambda=1}^t \frac{\varpi_\lambda (1 + f(x_{ij}^\lambda))}{\sum_{\lambda=1}^t \varpi_\lambda (1 + f(x_{ij}^\lambda))} \cdot x_{ij}^\lambda, \tag{14}$$

In which, the function $f(x_{ij}^\lambda)$ is defined as follows:

$$f(x_{ij}^\lambda) = \sum_{\lambda'=1, \lambda' \neq \lambda}^t Sup(x_{ij}^\lambda, x_{ij}^{\lambda'}) \tag{15}$$

where the support function $Sup(x_{ij}^\lambda, x_{ij}^{\lambda'})$ represents the support for x_{ij}^λ from $x_{ij}^{\lambda'}$, which should meet the following requirements listed as follows:

- ① $Sup(x_{ij}^\lambda, x_{ij}^{\lambda'}) \in [0,1]$
- ② $Sup(x_{ij}^\lambda, x_{ij}^{\lambda'}) = Sup(x_{ij}^{\lambda'}, x_{ij}^\lambda)$
- ③ $Sup(x_{ij}^\lambda, x_{ij}^{\lambda'}) \geq Sup(x_{ij}^\lambda, x_{ij}^{\lambda'}), \text{ if } |x_{ij}^\lambda - x_{ij}^{\lambda'}| < |x_{ij}^{\lambda'} - x_{ij}^{\lambda''}|$

Under the circumstances, we introduce the similarity measure based on the distance among two-interval triplet linguistic risk rating scores to figure out the support function. The support function based on similarity measure can be derived from the following:

$$Sup(x_{ij}^\lambda, x_{ij}^{\lambda'}) = 1 - d(x_{ij}^\lambda, x_{ij}^{\lambda'}) \tag{16}$$

In which, $Sup(x_{ij}^\lambda, x_{ij}^{\lambda'})$ is the distance-based support function. $d(x_{ij}^\lambda, x_{ij}^{\lambda'})$ is on behalf of the distance between x_{ij}^λ and $x_{ij}^{\lambda'}$, which can be signified as follows:

$$d(x_{ij}^\lambda, x_{ij}^{\lambda'}) = \left[|\alpha_{ij}^{\lambda q} - \alpha_{ij}^{\lambda' q}|^2 + |\beta_{ij}^{\lambda q} - \beta_{ij}^{\lambda' q}|^2 + |\gamma_{ij}^{\lambda q} - \gamma_{ij}^{\lambda' q}|^2 \right]^{\frac{1}{2}} \tag{17}$$

Finally, the fusion matrix $X = [x_{ij}]_{m \times n}$ can be obtained.

3.2 The compound method determining the weight vectors of criteria

In this section, let each expert evaluate the factors, the language scale for risk evaluation is shown in Table 1. The entropy measure for TSFS is introduced as a weighting technique to ascertain the significance of every criterion. The calculation procedure is shared as follows.

Table 1
 The language scale for risk evaluation

language scale	labels	TSFN
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Very low	VL	(0.85, 0.15, 0.10)
Low	L	(0.75, 0.25, 0.20)
Medium	M	(0.55, 0.50, 0.25)
High	H	(0.25, 0.75, 0.20)
Very high	VH	(0.15, 0.85, 0.10)

Definition 5 Let X_1 and X_2 be two TSFSs on X . A real-valued function $E: TSFS \rightarrow [0,1]$ is an entropy measure for TSFSs if it is provided with the following properties:

- (i). $E(X_1) = 0$ if X_1 is a crisp set;
- (ii). $E(X_1) = 1$ if $\alpha_1(x) = \gamma_1(x)$ and $\beta_1(x) = \sqrt[3]{0.25}$ for all $x \in X$;
- (iii). $E(X_1) = E(X_1^c)$;
- (iv). $E(X_1) \leq E(X_2)$ if $\beta_2^r(x) \leq \beta_1^r(x)$ and $\alpha_1^r(x) \leq \alpha_2^r(x) \leq \gamma_2^r(x) \leq \gamma_1^r(x)$ or $\gamma_1^r(x) \leq \gamma_2^r(x) \leq \alpha_2^r(x) \leq \alpha_1^r(x)$ for all $x \in X$.

