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Enhancing Economic, Resilient, and Sustainable Outcomes Through Supplier Selection and Order Allocation in the Food Manufacturing Industry: A Hybrid Delphi-FAHP-FMOP Method

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Abstract: In the food manufacturing industry, which is critical to national economies, there is a growing imperative to meet heightened safety, quality, and environmental standards, particularly in the face of supply chain disruptions. This study addresses the gap in literature by integrating sustainable and resilient supply chain theories with risk management and low-carbon principles into a supplier selection framework. Utilizing the Delphi method, fuzzy analytic hierarchy process (FAHP), and fuzzy multi-objective programming (FMOP), we develop a decision-making model specifically calibrated for the food sector. Initially, the study establishes a comprehensive criteria system encompassing quality, cost, delivery, low-carbon, and risk management through a literature review and expert consultation. Subsequently, FAHP is employed to determine the relative importance of each criterion in supplier selection. Furthermore, FMOP is utilized to develop a decision-making model for optimizing supplier selection and order allocation. Validated through a numerical study based on a Chinese food manufacturer, the framework presents a practical tool for food manufacturers, ensuring supply chain stability while aligning with sustainability objectives. This research refines decision making and strengthens the competitive stance of food manufacturers, significantly propelling the industry's green transformation.

Keywords: supplier selection; order allocation; food manufacturing industry; hybrid Delphi-FAHP-FMOP method

MSC: 90B06; 90B50; 90C05; 90C11; 90C29; 94D05



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1. Introduction

As consumer preferences evolve and food safety regulations become more stringent, food manufacturers face the dual challenge of continuous innovation and compliance to ensure competitiveness and sustainable development [1,2]. Central to these efforts is the enhancement of food supply chain management [3], where supplier management plays a pivotal role in maintaining the supply chain's seamless operation [1,4].

Sustainability in production and services is now a key concern in the food manufacturing industry [5,6], with companies aiming for a balance between economic prosperity, social responsibility, and environmental stewardship [7]. This shift emphasizes the importance of sustainable suppliers in procurement decisions [6,8]. Amid global warming concerns, there is a growing focus on low-carbon initiatives [9,10]. Selecting suppliers with sustainable practices is essential for reducing carbon emissions and achieving low-carbon objectives [11–16].

Furthermore, globalization introduces uncertainties such as disasters and epidemics, highlighting the need for resilient food supply chains [17–19]. The ability of suppliers to adapt and manage disruptions is crucial [20,21], so choosing resilient suppliers is key to mitigating

risks and ensuring operational continuity amidst potential disruptions [17–19,22,23]. Therefore, supplier selection involves evaluating multiple criteria, and in order to gain and sustain a competitive edge, it is imperative for companies to adapt their supplier selection strategies to the dynamic business environment [24].

The pivotal role of supplier selection within the food supply chain merits intensified scrutiny, particularly in the context of food manufacturing where research has been notably sparse regarding the integration of resilience and sustainability criteria [25]. It is imperative for the food industry to assess suppliers across a spectrum of factors beyond mere economics, encompassing sustainability and resilience as well. However, extant research is characterized by a paucity of quantitative methodologies, empirical studies, and a framework that is specifically designed to address the food industry's unique requirements, which include economic, sustainable, and resilient dimensions [2,7]. Moreover, the determination of optimal order allocation post-supplier selection for food manufacturers is a critical juncture that has been understudied [26]. Consequently, there is an urgent requirement for a holistic approach that addresses these research gaps within the food manufacturing sector.

In light of this, the present study introduces a multi-objective perspective, integrating risk management capabilities and low-carbon principles to formulate a comprehensive evaluation framework for supplier selection and order allocation in the food manufacturing industry. The main research questions to achieve these goals include:

RQ1: What criteria can be used to evaluate and select suppliers based on the potential disruptions and low carbon in the food manufacturing industry?

RQ2: How can suppliers be systematically selected using these criteria and methods?

RQ3: How can orders be reasonably allocated among suppliers considering conflicts in different objectives?

This study proposes a hybrid model combining the Delphi method, Fuzzy Analytical Hierarchy Process (FAHP), and Fuzzy Multi-Objective Programming (FMOP). The criteria for supplier selection including quality, cost, delivery, sustainability, and risk management are established through a literature review. The selection and order allocation strategy are derived by implementing FAHP and FMOP, presenting a comprehensive framework for managing suppliers in the food manufacturing industry. The main contributions are outlined as follows:

- Integration of sustainability and resilience: constructs a systematic supplier selection framework by merging general criteria with sustainability and resilience needs in the food supply chains, bridging research gaps.
- Hybrid decision-making model: develops a novel model integrating Delphi, FAHP, and FMOP, blending qualitative and quantitative analysis with fuzzy theory for uncertainty management, improving decision effectiveness and applicability in the dynamic and turbulent environment.
- Enhanced supplier management capability: boosts the food industry's supplier management, enhances decision quality, and enables rapid strategy adjustments to market dynamics through iterative optimization.

The remaining sections are organized in the following manner: Section 2 reviews the literature on supplier selection criteria and methods. Section 3 outlines the two-phase research methodology, detailing steps to develop the supplier selection criteria system (Phase 1) and model the supplier selection and order allocation problem (Phase 2). Section 4 validates the criteria system and selection model through a real case study. Section 5 summarizes the main conclusions and suggests avenues for future research.

2. Literature Review

2.1. Supplier Selection and Order Allocation

The supplier selection process is crucial in supply chain management, significantly impacting product quality, safety, and sustainability. As highlighted in Table 1 and detailed in Appendix A, key criteria such as cost, quality, and delivery have been validated across various sectors for their role in ensuring product integrity and market competitiveness [2,7,20,23,27–41]. In the food manufacturing sector, these criteria are particularly

relevant due to the industry's need to balance high-quality standards with operational efficiency. Furthermore, the increasing emphasis on environmental protection has led to the incorporation of sustainability principles into the supplier selection process. Early studies expanded traditional economic metrics to include environmental and social considerations, advocating for comprehensive criteria that address carbon management and low-carbon supply chains [11,12,16]. This study aims to introduce a low-carbon criterion into the supplier evaluation framework, specifically targeting the environmental challenges faced by food manufacturers. Additionally, in light of rising supply chain uncertainties, resilience has emerged as a critical factor, often taking precedence over mere stability [36,42]. Recent frameworks emphasize flexibility, cooperation, and backup capacity as essential indicators of a supplier's ability to adapt to disruptions [17–19,43–45]. Therefore, this study integrates risk management as a vital criterion, focusing on suppliers' capacities to manage dynamic conditions and ensure operational continuity amidst unforeseen challenges. By addressing these multifaceted criteria, this research contributes to a more robust and adaptable supplier selection framework tailored for the food manufacturing industry.

Table 1. Supplier selection criteria and analytical method.

Authors (Year)	Selection Criteria																										Methodology	Research Industry			
	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z			A	B	
Lee et al. (2009) [46]	✓	✓				✓																							FAHP-FGP	Electronic industry	
Kannan et al. (2013) [47]	✓	✓				✓	✓															✓							FAHP-FMOP	Automotive industry	
Sivrikaya et al. (2015) [27]	✓	✓				✓								✓															FAHP-FGP	Textile industry	
Dweiri et al. (2016) [28]	✓	✓				✓							✓	✓				✓											AHP	Automotive industry	
Haikal & Setio (2017) [29]	✓	✓	✓			✓	✓					✓		✓								✓							AHP	Food and Beverage industry	
Luthra et al. (2017) [30]	✓	✓			✓	✓	✓					✓				✓					✓	✓	✓	✓	✓				AHP-VIKOR	Automotive industry	
Cheraghalipour et al. (2018) [31]	✓	✓			✓	✓	✓				✓	✓		✓				✓											Hybrid BWM-VIKOR	Agricultural industry	
Guarnieri & Trojan (2019) [32]	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓			✓		✓	✓	✓	✓	✓	✓	✓	✓	✓			AHP, ELECTRE-TRI	Textile industry	
Fu (2019) [33]	✓	✓							✓		✓																		AHP-ARAS-MCGP	Food and Beverage industry	
Lei et al. (2020) [48]	✓					✓		✓			✓											✓	✓						PL-TOPSIS	Hypothetical case	
Beiki et al. (2021) [34]	✓	✓		✓		✓									✓	✓	✓		✓	✓	✓	✓	✓	✓	✓				LEWM-MOP	Automotive industry	
Fallahpour et al. (2021) [49]	✓	✓	✓			✓		✓						✓					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	FDEMATEL-FBWM-FANP-FIS	Palm oil industry	
Sun et al. (2022) [50]	✓	✓				✓				✓	✓	✓		✓	✓				✓			✓	✓						Factor analysis, SEM, and FTOPSIS	Electronic manufacturing industry	
Göncü et al. (2022) [35]	✓	✓		✓	✓	✓			✓				✓			✓	✓		✓	✓	✓	✓	✓	✓	✓				Dematel-ANP	Healthcare industry	
Aungkulanon, Pasura, et al. (2024) [36]	✓	✓				✓		✓		✓									✓	✓		✓					✓		EFA, FAHP, PROMETHEE II	Agri-food industry	
This paper	✓	✓				✓		✓		✓	✓			✓		✓			✓	✓	✓	✓	✓			✓	✓	✓	✓	Delphi-FAHP-FMOP	Food manufacturing industry

Despite the progress made in supplier selection research, there is a notable lack of empirical studies focused specifically on the food manufacturing industry. Much of the existing literature has been concentrated on other sectors, often overlooking the unique challenges such as perishability and strict regulatory requirements inherent to food production. The need for an integrated approach combining sustainability with resilience is especially critical for food manufacturers. This study seeks to address this gap by proposing a comprehensive supplier selection framework that integrates sustainability and resilience criteria alongside traditional factors, tailored specifically to the food industry's unique challenges.

Order allocation is also a fundamental aspect of multiple supplier management, significantly influencing inventory levels, production efficiency, and operational performance. Research has focused on optimizing order allocation models, emphasizing cost minimization and service level maximization to align order quantities with supplier capabilities effectively [11,17,22]. Recently, there has been a growing recognition of the need to incorporate sustainability into these models, as integrating environmental criteria can enhance corporate social responsibility and foster long-term supplier relationships [34]. However, many existing frameworks rely on static parameters, failing to account for the dynamic

nature of supply chains, particularly in the food manufacturing industry, where demand variability and regulatory pressures are common [1–3,7,10]. This study addresses these limitations by proposing a hybrid model that employs fuzzy logic and multi-objective optimization, enabling more flexible and responsive order allocation strategies. By enhancing adaptability, this research aims to improve the effectiveness of supply chain management in a sector that requires resilience in the face of fluctuating market conditions.

2.2. Related Methods

Supplier selection and order allocation are essential components of effective supply chain management, significantly influencing product quality, operational efficiency, and sustainability. Initially, research relied on qualitative methods emphasizing experience and relationships, but these proved insufficient as procurement environments grew more complex. This shift prompted the integration of quantitative optimization techniques, allowing for more structured assessments of suppliers and effective order allocation strategies. Among these, the Analytic Hierarchy Process (AHP) gained prominence for quantifying qualitative factors through systematic judgments [28,29,51,52]. The Analytic Network Process (ANP) further refined this approach by considering inter-relationships among selection criteria [53]. Other notable methodologies include the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [48] and neural network approaches [54], enhancing decision-making accuracy by leveraging data patterns. Multi-objective programming (MOP) has also become relevant, enabling optimization of conflicting objectives—such as cost, quality, delivery time, and environmental sustainability—simultaneously [33,47,55–57]. Recent studies advocate for hybrid models combining these methodologies, addressing the subjectivity and ambiguity in criteria assessments through fuzzy set theory [50,52,58,59]. Approaches like Fuzzy AHP (FAHP) and Fuzzy Goal Programming (FGP) provide more realistic weight calculations, mitigating issues associated with traditional AHP methods [27,46].

