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Risk Analysis in the Food Cold Chain Using Decomposed Fuzzy Set-Based FMEA Approach

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Abstract: Risk analysis is employed across various domains, including the increasingly vital food supply chain, particularly highlighted by the COVID-19 pandemic. This study focuses on applying decomposed fuzzy sets (DFS), a novel extension of intuitionistic fuzzy sets, within the context of the food cold chain. The objective is to develop "Decomposed Fuzzy Set-Based FMEA (DF FMEA)" by extending the well-known failure mode and effect analysis (FMEA) method to DFS, to assess risks in the food cold chain. The functional and dysfunctional questions related to the severity, occurrence, and detectability of the identified risks; they were addressed to three experts working on the food cold chain. The purpose is to prevent an inconsistent assignment considering the uncertainty and indecision of decision makers. Due to the implementation of the DF FMEA, the identified risks were prioritized as follows: "*Financial Risks*" held the highest priority, followed by "*Delivery Risks*", "*Technological Ability Risks*", "*Environmental Risks*", "*Quality Risks*", and "*Social Risks*" with the lowest priority. The study's practical impact lies in the innovative risk assessment method. By considering decision makers' preferences and uncertainties, the DF FMEA approach enhances informed decision making. This contributes to a robust framework for addressing risks in the food cold chain, aiding practitioners in more effective risk management.

Keywords: food cold chain; risk analysis; decomposed fuzzy sets (DFS); failure mode and effect analysis (FMEA)

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1. Introduction

A cold chain plays a crucial role in the supply chain of perishable products, encompassing the necessary cooling and freezing technology to transport these items from their origin to their final consumption. In recent times, the world's population increase and the impact of the COVID-19 pandemic have led to a significant surge in the demand for frozen and fresh food products. This upswing has prompted remarkable development and growth within the food cold chain industry [1]. Every day, tons of perishable food products are produced and distributed to customers, making it imperative to deliver these products safely and with uncompromised quality. Maintaining the appropriate temperature range for each perishable food product, based on its category, becomes paramount during logistics operations. Deviations from the prescribed temperatures may lead to food deterioration, posing health risks from hazardous bacteria [2]. Furthermore, such deviations have resulted in an alarming increase in food waste, making the food industry more vulnerable to risk compared with other production sectors [3].

Effective supplier selection stands as a critical determinant in ensuring the seamless operation and reliability of the food cold chain, an integral component of the broader food supply chain network. The choice of suppliers directly influences the quality, timeliness, and safety of perishable products as they traverse from source to consumer. Optimal supplier selection entails a meticulous evaluation of factors such as transportation capabilities, adherence to temperature standards, product handling expertise, and adherence to safety regulations. A well-structured supplier selection process not only mitigates risks associated with subpar performance or product compromise but also contributes to enhanced cold chain management, reduced food waste, and bolstered consumer confidence. Thus, within the dynamic landscape of the food cold chain industry, effective supplier selection emerges as a pivotal factor in shaping the reliability, efficiency, and resilience of the entire perishable product distribution network.

The significance of effective risk management in the cold chain is evident, as potential risks may cause harm to human health and lead to negative economic consequences [4]. However, current risk management practices in the cold chain are perceived to be less effective than desired [5]. Risk and reliability assessment methods are broadly classified into two categories: knowledge-based and data-based methods [6]. Some of the knowledge-based methods include hazard analysis critical control points (HACCP), fault tree analysis (FTA), and root cause analysis [7]. Among them, failure mode and effect analysis (FMEA) is widely employed in the food industry for risk assessment purposes [8,9]. Previous literature has successfully applied FMEA to various food products, including Turkish delight [10], dairy products [11], salmon [12], red pepper [13], and corn curls [14], for risk analysis. However, limited attention has been given to risk assessment in the food cold chain, despite its high susceptibility to potential hazards.

The research gap arises from the scarcity of studies on risk assessment in the food cold chain. While risk assessment methods are widely utilized in the food sector, the specific complexities and unique challenges of the cold chain have not been adequately explored. Addressing this gap is crucial to ensuring the safety and quality of food products throughout the cold chain's transportation and storage processes.

The primary research objective of this paper is to introduce a novel approach, namely, the "Decomposed Fuzzy Set-Based FMEA" (DF FMEA) method, for analyzing risks in the food cold chain industry. The DF FMEA method is newly introduced in the literature. The proposed method takes into account the uncertainties and indecision inherent in decision makers' perspectives when assessing risks. By integrating DF FMEA, decision makers can provide evaluations for the occurrence, severity, and detectability parameters from both optimistic and pessimistic viewpoints, allowing for a more comprehensive and accurate assessment by using functional and dysfunctional questions.

The rest of this paper is structured as follows. Section 2 investigates a literature review of the food cold chain. The proposed methodology is given in Section 3. The application of the proposed method and comparison are given in Sections 4 and 5, respectively. Finally, the conclusion is presented in Section 6.

2. Literature Review

The problem of global warming has led to issues such as reduced production resources and inefficient agricultural lands, making the effective management of supply chains increasingly important. This has resulted in a significant increase in research on supplier selection in the food sector. Food supplier selection has been studied using a variety of methods, including MCDM techniques such as scoring and pairwise comparison, as well as statistical and mathematical programming methods. In recent years, MCDM methods have been particularly popular in this area. A summary table of the methods used in the literature is given in Table 1. According to the findings from the presented table, fuzzy set theory garnered preference in the majority of the studies, accounting for 53% of cases, while classical set theory was adopted in the remaining instances. Intriguingly, the landscape of integrated methods emerged as a prominent trend across the studies. Specifically, a notable 12.5% of the investigations employed scoring-based MCDM techniques, while outranking-based approaches were embraced by 34.5% of the endeavors. Remarkably, the preponderance of 53% relied upon pairwise comparison-based methodologies, signifying their substantial prevalence. Furthermore, it is noteworthy that the outranking domain prominently featured the PROMETHEE method, while within the scoring-based realm, the TOPSIS method stood out as a favored choice. Among the array of pairwise comparison-based techniques, the analytic hierarchy process (AHP) surfaced as the most extensively employed approach, exemplifying its stature in this analytical landscape. Notably, when considering recent studies, the best worst method (BWM) has ascended in prominence.

Table 1. Crisp and fuzzy models used in food supplier selection.

