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An Integrated Q-Rung Orthopair Fuzzy (Q-ROF) for the Selection of Supply-Chain Management

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Abstract: The integration of sustainable indicators into supply-chain management (SCM), including cost, innovation capability, quality, service capability, long-term cooperation, environmental management system, pollution reduction, green image, social responsibility, and employment practices, has become essential for conducting strategic analyses of the entire supply-chain process competitive advantage. This study proposes a fuzzy integration multi-criteria decision-making (MCDM) method to solve SCM issues. To navigate this complexity, a multi-criterion decision-making (MCDM) framework is employed, integrating MCDM methods with fuzzy logic to effectively address subjective environmental criteria. This innovative approach not only enhances supply-chain management (SCM) but also emphasizes the necessity for ongoing innovation in tackling contemporary supply-chain challenges. It serves as a cornerstone for sustainable supplier selection practices and optimizing SCM processes. In this study, a hybrid fuzzy MCDM method is proposed for supplier selection. The method addresses supplier selection by utilizing evaluations from expert decision-makers based on predetermined criteria. This comprehensive approach ensures that all relevant factors are considered, promoting sustainable and efficient supply-chain management.

Keywords: multi-criteria decision-making (MCDM); fuzzy set; q-rung orthopair fuzzy (Q-ROF); supply-chain management (SCM)

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1. Introduction

The supply chain is a complex network involving organizations, technologies, and resources facilitating the movement of products from suppliers to customers. Supply-chain management (SCM) has traditionally prioritized economic objectives, often neglecting societal and environmental considerations. However, given current environmental concerns and societal expectations for sustainability, it is imperative to integrate environmental and social issues into SCM metrics. In today's globalized business landscape, sustainability is increasingly viewed as a competitive advantage. Adverse impacts on sustainability experienced by upstream suppliers can ultimately affect downstream industries, highlighting the interconnectedness of supply chains and the importance of adopting sustainable practices [1].

SCM orchestrates this system to efficiently meet consumer demand while minimizing costs. Originating in the 1980s, SCM emphasizes integrating business processes from end users to original suppliers to add value. Decision-making is integral to SCM, where multi-criteria decision-making (MCDM) aids in resolving conflicts and reaching compromises transparently. MCDM plays a crucial role in SCM processes such as inventory management and supplier selection, enabling informed decision-making amid evaluations and potential conflicts.

As the global emphasis on sustainability intensifies, the significance of SCM in businesses has grown substantially. This shift is driven by environmental concerns and stricter

regulations, pushing companies to adopt eco-friendly practices. SCM now aims to minimize environmental impacts, improve energy efficiency, reduce carbon footprints, and embrace sustainability principles. MCDM has become essential to managing the complexities of SCM. MCDM integrates various factors into the decision-making process, helping organizations evaluate diverse environmental, economic, and social criteria for optimal sustainable strategies. A comprehensive review of the intersection between green SCM and MCDM methods revealed significant research interest, with 743 articles and 135 conference proceedings out of 959 research outcomes. This highlights the increasing academic and practical importance of using MCDM methodologies to address the challenges of sustainable supply-chain management. The results indicate that the proposed approach is an effective decision-making tool for SCM in uncertain environments. An expert system based on a hierarchical structure has been suggested for the further evaluation of potential alternatives in future studies.

This paper aims to introduce an efficient and practical MCDM method for assessing the performance of suppliers using subjective evaluations from experts. The proposed methodology addresses these challenges and enhances SCM decision-making. It is one of the first studies to combine the Q-rung orthopair fuzzy (Q-ROF) technique for order preference by similarity to ideal solution (TOPSIS) and Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods in this context. Ref. [2] extended Zadeh's fuzzy set theory to intuitionistic fuzzy sets (IFS), but its application is limited due to a constraint on membership and non-membership degrees. Ref. [3] proposed Pythagorean fuzzy sets (PFS) to address this constraint. Q-rung orthopair fuzzy (Q-ROF) sets, introduced by [4], further expanded this concept, presenting IFS and PFS for different values of q. Additionally, Ref. [5] introduced spherical fuzzy sets (SFS) based on logarithmic operations, providing improved predictions. Ref. [6] measured similarities between SPF sets using the cosine function, while Ref. [7] demonstrated the effectiveness of their algorithm with different aggregation operators in SFS. Furthermore, Ref. [8] utilized Fermatean fuzzy sets, and [9] introduced single-valued intuitive trapezoidal neutrosophic fuzzy sets.

By adopting the "relative distance" measurement formula, the method's effectiveness is assessed through sensitivity analysis and comparison with other methods. Following a thorough evaluation of relevant studies, this paper outlines several objectives:

1. Define criteria metrics for selecting sustainable suppliers and efficiently assess supplier qualifications;
2. Define evaluation metrics for selecting sustainable suppliers and efficiently assess supplier qualifications;
3. Address uncertainty in evaluation data;
4. Address inconsistency in evaluation data;
5. Determine the weighting of evaluation metrics;
6. Select the most suitable sustainable supplier; and
7. Develop an effective tool for selecting the optimal sustainable suppliers.

This study presents a comprehensive model that integrates robust fuzzy MCDM methods for evaluating suppliers based on specified criteria. Initially, criteria and sub-criteria are identified from existing research and refined based on expert input to align with sustainability goals. Subsequently, optimal weights for the finalized criteria and sub-criteria are determined through a nonlinear optimization model, incorporating experts' fuzzy evaluations into the Q-ROF VIKOR method. Suppliers are then prioritized using a hybrid MCDM approach, combining the Q-ROF TOPSIS method within a fuzzy environment.