Despite advancements in supplier selection and order allocation methodologies, significant gaps persist, particularly regarding empirical studies in the food manufacturing sector. Existing literature primarily focuses on supplier selection in other industries, neglecting the unique challenges faced by food manufacturers, such as perishability and stringent regulatory requirements. Additionally, many frameworks inadequately incorporate sustainability and resilience into their criteria. This study addresses these gaps by proposing a comprehensive supplier selection framework tailored to the food industry, integrating sustainability and resilience alongside traditional factors. By employing a mixed-method approach that combines fuzzy AHP (FAHP) and fuzzy multi-objective programming (FMOP), this research aims to produce more objective results, mitigating biases from subjective judgments and leading to more robust outcomes in supplier selection and order allocation.

3. Methodology

3.1. Two-Phase Investigation Design

This study devises a two-phase approach to food manufacturing supplier selection and order allocation (see Figure 1), incorporating general, sustainability, and resilience criteria. Phase one refines criteria through expert consensus using the Delphi method. Phase two uses FAHP and FMOP to weigh criteria and optimize order allocation. A case study verifies the framework's applicability.

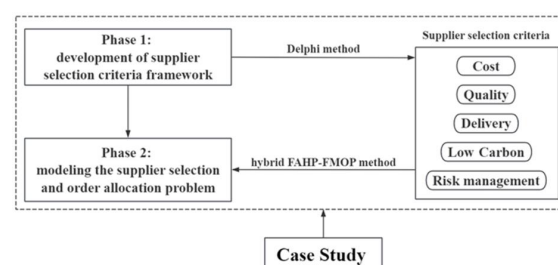


Figure 1. Two-phase method design.

3.2. Phase 1: Development of Supplier Evaluation Criteria Framework

This study creates a refined criteria system for supplier selection in food manufacturing through a literature review and the Delphi method, considering industry-specific characteristics [60–63]. This study employs two rounds of this process (Figure 2).

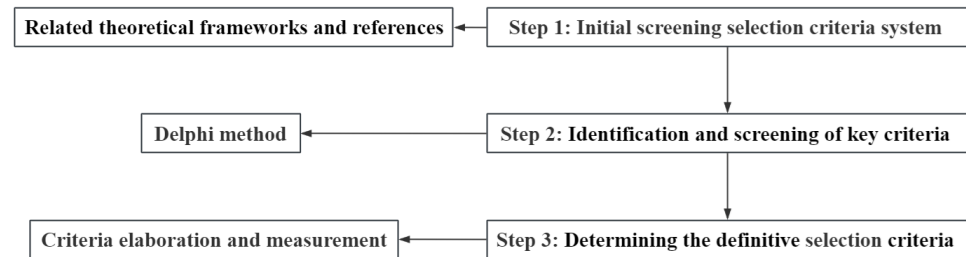


Figure 2. The process of establishing a supplier selection criteria framework.

3.3. Phase 2: Modeling the Supplier Selection and Order Allocation Problem

In order to assist food manufacturing companies in considering the impact of supply chain disruption risks and low carbon when selecting suppliers, this study develops a hybrid decision-making model that combines FAHP and FMOP. The selection of the FAHP-FMOP model for this study is driven by its effectiveness in addressing the complex challenges of supplier selection and order allocation in the food manufacturing industry. FAHP facilitates the quantification of qualitative judgments, essential for evaluating multifaceted criteria such as quality, cost, delivery, and sustainability. When combined with FMOP, this model optimizes multiple conflicting objectives, offering adaptability and precision that traditional methods like AHP and TOPSIS lack, particularly in dynamic environments [8,64,65]. Figure 3 outlines the implementation steps of this integrated approach using FAHP and FMOP.

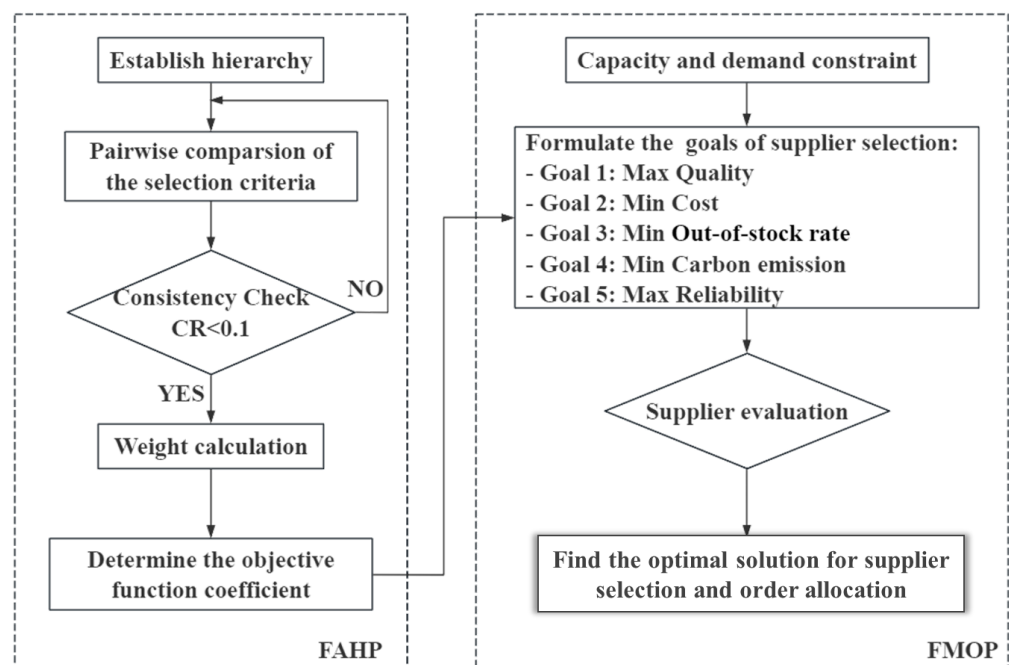


Figure 3. The hybrid FAHP-FMOP method.

3.3.1. Supplier Evaluation Using FAHP

Zadeh [66] introduced fuzzy set theory to address real-world uncertainty, which FAHP extends into AHP to quantify criterion performance with membership degrees, enhancing traditional AHP with subjective and objective analysis for supplier selection [59]. The

development of the FAHP model generally follows the process of developing an AHP model, with the following specific steps:

Step 1: Establish the hierarchy model.

Based on the supplier selection criteria system constructed in the first stage, the overall goal layer, the criteria layer (the main evaluation factor criteria), and the sub-criteria layer (the refinement of factor criteria) are established for supplier selection in the food manufacturing industry.

Step 2: Construct fuzzy judgment matrices.

In this study, judgment matrices are constructed using AHP, with pairwise comparisons in FAHP represented by linguistic variables and triangular fuzzy numbers (TFNs) due to their simplicity and efficiency in processing complex data (Table 2). TFNs are ideal for capturing uncertainty in expert judgments, offering a balance between complexity and interpretability, and enhancing the reliability of decision-making outcomes through their robust and flexible structure [59,67].

Table 2. The value of TFNs in the FAHP.

Saaty Scale	Description	Triangular Fuzzy Numbers (TFNs)	Reciprocal of TFNs
1	Equally important	(1, 1, 1)	(1, 1, 1)
3	Weakly important	(2, 3, 4)	(1/4, 1/3, 1/2)
5	Fairly important	(4, 5, 6)	(1/6, 1/5, 1/4)
7	Strongly important	(6, 7, 8)	(1/8, 1/7, 1/6)
9	Absolutely important	(9, 9, 9)	(1/9, 1/9, 1/9)
2		(1, 2, 3)	(1/3, 1/2, 1)
4	The intermittent values between two adjacent scales	(3, 4, 5)	(1/5, 1/4, 1/3)
6		(5, 6, 7)	(1/7, 1/6, 1/5)
8		(7, 8, 9)	(1/9, 1/8, 1/7)

In this study, TFNs gauged by expert opinions construct fuzzy judgment matrices to determine criterion weights. TFNs, like (4, 5, 6), indicate criterion importance. The geometric mean averages these TFNs to reduce subjectivity [59].

Step 3: Check for consistency.

In FAHP analysis, individual expert comparisons can be subjective, necessitating consistency checks with the Consistency Ratio (CR). A $CR < 0.1$ is acceptable, but a higher CR indicates the need for reassessment [59].

Step 4: Calculate fuzzy weights.

This phase is supplementary in comparison to AHP. In this step, the current study uses the extent analysis method [67] to determine weights and transform TFNs into precise values in the fuzzy pairwise comparison matrix.

First, let D_i represent the comprehensive importance of criterion i relative to other criteria in the fuzzy judgment matrix, and M_{ij} represent the importance of criterion i relative to criterion j in the fuzzy judgment matrix, i.e., $M_{ij} = a_{ij}$. The initial weights D_i for each element can be obtained from the fuzzy judgment matrix constructed in step 2.

$$D_i = \sum_{j=1}^n M_{ij} \odot \left[\sum_{i=1}^n \sum_{j=1}^n M_{ij} \right]^{-1}, i, j = 1, 2, \dots, n \quad (1)$$

Following that, comparisons between fuzzy sets are performed. Let $D_1 = (l_1, m_1, u_1)$ and $D_2 = (l_2, m_2, u_2)$ represent the initial weights of two triangular fuzzy numbers. Fuzzy sets represented by comprehensive fuzzy values are compared to each other. The possibility degree $V(D_1 \geq D_2)$ of the triangular fuzzy number $D_1 \geq D_2$ is defined using a triangular fuzzy function.

$$V(D_1 \geq D_2) = \begin{cases} 1, & \text{if } m_1 > m_2 \\ \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)}, & \text{if } m_1 \leq m_2, u_1 \geq l_2 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Then, the possibility degree of one fuzzy number being greater than the other fuzzy numbers is used as the final weight for that criterion. Let $d(D_i)$ represent the superiority of the criterion D_i over the other criteria.

$$d(D_i) = V(D_i \geq D_1, \dots, D_n) = \min(D_i \geq D_k), k \neq i \quad (3)$$

Step 5: Calculate the normalized weights of evaluation criteria.

From step 4, we obtain the weight vector for all criteria:

$$W = (d(D_1), d(D_2), \dots, d(D_n)), D_i (i = 1, 2, \dots, n) \text{ are } n \text{ elements} \quad (4)$$

By normalizing the obtained weight vector, we can obtain the normalized final weights, denoted as W' . These weights can be used as coefficients for the objective functions in fuzzy multi-objective programming.

3.3.2. Problem Description, Assumptions and Notation

In the food manufacturing industry, supplier selection involves complex decisions on sourcing and procurement quantities, influenced by criteria like quality, cost, delivery, low-carbon practices, and risk management [2,21,60]. Multi-objective programming offers a comprehensive evaluation approach, providing non-dominated solutions and allowing for a nuanced understanding of trade-offs. This study aims to develop a multi-objective model for supplier selection, considering the unique strengths and weaknesses of each supplier to align with the industry's specific criteria.