Ref.	Crisp	Fuzzy	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	Others
[15]	✓															
[16]		✓								✓						CoCoSo
[17]		✓			✓						✓					
[18]	✓									✓						Factor Analysis
[19]	✓					✓							✓			
[20]	✓														✓	
[21]	✓		✓										✓			
[22]	✓															
[23]		✓				✓				✓						
[24]		✓											✓			Game Theory
[25]		✓			✓											ISM
[26]		✓						✓								
[27]		✓									✓					WASPAS
[28]		✓					✓									
[29]		✓				✓				✓						
[30]	✓									✓						SWARA
[31]		✓								✓						
[32]		✓		✓		✓				✓						
[33]	✓		✓											✓		
[34]		✓			✓					✓						
[35]	✓		✓											✓		
[36]		✓											✓			
[37]		✓				✓				✓						
[38]		✓						✓								
[39]	✓									✓						
[40]	✓					✓				✓						
[41]		✓								✓						
[42]		✓								✓					✓	
[43]		✓				✓			✓							
[44]		✓				✓				✓			✓			
[45]		✓									✓					ISM
[46]		✓				✓										
[47]	✓		✓													
[48]	✓															LP
[49]		✓				✓				✓					✓	
[50]	✓						✓					✓				FITM
[51]		✓			✓	✓			✓							
[52]		✓		✓		✓				✓						
[53]	✓															QFD
[54]	✓												✓			Stochastic MIP
[55]	✓									✓						
[56]		✓							✓	✓						DELPHI, LP
[57]	✓		✓													
[58]		✓				✓			✓							
[59]	✓		✓													
[60]	✓														✓	DELPHI
[61]		✓								✓						
[62]	✓									✓						
[63]		✓								✓						GP
[64]	✓															
[65]	✓															
[66]		✓								✓						Taguchii Loss Function
[67]		✓				✓										GP
[68]	✓										✓					
[69]	✓										✓					

Table 1. *Cont.*

Ref.	Crisp	Fuzzy	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	Others
[70]	✓															
[71]	✓															
[72]	✓															

M1: PROMETHEE; M2: ELECTRE; M3: VIKOR; M4: TOPSIS; M5: COPRAS; M6: TODIM; M7: GRA; M8: AHP; M9: ANP; M10: DEMATEL; M11: BWM; M12: MAUT; M13: DEA.

The methods given in Table 1 and their focus areas in the literature on the food industry resulted in the consideration of a variety of criteria. Upon analysis of the criteria used for evaluating suppliers in existing literature, they were categorized into six primary groups, including Delivery, Social, Environmental, Financial, Quality, and Technological Capability factors. A comprehensive enumeration of the sub-factors for each category is presented in Table 2.

Table 2. Criteria used in food supplier selection.

Delivery	**Source**
On time delivery	[20,29,42,44,45,56,60,61,68,69]
Delivery speed	[20,25,27,28,40,58,68,69]
Order fulfillment rate	[28,46,47,68–70]
Delivery reliability	[16,17,39,45,63]
Delivery capabilities	[40,46,47]
Social	**Source**
Reputation	[29,34,42,44,45,56,60,62]
Customer satisfaction	[24,25,27,29,40,42,44,56,58,60–62]
Safety	[16,21,25,39,41,45–47,61,63]
Stakeholder rights	[21,25,28,39,41,45]
Employee rights	[21,28,37,39,41,45]
Value added influence	[16,25,26,37,39]
Education	[39,41,63]
Environmental	**Source**
Eco-design	[16,17,21,25,39,42,44,58,60]
Management system	[16,25,26,28,39,46,47,63,73]
Green supply chain	[17,25,28,34,37,68]
Waste management	[28,37,39,46,47]
Pollution production	[16,26,37,39,63,73]
Energy consumption	[16,28,39,46,47]
Air emissions	[39,46,47,63]
Carbon footprint reduction	[25,26,42,60]
Financial	**Source**
Price	[17,20,25,27–29,34,39,40,44,46,47,55,56,60,70,73]
Cost	[16,17,21,29,37,39,44,56,60,63,68,69,74]
Financial power	[17,21,29,34,40,44,56,60]
Flexibility on price	[17,20,21,26,39,40]
Logistics cost	[27,46,47,55,62]
Operational cost	[39,56,68,69]
Profit	[20,21,26]
Quality	**Source**
Product quality	[16,26,27,29,39,42,44–47,56,58,60,61,63,68–71,73]
Quality control and planning	[27–29,42,44,56,58,60]
Quality assurance	[17,27,34,40,45–47,70,71]
Quality management system	[20,28,45,70,71]
Steadiness of quality	[68,69]

Table 2. *Cont.*

Technological Ability	Source
Technological/technical capabilities	[16,17,21,24,25,28,29,39,42,44,56,58,60,62,63,69,71]
Production capacity	[28,29,42,44,56,58,60,61,65]
R&D capacity	[17,20,21,28,45–47]
Capability of resources	[20,28,45,46,62,65]
Communication system	[21,29,42,44,56,60]
Ability to solve technical problem	[45,65,68–70]
Information technology	[17,24,62]

Under the main criterion of Delivery, there exist five sub-criteria. These criteria are entirely related to the delivery process. Sequentially, these encompass whether the delivery is on time, the speed of delivery, the percentage of orders fulfilled, the safety of the delivery, and finally, the adequacy of resources for delivery (such as vehicle fleet capacity). Secondly, under the primary criterion of 'Social', there exist seven sub-criteria. These are, sequentially, corporate reputation and visibility, customer satisfaction and contentment, security, the rights of employers and stakeholders, the rights of employees, the value generated within its social environment, and the dissemination of collective knowledge through the education of the region or employees, facilitating its spread among individuals. When the criteria utilized in the studies found in the literature are examined and categorized, the Environmental category emerges as the third main group. This criterion pertains to environmental aspects and encompasses the sub-criteria that form a green criterion pool. The sub-criteria encompass the overall design's environmental friendliness and ecological sustainability, the approach of the management system towards the environment, green procurement, and an environmentally conscious approach encompassing the entire chain, sustainable disposal of waste, pollution generated post logistics activities, energy consumption and the status of consumed energy being environmentally friendly, emission of greenhouse gases into the air, and activities aimed at reducing carbon footprint. The subsequent sub-criteria belong to the Financial category. Within this group, the criteria primarily relate to profit, revenue, cash flow, and costs. The first of these is the transportation price and its competitiveness, transportation cost, the financial strength and stability of the company, quantity discount and flexibility options in pricing, unit transportation and logistics cost, operational costs, and profitability. Another main criterion is Quality. The sub-criteria under this criterion can be listed as follows: the quality of the transported product, quality control processes, effort invested in delivering the product in a high-quality manner, quality management system and procedures, and the ability of quality to remain consistent over time and provide the same standards for many years. The final main criterion group is Technological Ability. Here, seven sub-criteria can be discussed, encompassing factors such as the company's research and development infrastructure, and technological aspects. The sequence of these criteria is as follows: technological/technical capabilities, production capacity, R&D capacity, capability of resources, communication system, ability to solve technical problem, and information technology.

