

Leveraging an Uncertainty Methodology to Appraise Risk Factors Threatening Sustainability of Food Supply Chain

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Abstract: By diminishing the risk factors associated with the food supply chain (FSC), we have recourse to strengthen the food supply chain's resilience, decrease food waste, and increase its sustainability. Prioritizing and identifying the risk factors impacting the sustainability of the food supply chain is essential for managing uncertainty and averting unfavorable consequences. This study attempts to identify and rank the most significant risks affecting the sustainability of the food supply chain under an uncertain environment. We use the α -Discounting multi-criteria decisionmaking (α -D MCDM) method for the main three risk factors: the risks of supply, the risks of demand, and the risks of operations. The primary causes of the challenges in assessing the food supply chain's risk elements include inaccurate assessment data, DMs' subjective preferences, and DMs' differing opinions and thoughts about the criteria. Unfortunately, earlier research fell short of fully resolving these issues. A hybrid three-phase neutrosophic MCDM method is proposed by integrating triangular neutrosophic numbers (TNNs), TNN-AHP, and TNN-CoCoSo to close this gap. In this manner, it may efficiently handle ambiguity. The application of the suggested framework is then explored using the top six food and beverage businesses in the world: Nestle (A1), PepsiCo (A2), Coca-Cola (A3), Danon (A4), Anheuser-Busch InBev SA (A5), and Mondelez International (A6). The results show the sustainability rankings from best to worst, which were established on the groups of decision-makers assessments based on the importance of the risk factors that have to be handled. To gain additional insight into the rationale and resilience of this framework, sensitivity evaluation and comparative analysis have been employed in this study.

Keywords: Food Supply Chain, Risk Factor, Sustainability, α-D MCDM, TNN-AHP, TNN-CoCoSo.

1. Introduction

The primary responsibility of the food supply chain (FSC) is to transport a variety of nourishment from farmers to end users via a network of food processors and intermediaries while maintaining high standards of quality, safety, and low food waste [1]. FSC is made up of wholesalers, retailers, warehouses, makers of food (processing facilities), and suppliers who work together to meet customer demands [2]. To ensure that customers receive safe, wholesome, and high-quality foods, it is crucial to handle each FSC stage properly. Each stage has a distinct set of issues and possibilities [3]. It is the common duty of all parties involved in the supply chain to deliver food that is safe, dependable, and of the highest caliber. Furthermore, food waste reduction and the development of sustainable national and regional economies depend on FSC [4]. As a result, sustainable FSC is critical for the development of sustainable agriculture, which is critical for guaranteeing an ongoing supply and production of food items [5]. Reduced food waste, carbon emissions, improved food quality, and increased food safety are all benefits of implementing sustainable food supply chain management methods in the food supply chain [6].

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Considerations about the sustainability of the food supply chain increase with the number of procedures since supply chain stages are exposed to risk factors. Food supply chain risk factors can lead to food scarcity, poor food quality distribution, and wasted food generation, which raises sustainability issues as a result [7]. FSC confronts high uncertainty risks, which might affect food product availability and quality. One of the greatest uncertainties is the variability of meteorological conditions, which can impair farming efficiency and result in food shortages. Another cause of uncertainty is the volatility of food costs, which can affect customers' accessibility to food goods, particularly in low-income nations [8].

FSC risk valuation is crucial to prevent resource waste and aids businesses in developing resilient food security policies. Examining risks in FSCs can improve their performance in terms of sustainability, equity, and efficiency [9]. Every supply chain participant must be aware of risks both inside and outside of their networks to deliver products that are reliable and secure. In this study, the food supply chain risk factors are classified into three main groups: the risks of supply, the risks of demand, and the risks of operations.

Given the importance of the impact of the risk factors on enhancing FSC performance, this study focuses on six of the top food companies in the world and measures their sustainability performance based on the main three risk groups (the risks of supply, the risks of demand, and the risks of operations) using proposed integrated MCDM framework. Firstly, to handle n-wise comparison, the weights of the three primary risk groups in the food supply chain are evaluated using the α discounting MCDM approach [10]. Secondly, AHP is used to calculate the relative importance of the risk factors that have an impact on the sustainability of the FSC. To deal with the ambiguity that decision-makers encounter in these evaluation situations, this phase is based on neutrosophic language variables. Thirdly, the CoCoSo approach is used to rank the top six food companies according to the weights assigned to the risk factors that have an impact on sustainability and discovered in the previous stage. This phase also is based on neutrosophic set theory to handle uncertainty in all phases of evaluation.

The main contributions of this study entail investigating the roles of risk factors in the food supply chain and how they affect sustainability; assessing the 12 risk factors of the food supply chain and the main three risk groups; and ranking the top food companies based on the impact of risk factors while taking uncertainty and consistency into serious consideration. In addition to that, risk factor weight and parameter sensitivity are employed in the sensitivity analysis to validate the suggested framework in this research.