Assumptions:

1. The products provided by suppliers to the company are assumed to be available without any shortages.
2. The company purchases a single type of product from each supplier.
3. Price discounts and costs related to product shortages are not considered.
4. The carbon emissions per unit of product during the procurement process are considered to be constant.
5. In the case of potential supply chain disruptions, the reliability of each supplier, as measured by certain risk metrics, is treated as a deterministic value.

Decision variables:

x_{ij} : The procurement quantity of product j from supplier i by the company.

Sets and Indices:

I : The set of potential suppliers, denoted by $I = \{1, 2, \dots, i, \dots, n\}$.

i : The suppliers that take values from 1 to n , where n is the total number of potential suppliers.

J : The set of products needed by the company, denoted by $J = \{1, 2, \dots, j, \dots, m\}$.

j : The products that take values from 1 to m , where m is the total number of products needed.

K : The set of objective functions, denoted by $K = \{1, 2, \dots, k, \dots, p\}$.

k : The objective functions that take values from 1 to p , where p is the total number of objective functions in the model.

Parameters:

D_j : The demand quantity of product j by the company.

U_{ij} : The maximum supply capacity of product j that supplier i can provide to the company.

G : The maximum allowed total carbon emissions.

c_{ij} : The unit procurement price of procuring product j from supplier i by the company.

q_{ij} : The overall quality level of product j supplied by supplier i .

d_{ij} : The average out-of-stock rate of procuring product j from supplier i .

g_{ij} : The carbon emissions per unit of procuring product j from supplier i .

r_{ij} : The reliability of supplier i in providing product j in the event of potential disruptions.

Objective functions:

1. Minimize the total procurement cost:

$$\text{Min } Z_1 = \sum_{i=1}^n \sum_{j=1}^m c_{ij} x_{ij} \quad (5)$$

2. Maximize the total quality of products supplied by suppliers:

$$\text{Max } Z_2 = \sum_{i=1}^n \sum_{j=1}^m q_{ij} x_{ij} \quad (6)$$

3. Minimize the number of delayed product deliveries:

$$\text{Min } Z_3 = \sum_{i=1}^n \sum_{j=1}^m d_{ij} x_{ij} \quad (7)$$

4. Minimize the total carbon emissions of products:

$$\text{Min } Z_4 = \sum_{i=1}^n \sum_{j=1}^m g_{ij} x_{ij} \quad (8)$$

5. Maximize supplier reliability, which is to minimize the probability of supply chain disruptions:

$$\text{Max } Z_5 = \sum_{i=1}^n \sum_{j=1}^m r_{ij} x_{ij} \quad (9)$$

Constraints:

1. The company faces limitations on the supply capacity of each supplier when purchasing products.

$$x_{ij} \leq U_{ij} \quad (10)$$

2. The order quantity for each product should meet the demand of the company.

$$\sum_{i=1}^n x_{ij} = D_j, \forall j \quad (11)$$

3. Due to government regulations, each company has a carbon emissions limit that should not be exceeded. Therefore, the company needs to control its emissions appropriately.

$$\sum_{i=1}^n g_{ij} x_{ij} \leq G, \forall j \quad (12)$$

4. The purchase quantity of products should be constrained to be non-negative.

$$x_{ij} \geq 0 \text{ and integer, } \forall i, j \quad (13)$$

3.3.3. Establishment of the FMOP Model

In the food manufacturing industry, supplier selection is complicated by uncertainties like supply chain disruptions and raw material price volatility [2,21]. Fuzzy set theory [66] and FMOP methods [64] offer structured approaches to handle such complexities, allowing for the integration of factors like reliability, quality, cost, and strategic alignment. These

methods transform fuzzy multi-objective models into crisp single-objective ones, aiding decision makers in evaluating supplier performance and risks amidst ambiguity. This study applies Zimmermann's method [64] and Lin's optimization technique [65] using Lingo 21.0 to develop a precise single-objective model for supplier selection, ensuring choices align with organizational goals while managing uncertainties. The detailed process is as follows.

Step 1: Construct a fuzzy multi-objective programming model based on known criteria, objectives, and constraints.

In food manufacturing, supplier selection involves fuzzy factors like quality and price; thus, the multi-objective model transforms into a fuzzy model, retaining constraints.

$$\sum_{i=1}^n \sum_{j=1}^m c_{ij} x_{ij} \lesssim \tilde{Z}_1 \quad (14)$$

$$\sum_{i=1}^n \sum_{j=1}^m q_{ij} x_{ij} \lesssim \tilde{Z}_2 \quad (15)$$

$$\sum_{i=1}^n \sum_{j=1}^m d_{ij} x_{ij} \lesssim \tilde{Z}_3 \quad (16)$$

$$\sum_{i=1}^n \sum_{j=1}^m g_{ij} x_{ij} \lesssim \tilde{Z}_4 \quad (17)$$

$$\sum_{i=1}^n \sum_{j=1}^m r_{ij} x_{ij} \lesssim \tilde{Z}_5 \quad (18)$$

Step 2: Ignore the other objectives, under the given constraints, and find the upper deviation limit Z_k^+ and lower deviation limit Z_k^- for each individual objective function $Z_k(x)$ [64]. For example, under the condition of satisfying all constraints, select the supplier combination that maximizes the value of the objective function. The maximum value obtained represents the upper limit of that particular objective function. The specific solution method can be found in Equation (19).

$$\begin{aligned} & \max(\min) Z_k(x) \\ & s.t. \left\{ \begin{array}{l} x_{ij} \leq U_{ij} \\ \sum_{i=1}^n x_{ij} = D_j, \forall j \\ \sum_{i=1}^n g_{ij} x_{ij} \leq G, \forall j \\ x_{ij} \geq 0 \text{ and integer, } \forall i, j \end{array} \right. \end{aligned} \quad (19)$$

Step 3: Construct the membership functions $\mu_{Z_k}(x)$.

This study uses trapezoidal membership functions in fuzzy multi-objective programming, applying them for minimization and maximization objectives (Figure 4). These functions effectively model uncertainty and provide flexibility by allowing smooth transitions between satisfaction levels, better reflecting real-world trade-offs. Their computational efficiency ensures tractability even in complex multi-objective environments, making them well-suited for optimizing conflicting objectives [64,66].

Therefore, for the five objectives proposed in this study, the expressions of their membership functions are as follows:

$$\mu_{Z_1}(x) = \begin{cases} 1, & Z_1 \leq Z_1^- \\ \frac{Z_1^+ - Z_1(x)}{Z_1^+ - Z_1^-}, & Z_1^- \leq Z_1 \leq Z_1^+ \\ 0, & Z_1 \geq Z_1^+ \end{cases} \quad (20)$$

$$\mu_{Z_2}(x) = \begin{cases} 1, & Z_2 \geq Z_2^+ \\ \frac{Z_2(x) - Z_2^+}{Z_2^+ - Z_2^-}, & Z_2^- \leq Z_2 \leq Z_2^+ \\ 0, & Z_2 \leq Z_2^- \end{cases} \quad (21)$$

$$\mu_{Z_3}(x) = \begin{cases} 1, & Z_3 \leq Z_3^- \\ \frac{Z_3^+ - Z_3(x)}{Z_3^+ - Z_3^-}, & Z_3^- \leq Z_3 \leq Z_3^+ \\ 0, & Z_3 \geq Z_3^+ \end{cases} \quad (22)$$

$$\mu_{Z_4}(x) = \begin{cases} 1, & Z_4 \leq Z_4^- \\ \frac{Z_4^+ - Z_4(x)}{Z_4^+ - Z_4^-}, & Z_4^- \leq Z_4 \leq Z_4^+ \\ 0, & Z_4 \geq Z_4^+ \end{cases} \quad (23)$$

$$\mu_{Z_5}(x) = \begin{cases} 1, & Z_5 \geq Z_5^+ \\ \frac{Z_5(x) - Z_5^+}{Z_5^+ - Z_5^-}, & Z_5^- \leq Z_5 \leq Z_5^+ \\ 0, & Z_5 \leq Z_5^- \end{cases} \quad (24)$$

These upper and lower bounds of the membership functions can be used to transform the fuzzy multi-objective programming model into a crisp single-objective model, enabling subsequent optimization and solution.

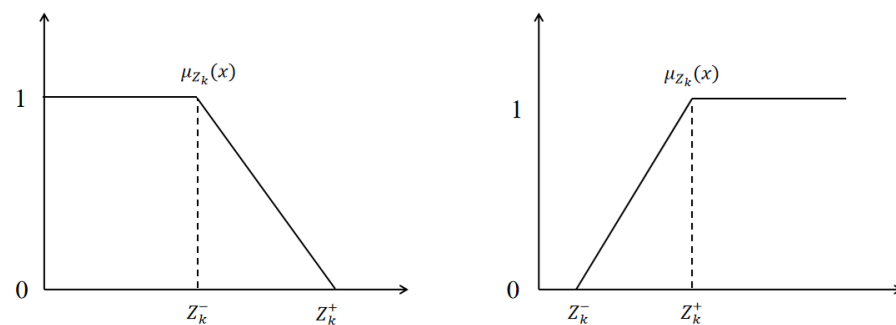


Figure 4. The corresponding schematic diagrams of the membership functions for the decreasing and the increasing trapezoidal method.

Step 4: Reconstruct the fuzzy multi-objective programming model into a single-objective programming model based on decision-maker preferences.

According to Zimmermann [64], the ideal model for the supplier selection problem assumes equal weights for each objective function. Therefore, the following single-objective programming model can be obtained:

$$\begin{aligned} & \max \lambda \\ & \text{s.t.} \left\{ \begin{array}{l} \lambda \leq \mu_{Z_k}(x), \forall k \\ x_{ij} \leq U_{ij} \\ \sum_{i=1}^n x_{ij} = D_j, \forall j \\ \sum_{i=1}^n g_{ij} x_{ij} \leq G, \forall j \\ x_{ij} \geq 0 \text{ and integer, } \forall i, j \\ \lambda \in [0, 1] \end{array} \right. \end{aligned} \quad (25)$$

In practical supplier selection, equal weights may not reflect the true importance of objectives; thus, Zimmermann's model [64] is idealized. Lin's weight model [65] addresses this by transforming the fuzzy multi-objective problem into a deterministic single-objective one, aligning membership degrees with weights to better represent decision-maker preferences. The particular configuration is as follows:

$$\begin{aligned} & \max \lambda \\ & s.t. \left\{ \begin{array}{l} w_k \lambda \leq \mu_{Z_k}(x), \forall k \\ x_{ij} \leq U_{ij} \\ \sum_{i=1}^n x_{ij} = D_j, \forall j \\ \sum_{i=1}^n g_{ij} x_{ij} \leq G, \forall j \\ \sum_{k=1}^p w_k = 1, \forall k \\ x_{ij} \geq 0 \text{ and integer, } \forall i, j \\ \lambda \in [0, 1] \end{array} \right. \end{aligned} \quad (26)$$

Since this study has already obtained the weights of all criteria using FAHP before applying FMOP, the criteria weights obtained from FAHP can be used as the coefficients of the objective functions in FMOP, and Equation (26) can be used to solve the model.