Therefore, the entropy measure for TSFSs is as follows.

$$E(X) = \frac{1}{m} \sum_{i=1}^m \left(1 - \frac{4}{5} \left[|\alpha^r(x_i) - \gamma^r(x_i)| + |\beta^r(x_i) - 0.25| \right] \right) \tag{18}$$

Step 3.1 Then, the weight vector of the parameters $\mathfrak{S} = (\omega_1, \omega_2, \dots, \omega_n)^T$ can be computed using the Eq. (18), and it can be depicted as follows.

$$\omega_n = \frac{1}{m} \sum_{i=1}^m \left(1 - \frac{4}{5} \left[|\alpha_{ij} - \gamma_{ij}| + |\beta_{ij} - 0.25| \right] \right) \tag{19}$$

3.3 The TSFS-GLDS model for prioritizing alternatives

This section introduces the TSFS-GLDS model to prioritize the alternatives in the FSC. This technique The detailed steps of this model is shown as follows.

Step 4.1 The dominance flow of alternative h_i over alternative h'_i is:

$$df_j(h_i, h'_i) = \begin{cases} \max\{x_{ij} - x'_{ij}, 0\}, & \text{for benefit criterion } q_j \\ \max\{x'_{ij} - x_{ij}, 0\}, & \text{for cost criterion } q_j \end{cases} \tag{20}$$

and normalize it:

$$df_j^N(h_i, h'_i) = \frac{df_j(h_i, h'_i)}{\sqrt{\sum_{i'}^m \sum_i^m (df_j(h_i, h'_i))^2}} \tag{21}$$

Step 4.2 The overall lost dominance score of h_i under q_j is:

$$GDS(h_i) = \sum_{j=1}^n \left[\omega_j \sum_{i'=1}^m df_j^N(h_i, h'_i) \right] \tag{22}$$

Step 4.3 The overall lost dominance score of h_i under q_j is:

$$LDS(h_i) = \max_j \left[\omega_j \max_{i'} df_j^N(h_i, h'_i) \right] \tag{23}$$

Step 4.4 Normalize the overall $GDS(h_i)$ and $LDS(h_i)$ using Eq. (21), and derive GDS^N and LDS^N .

Step 4.5 The final priority of alternatives is determined by the formula as follows:

$$HS_i = GDS^N(h_i) \times \frac{m - M_1(h_i) + 1}{m(m+1)/2} - LDS^N(h_i) \times \frac{M_2(h_i)}{m(m+1)/2} \quad (24)$$

Then acquire the subordinate order set M_1 in descending order of the overall $GDS(h_i)$.

Then obtain the subordinate order set M_2 in ascending order of the overall $LDS(h_i)$.

4. Conclusions

This section recommends the utilization process of the constructed hybrid GLDS method through a numerical example. What’s more, so as to improve the exactitude of the assessment results, we do the comparison analysis.

4.1. Case background

This sub-section is shown as an illustrative example to evaluate resiliency to FSC. Since food is the basic necessity of human life, the impact of food supply chain security on social stability is particularly important. Furthermore, due to the instability of the food supply chain, large-scale famine events have emerged one after another in the international community. Therefore, it is on purpose to study the resiliency in FSC. On the basis of previous research, the key players in various alternatives are the following: farmers (h_1), processors (h_2), wholesalers (h_3), supermarkets (h_4), and small retailers (h_5). According to above discussion and current literature review, to evaluate GLDS in TSFSs, thirteen main criteria ($q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8, q_9, q_{10}, q_{11}, q_{12}, q_{13}$) are identified in Fig. 2. Then, we invited three skilled experts (e^1, e^2, e^3) to estimate these alternatives under the special criteria that this current decision-making issue can be solved.

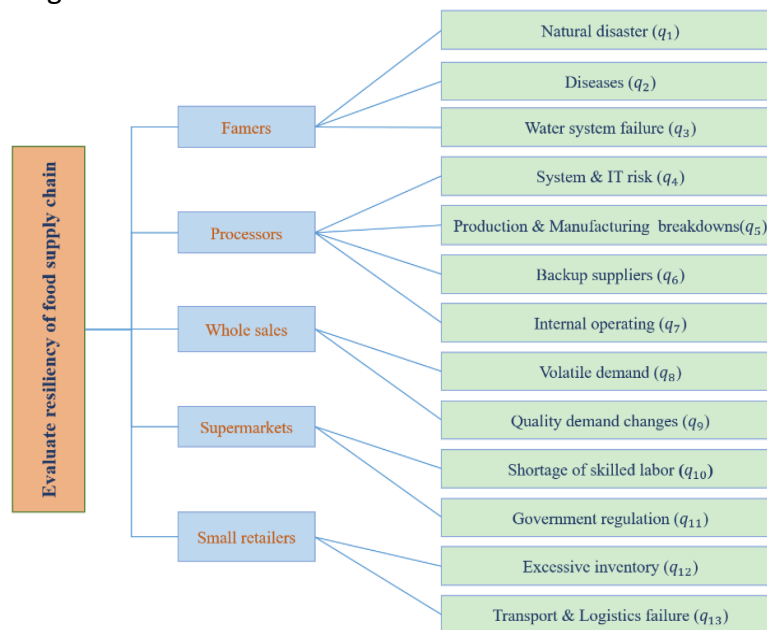


Fig. 2. The factors affecting the food supply chain

4.2. The application of the approach

In this subsection, a GLDS method integrated with TSFS is implemented to transform linguistic