This study is structured into a set of sections: Section 2 summarizes the research on decisionmaking techniques that concentrate on the sustainability of the food supply chain and associated risk factors. Section 3 is devoted to the proposed method, i.e., a hybrid three-phase decision-making approach for ranking food supply chains based on the importance of the risk factors. Section 4 presents a study case to illustrate how to use the proposed method to rank the top food companies in the world based on the risk factor effect on sustainability. Section 5 discusses a sensitivity analysis and comparative analysis to verify the results. Section 6 clarifies the conclusion future perspectives, and scopes.

2. Principles Conceptual Based Earlier Perspectives

2.1 Food Supply Chain

FSC is a network that links farmers and producers that collaborate to deliver food that is secure and safe for consumers [11]. A sustainable blockchain (BC) architecture for the halal FSC is suggested by Ali et al, in [12]. This study offers a practical solution to the issues surrounding the implementation of blockchain technology in SC for halal food. Chen et al. introduced the idea of integrated FSC management, which can improve product traceability throughout the entire chain. The benefit of

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smart packaging in decreasing food waste was then underlined [13]. Kittipanya-Ngam & Tan evaluated the benefits of digitalization in [14] utilizing three firms as examples. Their research looks at the strategies, problems, and opportunities that Thailand's food producers confront as they work to digitise their SCs.

Analysis of the COVID-19 scenario in 2020 by recent research and according to [15] revealed significant breakdowns, such as an increase in the proportion of people facing famine and food insecurity as the major crisis aggravated imbalances that had already hampered progress before the pandemic. Other scholars such as Aday, S., and Aday, M. S. (2019) analyze the implications of COVID-19 on the food and agricultural industries [16] to provide an overview of the recommendations needed to lessen and limit the pandemic's effects. Additionally, Barman et al. cover the macroeconomic effects of COVID-19 and the effects of lockdown on the food supply chain and agriculture [17].

2.2 Risk Management in the Food Supply Chain

Food is a perishable commodity, hence food FSCs are more complex than those for other kinds of businesses or services [18]. The volatility of food prices, food waste, the security of food, and problems with resources, have all presented ongoing concerns throughout time [19]. Food supply chain risk assessment is crucial to prevent resource waste and aids businesses in developing resilient food security policies [20]. Each component of the supply chain must be aware of risks both inside and outside of their networks to deliver reliable and secure products. In recent years, both local and global authorities have expressed concern about FSC risk management.

To better understand how knowledge management, risk management, and resilience relate to supply chain resilience in FSCs, Ali et al.'s research aims to combine these three ideas [21]. The main objective of Khan et al.'s study is to determine the risk variables associated with SCs for Halal food and to appropriately rank them to improve management [22]. Also, Zhao et al. classified the identified FSC hazards into many groups according to how reliable they were [24].

The organized literature work and the advice of specialists are shared to identify risk factors related to the FSC. The Scopus database was searched for the terms "food supply chain," "risk," and "challenges" in the related works. A thorough examination of the literature turned up 12 common risk factors in the FSC. The risk factors were categorized into three clusters based on their particular features, including the risks of supply, the risks of demand, and the risks of operations. Table 1 summarizes the 12 risk factors based on their categories.

The term "the risks of supply" describes the ambiguity surrounding the acquisition of the material along with its operations, including the failure of the supplier and the quality of the raw materials. On the other side, the risks resulting from changing market conditions and consumer demand fall under the following group, known as the risks of demand. The biggest risks in this category are those that deal with customers and how they view the good or service. The risks of operations are challenges for the supply chain to run effectively, the primary business outsources some tasks, like marketing, inventory, manufacturing, and shipping.

2.3 Risk Management in the Food Supply Chain

A decrease in food waste increases sustainability [38]. In addition to the moral concern of wasting away usable food items when people elsewhere suffer from hunger. Various techniques were offered by numerous researchers and academics to reduce food waste along the FSC. To prevent food waste, recent techniques include forecasting demand for a store shop using machine learning algorithms [39]. On a global scale, food supply chains are growing to keep up with seasonal food production and customers' rising expectations for safety, sustainability, and environmental repercussions that could have an impact on human communities and health. Since stakeholders have recently given the topic of sustainability in the FSC a lot of thought, the area of sustainable supply chain management has emerged [40].

Table 1. Food supply chain-related risks.

3. Study Framework

The three-phase framework is utilized in this study to evaluate the relative significance of risk factors in the FSC and how they may affect sustainability. The related works are used to recognize the risk factors for the FSC and classify them into three major groups based on their characteristics.