The key contributions of this study include promoting:

1. Application of Q-ROF MCDM in real-world scenarios with ambiguous or uncertain data; and
2. Providing a practical case study to assist managers in making informed decisions on related issues.

The following sections of this paper are organized as follows: Section 2 provides a review of pertinent research on sustainable suppliers and MCDM techniques, while Section 3 explores the approaches employed. Section 4 outlines the development of a sustainable supplier evaluation method, followed by an in-depth mathematical analysis in Section 5, elucidating the selected strategies. Finally, Section 6 offers a summary of the findings and suggests directions for future research.

2. Literature Review

In the dynamic business landscape, selecting sustainable suppliers is crucial for long-term growth, involving stages like identification, evaluation, and contract signing. Traditional metrics like cost and quality now integrate with environmental and social considerations, reflecting a shift towards sustainable supply-chain (SSC) practices that balance economic, environmental, and social factors in supplier selection and planning to achieve comprehensive results.

Over the past two decades, a variety of methods have been proposed to address economic, sustainable, and resilient supply-chain management (SCM) challenges. Many of these methods involve multi-criteria decision-making (MCDM) models, often incorporating fuzzy logic. The fuzzy analytic hierarchy process/analytic network process (AHP/ANP), fuzzy technique for order preference by similarity to ideal solution (TOPSIS), fuzzy decision-making trial and evaluation laboratory (DEMATEL), and fuzzy simple additive weighting (SAW) are among the commonly used approaches. The following is a brief overview of some fuzzy-oriented methods recently introduced to tackle SCM issues.

Ref. [10] introduced F-TOPSIS for supplier selection in the logistics sector, focusing on criteria such as environmentally friendly technology usage, green research and development projects, and green market share. Ref. [11] developed a model integrating the fuzzy DEMATEL method, ANP, and TOPSIS for green supplier selection in the automotive industry. Ref. [12] conducted a comparative analysis of F-TOPSIS, fuzzy grey relational analysis (GRA), and fuzzy VIKOR methods for evaluating green suppliers in agri-food companies, concluding that GRA offers the best computational complexity and effectively handles uncertain criteria.

Ref. [13] proposed an integrated approach combining F-TOPSIS and the best-worst method to select vendors for Khouzestan Steel Company in Iran based on green innovation skills and criteria such as environmental investments, economic benefits, and green purchasing capabilities. Ref. [14] explored a technique using single-valued neutrosophic linguistic TOPSIS for green supplier selection (GSS) in low-carbon supply chains in 2018. Ref. [15] developed a green performance index evaluation platform using an integrated grey TOPSIS and COPRAS-grey method to assess green suppliers. Ref. [16] devised a Cloud TOPSIS model for GSS in the automobile industry. Ref. [17] introduced an integrated method combining the intuitionistic fuzzy (IF) judgment matrix and TOPSIS for green supplier selection. Lastly, Ref. [18] proposed an Intuitionistic F-TOPSIS Model for green supplier selection to address ambiguity and aid decision-makers in selecting the best supplier in uncertain situations.

This paper presents a holistic approach to sustainable supplier selection, integrating human judgment, raw data, and sophisticated decision-making techniques. It employs the AHP for weighting indicators and the VIKOR method to evaluate various economic, social, and environmental factors comprehensively. The VIKOR method prioritizes alternatives based on their proximity to ideal solutions, ensuring robust decision-making. Additionally, the paper introduces the neutrosophic set approach to address qualitative measurements and subjective assessments within MCDM. By proposing a VIKOR model based on single-valued neutrosophic sets, it aims to reduce individual biases and enhance evaluation accuracy. This approach aims to balance individual regret and group utility, considering potential inaccuracies in the provided information. Overall, this methodology provides a precise and efficient framework for sustainable supplier selection, highlighting the importance of decision quality and simplicity.

The initial review process involved an extensive examination of 462 articles (2008–2023) extracted from highly reputable journals in the field of supply-chain management. Recognizing the complex landscape of this discipline, particularly regarding the utilization of multi-criteria decision-making methodologies, our analysis concentrated on papers that intersected various approaches within this realm.

The literature contains numerous studies across various sectors that have employed fuzzy MCDM methods and operators for diverse purposes.

Table 1 presents a classification concerning the focus and contribution of the studies mentioned above, showing the key features of each study.

Table 1. The classification concerning the focus and contribution.