information into evaluation matrices and prioritize the resiliency to FSC under uncertain and complex circumstance. The specific process is shown as follows:

To begin with, the individual linguistic evaluation information given by experts $e^\lambda (\lambda = 1, 2, 3)$ is revealed in Table 2.

Table 2
 The risk assessment language variables given by the experts.

		q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9	q_{10}	q_{11}	q_{12}	q_{13}
Expert 1	h1	VL	VH	M	VL	M	M	M	H	M	M	H	M	M
	h2	L	H	M	VL	M	H	M	VH	H	M	H	M	H
	h3	M	H	L	M	L	M	H	VH	VH	VH	H	H	VH
	h4	VH	VH	H	H	VH	VH	H	VH	VH	VH	H	H	VH
	h5	H	L	L	L	L	L	L	M	L	L	H	L	VL
Expert 2	h1	VL	H	M	VL	M	M	H	VH	VH	VH	VH	VH	H
	h2	M	M	L	H	L	M	M	H	M	M	H	M	H
	h3	L	VL	H	H	M	H	L	H	VH	H	H	H	VH
	h4	H	H	M	H	H	H	M	VH	VH	VH	H	H	H
	h5	L	L	VL	L	M	H	M	H	VH	M	H	H	H
Expert 3	h1	M	H	M	M	L	M	H	M	H	H	H	H	VH
	h2	M	VH	M	VH	M	H	H	M	H	H	H	H	H
	h3	VH	H	VH	H	M	M	VH	M	VH	M	H	M	VH
	h4	H	M	H	VH	M	H	H	H	H	M	VH	M	H
	h5	M	M	H	H	M	M	M	VH	H	M	H	M	M

Based on Steps 2.2-2.4, the weight vectors $\varpi_\lambda (\lambda = 1, 2, 3)$ of each expert is determined by Eq. (12) and Eq. (13), which is indicated as $\{\varpi_1 = 0.346, \varpi_2 = 0.283, \varpi_3 = 0.371\}$.

Then, in order to integrate matrices with the weight vectors of every expert, a PWA operator is applied by Eqs. (14)-(17), especially in Eq. (17), The final result is displayed in Table 4.

Table 4
 Information integration matrix

	h_1	h_2	h_3	h_4	h_5
q_1	(0.79,0.21,0.32)	(0.63,0.36,0.41)	(0.53,0.53,0.25)	(0.23,0.79,0.28)	(0.53,0.47,0.41)
q_2	(0.23,0.79,0.28)	(0.33,0.71,0.25)	(0.46,0.58,0.30)	(0.37,0.69,0.35)	(0.71,0.28,0.38)
q_3	(0.57,0.45,0.42)	(0.57,0.45,0.42)	(0.43,0.62,0.25)	(0.36,0.66,0.32)	(0.69,0.34,0.27)
q_4	(0.79,0.21,0.32)	(0.47,0.59,0.24)	(0.37,0.65,0.32)	(0.23,0.79,0.24)	(0.66,0.38,0.29)
q_5	(0.65,0.36,0.43)	(0.62,0.38,0.41)	(0.63,0.36,0.41)	(0.37,0.69,0.35)	(0.63,0.36,0.41)
q_6	(0.57,0.45,0.42)	(0.36,0.66,0.32)	(0.49,0.52,0.42)	(0.23,0.79,0.28)	(0.56,0.44,0.41)
q_7	(0.37,0.65,0.32)	(0.48,0.55,0.33)	(0.40,0.65,0.25)	(0.36,0.66,0.32)	(0.63,0.36,0.41)
q_8	(0.37,0.68,0.36)	(0.37,0.69,0.35)	(0.46,0.58,0.39)	(0.20,0.82,0.25)	(0.35,0.69,0.26)
q_9	(0.35,0.68,0.30)	(0.36,0.66,0.32)	(0.16,0.86,0.20)	(0.20,0.82,0.25)	(0.43,0.61,0.30)
q_{10}	(0.35,0.68,0.30)	(0.48,0.55,0.33)	(0.37,0.69,0.35)	(0.34,0.74,0.32)	(0.63,0.36,0.41)
q_{11}	(0.23,0.78,0.28)	(0.26,0.75,0.30)	(0.26,0.75,0.30)	(0.23,0.79,0.24)	(0.26,0.75,0.30)
q_{12}	(0.35,0.68,0.30)	(0.48,0.55,0.33)	(0.39,0.65,0.38)	(0.39,0.65,0.38)	(0.56,0.44,0.41)
q_{13}	(0.35,0.69,0.26)	(0.26,0.75,0.30)	(0.16,0.86,0.20)	(0.23,0.79,0.28)	(0.37,0.69,0.35)