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The first phase involves applying the α -D MCDM to weigh the major risk categories. In the next phase, the 12 FSC risk factors are assessed using the neutrosophic analytical hierarchy process (NAHP). Using the top six food and beverage companies in the world and the Combined Compromise Solution method (CoCoSo) under a neutrosophic environment, the third phase investigates how to apply the suggested framework. The adopted research framework is depicted in Figure 1.

Figure 1. A MCDM framework for evaluating sustainable FSC based on risk factors.

Rehab Mohamed and Mahmoud M. Ismail, Leveraging an Uncertainty Methodology to Appraise Risk Factors Threatening Sustainability of Food Supply Chain

3.1 Phase 1: α-D MCDM

Smarandache (2010) presented the α -D MCDM as an addition of AHP to address inconsistency and n-wise comparison. For pairwise comparison judgments requiring consistency, the α -D Method yields the same result as AHP when combined with the Fairness Principle. The main idea behind this strategy is to convert an inconsistent to a consistent problem by discounting the coefficients of the inconsistent problem to specified percentages [41]. For weak inconsistent decision-making issues, however, α-D provides a different result than AHP when paired with the Fairness Principle. Any set of preferences that can be converted into a set of homogeneous linear equations can be used in this method. A decision-making problem's degree of consistency is specified [42]. The phases of the α -D MCDM are as follows [43]:

■ Let $C = \{C_1, C_2, C_3, ..., C_n\}$, n≥2, be a set of criteria (in our study it is the main categories of food supply chain risks). The set of preferences is $P = \{P_1, P_2, P_3, ..., P_m\}$, m≥1. Then, the weights of the criteria $m: C \to [0, 1]$, where $m(C_i) = x_i, 0 < x_i < 1$ [19].

$$
\sum_{i=1}^{n} m(C_i) = \sum_{i=1}^{n} x_i = 1
$$

Construct $m \times n$ linear system and its matrix:

$$
\begin{cases} x_{1,1}w_1 + x_{1,2}w_2 + \dots + x_{1,n}w_n = 0 \\ \dots \\ x_{m,1}w_1 + x_{m,2}w_2 + \dots + x_{m,n}w_n = 0 \end{cases}
$$

$$
A = \begin{bmatrix} x_{1,1} & \dots & x_{1,n} \\ \dots & \dots & \dots \\ x_{m,1} & \dots & x_{m,n} \end{bmatrix}
$$

- Determine the matrix A's determinant.
	- $Det(A)=0$ indicates that the issue is consistent.
	- $Det(A) \neq 0$ indicates an inconsistent issue.
	- The right side of the system must then be parameterized with α .
	- Set every parameter using the Fairness principle: $\alpha_1 = \alpha_2 = \alpha_3 = \cdots = \alpha_p = \alpha > 0$.
	- After that, figure out the system's answer.
	- To get a specific outcome, multiply the secondary variables and parameter values by 1.
	- To normalize the solution, divide each result by the total of all results.
	- The α value is used to determine the initial degree of consistency and inconsistency of the decision-making problem.

Here is an example of the application of the α -D MCDM method:

Let us construct the relevant matrix and system of equations. Let Criteria 1 $(C_1)=x$, Criteria $2(C_2) = y$, and Criteria 3 (C_3)= z. The preference of each criteria must be formulated as a linear equation to build a system of comparisons.

$$
\begin{cases}\n x = 2y + 3z \\
 y = \frac{1}{2}x \\
 z = \frac{1}{3}x\n\end{cases}
$$

The corresponding matrix of the system is formulated as follows:

$$
A = \begin{bmatrix} 1 & -2 & -3 \\ -1/2 & 1 & 0 \\ -1/3 & 0 & 1 \end{bmatrix}
$$

Det(A) = -1 \neq 0

Using the Fairness Principle and adding α to the right-hand side (RHS) coefficient, we will parameterize the system and solve it.

$$
x = 2\alpha_1 y_1 + 3\alpha_2 z \tag{1}
$$

$$
y = \frac{1}{2}\alpha_3 x \tag{2}
$$

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3.2 Phase 2: Neutrosophic AHP

Saaty's AHP is a well-known method for managing complicated problems by breaking them down into smaller problems and then combining the answers to those smaller problems. There are various steps in the AHP. To better grasp the problem, the problem hierarchy must first be organized. A desired outcome, main criteria, sub-criteria, and all possible choices make up the structure of the AHP [44]. Decision makers build pair-wise comparison matrices to find criteria weight using Saaty's scale after designing the AHP hierarchy [45]. The ultimate weight of alternatives is then established and ordered. The steps of the NAHP in details as follows:

- The four layers of the problem hierarchy are organized. The objective that the organization aims to accomplish is at the top level. The criteria, or in our study, the major risk categories, make up the second level. The risk factors that fall within each category of the level before are included in the third level. The alternatives (food and beverage companies) that need to be assessed and contrasted are included in the last level.
- Utilize the linguistic expressions from Table 2 to organize the neutrosophic comparison matrix of risk factors.