Author	Year	Title	Focus
Kayani, SA; Warsi, SS and Liaqait, RA [19]	2023	A Smart Decision Support Framework for Sustainable and Resilient Supplier Selection and Order Allocation in the Pharmaceutical Industry	Supplier Selection
Luo, XC; Wang, ZL; Yang, LG; Lu, L; Hu, S [20]	2023	Sustainable supplier selection based on VIKOR with single-valued neutrosophic sets	Supplier selection
Zakeri, S; Konstantas, D; Bratvold, RB; Pamucar, D [21]	2023	A Supplier Selection Model Using the Triangular Fuzzy Grey Numbers	Supplier selection
Agarwal, R; Agrawal, A; Kumar, N; Ray, S [22]	2023	Evaluation and selection of sustainable suppliers using the fuzzy TOPSIS method in a dairy product company	Supplier selection
Farid, HMA; Bouye, M; Riaz, M; Jamil, N [23]	2023	Fermatean Fuzzy CODAS Approach with Topology and Its Application to Sustainable Supplier Selection	Supplier selection
Xu, LC; Hu, XJ; Zhang, Y; Feng, JS; Luo, SZ [24]	2023	A fuzzy multiobjective team decision model for CODP and supplier selection in customized logistics service supply chain	Supplier selection
Erdebilli, B; Yilmaz, I; Aksoy, T; Hacioglu, U; Yüksel, S; Dinçer, H [25]	2023	An Interval-Valued Pythagorean Fuzzy AHP and COPRAS Hybrid Methods for the Supplier Selection Problem	Supplier selection
Eghbali-Zarch, M; Zabihi, SZ and Masoud, S [26]	2023	A novel fuzzy SECA model based on fuzzy standard deviation and correlation coefficients for resilient-sustainable supplier selection	Supplier selection
Keshavarz-Ghorabaee, M [27]	2023	Sustainable Supplier Selection and Order Allocation Using an Integrated ROG-Based Type-2 Fuzzy Decision-Making Approach	Supplier selection
Nazari-Shirkouhi, S; Tavakoli, M; Govindan, K; Mousakhani, S [28]	2023	A hybrid approach using the Z-number DEA model and Artificial Neural Network for Resilient supplier Selection	Supplier selection
Ali, H; Zhang, JW and Shoaib, M [29]	2023	A hybrid approach for sustainable-circular supplier selection based on the Industry 4.0 framework to make the supply chain smart and eco-friendly	Supplier selection
Modares, A; Farimani, NM and Dehghanian, F [30]	2023	A New Vendor-Managed Inventory Four-Tier Model Based on Reducing Environmental Impacts and Optimal Suppliers Selection Under Uncertainty	Suppliers selection

3. Proposed Methodology-Based Framework

The process of selecting SCM strategies poses a challenging decision problem for decision-makers, particularly when evaluating criteria in a fuzzy context. In this section, we delve into the Q-ROFS theory, which provides a framework for handling uncertainty and imprecision in decision-making scenarios. Q-ROFS theory offers a nuanced approach to modeling vague and ambiguous information, making it suitable for addressing the inherent complexities of SCM selection processes. Subsequently, we introduce two prominent methodologies derived from Q-ROFS theory: Q-ROF TOPSIS and Q-ROF VIKOR. Q-ROF TOPSIS offers a systematic approach to rank alternative SCM strategies based on their similarity to ideal solutions, taking into account both positive and negative aspects of each alternative. Meanwhile, Q-ROF VIKOR provides a comprehensive method for identifying the most favorable SCM strategy that strikes a balance between maximizing benefits and minimizing drawbacks. By incorporating Q-ROFS theory into the decision-making process, decision-makers gain access to robust methodologies capable of handling uncertainty and imprecision inherent in SCM selection. These methodologies enable decision-makers to

make informed choices that align with their objectives and preferences, ultimately leading to more effective and efficient SCM strategies.

TOPSIS and VIKOR were chosen for their ease of application, universality, clear logic, computational efficiency, and ability to provide relative performance assessments for each alternative. They help determine the distances of alternative values from both negative and positive ideal solutions. Evaluation criteria for sustainable suppliers include economic, environmental, and social factors, with AHP weights determining their importance. The VIKOR approach, extended to Q-ROF, is used to streamline the process. However, the combination of Q-ROF's fuzzy logic and MCDM increases complexity and relies on accurate data inputs, which can introduce subjectivity. This integration requires substantial computational resources and may be difficult for stakeholders to interpret. These methodologies are best suited for situations involving uncertainty and qualitative criteria, while traditional models may be more appropriate in other scenarios.

3.1. Q-Rung Orthopair Fuzzy Set

Ref. [31] introduced the fuzzy set, as A in the universe of discourse $X = \{x_1, x_2, \ldots, x_n\}$ is a set of ordered pairs:

$$A = \{\langle x, \mu_A(x)\rangle | x \in X\} \tag{1}$$

where $\mu_A(x) : X \to [0,1]$ is the membership degree.

As an extension to Zadeh's fuzzy set, Atanassov (1986) [30] proposed an intuitionistic fuzzy set, of which A in X can be defined as:

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\} \tag{2}$$

where the functions $\mu_A(x) : X \to [0,1]$ and $v_A(x) : X \to [0,1]$ define the membership and non-membership degrees of x, respectively, and:

$$0 \leq \mu_A(x) + v_A(x) \leq 1 \tag{3}$$

Besides, $\pi_A(x)$ defines the hesitation degree:

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x) \text{ and } 0 \leq \pi_A(x) \leq 1 \tag{4}$$

which shows hesitation.

Ref. [4] introduced the q-rung orthopair fuzzy sets (q-ROFs), which is the general form of IFS and PFS. In q-ROFs, the sum of the qth powers of the membership degree and non-membership degree is restricted to one. A qth rung orthopair fuzzy subset A of X is as follows:

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\} \tag{5}$$

where $\mu_A : X \to [0,1]$ is membership degree and $v_A : X \to [0,1]$ is non-membership degree of $x \in X$ to A and their sum is as follows:

$$(\mu_A(x))^{\mathrm{q}} + (v_A(x))^{\mathrm{q}} \leq 1 \tag{6}$$

The hesitation degree $\pi_A(x)$ is as follows:

$$\pi_A(x) = \left(1 - (\mu_A(x))^q - (v_A(x))^q\right)^{1/q} \tag{7}$$

Therefore, q-ROF numbers give decision-makers the flexibility to define a more comprehensive information range than previous fuzzy sets.

Q-rung orthopair fuzzy sets represent an advanced extension of traditional fuzzy sets, offering a comprehensive framework that includes both intuitionistic fuzzy sets (IFS) and Pythagorean fuzzy sets (PFS). This innovative approach introduces the concept of a Q-rung orthopair, expressed as μq + νq ≤ 1, where Q denotes a positive integer. This formulation

enhances the flexibility in representing uncertainty, making Q-rung fuzzy sets applicable across various scenarios.