Step 5: Use Lingo 21.0 to solve the model and find the optimal solution.

Finally, based on the data produced from step 5, decision makers in the food manufacturing industry can use this information to make the final selection of suppliers and determine the most efficient order quantities for the chosen providers.

4. Numerical Analysis Based on a Real Case

4.1. Case Background

To test the suitability and efficiency of the supplier selection criteria system and the selection model created in the preceding two phases, both were implemented in a Chinese food manufacturing company, designated as Company S.

Company S, a leading food manufacturer in China with a significant market share (approximately 40%) in instant noodles and beverages, is developing a procurement strategy that prioritizes supplier selection based on cost, quality, delivery, low-carbon initiatives, and risk management. This approach comes in the wake of supply chain disruptions during the 2020 pandemic, which highlighted the need for resilient and sustainable supply chain practices. The company is also responding to environmental policies and consumer demands for greener products by incorporating carbon neutrality goals into its supply chain management. The methodology from Section 3 is utilized to aid in this strategic supplier selection process.

4.2. Phase 1 Analysis Process

4.2.1. Initial Selection Criteria

Through the literature review, this study builds upon prior research to construct a supplier selection criteria system for food manufacturing. It includes three dimensions: traditional, sustainable, and resilience criteria, resulting in 5 primary (B_i) and 29 sub-criteria (C_i). A hierarchical framework of these criteria was developed, as outlined in Table 3. Note that to effectively capture companies' sustainable practices and performance outcomes, this study uses a comprehensive framework defining "low carbon" by integrating economic, environmental, and social dimensions aligned with strategic goals and relevant standards.

Table 3. The initial criteria for supplier selection.

Aspect	Criteria (B _i)	Sub-Criteria (C _i)	Reference
General	Quality (B ₁)	Rejection rate (C ₁)	[7,28]
		Service quality (C ₂)	[29,33]
		Packaging Ability (C ₃)	[2,4]
		Quality Management System (C ₄)	[4,34,36]
		Facilities and environmental sanitation (C ₅)	[33]
		Reputation and Position in Industry (C ₆)	[21,33]
		Food safety (C ₇)	[33,36]
	Cost (B ₂)	Product price (C ₈)	[2,7]
		Logistics costs (C ₉)	[7,34]
		Inspection cost (C ₁₀)	[34]
		Terms of payment (C ₁₁)	[7]
		Quantity discount (C ₁₂)	[28,34]
	Delivery (B ₃)	Lead time (C ₁₃)	[31,34]
		Accuracy of delivery (C ₁₄)	[7,28]
		On time delivery (C ₁₅)	[2,31]
		Time to solve the complaint (C ₁₆)	[7]
		After sales service (C ₁₇)	[29,49]
Sustainability	Low-carbon (B ₄)	Environmental management system (C ₁₈)	[2,7]
		Pollution control (C ₁₉)	[7,49]
		Green product (C ₂₀)	[2,34]
		Green technology (C ₂₁)	[7]
		Resource consumption (C ₂₂)	[21,49]
		Recycle capability (C ₂₃)	[4,34,36]
Resilience	Risk management (B ₅)	Restorative capacity (C ₂₄)	[19,21]
		Responsiveness (C ₂₅)	[4,49]
		Visibility (C ₂₆)	[19,49]
		Agility (C ₂₇)	[49]
		Extra inventory (C ₂₈)	[2,19]
		Financial Stability (C ₂₉)	[19,36]

4.2.2. Identification and Selection of Key Criteria

This study employed the Delphi method through a questionnaire survey to refine supplier selection criteria for Company S, a major food manufacturer. Eight professionals from the purchasing, production, and management departments, along with two researchers in the supply chain management field (see Table A1), evaluated the criteria using a Likert 5-scale, leading to the refinement of the criteria system based on statistical analysis and consensus (see Table A2). To mitigate potential biases and limitations inherent in the Delphi method, several strategies were implemented. A diverse panel of experts was selected to ensure a wide range of perspectives, and the process involved two survey rounds within a month that allowed experts to revise their opinions based on peer feedback, fostering a balanced consensus. Additionally, anonymous responses encouraged open and honest feedback, minimizing the influence of dominant voices in the group [60,63]. This iterative process resulted in a significant increase in Kendall's coefficient of concordance from 0.851 to 0.928, ultimately identifying 16 significant sub-criteria to guide Company S in selecting optimal suppliers (see Table 4).

Table 4. Overall weight of supplier selection hierarchy in Company S.

Criteria (B _i)	W'_{B_i}	Sub-Criteria (C _i)	W'_{C_i}	OW
Quality (B ₁)	0.325	Rejection rate (C ₁)	0.256	0.083
		Quality management system (C ₂)	0.376	0.122
		Facilities and environmental sanitation (C ₃)	0.055	0.018
		Food safety (C ₄)	0.313	0.102
Cost (B ₂)	0.036	Product price (C ₅)	0.568	0.020
		Logistics costs (C ₆)	0.137	0.005
		Terms of payment (C ₇)	0.295	0.011
Delivery (B ₃)	0.256	Lead time (C ₈)	0.107	0.027
		Accuracy of delivery (C ₉)	0.465	0.119
		On time delivery (C ₁₀)	0.428	0.110
Low-carbon (B ₄)	0.112	Environmental management system (C ₁₁)	0.232	0.026
		Pollution control (C ₁₂)	0.467	0.052
		Resource consumption (C ₁₃)	0.301	0.034
Risk management (B ₅)	0.271	Restorative capacity (C ₁₄)	0.241	0.065
		Responsiveness (C ₁₅)	0.537	0.146
		Agility (C ₁₆)	0.222	0.060

4.3. Phase 2 Analysis Process

4.3.1. Determining Weights with FAHP

Based on the supplier selection criteria system established in the first phase, a hierarchical structure model is constructed for Company S. This model includes the goal level (A) of supplier selection, the criterion level (main evaluation criteria B_i), and the sub-criterion level (refinement of main evaluation criteria C_i), as shown in Figure 5.

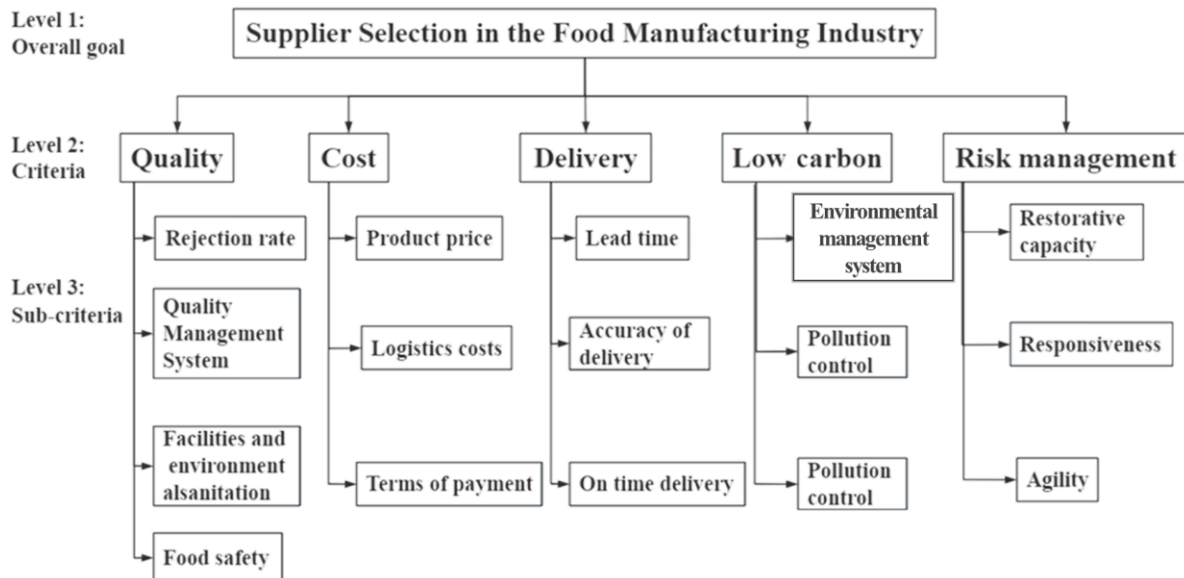


Figure 5. Hierarchy for supplier selection in the food manufacturing industry.

Following expert dialogue, four key staff from Company S evaluated each criterion in pairs. Final scores, based on the geometric mean, birthed a fuzzy judgement matrix, seen in Appendix C. Post-matrix creation, consistency was checked (all CR values under 0.1 indicate consistency), then fuzzy weights were calculated for level B_i , as outlined in Section 3.3.1.

Firstly, referring to Equation (1) in step 2, the initial weights D_i for each element are obtained from the fuzzy judgment matrix.

$$\sum_{j=1}^n M_{1j} = \left(\sum_{j=1}^n l_{1j}, \sum_{j=1}^n m_{1j}, \sum_{j=1}^n u_{1j} \right) = (6.29, 9.21, 11.95) \quad (27)$$

$$\sum_{j=1}^n M_{2j} = (2.41, 2.87, 3.97) \quad (28)$$

$$\sum_{j=1}^n M_{3j} = (4.95, 7.05, 9.22) \quad (29)$$

$$\sum_{j=1}^n M_{4j} = (2.96, 3.82, 5.44) \quad (30)$$

$$\sum_{j=1}^n M_{5j} = (5.27, 7.45, 9.78) \quad (31)$$

$$\sum_{i=1}^n \sum_{j=1}^n M_{ij} = (21.87, 30.41, 40.36) \quad (32)$$

$$\left[\sum_{i=1}^n \sum_{j=1}^n M_{ij} \right]^{-1} = (0.0248, 0.0329, 0.0457) \quad (33)$$

$$D_1 = \sum_{j=1}^n M_{1j} \odot \left[\sum_{i=1}^n \sum_{j=1}^n M_{ij} \right]^{-1} = (0.156, 0.303, 0.547) \quad (34)$$

$$D_2 = (0.060, 0.094, 0.182) \quad (35)$$

$$D_3 = (0.123, 0.232, 0.422) \quad (36)$$

$$D_4 = (0.073, 0.126, 0.249) \quad (37)$$

$$D_5 = (0.131, 0.245, 0.447) \quad (38)$$

Secondly, Equation (2) is utilized as a reference to compare the fuzzy sets with each other.