Table 5
The final ranking result of GLDS method

h_i	HS_i	ranking
h_1	-0.085	5
h_2	-0.045	4
h_3	-0.040	2
h_4	-0.044	3
h_5	-0.025	1

Therefore, we can discover that h_5 is the best alternative because its dominance value is the highest among all alternatives.

5. Conclusions

This article introduces a unique and comprehensive method to evaluate resiliency in FSC by integrating the GLDS method and the TSFS. This method consists of three phases: creating a risk assessment matrix with fuzzy numbers, combining expert weights to obtain a comprehensive risk assessment information matrix and calculating weights of parameters to determine the priority ranking. The practical application of this method framework is showcased through a food supply chain analysis. Moreover, the comparative analysis reveals that this framework enhances the effectiveness and reliability of the resiliency evaluation and ranking process. What's more, the results show that this information integration method and the extended GLDS method can improve the smooth operation and sustainability of food distribution systems.

However, it also has some limitations. Firstly, the information from each expert may not accurately depict the resiliency of FSC in complex situations. What's more, only one approach is applied to determine the importance of individuals. Their personality traits may be ignored, and it can cause incomplete information. Thus, how to effectively convey intricate and ambiguous information is a considerable issue. In addition, an effective priority sorting framework is able to resolve other similar issues. Therefore, this framework can potentially evaluate barriers in various other fields in future study.

Acknowledgement

This work was supported by Project of the National Quality Engineering of Colleges and Universities in Anhui Province (202310370192).

This work was supported by Project of the Provincial Quality Engineering of Colleges and Universities in Anhui Province (2023xscx038).

References

1. Blessley, M. and S.M. Mudambi, *A trade war and a pandemic: Disruption and resilience in the food bank supply chain*. Industrial Marketing Management, 2022. **102**: p. 58-73.
2. Gomez, M. and C. Grady, *A balancing act: the interplay of food supply chain resilience and environmental sustainability in American cities*. Environmental Research Letters, 2023. **18**(12): p. 124022.
3. Mu, W., E.D. van Asselt, and H.J. van der Fels-Klerx, *Towards a resilient food supply chain in the context of food safety*. Food Control, 2021. **125**: p. 107953.