Explanation	Triangular neutrosophic number (TNN)
Vey weakly important VWI	((0.1, 0.2, 0.45), 0.2, 0.6, 0.5)
Weakly important WI	((0.2, 0.3, 0.5), 0.3, 0.6, 0.5)
Partial important PI	((0.3, 0.5, 0.7), 0.5, 0.6, 0.45)
Equally important EI	((1,1,1),0.5,0.5,0.5)
Strongly important SI	((0.7, 0.8, 0.9), 0.8, 0.1, 0.2)
Very strongly important for VSI	((0.8, 0.9, 0.8), 0.9, 0.1, 0.1)
Absolutely important AI	((0.9, 0.9, 0.9), 1, 0, 0)

Table 2. Linguistic terms and the TNN.

To get the crisp weights of the alternatives, use the de-neutrosopic formula in Eq. (5). $S(a) = \frac{1}{8} \times (a_1 + a_2 + a_3) \times (2 + T - I - F)$ (5)

- Normalize the crisp weights of alternatives by dividing each column element by the appropriate sum after adding the columns.
- Calculate the average of each row to obtain the weight vector of the risk factors. Verify the consistency of the experts' judgment. Consistency may be checked by dividing the random index (RI) by the consistency index (CI). Following that, the result should be less than 0.1. If not, a new comparison must be made.

3.3 Phase 3: Neutrosophic CoCoSo

When developing mathematical and computing techniques to choose the best option among several options based on predetermined criteria, MCDM is a crucial area of operations research.

A CoCoSo method was developed by Yazdani et al. [46] that delivers a collection of aggregated solutions employing compromise approaches and aggregation strategies. Due to shifting weight distributions of criteria, the preference outcomes derived by current decision-making systems have limited dependability and stability, making it potentially unreasonable for decision-makers to choose the best alternative. CoCoSo eliminates this restriction. This method is based on a combination of the exponentially weighted product approach and the weighted sum technique, as shown in the steps below:

 To assess the alternatives in light of the relevant risk factors, the initial decision-making matrix is created. The evaluation of the alternatives is based on a triangular neutrosophic scale to ensure a more accurate evaluation using Table 3.

Importance scale	Triangular neutrosophic Number (TNN)
Very low influence (VLI)	((0.10, 0.30, 0.35), 0.1, 0.2, 0.15)
Low influence (LI)	((0.3, 0.4, 0.10), 0.6, 0.2, 0.3)
Partially influence (PI)	((0.40, 0.35, 0.50), 0.6, 0.1, 0.2)
Medium important (MI)	(0.5, 0.50, 0.50), 0.8, 0.1, 0.1)
High influence (HI)	((0.70, 0.65, 0.80), 0.9, 0.2, 0.1)
Very high influence (VHI)	((0.90, 0.85, 0.90), 0.7, 0.2, 0.2)
Absolute influence (AI)	((0.95, 0.90, 0.95), 0.9, 0.10, 0.10)

Table 3. Importance scale based on triangular neutrosophic numbers.

- Using the de-neutrosophic formula found in Eq. (5), get a clear assessment of the alternatives.
- The compromise normalization Eqs. (6) and (7) are used to achieve the normalization of criteria values.

$$
r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \qquad \text{For beneficial criteria} \tag{6}
$$

$$
r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \qquad \text{For non-beneficial criteria} \tag{7}
$$

 Eqs. (8) and (9), respectively, reflect the total of the weighted comparability sequence and an amount of the power weight of comparability sequences for each choice. as S_i and P_i . The approach of grey relational generation was used to get the S_i value.

$$
S_i = \sum_{j=1}^n (w_j r_{ij})
$$

\n
$$
P_i = \sum_{j=1}^n (r_{ij})^{w_j}
$$
\n(8)

• The CoCoSo approach ranks based on the relative score k_i , which is derived from three summed evaluation scores k_{ia} , k_{ib} , and k_{ic} , as described in the following in Eqs. (10-13):

$$
k_{ia} = \frac{P_i + s_i}{\sum_{i=1}^{m} (P_i + s_i)}
$$

\n
$$
k_{ia} = \frac{P_i + s_i}{\sum_{i=1}^{m} (P_i + s_i)}
$$
 (10)

$$
k_{ib} = \frac{s_i}{\frac{m s_i}{m n} + \frac{r_i}{m n}} \tag{11}
$$
\n
$$
k_{ic} = \frac{\lambda(s_i) + (1 - \lambda)(p_i)}{\lambda m \alpha s_i} \tag{12}
$$

$$
k_i = (k_{ia} + k_{ib} + k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic})
$$
\n(13)