$$V(D_1 \geq D_2) = 1 \quad (39)$$

$$V(D_1 \geq D_3) = 1 \quad (40)$$

$$V(D_1 \geq D_4) = 1 \quad (41)$$

$$V(D_1 \geq D_5) = 1 \quad (42)$$

$$V(D_2 \geq D_1) = \frac{0.156 - 0.182}{(0.094 - 0.182) - (0.303 - 0.156)} = 0.111 \quad (43)$$

$$V(D_2 \geq D_3) = \frac{0.123 - 0.182}{(0.094 - 0.182) - (0.233 - 0.123)} = 0.299 \quad (44)$$

$$V(D_2 \geq D_4) = \frac{0.073 - 0.182}{(0.094 - 0.182) - (0.126 - 0.073)} = 0.773 \quad (45)$$

$$V(D_2 \geq D_5) = \frac{0.131 - 0.182}{(0.094 - 0.182) - (0.245 - 0.131)} = 0.252 \quad (46)$$

$$V(D_3 \geq D_1) = \frac{0.156 - 0.422}{(0.232 - 0.422) - (0.303 - 0.156)} = 0.789 \quad (47)$$

$$V(D_3 \geq D_2) = 1 \quad (48)$$

$$V(D_3 \geq D_4) = 1 \quad (49)$$

$$V(D_3 \geq D_5) = \frac{0.131 - 0.422}{(0.232 - 0.422) - (0.245 - 0.131)} = 0.957 \quad (50)$$

$$V(D_4 \geq D_1) = \frac{0.156 - 0.249}{(0.126 - 0.249) - (0.303 - 0.156)} = 0.344 \quad (51)$$

$$V(D_4 \geq D_2) = 1 \quad (52)$$

$$V(D_4 \geq D_3) = \frac{0.123 - 0.249}{(0.126 - 0.249) - (0.232 - 0.123)} = 0.543 \quad (53)$$

$$V(D_4 \geq D_5) = \frac{0.131 - 0.249}{(0.126 - 0.249) - (0.245 - 0.131)} = 0.498 \quad (54)$$

$$V(D_5 \geq D_1) = \frac{0.156 - 0.447}{(0.245 - 0.447) - (0.303 - 0.156)} = 0.834 \quad (55)$$

$$V(D_5 \geq D_2) = 1 \quad (56)$$

$$V(D_5 \geq D_3) = 1 \quad (57)$$

$$V(D_5 \geq D_4) = 1 \quad (58)$$

Thirdly, Equation (3) is referred to obtain the final weights for the criteria.

$$d(D_1) = \min(D_1 \geq D_2, D_3, D_4, D_5) = \min(1, 1, 1, 1) = 1 \quad (59)$$

$$d(D_2) = \min(0.111, 0.299, 0.773, 0.252) = 0.111 \quad (60)$$

$$d(D_3) = \min(0.789, 1, 1, 0.957) = 0.789 \quad (61)$$

$$d(D_4) = \min(0.344, 1, 0.543, 0.498) = 0.344 \quad (62)$$

$$d(D_5) = \min(0.834, 1, 1, 1) = 0.834 \quad (63)$$

Fourthly, the normalized weights for the evaluation criteria are calculated. Based on the above steps, the weight vectors for all criteria can be obtained:

$$W = (1, 0.111, 0.789, 0.344, 0.834) \quad (64)$$

Normalization of these weights yields the normalized weights for the criteria:

$$W' = (0.325, 0.036, 0.256, 0.112, 0.271) \quad (65)$$

Similarly, using the same method, the weights for sub-criteria C_1 to C_{16} can be obtained:

$$(W'_{C_1}, W'_{C_2}, W'_{C_3}, W'_{C_4}) = (0.256, 0.376, 0.055, 0.313) \quad (66)$$

$$(W'_{C_5}, W'_{C_6}, W'_{C_7}) = (0.568, 0.137, 0.295) \quad (67)$$

$$(W'_{C_8}, W'_{C_9}, W'_{C_{10}}) = (0.107, 0.465, 0.428) \quad (68)$$

$$(W'_{C_{11}}, W'_{C_{12}}, W'_{C_{13}}) = (0.232, 0.467, 0.301) \quad (69)$$

$$(W'_{C_{14}}, W'_{C_{15}}, W'_{C_{16}}) = (0.241, 0.537, 0.222) \quad (70)$$

Concisely, this study employed the FAHP to examine the significance of supplier selection criteria for Company S, according to the viewpoints of four experts. The weights for each criterion were acquired and consolidated in Table 4.

4.3.2. Determining Order Allocation with FMOP

Company S, a prominent food manufacturer, faces the challenge of selecting suppliers and determining order quantities for key raw materials like flour and sugar used in their main products: instant noodles and beverages. The procurement team has shortlisted three flour and four sugar suppliers. To optimize order quantity allocation, this study applies an FMOP model that overlooks stockouts, discounts, and shortages, treating carbon emissions and supplier reliability as constants. Company S provides data for analysis, aiming to achieve an optimal procurement plan where Product 1 is flour, and Product 2 is sugar (Table 5).

Next, this study takes Product 1 as an example and applies the FMOP model proposed in Section 3 of this research. Based on the information of the suppliers and the weights obtained for the five criteria of supplier selection in Section 4.3.1., it seeks the optimal allocation scheme for supplier order quantities for Product 1.

The FMOP model is developed to minimize total procurement costs, maximize product quality, minimize delivery delays and carbon emissions, and enhance supplier reliability.

Constraints include supplier capacity, total quantity meeting company demand, non-negativity, and adherence to maximum allowable carbon emissions.

Table 5. Relevant data for each supplier.

Product j	Supplier i	c_{ij}	q_{ij}	d_{ij}	g_{ij}	r_{ij}	U_{ij}	D_j	G
1	1	5	0.96	0.04	1.4	0.90	3000	8000	12,000
	2	5.5	0.95	0.02	1.5	0.87	4000		
	3	4.5	0.94	0.03	1.6	0.89	3000		
2	4	6	0.92	0.05	0.4	0.92	1500	5000	2000
	5	7	0.91	0.03	0.4	0.88	2000		
	6	5.5	0.89	0.04	0.5	0.89	1500		
	7	6	0.88	0.03	0.3	0.88	1000		

Second, by ignoring the other objectives and considering the given constraints, the upper deviation limit Z_k^+ and lower deviation limit Z_k^- for each individual objective function $Z_k(x)$ can be obtained sequentially using Equation (19). The results are shown in Table 6.

Table 6. Upper and lower deviation limits of the objective function.

	Z_k^-	Z_k^+
Z_1	39,500	41,500
Z_2	7600	7620
Z_3	220	250
Z_4	11,800	12,000
Z_5	7060	7110

Third, the membership functions $\mu_{Z_k}(x)$ for each objective function can be constructed. Based on Equations (20)–(24), the membership functions for the five objective functions are established.

Fourth, the FMOP model can be transformed into a single-objective programming model based on decision-maker preferences.

First and foremost, this study reconstructs the FMOP model into a single-objective programming model based on the ideal model for supplier selection proposed by Zimmermann [64]. This assumes that the weights of each objective function are equal. If Company S has no preference differences among the five objectives of cost, quality, delivery, low carbon, and risk management, the following single-objective programming model can be derived. Using the Lingo 21.0 to solve the above model, the following results can be obtained (Table 7).

Table 7. Optimal solution sets with equal weights.

Variable	Value
x_{11}	2852
x_{21}	3185
x_{31}	1963

For optimal order allocation of Product 1, Company S is advised to purchase 2852 units from Supplier 1, 3185 from Supplier 2, and 1963 from Supplier 3, based on Zimmermann's method [64]. However, this allocation is idealized as it assigns equal weights to all objectives, not reflecting Company S's preferences. This study uses Lin's reconstruction method [65] to adjust the weights of objectives, transforming the fuzzy multi-objective problem into a deterministic single-objective problem while maintaining consistency in membership degrees. The FAHP analysis established the following weights: quality (0.325), cost (0.036), delivery (0.256), low carbon (0.112), and risk management (0.271), which are applied in the FMOP model (Tables 8 and 9).

Table 8. Optimal solution sets with equal weights.

Variable	Value
x_{11}	3000
x_{21}	2650
x_{31}	2350

Table 9. Comparing optimal solution sets under different preferences.

Variable	Value (Zimmermann [64])	Value (Lin [65])	Difference
x_{11}	2852	3000	148
x_{21}	3185	2650	−535
x_{31}	1963	2350	387
Z_1	40,611	40,150	−461
Z_2	7608.89	7606.5	−2.39
Z_3	236.67	243.5	6.83
Z_4	11,911.1	11,935	23.9
Z_5	7084.82	7097	12.18

Similarly, the FMOP approach can be applied to seek the optimal supplier order quantity allocation for Product 2. The results are shown in Table 10.

Table 10. Optimal supplier order quantity allocation scheme for Product 2.

Variable	Value (Zimmermann [64])	Value (Lin [65])	Difference
x_{42}	1393	1500	107
x_{52}	1821	2000	179
x_{62}	786	500	−286
x_{72}	1000	1000	0
Z_1	31,428	31,750	322
Z_2	4518.21	4525	6.79
Z_3	185.72	185	−0.72
Z_4	1978.6	1950	−28.6
Z_5	4463.58	4465	1.42

4.4. Main Results and Discussion

4.4.1. Results for Supplier Evaluation

The supplier selection process for Company S, as revealed by the FAHP-derived weights, prioritizes quality (0.325), risk management (0.271), and delivery (0.256), with lower emphasis on low carbon (0.112) and cost (0.036). This ranking reflects the company's strategic focus on ensuring high product quality and supply chain stability while promptly meeting market demands. Although low-carbon practices are considered important for sustainable development, cost is of minimal concern, as the case company prefers suppliers that offer reliability and quality over lower prices. These priorities are aligned with findings from existing literature (e.g., [11]), which emphasizes the need to integrate sustainability and resilience into supplier evaluation frameworks. As environmental regulations and consumer demand for sustainable products continue to rise, this model helps companies prioritize low-carbon and reliable suppliers to align with industry trends. Additionally, the model's flexible structure allows for adaptation in other sectors, such as electronics and pharmaceuticals, where sustainability and supplier reliability are also critical factors. By adjusting criteria weights, industries can tailor the model to balance their unique supply chain challenges and strategic goals.

4.4.2. Results for Order Allocation

Regarding Product 1, based on Tables 6 and 10, we can observe certain patterns in the order quantity allocation to suppliers by Company S. The method proposed by

Zimmermann [64] is referred to as “Method 1”, while the method proposed by Lin [65] is referred to as “Method 2”. Company S prefers Supplier 1 for Product 1 procurement due to superior quality, risk management, and low carbon emissions, aligning with its low-carbon strategy. However, Supplier 1’s limited capacity suggests that Company S would buy more if not constrained. Supplier 3 is less favored due to inferior performance across criteria despite competitive pricing.

By analyzing Tables 6 and 10, we observe that Company S consistently allocates the same order quantity to Supplier 7 across both methods due to its low carbon emissions and delivery reliability, though capacity constraints limit further purchases. After optimizing weights in Method 2, Supplier 6’s allocation decreases significantly despite offering the lowest price, as it has the highest carbon emissions, conflicting with Company S’s low-carbon focus. Since other suppliers have reached maximum capacity, selecting Supplier 6 is a compromise, suggesting that Company S should consider reevaluating this supplier relationship in the future.

Overall, the comparison between Zimmermann’s equal-weight method and Lin’s differentiated-weight method reveals Company S’s significant shift in order allocation toward more sustainable and reliable suppliers, emphasizing the company’s commitment to low-carbon practices. This shift aligns with the broader literature on fuzzy optimization, which indicates that dynamic weighting models, such as Lin’s, better reflect real-world trade-offs (e.g., [49]). Such adaptability is crucial for companies aiming to adjust procurement strategies in response to evolving priorities, including sustainability, and highlights the practical relevance of integrating flexible, multi-objective optimization models into supply chain management. Beyond food manufacturing, this adaptable framework can also be applied in industries like electronics, which face similar sustainability challenges, or pharmaceuticals, where reliable and compliant suppliers are paramount.