4. Yazdani, M., et al., *A fuzzy group decision-making model to measure resiliency in a food supply chain: A case study in Spain*. Socio-Economic Planning Sciences, 2022. **82**: p. 101257.
5. Ching-Pong Poo, M., T. Wang, and Z. Yang, *Global food supply chain resilience assessment: A case in the United Kingdom*. Transportation Research Part A: Policy and Practice, 2024. **181**: p. 104018.
6. Orengo Serra, K.L. and M. Sanchez-Jauregui, *Food supply chain resilience model for critical infrastructure collapses due to natural disasters*. British Food Journal, 2022. **124**(13): p. 14-34.
7. Sharma, M., R. Antony, and K. Tsagarakis, *Green, resilient, agile, and sustainable fresh food supply chain enablers: evidence from India*. Annals of Operations Research, 2023.
8. Krishankumaar, R., et al., *New ranking model with evidence theory under probabilistic hesitant fuzzy context and unknown weights*. Neural Computing and Applications, 2022. **34**(5): p. 3923-3937.
9. Qi, G., M. Atef, and B. Yang, *Fermatean fuzzy covering-based rough set and their applications in multi-attribute decision-making*. Engineering Applications of Artificial Intelligence, 2024. **127**: p. 107181.
10. Liu, P., et al., *A novel fuzzy TOPSIS method based on T-spherical fuzzy Aczel–Alsina power Heronian mean operators with applications in pharmaceutical enterprises' selection*. Complex & Intelligent Systems, 2023. **10**(2): p. 2327-2386.
11. Wang, H., et al., *An Approach Toward Pattern Recognition and Decision-Making Using the Concept of Bipolar T-Spherical Fuzzy Sets*. International Journal of Fuzzy Systems, 2023. **25**(7): p. 2649-2664.
12. Garg, H., et al., *Multi-attribute decision-making based on sine trigonometric aggregation operators for T-spherical fuzzy information*. Soft Computing, 2023: p. <https://doi.org/10.1007/s00500-023-08899-y>.
13. Nazeer, M.S., K. Ullah, and A. Hussain, *A novel decision-making approach based on interval-valued T-spherical fuzzy information with applications*. Journal of AppliedMath, 2023. **1**(2): p. 79.
14. Yang, Z., et al., *Digital transformation solutions of entrepreneurial SMEs based on an information error-driven T-spherical fuzzy cloud algorithm*. International Journal of Information Management, 2023. **69**: p. 102384.
15. Özdemirci, F., et al., *An assessment of alternative social banking systems using T-Spherical fuzzy TOP-DEMATEL approach*. Decision Analytics Journal, 2023. **6**: p. 100184.
16. Naseem, A., et al., *Assessment of Smart Grid Systems for Electricity Using Power Maclaurin Symmetric Mean Operators Based on T-Spherical Fuzzy Information*. 2022. **15**(21): p. 7826.
17. Albahri, A.S., et al., *Towards physician's experience: Development of machine learning model for the diagnosis of autism spectrum disorders based on complex T - spherical fuzzy - weighted zero - inconsistency method*. Computational Intelligence, 2022. **39**(2): p. 225-257.
18. Wang, Y., P. Liu, and Y. Yao, *BMW-TOPSIS: A generalized TOPSIS model based on three-way decision*. Information Sciences, 2022. **607**: p. 799-818.
19. Rathod, N.J., et al., *Optimization on the Turning Process Parameters of SS 304 Using Taguchi and TOPSIS*. Annals of Data Science, 2022. **10**(5): p. 1405-1419.
20. Lin, X., et al., *Evaluation of the Social Effects of Enterprise Carbon Accounts Based on Variable Weight CFPR Fuzzy VIKOR*. 2023. **20**(4): p. 3704.
21. Ding, Q., Y.-M. Wang, and M. Goh, *An extended TODIM approach for group emergency decision making based on bidirectional projection with hesitant triangular fuzzy sets*. Computers & Industrial Engineering, 2021. **151**: p. 106959.
22. He, J., et al., *Research on the Optimization for Acidification Modification Scheme Considering Coal's Wettability Based on the AHP–TOPSIS Method*. ACS Omega, 2023. **8**(36): p. 32667-32676.
23. Luo, X., et al., *Sustainable supplier selection based on VIKOR with single-valued neutrosophic sets*. PLOS ONE, 2023. **18**(9): p. e0290093.
24. Ding, Q., M. Goh, and Y.-M. Wang, *Interval-valued hesitant fuzzy TODIM method for dynamic emergency responses*. Soft Computing, 2021. **25**(13): p. 8263-8279.
25. Wang, X., X. Gou, and Z. Xu, *A continuous interval-valued double hierarchy linguistic GLDS method and its application in performance evaluation of bus companies*. Applied Intelligence, 2021. **52**(4): p. 4511-4526.

26. Liu, L., et al., *Entropy-Based GLDS Method for Social Capital Selection of a PPP Project with q-Rung Orthopair Fuzzy Information*. 2020. **22**(4): p. 414.
27. Liao, N., et al., *Novel Gained and Lost Dominance Score Method Based on Cumulative Prospect Theory for Group Decision-Making Problems in Probabilistic Hesitant Fuzzy Environment*. International Journal of Fuzzy Systems, 2023. **25**(4): p. 1414-1428.
28. Zhai, T., et al., *Assessment of the agriculture supply chain risks for investments of agricultural small and medium-sized enterprises (SMEs) using the decision support model*. Economic Research-Ekonomska Istraživanja, 2023. **36**(2): p. 2126991.
29. Mathew, M., R.K. Chakraborty, and M.J. Ryan, *A novel approach integrating AHP and TOPSIS under spherical fuzzy sets for advanced manufacturing system selection*. Engineering Applications of Artificial Intelligence, 2020. **96**: p. 103988.
30. Mahmood, T., et al., *An approach toward decision-making and medical diagnosis problems using the concept of spherical fuzzy sets*. Neural Computing and Applications, 2018. **31**(11): p. 7041-7053.
31. Ju, Y., et al., *T-spherical fuzzy TODIM method for multi-criteria group decision-making problem with incomplete weight information*. Soft Computing, 2020. **25**(4): p. 2981-3001.