Scrutinizing the prevalence of these criteria across the landscape of pertinent studies evinces compelling trends. Foremost among these criteria is Financial, accounting for a substantial share of approximately 20%. Technological Capability and Social factors are next, with each featuring in 19% and 18% of discussions, respectively. Environmental factors constitute a significant portion at 17%, while Quality factors are present in 14% of the discussions. Lastly, Delivery factors, crucial for effective supply chain management, are considered in 12% of the instances. This comprehensive evaluation sheds light on the prevalence and importance of these diverse factors in supplier evaluation.

Table 3 depicts a chronological overview of research studies conducted in various sub-domains of the food industry, specifically focusing on Agrifood, Processed Food, Beverage, Fresh Food, Food Cold Chain, Dairy Products, and Food Packaging. The studies are concentrated in the more recent years, with the majority conducted from 2016 onwards, and certain studies delve into multiple applications concurrently, illustrating the interdisciplinary nature inherent in the research pursuits. The studies in "Agrifood" exhibit a consistent presence over multiple years, underscoring their enduring significance. Research into the "Processed Food" and "Beverage" sectors has primarily concentrated in recent years, indicating a heightened interest in these sectors. The studies in "Fresh Food", "Dairy Products", and "Food Packaging" show intermittent representation across the timeline. Starting in 2018, research on the "Food Cold Chain" gained prominence, highlighting an increasing focus on the intricacies of cold chain management. The table highlights the evolving nature of research interests within the food industry, with a focus on improving various aspects of food production, processing, distribution, and safety.

Table 3. Distribution of sectors in food supplier selection.

Food Sector	Source
Processed food	[15,16,18,19,21,32,38–41,45,46] [50,53,55–57,59,64,65,67–70]
Food packaging	[28,31,48,50,56,61,63,66,68,70]
Agrifood	[17,20,23,30,37,43,44,51,72,73]
Beverage	[15,18,22,31,50,68–70]
Food cold	[25,27,62,68,70–72]
Dairy	[26,28,50,68,70]
Fresh food	[24,33,35,52]

These studies reveal a lack of research on the food cold chain and the use of fuzzy extensions for risk analysis in this area. Therefore, this study will be the first time the DFS-based FMEA method has been proposed to the literature and applied to the food cold chain.

3. Methods

3.1. Decomposed Fuzzy Sets (DFS)

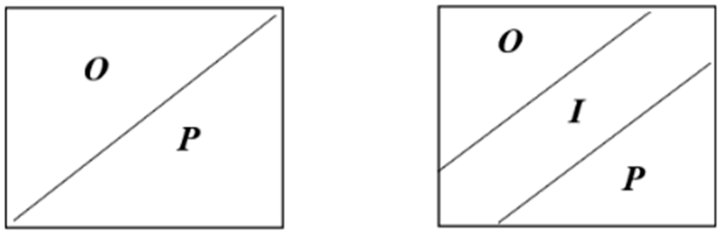
Qualitative data, often obtained through surveys or interviews, are frequently used to solve real-world problems. Subjective assessments from those involved in the problem, such as experts or decision makers, can contribute to finding a solution through their individual perspectives. However, the same question can be asked in a positive or negative way, and an individual's response may vary depending on their point of view [75].

- *Optimistic way of asking the question:* What is the probability that the identified risk will not occur?
- *Pessimistic way of asking the question:* What is the probability that the identified risk will occur?

Under normal circumstances, the probability of both having and not having a risk is expected to be 1. However, asking the same question in different ways may lead to varying perspectives among individuals, resulting in variability in their evaluations.

To illustrate with another example, suppose the decision maker is asked about the likelihood of an event occurring, the answer is O ($0 < O < 1$). Later, when the same question is asked as "the probability of an event not happening", let the answer received from the decision maker be expressed as P ($0 < P < 1$). While it is expected that the sum of O and P will be exactly 1 under normal conditions, this may not be the situation due to the decision maker's point of view and uncertain evaluations [75].

As seen in Figure 1, O represents the optimistic point of view of the decision maker, while P represents the pessimistic point of view. While mathematically O and P are supposed to complement each other, this may not be the case if the human point of view is considered. This situation is represented by area I in the middle of O and P [75].



(**a**) (**b**)

Figure 1. (**a**) Visualization of decision making under certainty. (**b**) Visualization of decision making under uncertainty.

For these reasons, decomposed fuzzy sets have been developed as new fuzzy set extensions.

Definition 1. *The representation of decomposed fuzzy sets is as follows:*

$$\widetilde{\mathrm{A}} = \left\{ \langle x, \left(O\left(\mu^o_{\widetilde{\mathrm{A}}}(x), v^o_{\widetilde{\mathrm{A}}}(x)\right), P\left(\mu^p_{\widetilde{\mathrm{A}}}(x), v^p_{\widetilde{\mathrm{A}}}(x)\right)\right) \mid x \in X \rangle \right\} \tag{1}$$

Definition 2. *Let* $\widetilde{\alpha} = \{O(a,b),\ P(c,d)\}$, $\widetilde{\alpha}_1 = \{O(a_1,b_1),\ P(c_1,d_1)\}$ *and* $\widetilde{\alpha}_2 = \{O(a_2,b_2),\ P(c_2,d_2)\}$ *be DFS. The operators can be described as follows:*

Addition:

$$\widetilde{\alpha}_1 + \widetilde{\alpha}_2 = \left\{ O\left(\frac{a_1 + a_2 - 2a_1a_2}{1 - a_1a_2}, \frac{b_1 + b_2 - 2a_1a_2}{b_1 + b_2 - b_1b_2} \right),\ P(c_1 + c_2 - c_1c_2, d_1d_2) \right\} \tag{2}$$

Multiplication:

$$\widetilde{\alpha}_1 \times \widetilde{\alpha}_2 = \left\{ O(\widetilde{\alpha}_1\widetilde{\alpha}_2, b_1 + b_2 - b_1b_2),\ P\left(\frac{c_1c_2}{c_1 + c_2 - c_1c_2}, \frac{d_1 + d_2 - 2d_1d_2}{1 - d_1d_2} \right) \right\} \tag{3}$$

Multiplication by a scalar:

$$\gimel\cdot\widetilde{\alpha} = \left\{ O\left(\frac{\gimel a}{(\gimel - 1)a + 1}, \frac{b}{\gimel - (\gimel - 1)b} \right), P\left(\left(1 - (1 - c)^{\gimel}\right), d^{\gimel} \right) \right\} \text{ for } \gimel > 0. \tag{4}$$

$\gimel$*th power of* $\widetilde{\alpha}$, $\gimel > 0$:

$$\widetilde{\alpha}^{\gimel} = \left\{ O\left(a^{\gimel}, 1 - (1 - b)^{\gimel}\right),\ P\left(\frac{c}{\gimel - (\gimel - 1)c}, \frac{\gimel d}{(\gimel - 1)d + 1} \right) \right\} \text{ for } \gimel > 0. \tag{5}$$