4. Evaluation of the Influence of Risk Factors on Sustainability of Food Supply Chain Based on Constructed Framework

In this section, an alternative food supply chain is evaluated as a numerical illustration of the proposed method. To be specific, six food and beverage companies, including Nestle (A1), PepsiCo (A2), Coca-Cola (A3), Danone (A4), Anheuser-Busch InBev SA (A5), and Mondelez International (A6) are studied to select the most sustainable food supply chain according to the risk factor influence by using the proposed method in this study, and the problem hierarchy is summarized in Figure 2. The risk factors are specified based on the literature reviews as mentioned in Section 2.2 and summarized

as Table 1 shows. The risk factors are categorized into three main groups based on their characteristics: the risks of supply, the risks of demand, and the risks of operations. The first phase is to evaluate the three risk categories using the α -D MCDM. The second phase is to evaluate the 12 risk factors of the food supply chain using the neutrosophic AHP to handle uncertainty in the evaluation process. The third phase is to evaluate the sustainability of the top six food and beverage companies based on the influence of the risk factors according to their performance using the neutrosophic CoCoSo method. The application steps of the proposed framework are illustrated in detail in this section.

Figure 2. Food supply chain risk factors hierarchy.

^{4.1} Evaluation of the Main Risk Categories using α-D MCDM

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This study's main goal is to rank the food supply chain according to how risk factors affect its sustainability. A hierarchy is created after the decision problem is divided. In this hierarchy, the first level denotes the main objective of the decision problem, the middle levels denote the primary risk categories that affect the food supply chain (i.e., supply-related risks, demand-related risks, and operational-related risks) and corresponding risk factors (the 12 risk elements as Figure 2 shows) that affect the FSC. The last level denotes the alternatives (i.e., the six food and beverage companies).

In terms of decision makers' selection, the diverse decision makers' preferences should be measured in ranking the food supply chain sustainability according to risk factors effect. Three groups of representative decision-makers participated in evaluating the sustainability of the six food and beverage companies. These decision-makers are academics and researchers who are interested in studying supply chain sustainability, supply chain risk management, and decision-making process. We conducted two questionnaires related to determining the main risk categories and the corresponding risk factors that affect food supply chain sustainability through which to assess the priority of food and beverage companies, the questionnaires were conducted using linguistic terminology.

In the first phase, we can see that this problem has a hierarchical structure, making AHP one of the most efficient and useful techniques. It is now unable to employ the AHP theory since the first preferences are not taken into account as a pairwise comparison, which is one of the main reasons for the theory's shortcomings. As a result, the following formula will be used to calculate the weight of these three risk categories. The three decision-makers are evaluating the main categories of food supply chain risks as follows:

- The risks of supply are as important as the risks of demand plus half as important as the risks of operations.
- The risks of demand are two times as important as the risks of supply
- The risks of operations are three times as important as the risks of supply.
- Let us construct equations and their corresponding matrix. Let the risks of supply= C_1 , the risks of demand = C_2 , and the risks of operations = C_3 . The preference of each category must be formulated as a linear equation to build a system of comparisons.

$$
\begin{cases}\nx = y + \frac{1}{2}z \\
y = 2x \\
z = 3x\n\end{cases}
$$

The corresponding matrix of the system is formulated as follows: $A = |$ $1 \quad 1 \quad \frac{1}{2}$ $\begin{bmatrix} 2 & 1 & 0 \\ 2 & 1 & 0 \end{bmatrix}$ 3 0 1]

$$
\mathrm{Det}(A) = -\frac{5}{2} \neq 0
$$

 $S = \begin{bmatrix} 1 & 1.069 & 1.6035 \end{bmatrix}$

To solve this system we will parameterize the right-hand side (RHS) coefficient by adding α and using the Fairness Principle.

$W = [0.27 \quad 0.29 \quad 0.44]$

The result of α -D MCDM shows that economic the risk of supply weight is 0.27, the risk of demand is 0.29, and the risk of operations is 0.44 as Figure 3 shows.

Figure 3. Evaluation of three main categories of food supply chain.

4.2 Evaluation of the Food Supply Chain Risk Factors using Neutrosophic AHP

In this sub-section, the second phase of the proposed method is applied to evaluate the risk factors using neutrosophic AHP.

- The questionnaire is applied to the three decision-makers and the results are applied using the linguistic terms as shown in Table 2. The pairwise evaluation is applied between the 12 risk factors for the three decision-makers as shown in Table A-1 (See Appendix).
- The pairwise comparison is applied using the corresponding neutrosophic scale, then, using Eq. (5) converted into crisp values as Table A-2 (see Appendix) shows.
- The normalized pairwise comparison is shown in Table A-3 (see Appendix).
- The weight of the risk factors by each decision maker according to neutrosophic AHP is shown in Table 4 and summarized in Figure 4.