Its adaptability makes it particularly useful in complex decision-making and classification tasks, providing tailored solutions for addressing different types and degrees of uncertainty. Overall, Q-ROF Fuzzy Sets, alongside IFS and PFS, offer versatile tools for navigating diverse challenges in decision-making and classification, as shown in Figure 1.

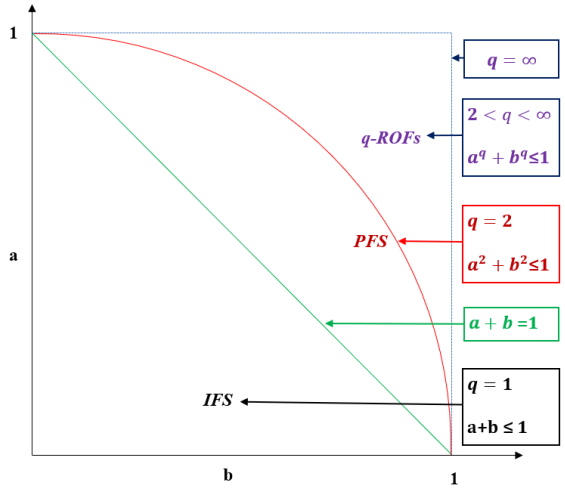


Figure 1. Q-rung orthopair fuzzy sets.

3.2. Q-ROF VIKOR Method

The current Q-ROF VIKOR method proposed by [32] was used. Below are the steps of this method.

Step 1: *Determination of the weights of decision-makers (DMs) involved in translating their assessments*	The process involves translating assessments into Q-level fuzzy numbers for a more precise representation of decision-makers' relative importance (AHP). This approach captures nuances and uncertainties in decision-making, improving assessments of preferences. It enhances reliability and robustness, contributing to the overall effectiveness of the decision-making framework. *Linguistic terms: Extremely High (0.95, 0.15), Very High (0.85, 0.25), High (0.75, 0.35), Medium High (0.65, 0.45), Medium (0.55, 0.55), Medium Low (0.45, 0.65), Low (0.35, 0.75), Very Low (0.25, 0.85) Extremely Low (0.15, 0.95)* *A Q-ROFN is shown as;* $D_k = [\mu_k, v_k, \pi_k]$ The final Q-ROF Number (Q-ROFN) score is computed utilizing Equation (8). $\lambda_k = \frac{(1+\mu_k^q(x_i)-v_k^q(x_i))}{\sum_{k=1}^{l}(1+\mu_k^q(x_i)-v_k^q(x_i))}$, (8) and where $\sum_{k=1}^{l}\lambda_k = 1$
Step 2: *Assessment of alternatives and constructing a normalized decision matrix*	All alternative evaluations made by the DMs are converted into Q-ROFN using Table 4. Supposed $\alpha_k = \langle \mu_k(x), v_k(x) \rangle$ (k = 1,2,3 $\cdots$, l) is a group of Q-ROFN sets(Q-ROFNs) combined with DMs weights (λ_k) using the Q-ROF weighted averaging (Q-ROFWA) operator proposed in Equation (9). $q-\mathrm{ROFWA}(\alpha_1, \alpha_2, \ldots \alpha_1,) = \left\langle \left(1 - \prod_{k=1}^{l}(1 - \mu_k(x)^q)^{\lambda_k}\right)^{\frac{1}{q}}, \prod_{k=1}^{l} v_k(x)^{\lambda_k} \right\rangle$ (9) The final state of the Q-ROF decision matrix is as in Equation (10). $R = \begin{bmatrix} \mu_{A1}(x_1), v_{A1}(x_1), \pi_{A1}(x_1), \mu_{A1}(x_2), v_{A1}(x_2), \pi_{A1}(x_2) \ldots \mu_{A1}(x_n), v_{A1}(x_n), \pi_{A1}(x_n) \\ \mu_{A2}(x_1), v_{A1}(x_1), \pi_{A1}(x_1), \mu_{A2}(x_2), v_{A1}(x_2), \pi_{A1}(x_2) \ldots \mu_{A2}(x_n), v_{A1}(x_n), \pi_{A1}(x_n) \\ \vdots \quad \ddots \quad \vdots \\ \mu_{Am}(x_1), v_{Am}(x_1), \pi_{Am}(x_1), \mu_{Am}(x_2), v_{Am}(x_2), \pi_{Am}(x_2) \ldots \mu_{Am}(x_n), v_{Am}(x_n), \pi_{Am}(x_n) \end{bmatrix}$ (10) where R = (r_{ij}) and $((\mu_{Ai}(x_j), v_{Aj}(x_j), \pi_{Aj}(x_j)), (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$
Step 3: *Determination of criterion weights*	To determine the importance (Wj) of the criteria, the linguistic terms evaluated by the DMs are converted into Q-ROFNs using Equation (11). $W_j = \frac{\sum_{k=1}^{l}\lambda_k(1+\mu_k^q(x_j)-v_k^q(x_j))}{\sum_{j=1}^{n}W_j\sum_{k=1}^{l}\lambda_k(1+\mu_k^q(x_i)-v_k^q(x_i))}$ (11) where W = [$w_1 + w_2 + w_3 + \ldots + w_j$] and $w_j = (\mu_j, v_j, \pi_j)$, ($j$ = 1, 2, 3, . . ., n)