Definition 3. *Let* $a_i = \{O(a_i,\ b_i),\ P(c_i, d_i)\}$ *be a collection of decomposed weighted arithmetic mean (DWAM) with respect to,* $\gimel_i = (\gimel_1, \gimel_2, \ldots, \gimel_n)$, $\gimel_i \in [0,1]$ *and* $\sum_{i=1}^n \gimel_i = 1$,

$$\begin{aligned} &\mathrm{DWAM}\ (\widetilde{\alpha}_1, \widetilde{\alpha}_2, \ldots, \widetilde{\alpha}_n) = \gimel_1\cdot\widetilde{\alpha}_1 + \gimel_2\cdot\widetilde{\alpha}_2 + \ldots + \gimel_n\cdot\widetilde{\alpha}_n \\ &= \left\{ O\left(\frac{\sum_{i=1}^n \gimel_i a_i}{1 + \sum_{i=1}^n \left(\gimel_i a_i - \frac{a_i}{n}\right)}, \frac{\prod_{i=1}^n b_i}{\sum_{i=1}^n b_i^{n-1}\gimel_i(1 - b_i) + \prod_{i=1}^n b_i} \right),\ P\left(1 - \prod_{i=1}^n (1 - c_i)^{\gimel_i}, \prod_{i=1}^n d_i^{\gimel_i} \right) \right\} \end{aligned} \tag{6}$$

Definition 4. *Let* $a_i = \{O(a_i,\ b_i),\ P(c_i, d_i)\}$ *be a collection of decomposed weighted geometric mean (DWGM) with respect to* $\gimel_i = (\gimel_1, \gimel_2, \ldots, \gimel_n)$, $\gimel_i \in [0,1]$ *and* $\sum_{i=1}^n \gimel_i = 1$.

$$\begin{aligned} &\mathrm{DWGM}\ (\widetilde{\alpha}_1, \widetilde{\alpha}_2, \ldots, \widetilde{\alpha}_n) = \widetilde{\alpha}_1^{\gimel_1} \times \widetilde{\alpha}_2^{\gimel_2} \times \ldots \widetilde{\alpha}_n^{\gimel_n} \\ &= \left\{ O\left(\prod_{i=1}^n a_i^{\gimel_i}, -\prod_{i=1}^n (-b_i)^{\gimel_i} \right), P\left(\frac{\prod_{i=1}^n c_i}{\sum_{i=1}^n c_i^{n-1}\gimel_i(1 - c_i) + \prod_{i=1}^n c_i}, \frac{\sum_{i=1}^n \gimel_i d_i}{1 + \sum_{i=1}^n \left(\gimel_i d_i - \frac{d_i}{n}\right)} \right) \right\} \end{aligned} \tag{7}$$

Definition 5. *For the two DFS $\widetilde{A}$ and $\widetilde{B}$, intersection and union can be defined as follows:*

$$\widetilde{A} \cup \widetilde{B} = \begin{Bmatrix} \forall x \in X,\ max\left(\mu^{O}_{\widetilde{A}}(x), \mu^{O}_{B}(x)\right),\ min\left(v^{o}_{\widetilde{A}}(x), v^{o}_{B}(x)\right) \\ min\left(\mu^{P}_{\widetilde{A}}(x), \mu^{P}_{B}(x)\right),\ max\left(v^{P}_{\widetilde{A}}(x), v^{P}_{B}(x)\right) \end{Bmatrix} \tag{8}$$

$$\widetilde{A} \cap \widetilde{B} = \begin{Bmatrix} \forall x \in X,\ min\left(\mu^{O}_{\widetilde{A}}(x), \mu^{O}_{B}(x)\right),\ max\left(v^{o}_{\widetilde{A}}(x), v^{o}_{B}(x)\right) \\ max\left(\mu^{P}_{\widetilde{A}}(x), \mu^{P}_{B}(x)\right),\ min\left(v^{P}_{\widetilde{A}}(x), v^{P}_{B}(x)\right) \end{Bmatrix} \tag{9}$$

Definition 6. *The consistency index (CI) of the decomposed fuzzy number $(\widetilde{a} = \{O(a,b), P(c,d)\})$ is defined as:*

$$CI = 1 - \sqrt{\frac{(a-d)^2 + (b-c)^2 + (1-a-b)^2 + (1-c-d)^2}{2}} \tag{10}$$

Definition 7. *The score index (SI) of the decomposed fuzzy number $(\widetilde{a} = \{O(a,b), P(c,d)\})$ is defined as:*

$$SI(\widetilde{a}) \begin{cases} \frac{(a+b-c+d)CI(\widetilde{a})}{2k}, & SI(\widetilde{a}) \geq 0 \\ 0, & SI(\widetilde{a}) \leq 0 \end{cases} \tag{11}$$

The linguistic scale multiplier k is obtained by applying the formula below:

$$k = (a_{max} + b_{min} - c_{min} + d_{max}) \times CI^{*}(\widetilde{a})/2 \tag{12}$$

$CI^{*}(\widetilde{a})$ is named as the consistency index of the linguistic scale and can be found by:

$$CI^{*}(\widetilde{a}) = 1 - \sqrt{\frac{(a_{max} - d_{max})^2 + (b_{min} - c_{min})^2 + (1 - a_{max} - b_{min})^2 + (1 - c_{min} - d_{max})^2}{2}} \tag{13}$$

where a_{max} is the maximum membership value of the optimistic linguistic evaluation scale,

b_{min} is the minimum non-membership value of the optimistic linguistic evaluation scale,

c_{min} is the minimum membership value of the pessimistic linguistic evaluation scale,

d_{max} is the maximum non-membership value of the pessimistic linguistic evaluation scale.

3.2. Failure Mode and Effect Analysis (FMEA)

The FMEA is a technique in which probable risks are analyzed and the root cause and failure modes of these risks are investigated. Thus, design risks are identified and handled or even eliminated, if possible. FMEA is conducted mostly by a team and consists of five steps for implementation:

1. Implementation subject is determined;
2. A team consisting of members having different fields of expertise formed;
3. Information is acquired for the subject;
4. Hazard analysis is executed;
5. Actions are determined and implemented.

FMEA has been used for more than 60 years, after first being employed in the aerospace industry. FMEA is a simple method that especially low-education employees can participate in and understand the process. It is a method widely used in various sectors such as automotive, manufacturing, food, chemistry, and product design [74,76–80].