4.5. Sensitivity Analysis

In this section, we conduct a sensitivity analysis to assess how variations in the weights assigned to multiple objectives impact decision-making outcomes. To isolate the effect of a specific objective’s weight, we maintain the weights of other objectives constant while incrementally varying the weight of the selected objective from 0 to 1. Using Product 1 as the analysis target, we analyze the implications of these weight changes on order allocation, as illustrated in Figure 6.

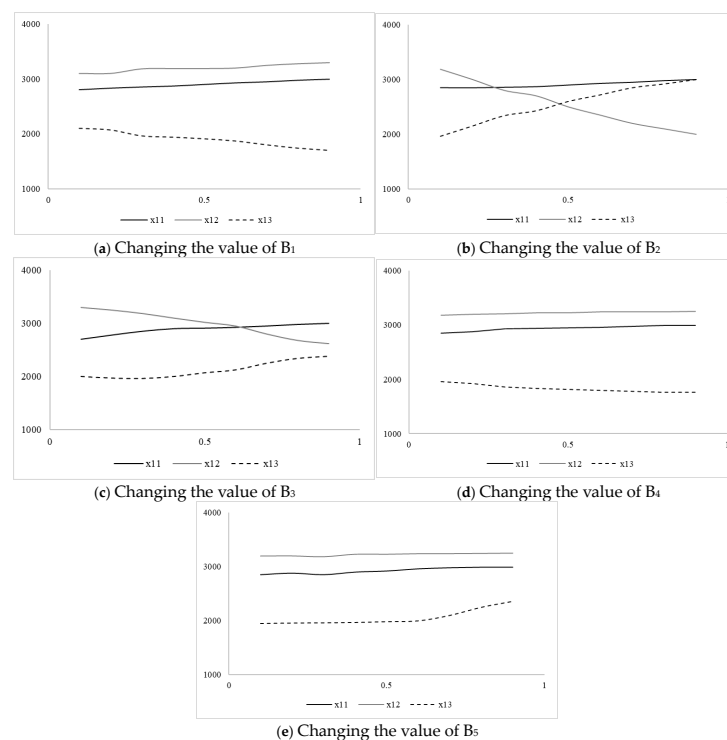


Figure 6. Effect of preferences on order allocation decisions.

The findings indicate that fluctuations in the weights of different objective functions significantly influence the order allocation results. For instance, increasing the weight of the cost objective results in a reduced order allocation for Supplier 2, which has higher prices. Conversely, due to the interplay and trade-offs among various objectives, the influence of any single objective's importance on order allocation decisions is limited. For example, elevating the weights of low-carbon and risk management objectives only marginally affects the order distribution between Suppliers 1 and 2. Ultimately, suppliers with greater capacity, such as Supplier 2, consistently emerge as the most favored in terms of order allocation across various scenarios.

5. Conclusions, Implications and Limitations

5.1. Main Conclusions

Supplier selection significantly impacts business performance and involves complex multi-objective decision making. This study develops a tailored supplier selection framework for the food manufacturing industry, addressing economic, sustainability, and resilience expectations. For RQ1, an initial framework with 5 criteria and 29 sub-criteria was refined through expert interviews and the Delphi method, resulting in a final framework of 5 criteria and 16 sub-criteria. For RQ2, FAHP was employed to analyze criterion importance, revealing quality (0.325), delivery (0.256), and risk management (0.271) as the most critical factors. Lastly, for RQ3, FMOP was utilized to optimize supplier order allocations, balancing criteria weights and ensuring appropriate allocations, such as 3000 units to the highest-ranked supplier for quality.

In conclusion, this study presents a Delphi-FAHP-FMOP framework that offers a valuable and practical approach for optimizing supplier selection in the food manufacturing industry, integrating key economic, sustainability, and resilience criteria. The methodology provides a structured and quantifiable decision-making tool, which can support practitioners in making informed choices about supplier selection and order allocation. The practical relevance of this approach lies in its ability to guide real-world applications effectively. Although some necessary simplifying assumptions, such as constant carbon emissions and deterministic supplier reliability, were made to streamline the model, these do not diminish the overall value of the research. While these assumptions may introduce certain limitations in reflecting the full complexity of real-world conditions, they enhance the model's feasibility and applicability, without compromising the significance of the study's contributions to both theory and practice.

5.2. Main Implications

This study makes significant theoretical contributions by addressing a key research gap in supply chain management, specifically within the food manufacturing industry. It unifies sustainability and resilience perspectives, which have often been explored separately in previous literature, into a single, multi-objective decision-making framework. By incorporating both dimensions, this study recognizes the critical need to evaluate suppliers not only based on traditional criteria but also on their ability to withstand disruptions and their environmental practices. This is particularly important in the food industry, where factors such as perishability and regulatory compliance intensify the need for a resilient and sustainable supply chain. Additionally, this study leverages fuzzy techniques (such as TFNs) to quantify qualitative judgments, mitigating subjective biases and improving decision making in the face of uncertainty, which is common in real-world supply chain scenarios.

From a practical standpoint, this study provides a hybrid Delphi-FAHP-FMOP framework that is highly adaptable to the dynamic and complex nature of food supply chains. The model supports the integration of low-carbon practices, risk management, and other traditional criteria, enabling companies to make well-informed supplier selection and order allocation decisions. By promoting long-term partnerships with suppliers committed to both sustainability and resilience, the framework enhances supply chain efficiency and competitiveness. The adaptability of the model allows it to be applied beyond the food

industry, to other sectors such as electronics and pharmaceuticals, where similar challenges around sustainability and supply chain risk are prevalent. The flexible, dynamic nature of the model ensures that it can evolve alongside changing business needs, making it an effective decision-making tool in uncertain environments.

5.3. Limitations and Future Research Agenda

While this study provides valuable insights into supplier selection with a focus on sustainability and resilience, the framework could be further expanded and validated. Given the dynamic nature of industries, criteria may need regular adjustments over time. The current Delphi-FAHP-FMOP model is tailored to food manufacturing but may require customization for other sectors with different priorities. Future research could extend this model to industries such as electronics, which are sensitive to disruptions and environmental concerns. Additionally, integrating more dynamic and stochastic elements—such as variable emissions, probabilistic supplier reliability, and price fluctuations—would enhance the model’s real-world applicability.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The notation for supplier selection criteria is used in Table 1.

a	Quality	o	Attitude
b	Delivery	p	Packaging Ability
c	Performance History	q	Labor Relations Record
d	Warranties and Claims Policies	r	Geographical Location
e	Production Facilities and Capacity	s	Pollution Control
f	Price/Cost	t	Resource Consumption
g	Technical Capability	u	Recycle Capability
h	Financial Position	v	Environmental Management
i	Procedural Compliance	w	Green Product
j	Communication	x	Flexibility
k	Reputation and Position in Industry	y	Restorative Capacity
l	Management and Organization	z	Extra Inventory
m	Operating Controls	A	Responsiveness
n	Service	B	Visibility

Appendix B

Table A1. Experts’ information.

	Name	Department/Workplace	Position	Years of Experience
1	Expert A	Purchasing department	Middle Manager	2 to 5 years
2	Expert B	Purchasing department	Middle Manager	More than 10 years
3	Expert C	Purchasing department	Middle Manager	5 to 10 years
4	Expert D	Purchasing department	Top Manager	More than 10 years
5	Expert E	Production Management Department	Middle Manager	5 to 10 years
6	Expert F	Production Management Department	Middle Manager	5 to 10 years
7	Expert G	Production Management Department	First-line Manager	2 to 5 years
8	Expert H	Production Management Department	Top Manager	More than 10 years
9	Expert I	Business School of a Renowned University	Associate Professor	2 to 5 years
10	Expert J	Supply Chain Management Consulting Firm	Senior Consultant	5 to 10 years

Table A2. Expert rating scale.

Criteria (B _i)	Sub-Criteria (C _i)	First Round	Second Round	Overall Score	Screening Results
Quality (B ₁)	Rejection rate (C ₁)	4.6	4.8	4.7	1
	Service quality (C ₂)	2.2	2.1	2.15	2
	Packaging Ability (C ₃)	2.1	2	2.05	2
	Quality Management System (C ₄)	5	5	5	1
	Facilities and environmental sanitation (C ₅)	3.9	4	3.95	1
	Reputation and Position in Industry (C ₆)	2.3	2.1	2.2	2
	Food safety (C ₇)	4.9	5	4.95	1
Cost (B ₂)	Product price (C ₈)	4.8	4.9	4.85	1
	Logistics costs (C ₉)	3.6	3.9	3.75	1
	Inspection cost (C ₁₀)	2.5	2.8	2.65	2
	Terms of payment (C ₁₁)	4.5	4.5	4.5	1
	Quantity discount (C ₁₂)	2.3	2.2	2.25	2
Delivery (B ₃)	Lead time (C ₁₃)	4.1	4.2	4.15	1
	Accuracy of delivery (C ₁₄)	4.8	4.9	4.85	1
	On time delivery (C ₁₅)	5	5	5	1
	Time to solve the complaint (C ₁₆)	2.1	2	2.05	2
	After sales service (C ₁₇)	2.4	2	2.2	2
Low-carbon (B ₄)	Environmental management system (C ₁₈)	4.5	4.4	4.45	1
	Pollution control (C ₁₉)	4.9	5	4.95	1
	Green product (C ₂₀)	2.9	2.7	2.8	2
	Green technology (C ₂₁)	2	2	2	2
	Resource consumption (C ₂₂)	4.1	4.2	4.15	1
	Recycle capability (C ₂₃)	2.3	2	2.15	2
Risk management (B ₅)	Restorative capacity (C ₂₄)	4.1	4.1	4.1	1
	Responsiveness (C ₂₅)	4.9	5	4.95	1
	Visibility (C ₂₆)	2.8	2.7	2.75	2
	Agility (C ₂₇)	4.5	4.3	4.4	1
	Extra inventory (C ₂₈)	2.3	2.1	2.2	2
	Financial Stability (C ₂₉)	2.6	2.7	2.65	2

Appendix C**Table A3.** Expert rating table.

Criteria (B _i)	E1	E2	E3	E4	Score
B ₁ –B ₂	(2, 3, 4)	(2, 3, 4)	(1, 2, 3)	(2, 3, 4)	(1.68, 2.71, 3.72)
B ₁ –B ₃	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 2, 3)	(1.00, 1.19, 1.32)
B ₁ –B ₄	(2, 3, 4)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)	(1.41, 2.45, 3.46)
B ₁ –B ₅	(1, 2, 3)	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)	(1.19, 1.86, 2.45)
B ₂ –B ₃	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(0.31, 0.45, 0.84)
B ₂ –B ₄	(1, 1, 1)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)	(0.58, 0.71, 1.00)
B ₂ –B ₅	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(0.25, 0.34, 0.54)
B ₃ –B ₄	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1.00, 2.00, 3.00)
B ₃ –B ₅	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1.00, 1.00, 1.00)
B ₄ –B ₅	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(0.33, 0.500, 1.00)

Table A4. Fuzzy judgment matrix A–B_i.