Step 4: *Creation of a combined weight matrix*	The aggregated weight matrix (R′) is created with the following Equations (12)–(14). $w_k\alpha_1 = \left(\left(1 - \left(1 - \mu_1(x)^q \right)^{w_k} \right)^{\frac{1}{q}}, v_1(x)^{w_k} \right)$ (12) $\pi_{Ai}(x_j) = \left(1 - \mu_{Ai}^q(x_j) - v_{Ai}^q(x_j)\right)^{1/q}$, (13) $R\prime = \begin{bmatrix} \mu_{A1}w(x1), v_{A1}w(x1), \pi_{A1}w(x1), \mu_{A1}w(x_n), v_{A1}w(x_n), \pi_{A1}w(x_n) \\ \mu_{A2}w(x1), v_{A1}w(x1), \pi_{A1}w(x1), \mu_{A2}w(x_n), v_{A1}w(x_n), \pi_{A1}w(x_n) \\ \vdots \quad \ddots \quad \vdots \\ \mu_{Am}w(x1), v_{Am}w(x1), \pi_{Am}w(x1), \mu_{Am}w(x_n), v_{Am}w(x_n), \pi_{Am}w(x_n) \end{bmatrix}$ (14) $r\prime ij = \left(\prime_{ij}, v'_{ij}, \pi'_{ij}\right) = \left({}_{Ai}\, w(x_j), v_{Ai}w(x_j), \pi_{Ai}w(x_j) \right)$ is an element of the R$\prime$ matrix.
Step 5: *Determination of Positive and Negative Ideal Solutions*	Benefit and cost criteria are identified, and the positive ideal solution (PIS) and negative ideal solution (NIS) are computed utilizing Equations (15) and (16). $Q^{PIS} = \underset{j \in benefit}{max}\left(M(Q_j)\right)$ or $\underset{j \in cost}{min}\left(M(Q_j)\right)$ (15) $Q^{NIS} = \underset{j \in benefit}{min}\left(M(Q_j)\right)$ or $\underset{j \in cost}{max}\left(M(Q_j)\right)$ (16)
Step 6: *Determination of separation measures*	With the help of Equations (17) and (18), the *Si* and R_i values of each alternative are calculated. $Si = \Sigma_{j=1}^{n} w_j \frac{d\left(Q_j, Q^{PIS}\right)}{d\left(Q^{PIS}, Q^{NIS}\right)}$ (17) $R_i = \underset{j \in n}{max}\left(w_j \frac{d\left(Q_j, Q^{PIS}\right)}{d\left(Q^{PIS}, Q^{NIS}\right)} \right)$ (18) The Euclidean distance formula, as denoted in Equation (19), was employed to calculate the distances among Q-ROFN [33]. where $d(Q_1, Q_2) = \sqrt{\left(\mu_1^q - \mu_2^q\right)^2 + \left(v_1^q - v_2^q\right)^2 + \left(\pi_1^q - \pi_2^q\right)^2}$ (19) w_j are the weight of the jth criteria and the total number of criteria is n.
Step 7: *Calculating the merit function*	The merit function Q_i^{mf} of each alternative is calculated using Equation (20). $Q_i^{mf} = v\left(\frac{Si - S^*}{S^- - S^*}\right) + 1 - v\left(\frac{Ri - R^*}{R^- - R^*}\right)$ (20) where v ∈ [0, 1] is the strategy of the DMs. In this study, v is taken as 0.5. $S^- = max_i(S_i)$, $S^* = min_i(S_i)$ $R^- = max_i(R_i)$, $R^* = min_i(R_i)$
Step 8: *The Qj values of each alternative are ordered from largest to smallest*	

3.3. Q-ROF TOPSIS

Let X = {X_1, X_2, X_3, … X_n} represent a set of *n* criteria, and let A = {A_1, A_2, A_3, … A_m} denotes a set of *m* alternatives. Below, we outline the steps of the algorithm [34,35]:

Q-ROF TOPSIS	Definition
Step 1: *Translating their assessments*	
In the Q-ROF TOPSİS method, the initial four steps are iterated to establish the weighted decision matrix with consistency. These steps involve meticulously assessing the criteria, normalizing the decision matrix, determining the relative closeness coefficients, and calculating the separation measures. By repeating these foundational steps, the weighted decision matrix is refined to accurately represent the importance of the criteria and the performance of the alternatives across various dimensions. This iterative process ensures a robust and comprehensive analysis, laying the groundwork for subsequent stages of the decision-making process within the Q-ROF VIKOR framework.	
Step 2: *Determining Positive and Negative Ideal Solutions*	
The Q-ROF Positive Ideal Solution (A^*) maximizes the benefit criteria while minimizing the cost criteria. On the other hand, Q-ROF Negative Ideal Solution (A^-) maximizes the benefit criteria while minimizing the benefit criteria. A^* and A^- values are calculated with the following Equations (21)–(25). $A^* = \mu_{A*W}(x_j), v_{A*W}(x_j), \pi_{A*W}(x_j)$ and $A^- = \mu_{A-W}(x_j), v_{A-W}(x_j), \pi_{A-W}(x_j)$ (21) where $\mu_{A*W}(x_j) = \left(\left({}_i^{max}\mu_{A_i}w(x_j) \middle|\, j \in j_1 \right), \left({}_i^{min}\mu_{A_i}w(x_j) \middle|\, j \in j_2 \right) \right)$ (22) $v_{A*W}(x_j) = \left(\left({}_i^{min}v_{A_i}w(x_j) \middle|\, j \in j_1 \right), \left({}_i^{max}v_{A_i}w(x_j) \middle|\, j \in j_2 \right) \right)$ (23) $\mu_{A-W}(x_j) = \left(\left({}_i^{min}\mu_{A_i}w(x_j) \middle|\, j \in j_1 \right), \left({}_i^{max}\mu_{A_i}w(x_j) \middle|\, j \in j_2 \right) \right)$ (24) $v_{A-W}(x_j) = \left(\left({}_i^{max}v_{A_i}w(x_j) \middle|\, j \in j_1 \right), \left({}_i^{min}v_{A_i}w(x_j) \middle|\, j \in j_2 \right) \right)$ (25)	