FMEA employs three different factors in order to obtain a risk-related numerical value. These elements are severity, occurrence, and detection. The severity of the failure determines how severe or extreme the outcome can be. Low severity numbers mean minor impacts, while high numbers refer to major impacts. The occurrence value represents the frequency of the root cause. Instead of being directly time-dependent, it is mostly described as linguistic expressions. The detection, finally, expresses the probability of locating related root causes. The risk priority number (RPN) is obtained by multiplication of these three value scores. The equation for RPN score calculation is given in Equation (10). In the formula, S, O, and D stand for "Severity", "Occurrence", and "Detectability" scores, respectively. The higher the RPN score is, the higher the risk of the system. Elements in design with high RPN scores must be addressed with specific measures [81].

$$RPN = S * O * D \tag{14}$$

Recently, fuzzy set based FMEA [82,83] and fuzzy extensions-based FMEA approaches have been proposed in the literature [84,85]. Severity, occurrence, and detectability factors are converted into linguistic fuzzy expressions via pre-defined triangular and trapezoidal membership functions. The severity value of the design is expressed as *None*, *Minor*, *Very Low*, *Low*, *Moderate*, *High*, *Very High*, and Hazardous. Occurrence value is expressed linguistically as *Remote*, *Very Low*, *Low*, *Moderate*, *High*, and *Very High*. Detectability sets are *Certain*, *Very High*, *High*, *Moderate*, *Fair*, *Low*, *Rare*, and *None*.

3.3. Proposed Approach

The algorithmic steps of the DFS-based FMEA method are given below as a pseudo code (Algorithm 1).

Algorithms 1: Pseudo representation of proposed approach

Input*:* *n: number of evaluation dimensions* (occurrence $(j = 1)$, severity $(j = 2)$, detectability $(j = 3)$), *m: number of risks* $(i = 1, 2, \ldots m)$, *s: number of experts* $(k = 1, 2, \ldots s)$.
Output: Scores of the risks.
begin
for k = 1: s **do**:
Step 1: Construct the linguistic decomposed fuzzy decision matrices based on Table 4.
$\widetilde{R} = \left(\widetilde{r}_{ij}\right)_{m \times n}$
Step 2: Convert these linguistic terms into corresponding decomposed fuzzy numbers based on Table 4.
$\widetilde{R} = \left(\widetilde{r}^k_{ij}\right)_{m \times n} = \left\{O\left(a^k_{ij}, b^k_{ij}\right), P\left(c^k_{ij}, d^k_{ij}\right)\right\}_{m \times n}$
Step 3: Aggregate the decomposed fuzzy decision matrices by using the DWGM operator given in Equation (7) for $\forall j$, separately.
end for.
Step 4: Multiply the decomposed fuzzy occurrence, severity and detectability values of the risks obtained from Step 3 by using Equation (3).
Step 5: Defuzzify the values in order to obtain crisp values.
for i = 1: m **calculate** the consistency ratio:
$CI(\widetilde{a}) = 1 - \sqrt{\frac{(a-d)^2 + (b-c)^2 + (1-a-b)^2 + (1-c-d)^2}{2}}$
end for
for i = 1: m **compute** score values:
if $SI(\widetilde{a}) \geq 0$:
$SI(\widetilde{a}) = \frac{(a+b-c+d) \cdot CI(\widetilde{a})}{2k}$
else *return* 0;
end for
end

Table 4. Fuzzy linguistic scale [86].

Linguistic Terms	μ	v
Absolutely low (AL)	0.05	0.9
Very low (VL)	0.25	0.6
Low (L)	0.4	0.5
Medium (M)	0.5	0.5
High (H)	0.7	0.2
Very high (VH)	0.85	0.05
Absolutely high (AH)	0.9	0.05

4. Application

A critical concern arises from the complicated interaction of diverse risks that can significantly impact the seamless functioning of the food supply chain ecosystem. These risks consist of various dimensions, including delivery, social, environmental, financial, quality, and technological factors (Table 5). Each of these risks has unique complexities and potential consequences, making it difficult to identify, assess, and mitigate them effectively. Making sure that orders are delivered on time and with the right quality is especially important (R1). Furthermore, the intricate social dynamics bring about risks that impact customer satisfaction, stakeholder rights, security, and broader value-added effects (R2). Additionally, considering the ecological impact and sustainability practices of the supply chain is vital for its resilience. Environmental risks related to waste management, energy use, and reducing carbon footprints require careful examination (R3). Similarly, financial implications are significant, including logistics, operation expenses, overall profits, and their connection to pricing (R4). Within this intricate framework, maintaining product quality and consistent delivery play a crucial role in building consumer trust and satisfaction (R5). At the same time, the rapid evolution of technology affects the supply chain, demanding a detailed understanding of the possible challenges and opportunities tied to information technology, research and development, and broader technological capabilities (R6).

Table 5. Risks, and what is meant by these risks.

	Risk	Explanation of the Risks
R1	Delivery	Risks related to delivering orders in the required quality and on time.
R2	Social	Risks related to security, value-added impact, employee and stakeholder rights, customer satisfaction, etc.
R3	Environmental	Risks related to waste management, carbon footprint reduction, energy consumption, etc.
R4	Financial	Risks related to logistics cost, operational cost, profit, price, etc.
R5	Quality	Risks related to product quality, steadiness of quality, quality assurance, etc.
R6	Technological ability	Risks related to information technology, R&D, technological capabilities, etc.

Thus, the crux of the problem lies in establishing a comprehensive approach that efficiently handles and lessens these diverse risks, guaranteeing the smooth movement of perishable goods while upholding quality, sustainability, and the interests of stakeholders. Achieving this requires an integrated strategy that not only recognizes and evaluates each risk category but also harmonizes their management tactics within the complex fabric of the food cold supply chain. The proposed method has been applied to a company operating in food cold chain logistics. Questions about the probability, severity, and detectability of the identified risks were asked to three different experts in food cold chain logistics. The questions were asked optimistically and pessimistically in order to follow the basic logic of DFS.

Functional question for optimistic manner (for delivery risk only):

FQ1: What is the probability that the delivery risk will not occur in transporting product X in the cold chain?

FQ2: If there is a delivery risk due to transporting product X, what is the probability that its severity will be low?

FQ3: What is the probability of detecting this delivery risk?

Dysfunctional question for pessimistic manner:

DQ1: What is the probability that the delivery risk will occur in transporting product X in the cold chain?

DQ2: If there is a delivery risk due to transporting product X, what is the probability that its severity will be high?

DQ3: What is the probability that the delivery risk will not be detected beforehand?

Tables 6 and 7 present the experts' linguistic evaluations for the pessimistic and optimistic questions, respectively, along with the corresponding decomposed fuzzy numbers. The DWGM operator in Equation (7) was used in order to aggregate the linguistic evaluations of experts, and the results are presented in Table 8.