A	Quality (B ₁)	Cost (B ₂)	Delivery (B ₃)	Low-Carbon (B ₄)	Risk Management (B ₅)
Quality (B ₁)	(1.00, 1.00, 1.00)	(1.68, 2.71, 3.72)	(1.00, 1.19, 1.32)	(1.41, 2.45, 3.46)	(1.19, 1.86, 2.45)
Cost (B ₂)	(0.27, 0.37, 0.59)	(1.00, 1.00, 1.00)	(0.31, 0.45, 0.84)	(0.58, 0.71, 1.00)	(0.25, 0.34, 0.54)
Delivery (B ₃)	(0.76, 0.84, 1.00)	(1.19, 2.21, 3.22)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)	(1.00, 1.00, 1.00)
Low-carbon (B ₄)	(0.29, 0.41, 0.71)	(1.00, 1.41, 1.73)	(0.33, 0.501, 1.00)	(1.00, 1.00, 1.00)	(0.33, 0.500, 1.00)
Risk management (B ₅)	(0.41, 0.54, 0.84)	(1.86, 2.91, 3.94)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)	(1.00, 1.00, 1.00)

CR = 0.010

Table A5. Fuzzy judgment matrix B_1-C_i .

B_1	Rejection Rate (C_1)	Quality Management System (C_2)	Facilities and Environmental Sanitation (C_3)	Food Safety (C_4)
Rejection rate (C_1)	(1.00, 1.00, 1.00)	(1.09, 1.15, 1.00)	(0.99, 1.09, 0.54)	(1.09, 1.15, 1.00)
Quality Management System (C_2)	(1.00, 1.41, 1.73)	(1.00, 1.00, 1.00)	(0.99, 1.08, 0.52)	(1.09, 1.32, 0.83)
Facilities and environmental sanitation (C_3)	(0.16, 0.19, 0.24)	(0.14, 0.16, 0.19)	(1.00, 1.00, 1.00)	(1.04, 1.15, 1.70)
Food safety (C_4)	(1.00, 1.41, 1.73)	(0.58, 0.71, 1.00)	(4.90, 5.92, 6.93)	(1.00, 1.00, 1.00)
CR = 0.006				

Table A6. Fuzzy judgment matrix B_2-C_i .

B_2	Product Price (C_5)	Logistics Costs (C_6)	Terms of Payment (C_7)
Product price (C_5)	(1.00, 1.00, 1.00)	(2.63, 3.66, 4.68)	(1.19, 2.21, 3.22)
Logistics costs (C_6)	(0.21, 0.27, 0.38)	(1.00, 1.00, 1.00)	(0.29, 0.41, 0.71)
Terms of payment (C_7)	(0.31, 0.45, 0.84)	(1.41, 2.45, 3.46)	(1.00, 1.00, 1.00)
CR = 0.016			

Table A7. Fuzzy judgment matrix B_3-C_i .

B_3	Lead Time (C_8)	Accuracy of Delivery (C_9)	On Time Delivery (C_{10})
Lead time (C_8)	(1.00, 1.00, 1.00)	(0.20, 0.25, 0.34)	(0.19, 0.23, 0.30)
Accuracy of delivery (C_9)	(2.91, 3.94, 4.95)	(1.00, 1.00, 1.00)	(1.00, 1.19, 1.32)
On time delivery (C_{10})	(3.31, 4.36, 5.38)	(0.76, 0.84, 1.00)	(1.00, 1.00, 1.00)
CR = 0.004			

Table A8. Fuzzy judgment matrix B_4-C_i .

B_4	Environmental Management System (C_{11})	Pollution Control (C_{12})	Resource Consumption (C_{13})
Environment management system (C_{11})	(1.00, 1.00, 1.00)	(0.41, 0.54, 0.84)	(0.58, 0.71, 1.00)
Pollution control (C_{12})	(1.19, 1.86, 2.45)	(1.00, 1.00, 1.00)	(1.00, 1.68, 2.28)
Resource consumption (C_{13})	(1.00, 1.41, 1.73)	(0.44, 0.59, 1.00)	(1.00, 1.00, 1.00)
CR = 0.016			

Table A9. Fuzzy judgment matrix B_5-C_i .

B_5	Restorative Capacity (C_{14})	Responsiveness (C_{15})	Agility (C_{16})
Restorative capacity (C_{14})	(1.00, 1.00, 1.00)	(0.29, 0.41, 0.71)	(1.00, 1.19, 1.32)
Responsiveness (C_{15})	(1.41, 2.45, 3.46)	(1.00, 1.00, 1.00)	(1.19, 2.21, 3.41)
Agility (C_{16})	(0.76, 0.84, 1.00)	(0.29, 0.45, 0.84)	(1.00, 1.00, 1.00)
CR = 0.016			

References

- İkinci, M.; Tipi, T. Food Supplier Selection in the Catering Industry Using the Analytic Hierarchy Process. *Food Sci. Technol* **2022**, *42*, e48420. [[CrossRef](#)]
- Yazdani, M.; Pamucar, D.; Chatterjee, P.; Torkayesh, A.E. A Multi-Tier Sustainable Food Supplier Selection Model under Uncertainty. *Oper. Manag. Res.* **2022**, *15*, 116–145. [[CrossRef](#)]

3. Zhong, R.; Xu, X.; Wang, L. Food Supply Chain Management: Systems, Implementations, and Future Research. *Ind. Manag. Data Syst.* **2017**, *117*, 2085–2114. [\[CrossRef\]](#)
4. Song, S.; Tappia, E.; Song, G.; Shi, X.; Cheng, T.C.E. Fostering Supply Chain Resilience for Omni-Channel Retailers: A Two-Phase Approach for Supplier Selection and Demand Allocation under Disruption Risks. *Expert Syst. Appl.* **2024**, *239*, 122368. [\[CrossRef\]](#)
5. Fathollahi-Fard, A.M.; Ahmadi, A.; Al-e-Hashem, S.M.J.M. Sustainable Closed-Loop Supply Chain Network for an Integrated Water Supply and Wastewater Collection System under Uncertainty. *J. Environ. Manag.* **2020**, *275*, 111277. [\[CrossRef\]](#)
6. Shang, Z.; Yang, X.; Barnes, D.; Wu, C. Supplier Selection in Sustainable Supply Chains: Using the Integrated BWM, Fuzzy Shannon Entropy, and Fuzzy MULTIMOORA Methods. *Expert Syst. Appl.* **2022**, *195*, 116567. [\[CrossRef\]](#)
7. Nugraha, I.; Hisjam, M.; Sutopo, W. Sustainable Criteria in Supplier Evaluation of the Food Industry. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *598*, 012006. [\[CrossRef\]](#)
8. Nguyen, T.L.; Nguyen, P.H.; Pham, H.A.; Nguyen, T.G.; Nguyen, D.T.; Tran, T.H.; Le, H.C.; Phung, H.T. A Novel Integrating Data Envelopment Analysis and Spherical Fuzzy MCDM Approach for Sustainable Supplier Selection in Steel Industry. *Mathematics* **2022**, *10*, 1897. [\[CrossRef\]](#)
9. Skea, J.; Nishioka, S. Policies and Practices for a Low-Carbon Society. *Climate Policy* **2008**, *8*, S5–S16. [\[CrossRef\]](#)
10. Hajiaghahi-Keshmeli, M.; Cenk, Z.; Erdebilli, B.; Özdemir, Y.S.; Gholian-Jouybari, F. Pythagorean Fuzzy TOPSIS Method for Green Supplier Selection in the Food Industry. *Expert Syst. Appl.* **2023**, *224*, 120036. [\[CrossRef\]](#)
11. Govindan, K.; Sivakumar, R. Green Supplier Selection and Order Allocation in a Low-Carbon Paper Industry: Integrated Multi-Criteria Heterogeneous Decision-Making and Multi-Objective Linear Programming Approaches. *Ann. Oper. Res.* **2016**, *238*, 243–276. [\[CrossRef\]](#)
12. Das, C.; Jharkharia, S. Low Carbon Supply Chain: A State-of-the-Art Literature Review. *J. Manuf. Technol. Manag.* **2018**, *29*, 398–428. [\[CrossRef\]](#)
13. Wang, C.-N.; Nguyen, V.T.; Thai, H.T.N.; Tran, N.N.; Tran, T.L.A. Sustainable Supplier Selection Process in Edible Oil Production by a Hybrid Fuzzy Analytical Hierarchy Process and Green Data Envelopment Analysis for the SMEs Food Processing Industry. *Mathematics* **2018**, *6*, 302. [\[CrossRef\]](#)
14. Wang, C.-N.; Yang, C.-Y.; Cheng, H.-C. Fuzzy Multi-Criteria Decision-Making Model for Supplier Evaluation and Selection in a Wind Power Plant Project. *Mathematics* **2019**, *7*, 417. [\[CrossRef\]](#)
15. Baek, Y.; Yun, U.; Lin, J.C.-W.; Yoon, E.; Fujita, H. Efficiently Mining Erasable Stream Patterns for Intelligent Systems over Uncertain Data. *Int. J. Intell. Syst.* **2020**, *35*, 1699–1734. [\[CrossRef\]](#)
16. Wei, D.; Meng, D.; Rong, Y.; Liu, Y.; Garg, H.; Pamucar, D. Fermatean Fuzzy Schweizer–Sklar Operators and BWM-Entropy-Based Combined Compromise Solution Approach: An Application to Green Supplier Selection. *Entropy* **2022**, *24*, 776. [\[CrossRef\]](#)
17. Hosseini, S.; Tajik, N.; Ivanov, D.; Sarder, M.D.; Barker, K.; Khaled, A.A. Resilient Supplier Selection and Optimal Order Allocation under Disruption Risks. *Int. J. Prod. Econ.* **2019**, *213*, 124–137. [\[CrossRef\]](#)
18. Valipour Parkouhi, S.; Safaei Ghadikolaei, A.; Fallah Lajimi, H. Resilient Supplier Selection and Segmentation in Grey Environment. *J. Clean Prod.* **2019**, *207*, 1123–1137. [\[CrossRef\]](#)
19. Leong, W.Y.; Wong, K.Y.; Wong, W.P. A New Integrated Multi-Criteria Decision-Making Model for Resilient Supplier Selection. *Appl. Syst. Innov.* **2022**, *5*, 8. [\[CrossRef\]](#)
20. Chang, J.-F.; Lai, C.-J.; Wang, C.-N.; Hsueh, M.-H.; Nguyen, V.T. Fuzzy Optimization Model for Decision-Making in Supply Chain Management. *Mathematics* **2021**, *9*, 312. [\[CrossRef\]](#)
21. Rostami, O.; Tavakoli, M.; Tajally, A.; Ghanavati-Nejad, M. A Goal Programming-Based Fuzzy Best–Worst Method for the Viable Supplier Selection Problem: A Case Study. *Soft Comput.* **2023**, *27*, 2827–2852. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Mari, S.I.; Memon, M.S.; Ramzan, M.B.; Qureshi, S.M.; Iqbal, M.W. Interactive Fuzzy Multi Criteria Decision Making Approach for Supplier Selection and Order Allocation in a Resilient Supply Chain. *Mathematics* **2019**, *7*, 137. [\[CrossRef\]](#)
23. Ulutaş, A.; Krstić, M.; Topal, A.; Agnusdei, L.; Tadić, S.; Miglietta, P.P. A Novel Hybrid Gray MCDM Model for Resilient Supplier Selection Problem. *Mathematics* **2024**, *12*, 1444. [\[CrossRef\]](#)
24. Dickson, G.W. An Analysis Of Vendor Selection Systems And Decisions. *J. Purch. Supply Manag.* **1966**, *2*, 5–17. [\[CrossRef\]](#)
25. Mohammed, A.; Yazdani, M.; Oukil, A.; Santibanez Gonzalez, E.D.R. A Hybrid MCDM Approach towards Resilient Sourcing. *Sustainability* **2021**, *13*, 2695. [\[CrossRef\]](#)
26. Bohner, C.; Minner, S. Supplier Selection under Failure Risk, Quantity and Business Volume Discounts. *Comput. Ind. Eng.* **2017**, *104*, 145–155. [\[CrossRef\]](#)
27. Sivrikaya, B.T.; Kaya, A.; Dursun, M.; Çebi, F. Fuzzy AHP–GOAL Programming Approach for a Supplier Selection Problem. *Res. Logist. Prod.* **2015**, *5*, 271–285.
28. Dweiri, F.; Kumar, S.; Khan, S.A.; Jain, V. Designing an Integrated AHP Based Decision Support System for Supplier Selection in Automotive Industry. *Expert Syst. Appl.* **2016**, *62*, 273–283. [\[CrossRef\]](#)
29. Haekal, J.; Setio, H. Selection of Raw Material Suppliers Using Analytical Hierarchy Process in Food and Beverage Company, South Jakarta. *Com Tech.* **2017**, *8*, 63. [\[CrossRef\]](#)
30. Luthra, S.; Govindan, K.; Kannan, D.; Mangla, S.K.; Garg, C.P. An Integrated Framework for Sustainable Supplier Selection and Evaluation in Supply Chains. *J. Clean Prod.* **2017**, *140*, 1686–1698. [\[CrossRef\]](#)
31. Alora, A.; Gupta, H. Supplier selection among manufacturing companies based on their MSME partners' supply chain finance adoption capability using BWM and VIKOR. *J. Bus. Ind. Mark.* **2024**, *39*, 1337–1351. [\[CrossRef\]](#)