Step 3: *Determination of separation measures*

The distance measures were calculated using Equations (26) and (27) [36].

$$S_i^* = \sqrt[p]{\frac{1}{2n}\Sigma_{j=1}^{n}\left\{\begin{array}{c}\left|(1-k)\left(\mu_{A_i}w(x_j)-\mu_{A*W}(x_j)\right)+k\left(\sqrt[q]{1-v_{Ai}^{q}w(x_j)}-\sqrt[q]{1-v_{A*w}^{q}(x_j)}\right|^{p}+\\ \left|(1-k)\left(v_{A_i}w(x_j)-v_{A*W}(x_j)\right)+k\left(\sqrt[q]{1-\mu_{Ai}^{q}w(x_j)}-\sqrt[q]{1-\mu_{A*W}^{q}(x_j)}\right|^{p}\end{array}\right\}} \quad (26)$$

$$S_i^- = \sqrt[p]{\frac{1}{2n}\Sigma_{j=1}^{n}\left\{\begin{array}{c}\left|(1-k)\left(\mu_{A_i}w(x_j)-\mu_{A-W}(x_j)\right)+k\left(\sqrt[q]{1-v_{Ai}^{q}w(x_j)}-\sqrt[q]{1-v_{A-w}^{q}(x_j)}\right|^{p}+\\ \left|(1-k)\left(v_{A_i}w(x_j)-v_{A-W}(x_j)\right)+k\left(\sqrt[q]{1-\mu_{Ai}^{q}w(x_j)}-\sqrt[q]{1-\mu_{A-W}^{q}(x_j)}\right|^{p}\end{array}\right\}} \quad (27)$$

where $p = 1, 2, \ldots, n$ and $k = \frac{\left(\frac{1}{2}q^2+\frac{3}{2}q-\frac{1}{3}\right)}{\left(q^2+3q+1\right)}$, $k \in \left[\frac{1}{3}, \frac{1}{2}\right]$

Step 4. *Calculation of the relative closeness coefficient (Ci_*).*

Ci_* is calculated using Equation (15).

$Ci_* = \frac{S^-}{S^+ + S^-}$ where $0 \leq C_{i*} \leq 1$,

4. Case Study

This section presents the results obtained from implementing the proposed methodology to solve the SCM selection within a real-life case study conducted by the producer of an industrial company in Turkey. In the conventional evaluation process, the first crucial step involves the selection of optimal evaluation criteria before proceeding to assess alternatives and select suppliers. Establishing suitable metrics presents a significant challenge in supplier selection. This study addresses the issue of SCM selection by evaluating five suppliers across ten criteria, with three experts serving as decision-makers (DMs). The decision to use three experts was based on the following points: Experience and specialization: Each expert brings unique skills and deep knowledge in their respective areas of supply-chain management, logistics, and optimization. This ensures a comprehensive assessment of different perspectives in the field. Quality over quantity: While a larger number of experts could provide more diverse opinions, the three selected experts have considerable qualifications and experience that we believe adequately represent the necessary expertise. Practicality and efficiency: Managing and combining inputs from a larger group of experts can be difficult and can lead to logistical inefficiencies. By limiting ourselves to three highly qualified experts, we can ensure a smoother and more efficient decision-making process. Table 2 offers an in-depth analysis of the decision-makers (DMs) involved in the study.

Table 2. DMs in detail.

DMs Education	Experiences	Area
Masters (Business)	15	Supply-Chain Optimization
PhD (Supply Chain)	18	Supply-Chain Management
PhD (Industrial Eng.)	12	Logistics Management

Based on the literature, it was found that the following ten criteria are often considered in various studies on this topic:

Cost [37–48], innovation capability [49–59], quality [60–71], service capability [57–59,72–79], long-term cooperation [80–88], environmental management system [89–97], reduce pollution [95,98–104], green image [105–114], social responsibility [115–122]), and employment practices [123–129].

Alternatives is committed to strategic progress, recognizing the importance of strengthening sustainable supply-chain management for long-term viability. Following a meticulous assessment, the company has identified five alternative suppliers: A1, A2, A3, A4, and A5, all capable of meeting its needs. The evaluation process is focused on identifying suppliers that best align with companies' long-term development goals, fostering sustainable and enduring partnerships.

Through a meticulous process combining literature review and expert evaluations, this study identifies the key criteria that heavily influence SCM selection. With these criteria

established, the next step involves comparing five suppliers across ten distinct metrics. This comparison is conducted using both the Q-ROF TOPSIS and Q-ROF VIKOR methods, which offer robust frameworks for supplier evaluation and selection. The expertise of the decision-makers has been evaluated by considering their extensive industry experience, educational background, professional qualifications, and relevant certifications. Additionally, their track record of successful decision-making in similar contexts and their familiarity with the specific challenges and nuances of the industry are taken into account. Furthermore, their ability to analyze complex situations, make informed judgments, and anticipate potential risks and opportunities is also considered to be part of their expertise assessment. Overall, a comprehensive evaluation of decision-makers' capabilities ensures that their input contributes effectively to the decision-making process.