Table 6. Judgements on the probability, potential impact, and detectability of each risk.

	Occurrence of the Potential Risk					
	DM1		**DM2**		**DM3**	
	ow	pw	ow	pw	ow	pw
R1	H	AL	H	M	L	H
R2	VL	AL	M	H	L	H
R3	VL	M	M	H	L	M
R4	M	H	M	VH	L	H
R5	VL	VL	M	AH	L	VH
R6	H	VL	M	L	M	M
	Severity of the Potential Risk					
	DM1		**DM2**		**DM3**	
	ow	pw	ow	pw	ow	pw
R1	H	M	M	H	L	H
R2	H	H	M	M	L	M
R3	M	M	M	H	M	M
R4	H	H	M	VH	L	H
R5	VL	VH	M	AH	L	VH
R6	VL	VL	M	L	M	L
	Detectability of the Potential Risk					
	DM1		**DM2**		**DM3**	
	ow	pw	ow	pw	ow	pw
R1	H	VL	M	L	L	M
R2	VL	AH	M	M	L	L
R3	M	L	M	M	M	M
R4	M	M	M	M	L	H
R5	VL	VL	M	M	L	H
R6	M	VL	VH	H	L	M

Table 7. Decomposed fuzzy numbers based on experts' linguistic evaluation.

	Occurrence of the Potential Risk											
	DM1				DM2				DM3			
	ow		pw		ow		pw		ow		pw	
R1	0.7	0.2	0.05	0.9	0.7	0.2	0.5	0.5	0.4	0.5	0.7	0.2
R2	0.25	0.6	0.05	0.9	0.5	0.5	0.7	0.2	0.4	0.5	0.7	0.2
R3	0.25	0.6	0.5	0.5	0.5	0.5	0.7	0.2	0.4	0.5	0.5	0.5
R4	0.5	0.5	0.7	0.2	0.5	0.5	0.9	0.05	0.4	0.5	0.7	0.2
R5	0.25	0.6	0.25	0.6	0.5	0.5	0.9	0.05	0.4	0.5	0.85	0.05
R6	0.7	0.2	0.25	0.6	0.5	0.5	4	0.5	0.5	0.5	0.5	0.5
	Severity of the Potential Risk											
	DM1				DM2				DM3			
	ow		pw		ow		pw		ow		pw	
R1	0.7	0.2	0.5	0.5	0.5	0.5	0.7	0.2	0.4	0.5	0.7	0.2
R2	0.7	0.2	0.7	0.2	0.5	0.5	0.5	0.5	0.4	0.5	0.5	0.5
R3	0.5	0.5	0.5	0.5	0.5	0.5	0.7	0.2	0.5	0.5	0.5	0.5
R4	0.7	0.2	0.7	0.2	0.5	0.5	0.85	0.05	0.4	0.5	0.7	0.2
R5	0.25	0.6	0.85	0.05	0.5	0.5	0.9	0.05	0.4	0.5	0.85	0.05
R6	0.25	0.6	0.25	0.6	0.5	0.5	0.4	0.5	0.5	0.5	0.4	0.5
	Detectability of the Potential Risk											
	DM1				DM2				DM3			
	ow		pw		ow		pw		ow		pw	
R1	0.7	0.2	0.25	0.6	0.5	0.5	0.4	0.5	0.4	0.5	0.5	0.5
R2	0.25	0.6	0.9	0.05	0.5	0.5	0.5	0.5	0.4	0.5	0.4	0.5
R3	0.5	0.5	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
R4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.5	0.7	0.2
R5	0.25	0.6	0.25	0.6	0.5	0.5	0.5	0.5	0.4	0.5	0.7	0.2
R6	0.5	0.5	0.25	0.6	0.85	0.05	0.7	0.2	0.4	0.5	0.5	0.5

Table 8. Judgements on the probability, potential impact, and detectability of each risk.

	Occurrence of the Potential Risk			
	ow		pw	
R1	0.581	0.316	0.161	0.533
R2	0.368	0.536	0.199	0.433
R3	0.368	0.536	0.569	0.400
R4	0.464	0.499	0.780	0.150
R5	0.368	0.536	0.708	0.233
R6	0.559	0.415	0.359	0.383
	Severity of the Potential Risk			
	ow		pw	
R1	0.519	0.415	0.637	0.300
R2	0.519	0.415	0.569	0.400
R3	0.500	0.500	0.569	0.400
R4	0.519	0.415	0.756	0.150
R5	0.368	0.536	0.868	0.050
R6	0.397	0.536	0.344	0.533
	Detectability of the Potential Risk			
	ow		pw	
R1	0.519	0.415	0.359	0.533
R2	0.368	0.536	0.641	0.350
R3	0.500	0.500	0.464	0.500
R4	0.464	0.500	0.569	0.500
R5	0.368	0.536	0.452	0.433
R6	0.554	0.381	0.452	0.433

Calculation for probability of R1 occurrence using DWGM operator (weights of experts are considered equal):

$$\mathrm{DWGM}(\widetilde{a_1},\ \widetilde{a_2}, \widetilde{a_3}) = \widetilde{a_1}^{\daleth_1}\widetilde{a_2}^{\daleth_2}\widetilde{a_3}^{\daleth_3}$$

$$\left\{\begin{array}{c} \mathrm{O}\left((0.7)^{0.3333}(0.7)^{0.3333}(0.4)^{0.3333}\right), \left(1-(1-0.2)^{0.3333}\cdot(1-0.2)^{0.3333}\cdot(1-0.5)^{0.3333}\right), \\ \mathrm{P}\left(\begin{array}{c} \frac{(0.05)\cdot(0.5)(0.7)}{(0.05)^2(0.3333)(1-0.05)+(0.5)^2(0.3333)(1-0.5)+(0.7)^2(0.3333)(1-0.7)+(0.05)\cdot(0.5)(0.7)}, \\ \frac{(0.3333)(0.9)+(0.3333)(0.5)+(0.3333)(0.5)}{1+(0.3333)(0.9)+(0.3333)(0.5)+(0.3333)(0.2)-\left(\frac{0.9}{3}+\frac{0.5}{3}+\frac{0.2}{3}\right)} \end{array}\right) \end{array}\right\}$$

$$= \mathrm{O}(0.58091, 0.31598),\ \mathrm{P}(0.16063,\ 0.53331)$$

The FMEA formula (O × S × D) was applied using Equation (3) in order to obtain the final risk magnitudes. Finally, consistency and score indexes of risks were calculated. The results are summarized in Table 9.

Table 9. Risk magnitude, consistency indexes and score indexes of the risks using DFS.