32. Guarnieri, P.; Trojan, F. Decision Making on Supplier Selection Based on Social, Ethical, and Environmental Criteria: A Study in the Textile Industry. *Resour. Conserv. Recycl.* **2019**, *141*, 347–361. [\[CrossRef\]](#)
33. Fu, Y.-K. An Integrated Approach to Catering Supplier Selection Using AHP-ARAS-MCGP Methodology. *J. Air Transp. Manag.* **2019**, *75*, 164–169. [\[CrossRef\]](#)
34. Beiki, H.; Mohammad Seyedhosseini, S.; Ponkratov, V.V.; Olegovna Zekiy, A.; Ivanov, S.A. Addressing a Sustainable Supplier Selection and Order Allocation Problem by an Integrated Approach: A Case of Automobile Manufacturing. *J. Ind. Prod. Eng.* **2021**, *38*, 239–253. [\[CrossRef\]](#)
35. Göncü, K.K.; Çetin, O. A Decision Model for Supplier Selection Criteria in Healthcare Enterprises with Dematel ANP Method. *Sustainability* **2022**, *14*, 13912. [\[CrossRef\]](#)
36. Aungkulanon, P.; Atthirawong, W.; Luangpaiboon, P.; Chanpuypetch, W. Navigating Supply Chain Resilience: A Hybrid Approach to Agri-Food Supplier Selection. *Mathematics* **2024**, *12*, 1598. [\[CrossRef\]](#)
37. Weber, C.A.; Current, J.R.; Benton, W.C. Vendor Selection Criteria and Methods. *Eur. J. Oper. Res.* **1991**, *50*, 2–18. [\[CrossRef\]](#)
38. Cheraghi, S.H.; Dadashzadeh, M.; Subramanian, M. Critical Success Factors for Supplier Selection: An Update. *JABR* **2011**, *20*, 91–108. [\[CrossRef\]](#)
39. Ho, W.; Xu, X.; Dey, P.K. Multi-Criteria Decision Making Approaches for Supplier Evaluation and Selection: A Literature Review. *Eur. J. Oper. Res.* **2010**, *202*, 16–24. [\[CrossRef\]](#)
40. Kirytopoulos, K.; Leopoulos, V.; Voulgaridou, D. Supplier Selection in Pharmaceutical Industry: An Analytic Network Process Approach. *Benchmarking* **2008**, *15*, 494–516. [\[CrossRef\]](#)
41. Qiao, J.; Li, S.; Capaldo, A. Green Supply Chain Management, Supplier Environmental Commitment, and the Roles of Supplier Perceived Relationship Attractiveness and Justice: A Moderated Moderation Analysis. *Bus. Strateg. Environ.* **2022**, *31*, 3523–3541. [\[CrossRef\]](#)
42. Micheli, G.J.L.; Cagno, E.; Zorzini, M. Supply Risk Management vs Supplier Selection to Manage the Supply Risk in the EPC Supply Chain. *Manag. Res. News* **2008**, *31*, 846–866. [\[CrossRef\]](#)
43. Govindan, K.; Shankar, M.; Kannan, D. Supplier Selection Based on Corporate Social Responsibility Practices. *Int. J. Prod. Econ.* **2018**, *200*, 353–379. [\[CrossRef\]](#)
44. Wadhwa, V.; Ravindran, A.R. Vendor Selection in Outsourcing. *Comput. Oper. Res.* **2007**, *34*, 3725–3737. [\[CrossRef\]](#)
45. Ng, W.L. An Efficient and Simple Model for Multiple Criteria Supplier Selection Problem. *Eur. J. Oper. Res.* **2008**, *186*, 1059–1067. [\[CrossRef\]](#)
46. Lee, A.H.I.; Kang, H.-Y.; Chang, C.-T. Fuzzy Multiple Goal Programming Applied to TFT-LCD Supplier Selection by Downstream Manufacturers. *Expert Syst. Appl.* **2009**, *36*, 6318–6325. [\[CrossRef\]](#)
47. Kannan, D.; Khodaverdi, R.; Olfat, L.; Jafarian, A.; Diabat, A. Integrated Fuzzy Multi Criteria Decision Making Method and Multi-Objective Programming Approach for Supplier Selection and Order Allocation in a Green Supply Chain. *J. Clean Prod.* **2013**, *47*, 355–367. [\[CrossRef\]](#)
48. Lei, F.; Wei, G.; Gao, H.; Wu, J.; Wei, C. TOPSIS Method for Developing Supplier Selection with Probabilistic Linguistic Information. *Int. J. Fuzzy Syst.* **2020**, *22*, 749–759. [\[CrossRef\]](#)
49. Fallahpour, A.; Nayeri, S.; Sheikhalishahi, M.; Wong, K.Y.; Tian, G.; Fathollahi-Fard, A.M. A Hyper-Hybrid Fuzzy Decision-Making Framework for the Sustainable-Resilient Supplier Selection Problem: A Case Study of Malaysian Palm Oil Industry. *Environ. Sci. Pollut. Res.* **2021**, 1–21. [\[CrossRef\]](#)
50. Sun, H.; Zhang, B.; Ni, W. A Hybrid Model Based on SEM and Fuzzy TOPSIS for Supplier Selection. *Mathematics* **2022**, *10*, 3505. [\[CrossRef\]](#)
51. Akarte, M.M.; Surendra, N.V.; Ravi, B.; Rangaraj, N. Web Based Casting Supplier Evaluation Using Analytical Hierarchy Process. *J. Oper. Res. Soc.* **2001**, *52*, 511–522. [\[CrossRef\]](#)
52. Ecer, F. Multi-Criteria Decision Making for Green Supplier Selection Using Interval Type-2 Fuzzy AHP: A Case Study of a Home Appliance Manufacturer. *Oper. Res. Int. J.* **2022**, *22*, 199–233. [\[CrossRef\]](#)
53. Gencer, C.; Gürpınar, D. Analytic Network Process in Supplier Selection: A Case Study in an Electronic Firm. *Appl. Math. Model.* **2007**, *31*, 2475–2486. [\[CrossRef\]](#)
54. Gupta, M. Supplier Selection Using Artificial Neural Network and Genetic Algorithm. *Int. J. Indian Cult. Bus. Manag.* **2015**, *11*, 457–472. [\[CrossRef\]](#)
55. Song, W.; Chen, Z.; Liu, A.; Zhu, Q.; Zhao, W.; Tsai, S.-B.; Lu, H. A Study on Green Supplier Selection in Dynamic Environment. *Sustainability* **2018**, *10*, 1226. [\[CrossRef\]](#)
56. Ghodsypour, S.H.; O'Brien, C. The Total Cost of Logistics in Supplier Selection, under Conditions of Multiple Sourcing, Multiple Criteria and Capacity Constraint. *Int. J. Prod. Econ.* **2001**, *73*, 15–27. [\[CrossRef\]](#)
57. Büyüközkan, G.; Çifçi, G. A Novel Hybrid MCDM Approach Based on Fuzzy DEMATEL, Fuzzy ANP and Fuzzy TOPSIS to Evaluate Green Suppliers. *Expert Syst. Appl.* **2012**, *39*, 3000–3011. [\[CrossRef\]](#)
58. Chai, J.; Liu, J.N.K.; Ngai, E.W.T. Application of Decision-Making Techniques in Supplier Selection: A Systematic Review of Literature. *Expert Syst. Appl.* **2013**, *40*, 3872–3885. [\[CrossRef\]](#)
59. Liu, Y.; Eckert, C.M.; Earl, C. A Review of Fuzzy AHP Methods for Decision-Making with Subjective Judgements. *Expert Syst. Appl.* **2020**, *161*, 113738. [\[CrossRef\]](#)
60. Rabieh, M.; Babaee, L.; Fadaei Rafsanjani, A.; Esmaeili, M. Sustainable Supplier Selection and Order Allocation: An Integrated Delphi Method, Fuzzy TOPSIS and Multi-Objective Programming Model. *Scientia Iranica* **2018**, *26*, 2524–2540. [\[CrossRef\]](#)
61. Roy, S.A.; Ali, S.M.; Kabir, G.; Enayet, R.; Suhi, S.A.; Haque, T.; Hasan, R. A Framework for Sustainable Supplier Selection with Transportation Criteria. *Int. J. Sustain. Eng.* **2020**, *13*, 77–92. [\[CrossRef\]](#)

62. Güneri, B.; Deveci, M. Evaluation of Supplier Selection in the Defense Industry Using Q-Rung Orthopair Fuzzy Set Based EDAS Approach. *Expert Syst. Appl.* **2023**, *222*, 119846. [[CrossRef](#)]
63. Luzon, B.; El-Sayegh, S.M. Evaluating Supplier Selection Criteria for Oil and Gas Projects in the UAE Using AHP and Delphi. *Int. J. Constr. Manag.* **2016**, *16*, 175–183. [[CrossRef](#)]
64. Zimmermann, H.-J. Fuzzy Programming and Linear Programming with Several Objective Functions. *Fuzzy Sets Syst.* **1978**, *1*, 45–55. [[CrossRef](#)]
65. Lin, C.-C. A Weighted Max–Min Model for Fuzzy Goal Programming. *Fuzzy Sets Syst.* **2004**, *142*, 407–420. [[CrossRef](#)]
66. Zadeh, L.A. Fuzzy Sets. *Inf. Control.* **1965**, *8*, 338–353. [[CrossRef](#)]
67. Chang, D.-Y. Applications of the Extent Analysis Method on Fuzzy AHP. *Eur. J. Oper. Res.* **1996**, *95*, 649–655. [[CrossRef](#)]

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