Table 4. Weight and rank of the risk factor via three decision-makers using neutrosophic AHP.

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 The results of the first stage show that R34, R23, and R31 are at the top of the ranking with concluding weights 0.1497,0.1279, and 0.1250, respectively. R33, R22, and R21 are at the end of the ranking with weights of 0.0522, 0.0401, and 0.0390, respectively.

4.3 Evaluation of the Six Food and Beverage Companies using Neutrosophic CoCoSo

In this Phase, we applied the neutrosophic CoCoSo based on the weight of the FSC risk factors that result from the second phase to rank the top six food and beverage companies.

- The decision matrix is built based on the importance scale as Table 3 shows. The decision matrix is shown in Table A-4 (see Appendix).
- Build the crisp decision matrix using the score function (Eq. (5)), as Table A-5 (see Appendix) shows.
- In the normalization step, the criteria must be specified whether it is beneficial or nonbeneficial criteria. Here, all criteria are beneficial while R24 is a non-beneficial criterion. The result of the normalization step is shown in Table A-6 (see Appendix) according to Eqs. (6) and (7).
- The Weighted normalized matrix is constructed using Eq. (8), as Table A-7 shows (see Appendix). The weight in this step is the result of the second stage of neutrosophic AHP.
- The power-weighted normalized matrix is constructed using Eq. (9), as Table A-8 shows (see Appendix).
- Using Eqs. (10-13) are applied to rank the top six food and beverage companies based on the risk factors of the food supply chain as Table 5 shows and summarized in Figure 5.
- The results of the neutrosophic CoCoSo show that Nestle (A1), PepseCo (A3), and Danone (A4) are at the top of the ranking. While Mondelez International (A6), Coca-Cola (A3), and Anheuser-Busch InBev SA (A5) are at the end of the ranking.

	Ka	- 27 Rank	Kь	־ר Rank	\mathbf{K}_{c}	 Rank	К	Rank
$\mathbf{A1}$	0.2422		11.4095		1.0000		5.6205	
A2	0.2403	2	10.8377	2	0.9921	2	5.3956	2
A ₃	0.1282	5	5.5650	5	0.5293	5	2.7970	5
A ₄	0.1932	3	7.7909	З	0.7975	3	3.9899	3
A ₅	0.0647	6	2.0000	6	0.2671	6	1.1030	6
A6	0.1314	4	5.9841	4	0.5426	4	2.9723	$\overline{4}$

Table 5. The ranking of the top six food and beverage companies using neutrosophic CoCoSo.

5. Result Analysis

5.1 Sensitivity Analysis

5.1.1 Sensitivity Analysis of Parameters

Since the calculation of the evaluation score k_{ic} is dependent on the values of λ parameter (0 \leq $\lambda \leq 1$), it is required to show its effect on the result of food companies' alternatives according to risk factors by varying parameter value. Thus, the nine scenarios of the possible values of λ are applied as Table 6 and Figure 6 show. As Figure 6 shows, while the value of γ changed from 0.1 to 0.9, the result is still the same as $A1 > A2 > A4 > A6 > A3 > A5$, which verifies the applicability of the proposed framework in this research.

	λ values												
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9				
A1	5.6205	5.6205	5.6205	5.6205	5.6205	5.6205	5.6205	5.6205	5.6205				
A2	5.3969	5.3967	5.3964	5.3961	5.3956	5.3949	5.3937	5.3916	5.3861				
A ₃	2.7983	2.7981	2.7978	2.7975	2.7970	2.7963	2.7952	2.7931	2.7877				
A ₄	3.9934	3.9928	3.9921	3.9912	3.9899	3.9880	3.9849	3.9792	3.9646				
A ₅	1.1057	1.1053	1.1047	1.1040	1.1030	1.1016	1.0992	1.0948	1.0836				
A6	2.9729	2.9728	2.9726	2.9725	2.9723	2.9720	2.9715	2.9706	2.9682				
					Rank								
	1	2	3	$\overline{4}$	5	6	7	8	9				
A1	1	1	$\mathbf{1}$										
A ₂	2	2	$\overline{2}$	2	2	$\overline{2}$	$\overline{2}$	$\overline{2}$	$\overline{2}$				
A ₃	5	5	5	5	5	5	5	5	5				
A ₄	3	3	3	3	3	3	3	3	3				
A ₅	6	6	6	6	6	6	6	6	6				
A6	4	$\overline{4}$	$\overline{4}$	$\overline{4}$	$\overline{4}$	$\overline{4}$	$\overline{4}$	4	$\overline{4}$				

Table 6. Sensitivity analysis in the case of the parameter λ changes.

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Figure 6. Sensitivity analysis of parameters.