The comprehensive assessment of decision-makers' expertise helps significantly reduce subjectivity in decision-making by evaluating industry experience, education, qualifications, certifications, and decision-making track records. However, these measures cannot eliminate subjectivity due to inherent human biases and cognitive limitations. To further enhance objectivity, it is recommended to use decision-support tools, provide continuous training, conduct reflective assessments, and incorporate diverse perspectives to complement individual judgment.

DM_1 = (0.85, 0.25), DM_2 = MH (0.65, 0.45), and DM_3 = MH (0.65, 0.45)

$\lambda_{DM_1} = 0.799$

$\lambda_{DM_2} = 0.592$

$\lambda_{DM_3} = 0.592$

Table 3 presents the linguistic expressions used by decision-makers to evaluate alternatives. These linguistic terms have been translated into Q-ROF numbers based on the conversion guidelines outlined in Equation (1).

Table 3. Decision-maker ratings of alternatives in linguistic terms.

Criteria	Alternative	DM1		DM2		DM3	
C1	A1	0.85	0.25	0.55	0.55	0.25	0.85
	A2	0.85	0.25	0.85	0.25	0.95	0.15
	A3	0.65	0.45	0.65	0.45	0.65	0.45
	A4	0.85	0.25	0.85	0.25	0.65	0.45
	A5	0.95	0.15	0.55	0.55	0.65	0.45
C2	A1	0.85	0.25	0.65	0.45	0.65	0.45
	A2	0.85	0.25	0.75	0.35	0.95	0.15
	A3	0.55	0.55	0.55	0.55	0.55	0.55
	A4	0.75	0.35	0.85	0.25	0.65	0.45
	A5	0.95	0.15	0.95	0.15	0.75	0.35
C3	A1	0.75	0.35	0.85	0.25	0.75	0.35
	A2	0.75	0.35	0.75	0.35	0.95	0.15
	A3	0.65	0.45	0.65	0.45	0.65	0.45
	A4	0.75	0.35	0.55	0.55	0.75	0.35
	A5	0.95	0.15	0.95	0.15	0.85	0.25
C4	A1	0.75	0.35	0.55	0.55	0.65	0.45
	A2	0.55	0.55	0.45	0.65	0.55	0.55
	A3	0.75	0.35	0.65	0.45	0.75	0.35
	A4	0.75	0.35	0.75	0.35	0.85	0.25
	A5	0.75	0.35	0.85	0.25	0.75	0.35

Table 3. *Cont.*

Criteria	Alternative	DM1		DM2		DM3	
C5	A1	0.65	0.45	0.55	0.55	0.55	0.55
	A2	0.55	0.55	0.55	0.55	0.35	0.75
	A3	0.55	0.55	0.55	0.55	0.65	0.45
	A4	0.45	0.65	0.35	0.75	0.55	0.55
	A5	0.95	0.15	0.85	0.25	0.85	0.25
C6	A1	0.65	0.45	0.45	0.65	0.55	0.55
	A2	0.55	0.55	0.35	0.75	0.45	0.65
	A3	0.85	0.25	0.55	0.55	0.75	0.35
	A4	0.95	0.15	0.65	0.45	0.95	0.15
	A5	0.75	0.35	0.75	0.35	0.85	0.25
C7	A1	0.55	0.55	0.65	0.45	0.65	0.45
	A2	0.55	0.55	0.55	0.55	0.55	0.55
	A3	0.55	0.55	0.65	0.45	0.65	0.45
	A4	0.95	0.15	0.85	0.25	0.75	0.35
	A5	0.95	0.15	0.95	0.15	0.75	0.35
C8	A1	0.35	0.75	0.75	0.35	0.35	0.75
	A2	0.35	0.75	0.85	0.25	0.45	0.65
	A3	0.65	0.45	0.65	0.45	0.55	0.55
	A4	0.45	0.65	0.55	0.55	0.45	0.65
	A5	0.95	0.15	0.95	0.15	0.85	0.25
C9	A1	0.85	0.25	0.75	0.35	0.75	0.35
	A2	0.55	0.55	0.65	0.45	0.35	0.75
	A3	0.45	0.65	0.65	0.45	0.65	0.45
	A4	0.65	0.45	0.45	0.65	0.95	0.15
	A5	0.95	0.15	0.85	0.25	0.85	0.25
C10	A1	0.55	0.55	0.65	0.45	0.75	0.35
	A2	0.85	0.25	0.65	0.45	0.75	0.35
	A3	0.75	0.35	0.75	0.35	0.75	0.35
	A4	0.75	0.35	0.75	0.35	0.55	0.55
	A5	0.95	0.15	0.85	0.25	0.95	0.15

Table 4 displays the Q-ROF matrix, which has been normalized using the Q-ROFWA operator. This normalization process helps to standardize the data and facilitate comparisons among the different alternatives.

The significance assessments of the criteria by the decision-makers were transformed into Q-ROF numbers using Equation (1). Subsequently, the weights of these criteria were calculated using Equation (4) and are presented in detail in Table 5. This process enables a quantitative representation of the relative importance of each criterion in the decision-making process, aiding in the selection of the most suitable supplier.

Table 4. Normalized decision matrix.