	O × S × D				**CI**	**SI**	**Rank**
	Optimistic		**Pessimistic**				
R1	0.157	0.766	0.117	0.731	0.375	0.247	2
R2	0.070	0.874	0.158	0.663	0.329	0.204	6
R3	0.092	0.884	0.273	0.700	0.390	0.233	4
R4	0.112	0.854	0.423	0.575	0.552	0.264	1
R5	0.050	0.900	0.360	0.529	0.482	0.231	5
R6	0.123	0.832	0.169	0.717	0.365	0.234	3

Calculation for the risk magnitude of the R1

$$\begin{gathered} = O(0.58091,\ 0.31598),\ P(0.16063,\ 0.53331) \times O(0.51928,\ 0.41517),\ P(0.63694,\ 0.29998) \times O(0.51928,\ 0.41517), \\ P(0.35898,\ 0.53331) = O(0.58091,\ 0.31598),\ P(0.16063,\ 0.53331) \times O(0.51928,\ 0.41517),\ P(0.63694,\ 0.29998) \\ = \{O(0.58091\ \times\ 0.51928,\ 0.31598 + 0.41517 - 0.31598 \times 0.41517),\ P(\tfrac{0.16063*0.63694}{0.16063+0.63694-0.16063*0.63694}, \\ \tfrac{0.53331+0.29998-2*0.53331*0.29998}{1-0.53331*0.29998})\} = O(0.301657, 0.599964),\ P(0.147152,\ 0.611087) \\ O(0.301657, 0.599964),\ P(0.147152,\ 0.611087)\ \times\ O(0.51928,\ 0.41517),\ P(0.35898,\ 0.53331) \\ = O(0.156645,\ 0.766045), P(0.116532,\ 0.730749) \end{gathered}$$

The obtained ranking of the risks provides valuable insights into their relative significance within the context of the food cold supply chain. The numerical values associated with each risk indicate their prioritization based on the calculated results (Table 9). With a rank of 1, Financial Risk holds the highest priority. This suggests that financial concerns, such as logistics costs, operational expenses, profits, and pricing dynamics, are deemed the most critical factors impacting the food cold supply chain. Delivery Risk follows closely behind Financial Risk in importance. This indicates that ensuring timely and high-quality delivery of orders is of substantial significance for the smooth operation of the supply chain. With a rank of 3, Technological Ability Risk holds a notable position. This suggests that understanding and effectively managing technological aspects, including information technology, research and development, and broader technological capabilities, play a significant role in the supply chain's performance. With a rank of 4, Environmental Risk underscores the importance of sustainable practices and considerations such as waste management, energy consumption, and carbon footprint reduction in maintaining the supply chain's integrity. With a rank of 5, Quality Risk indicates the significance of maintaining product quality and consistency to uphold consumer trust and satisfaction. With a rank of 6, Social Risk pertains to security, stakeholder rights, customer satisfaction, and broader value-added impacts. While still important, this ranking suggests that other risks take precedence in terms of immediate impact on the supply chain. This information guides decision makers in allocating resources and developing strategies to effectively manage and mitigate risks within the food cold supply chain, ensuring its efficient functioning, sustainability, and stakeholder well-being.

5. Comparative Analysis

Since DFS is an extension of intuitionistic fuzzy sets (IFS), IFS FMEA was used for comparison. The basic arithmetic operations of IFS are summarized below [87].

$$A + B = (\mu_1 + \mu_2 - \mu_1\mu_2,\ \vartheta_1\ \vartheta_2) \quad (15)$$

$$A \times B = (\mu_1\mu_2, \vartheta_1 + \vartheta_2 - \vartheta_1\ \vartheta_2) \quad (16)$$

$$\gimel \cdot A = \left(1 - (1 - \mu_1)^{\gimel},\ (\vartheta_1)^{\gimel}\ \right),\ \gimel > 0 \quad (17)$$

$$A^{\gimel} = \left(\mu_1^{\gimel}, 1 - (1 - \vartheta_1)^{\gimel}\right),\ \gimel > 0 \quad (18)$$

Ranking can be provided based on score and accuracy function which are defined as follows [88,89]:

$$\text{Score function}:\ S(A) = \mu_1 + \mu_1(1 - \mu_1 - \vartheta_1) \quad (19)$$

$$\text{Accuracy function}:\ H(A) = \mu_1 + \vartheta_1 \quad (20)$$

For IFVs $a_i = (\mu_{a_i},\ \vartheta_{a_i})$ and $(i = 1, 2, \ldots, n)$, then the intuitionistic fuzzy weighted averaging operator $(IFWA)$ is defined by [90]:

$$IFWA = (a_1, a_2, \ldots, a_n) = w_1 a_1 + w_2 a_2 + \ldots + w_n a_n = \left(1 - \prod_{i=1}^{n}(1 - \mu_{a_i})^{w_i},\ \prod_{i=1}^{n} \vartheta_{a_i}^{w_i}\right) \quad (21)$$

The intuitionistic fuzzy weighted geometric $(IFWG)$ operator is defined by [90]:

$$IFWG(a_1, a_2, \ldots, a_n) = a_1{}^{w_1} \times\ a_2{}^{w_2} \times \ldots \times\ a_n{}^{w_n} = \left(\prod_{i=1}^{n} \mu_{a_i}{}^{w_i}, 1 - \prod_{i=1}^{n}(1 - \vartheta_{a_i})^{w_i}\right) \quad (22)$$

The primary distinction between DFS and IFS lies in the data collection approach, wherein DFS employs a combination of functional and dysfunctional questions. In other words, DFS can be defined as an ordered pair structure encompassing IFS. To facilitate a comparative analysis, the transformation of the DFS dataset into IFS is essential. This transformation was executed through the creation of two distinct scenarios.

In the first scenario, risk evaluations were exclusively calculated using the dataset pertaining to the functional questions in DFS. Contrarily, the second scenario entailed generating the IFS data set by averaging responses from both functional and dysfunctional questions. In the third scenario, risk magnitudes were calculated using the data obtained from the responses to the dysfunctional questions. These results were then organized in descending order, ranging from the highest to lowest risk.

The results are presented in Table 10. In the first IFS-based scenario, the ranking was R4, R5, R3, R2, R1, and R6, while in the second scenario, it was R4, R1, R5, R3, R2, and R6. In the third scenario, the ranks of these risks were R1, R6, R4, R3, R2, and R5. The disparity among these rankings obtained through IFS-based FMEA effectively demonstrates the distinctness in responses between functional and dysfunctional questions. The ranking obtained from DF FMEA was also R4, R1, R6, R3, R5, and R2. It can be observed that the ranking derived from DFS carries traces from the other three rankings, arising as a result of decision makers' uncertainty. This implies that the DF FMEA considers decision makers' indecision.

Table 10. Results obtained from IFS-based scenarios.