5.1.2 Sensitivity Analysis of Risk Factors Weight

In this section, the sensitivity of the risk factor weights is studied. The weight of the risk factor is changed for 20 scenarios as Table 7 shows. Thus, the adjusted weight of each risk factor is considered, and changes in risk factors have an impact on the ranking outcomes, as seen in Figure 7.

The ranking of the alternatives A3, A4, A5, and A6 remains the same when changing the risk factors. Noteworthy, simple adjustments take place in tests 10 to 20. The ranking results of alternatives A1 and A2 change slightly when the weights of risk factors are changed in experiments 10 to 20. As a result, this proposed framework yields strong results, as shown in Figure 7. Therefore, however the risk factor weights change, either A1 or A2 remain the optimal alternatives and remain stable, and the ranking results always remain $A4 > A3 > A6 > A5$ under the changing weights of risk factors, it shows that the strategy suggested in this study is efficient and reliable.

Table 7. Sensitivity analysis of risk factors weight.

Figure 7. Sensitivity analysis of risk factor weight.

5.2 Comparative Analysis

In this subsection, two current methods neutrosophic simple additive weighting (SAW) [47] and neutrosophic TOPSIS [48] are introduced to conduct a comparative analysis to assess the effectiveness and reliability of the technique provided in this work. The neutrosophic TOPSIS method, which effectively addresses uncertainty in the evaluation process, intends to solve MCDM problems in an ambiguous context. Its main goal is to select the best option that is closest to or farthest from the positive ideal solution or negative ideal solution. By multiplying the weight of each criterion by its real value, adding the results, and taking into account all of the criteria, the neutrosophic SAW is also used to deal with this challenging problem. The Two methods' input data are taken from Table A-5, and the ranking results are computed and displayed in Table 8.

Alternative Ranking										
	Neutrosophic $CoCo\overline{So}$	Neutrosophic TOPSIS	Neutrosophic SAW							
$\mathbf{A1}$										
A2										
A ₃										
A ₄										
A5										
A6										

Table 8. Ranking results were achieved by two other existing methods.

An International Journal on Informatics, Decision Science, Intelligent Systems Applications

Figure 8. Comparative analysis with neutrosophic SAW and neutrosophic TOPSIS.

From Figure 8, it can be seen that the Neutrosophic SAW's ranking findings match up with those of the suggested technique with ranking $A1 > A2 > A3 > A6 > A4$. In addition, the ranking results acquired by the neutrosophic TOPSIS are almost consistent with a slight change in the ranking of alternatives A3 and A6. As a result, it is possible to confirm the accuracy and dependability of the framework suggested in this study.

6. Conclusion

The food supply chain's many activities are exposed to a variety of risks. To reduce risks, this study proposes to determine and assign priority to the risk factors along the FSC. 12 risk factors have been determined overall utilizing systematic literature research, decision makers' feedback, and other considerations. Additionally, these elements are divided into three groups based on their characteristics: the risks of supply, the risks of demand, and the risks of operations. Six leading food and beverage firms are analyzed to understand the risk factors and how they affect the sustainability of the food supply chain.

Meanwhile, a hybrid MCDM framework was developed by combining α -D MCDM, neutrosophic AHP, and neutrosophic TOPSIS to measure the FSC risk factors and rank the top six food companies. The proposed framework's main advantage, it can effectively deal with uncertainty. The three main groups of food supply chain risks are evaluated using α -D MCDM to avoid the drawbacks of n-wise comparison of AHP to be the first stage. The results show that the the risks of operations are the most significant with a weight of 0.44 followed by the risks of demand and the risks of supply with weights of 0.29 and 0.27, respectively. In the second stage, the neutrosophic AHP was applied to evaluate the 12 risk factors of the food supply chain. The results show that R34, R23, and R31 are at the top of the ranking with concluding weights of 0.1497, 0.1279, and 0.1250, respectively. The third stage is conducted to rank the top six food and beverage companies to validate the effect of risk factors on the performance of the FSC. In this stage, the neutrosophic CoCoSo was applied to rank the six companies based on the weight that was found from the previous stage. The results show that Nestle (A₁), PepseCo (A₃), and Danone (A₄) are at the top of the ranking.

The accuracy and robustness of the framework suggested in this study were confirmed in three stages. Firstly, the influence on the ranking of food companies' alternatives according to risk factors by changing parameter values was examined. Secondly, the sensitivity of the risk factor weights was studied. Thirdly, the comparative analysis was applied with two other methods: neutrosophic SAW and neutrosophic TOPSIS. The results of the three sensitivity studies showed that the proposed framework is consistent and robust.

In future research work, the evaluation of the risk factors can be done using the other MCDM techniques, such as the Best Worst Method (BWM), Analytical Network Process (ANP), and Decision-

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Making Trial and Evaluation Laboratory (DEMATEL). Moreover, more decision-makers might be asked to increase the accuracy of the outputs of decision-making. The case study or statistical work from the next research might be used to validate this study, which is based on the opinions of the decision-makers.

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Author Contributions

All authors contributed equally to this research.

Data availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

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Conflict of interest

The authors declare that there is no conflict of interest in the research.

Appendix

Table A-1. Assessment of risk factors via three decision makers using the linguistic terms.

An International Journal on Informatics, Decision Science, Intelligent Systems Applications

R32 | 0.150 | 0.563 | 0.750 | 0.150 | 0.750 | 0.750 | 0.150 | 0.563 | 0.103 | 0.563 | 0.750 | 0.150 **R33** | 0.103 | 0.150 | 0.563 | 0.150 | 0.750 | 0.750 | 0.103 | 0.150 | 0.150 | 0.272 | 0.563 | 0.150 **R34** | 0.750 | 1.013 | 0.844 | 0.750 | 1.013 | 1.013 | 0.750 | 0.750 | 0.750 | 0.844 | 0.844 | 0.563

Table A-3. Normalized pairwise comparison of the risk factors.

Table A-4. Decision matrix of the top six food and beverages according to the risk factors.

An International Journal on Informatics, Decision Science, Intelligent Systems Applications

	Table A-5. Crisp decision matrix of the top six food and beverage companies according to the risk factors.													
	R11	R12	R13	R14	R21	R ₂₂	R23	R24	R31	R32	R33	R34		
A1	0.7619	0.4875	0.3594	0.6988	0.2100	0.3594	0.9450	0.6988	0.7619	0.4875	0.3594	0.9450		
A ₂	0.7619	0.4875	0.2100	0.6988	0.2100	0.2100	0.7619	0.4875	0.7619	0.4875	0.3594	0.9450		
A ₃	0.6988	0.2100	0.2100	0.4875	0.1641	0.1641	0.7619	0.4875	0.6988	0.4875	0.2100	0.7619		
A4	0.6988	0.3594	0.2100	0.6988	0.1641	0.2100	0.7619	0.4875	0.7619	0.4875	0.2100	0.7619		
A ₅	0.4875	0.2100	0.2100	0.4875	0.2100	0.2100	0.6988	0.4875	0.4875	0.3594	0.2100	0.6988		
A6	0.6988	0.4875	0.2100	0.4875	0.1641	0.1641	0.6988	0.4875	0.6988	0.4875	0.3594	0.6988		
MIN	0.488	0.210	0.210	0.488	0.164	0.164	0.699	0.488	0.488	0.359	0.210	0.699		
MAX	0.762	0.488	0.359	0.699	0.210	0.359	0.945	0.699	0.762	0.488	0.359	0.945		

Table A-6. Normalized decision matrix.

	R11	R12	R13	R14	R21	R ₂₂	R ₂₃	R24	R31	R32	R33	R34
A1	1.000	1.000	.000	.000	1.000	1.000	$1.000\,$	0.000	1.000	1.000	1.000	.000
A2	1.000	1.000	0.000	.000	1.000	0.235	0.256	000 .	1.000	1.000	1.000	000 .
A ₃	0.770	0.000	0.000	0.000	0.000	0.000	0.256	000.1	0.770	l.000	0.000	0.256
A4	0.770	0.538	0.000	.000	0.000	0.235	0.256	000.1	1.000	$1.000\,$	0.000	0.256
A5	0.000	0.000	0.000	0.000	1.000	0.235	0.000	1.000	0.000	0.000	0.000	0.000
A6	0.770	1.000	$0.000\,$	0.000	0.000	0.000	0.000	1.000	0.770	$1.000\,$	1.000	0.000

Table A-7. Weighted normalized decision matrix.

	R11	R12	R13	R14	◡ R21	R ₂₂	R ₂₃	R24	R31	R32	R33	R34
A1	1.000	1.000	l.000	.000	1.000	1.000	1.000	0.000	1.000	1.000	1.000	000.1
A2	1.000	1.000	0.000	000 .	$1.000\,$	0.235	0.256	000 .	1.000	1.000	1.000	000.1
A ₃	0.770	0.000	0.000	0.000	0.000	0.000	0.256	1.000	0.770	1.000	0.000	0.256
A4	0.770	0.538	0.000	.000	0.000	0.235	0.256	000.1	1.000	$1.000\,$	0.000	0.256
A ₅	0.000	0.000	0.000	0.000	$1.000\,$	0.235	0.000	1.000	0.000	0.000	0.000	0.000
A6	0.770	1.000	0.000	0.000	0.000	0.000	0.000	.000	0.770	L.000	1.000	0.000

Table A-8. Power-weighted normalized matrix.

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