	Scenario 1		Scenario 2		Scenario 3	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**
R1	0.063	2	0.142	5	0.169	1
R2	0.097	5	0.102	4	0.074	5
R3	0.149	4	0.122	3	0.094	4
R4	0.346	1	0.213	1	0.116	3
R5	0.254	3	0.133	2	0.053	6
R6	0.059	6	0.094	6	0.129	2

6. Discussion

The present study contributes to the field of risk assessment in the food cold supply chain by introducing a novel approach, the "Decomposed Fuzzy Set-Based FMEA" (DF FMEA) method. Through the application of this method, we have gained valuable insights into the relative significance of different risks within the context of the food cold supply chain. Our findings are consistent with previous literature that emphasizes the importance of risk assessment and effective supplier selection in the food sector [15,28,54,56,65,88]. While prior studies have predominantly focused on various methods of risk analysis [5,7,16,22,33,37,40,46,79], our research stands out by adapting the DF FMEA method to the specific challenges of the food cold chain. Our approach aligns with the trend of integrating multiple risk assessment methodologies and considering uncertainties, as evidenced by the prominence of fuzzy set theory in existing literature. Moreover, our study complements previous works by shedding light on the cold chain's unique complexities and the need for tailored risk assessment techniques.

The findings of this study have several important implications for future research. Firstly, the introduction of the DF FMEA method offers a novel approach to risk assessment that can be further refined and adapted for application in different industries and supply chain scenarios. This methodological advancement opens avenues for further research in risk assessment methodologies, allowing researchers to explore innovative ways of incorporating uncertainties and decision makers' preferences into the analysis.

Secondly, researchers can develop comprehensive risk management frameworks that consider decision makers' preferences and uncertainties, promoting more effective decision making across various sectors. The DF FMEA method equips decision makers with a comprehensive framework to assess and prioritize risks effectively. By considering both optimistic and pessimistic viewpoints, our approach offers a nuanced perspective that enables more informed decision making. Practitioners can leverage our method to identify, manage, and mitigate risks, thereby enhancing the safety, quality, and sustainability of the cold chain. Furthermore, our findings shed light on the critical areas that require immediate attention, such as financial and delivery-related concerns. This information guides the allocation of resources and the development of strategies to ensure the smooth functioning of the supply chain.

Thirdly, the cross-industry application of the DF FMEA method holds the potential for enhancing risk assessment in industries beyond the food cold chain, such as pharmaceuticals and electronics. Additionally, the study highlights the interplay between supplier selection and risk assessment, suggesting the need for integrated models that encompass both factors. Furthermore, researchers can investigate the integration of emerging technologies such as IoT and blockchain into risk assessment processes. Regional and global studies can provide insights into how cultural and regulatory differences influence risk management strategies. Lastly, addressing food waste through optimized supply chain practices presents a crucial avenue for future research, contributing to sustainable and efficient operations across industries.

In conclusion, this paper holds significant relevance for both practitioners and society. For practitioners in the food industry and specifically the cold chain sector, the paper introduces a novel risk assessment approach called "Decomposed Fuzzy Set-Based

FMEA" (DF FMEA). This innovative method incorporates decision makers' preferences and uncertainties, providing a more nuanced perspective on risk assessment. By applying this method, practitioners can effectively prioritize and manage risks within the food cold supply chain. The DF FMEA enhances decision making by offering a comprehensive evaluation of risks, helping practitioners allocate resources more efficiently and develop strategies to mitigate potential threats. This ultimately contributes to the improved functioning, sustainability, and well-being of the entire supply chain. In terms of societal impact, the proposed risk assessment method offers a proactive approach to improved practices, safer food supply chains, and a more resilient food industry overall. By focusing on risk management within the cold chain, the paper indirectly supports public health by reducing the likelihood of foodborne illnesses due to compromised products. Additionally, the research provides valuable insights into risk assessment methodologies and their practical applications, contributing to the advancement of knowledge in both academia and industry.

7. Conclusions

The food supply chain's importance has significantly expanded as a result of the COVID-19 pandemic, making it crucial to conduct risk studies and implement preventative measures. Risk analysis involves examining potential risks and their impacts, and is commonly employed in various industries, particularly in the workplace. There are numerous approaches to performing risk analysis, some of which are used individually while others are combined with fuzzy logic. One of the most well-known of these methods is the FMEA method. The FMEA method is a widely used risk analysis technique that involves identifying and evaluating the potential failure modes of a product or process, and the consequences of those failures. It is often used in the design or development phase of a product or process to identify potential problems and to take corrective actions to prevent or mitigate them.

There have been relatively few studies focused on the food cold chain compared with other areas of the food sector. The food cold chain refers to the storage and transportation of perishable foods at low temperatures in order to extend their shelf life and maintain their quality. It is an important aspect of the food industry, as it plays a crucial role in ensuring that fresh and safe foods are available to consumers. However, due to the complex and dynamic nature of the food cold chain, it can be challenging to study and understand. As a result, there have been fewer research studies conducted in this area compared with other areas of the food sector.

In order to fill this gap in the literature, in this paper, we proposed a new risk assessment method based on DF FMEA and applied the method on the food cold supply chain to illustrate its applicability. In the application, we collected data from three experts with sector experience. To ensure that the experts could express their views fully, the questions were asked from both an optimistic and a pessimistic perspective, following the DFS method. The questions were about the three basic parameters of the FMEA method: occurrence, severity, and detectability. Thus, the FMEA method was adapted to DFS, and the risks were listed as Financial Risks, Delivery Risks, Technological Ability Risks, Environmental Risks, Quality Risks, and Social Risks, from the most dangerous to the least dangerous. In summary, the interpretation of the ranking underscored the primacy of financial and delivery-related concerns, closely followed by technological, environmental, quality, and social factors. This information guides decision makers in allocating resources and developing strategies to effectively manage and mitigate risks within the food cold supply chain, ensuring its efficient functioning, sustainability, and stakeholder well-being.

The practical impact of the study primarily lies in the proposed risk assessment method. By introducing a nuanced perspective into risk assessment, and considering decision makers' preferences and uncertainties, the DF FMEA method facilitates more informed and reliable decision making. This methodological advancement contributes to the field by providing a robust framework for assessing and addressing risks in the food cold chain industry, ultimately aiding practitioners in making more effective risk management. While this study provides valuable insights into risk prioritization within the food cold supply chain, its limitations underscore the need for further research, broader samples, and a more holistic consideration of risk factors to ensure a comprehensive understanding of the complex risk landscape. For future studies, new methods can be introduced by adapting other risk analysis methods to DFS. These new methods can be applied in other areas of the cold supply chain, such as pharmaceuticals, and other temperature-sensitive products. This could help improve the efficiency and safety of these supply chains and reduce the risk of losses or failures.

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