R		C_1			C_2			C_3			C_4		
	A_1	0.710	0.456	0.818	0.759	0.355	0.803	0.787	0.317	0.783	0.677	0.432	0.848
	A_2	0.893	0.215	0.652	0.878	0.237	0.677	0.852	0.272	0.712	0.525	0.578	0.872
	A_3	0.650	0.450	0.859	0.550	0.550	0.874	0.650	0.450	0.859	0.725	0.377	0.827
	A_4	0.811	0.298	0.760	0.767	0.341	0.798	0.708	0.401	0.834	0.787	0.317	0.783
	A_5	0.847	0.307	0.714	0.922	0.193	0.594	0.931	0.175	0.571	0.787	0.317	0.783
		C_5			C_6			C_7			C_8		
	A_1	0.596	0.507	0.870	0.576	0.533	0.869	0.615	0.488	0.867	0.561	0.597	0.848
	A_2	0.508	0.603	0.866	0.477	0.634	0.860	0.550	0.550	0.874	0.655	0.518	0.834
	A_3	0.585	0.518	0.871	0.768	0.350	0.796	0.615	0.488	0.867	0.625	0.478	0.865
	A_4	0.465	0.645	0.858	0.916	0.208	0.606	0.891	0.225	0.654	0.485	0.618	0.866
	A_5	0.905	0.203	0.630	0.787	0.317	0.783	0.922	0.193	0.594	0.931	0.175	0.571
		C_9			C_{10}								
	A_1	0.798	0.306	0.773	0.657	0.453	0.855						
	A_2	0.550	0.568	0.866	0.780	0.329	0.788						
	A_3	0.590	0.522	0.867	0.750	0.350	0.812						
	A_4	0.805	0.362	0.755	0.708	0.401	0.834						
	A_5	0.905	0.203	0.630	0.931	0.175	0.571						

Table 5. Importance and weight of the criteria.

Weight of the DMs	DM_1		DM_2		DM_3		Criterion Weight
	0.799	**0.799**	**0.592**	**0.592**	**0.5920**	**0.592**	
C_1	0.45	0.65	0.85	0.25	0.95	0.15	0.095
C_2	0.95	0.15	0.85	0.25	0.85	0.25	0.126
C_3	0.85	0.25	0.75	0.35	0.85	0.25	0.112
C_4	0.65	0.45	0.95	0.15	0.75	0.35	0.105
C_5	0.95	0.15	0.35	0.75	0.55	0.55	0.094
C_6	0.95	0.15	0.65	0.45	0.25	0.85	0.095
C_7	0.95	0.15	0.75	0.35	0.65	0.45	0.113
C_8	0.95	0.15	0.85	0.25	0.95	0.15	0.130
C_9	0.65	0.45	0.35	0.75	0.45	0.65	0.068
C_{10}	0.75	0.35	0.15	0.95	0.35	0.75	0.061

Table 6 presents the weighted decision matrix obtained by amalgamating the criteria weights with the normalized decision matrix.

Table 6. Aggregated Weighted Decision Matrix.

R′=				C_1			C_2			C_3			C_4	
	A_1	0.352	0.924	0.552	0.412	0.877	0.634	0.418	0.877	0.631	0.339	0.914	0.582
	A_2	0.491	0.856	0.633	0.510	0.834	0.660	0.470	0.862	0.634	0.255	0.943	0.525
	A_3	0.317	0.923	0.568	0.283	0.927	0.565	0.330	0.913	0.587	0.369	0.901	0.602
	A_4	0.420	0.885	0.615	0.418	0.873	0.640	0.365	0.901	0.603	0.410	0.884	0.621
	A_5	0.448	0.888	0.595	0.560	0.812	0.660	0.555	0.820	0.652	0.410	0.884	0.621
				C_4			C_6			C_7			C_8	
	A_1	0.278	0.940	0.529	0.267	0.945	0.517	0.308	0.923	0.570	0.294	0.934	0.542
	A_2	0.234	0.955	0.489	0.218	0.960	0.473	0.272	0.935	0.545	0.349	0.917	0.572
	A_3	0.272	0.942	0.525	0.376	0.909	0.580	0.308	0.923	0.570	0.331	0.907	0.601
	A_4	0.213	0.961	0.470	0.499	0.867	0.607	0.506	0.846	0.643	0.251	0.939	0.540
	A_5	0.488	0.865	0.619	0.389	0.901	0.594	0.540	0.831	0.644	0.581	0.794	0.672
				C_9			C_{10}							
	A_1	0.360	0.923	0.550	0.268	0.955	0.479							
	A_2	0.230	0.963	0.457	0.333	0.937	0.519							
	A_3	0.249	0.957	0.476	0.316	0.941	0.515							
	A_4	0.365	0.934	0.516	0.293	0.948	0.497							
	A_5	0.443	0.898	0.573	0.451	0.903	0.555							

4.1. Selection with Q-ROF VIKOR Method

In this section, we proceed with the subsequent steps of the Q-ROF VIKOR method, incorporating both the combined weighted decision matrix and the criterion weights. By leveraging Equations (15) and (16), we compute the optimal and suboptimal values of the criteria. These values are meticulously documented and presented in Table 7, providing a comprehensive overview of the decision-making process and facilitating informed analysis and comparison of alternatives.

Table 7. Best and worst values of criteria.

Criteria	Best Values			Worst Values		
C_1	0.893488285	0.306827296	0.7137597	0.65	0.455779906	0.818085819
C_2	0.921863245	0.193158404	0.593791996	0.55	0.237323764	0.676869428
C_3	0.931418996	0.174703588	0.571463687	0.65	0.40054564	0.834237563
C_4	0.787076402	0.316560162	0.783349621	0.524867382	0.57811651	0.871620338
C_5	0.905176652	0.203475624	0.62989658	0.464913045	0.645369834	0.857585529
C_6	0.915872764	0.208203334	0.606158429	0.477081794	0.634185114	0.860132228
C_7	0.921863245	0.193158404	0.593791996	0.55	0.55	0.873835185
C_8	0.931418996	0.174703588	0.571463687	0.485260415	0.618387459	0.865909702
C_9	0.905176652	0.203475624	0.62989658	0.550258796	0.568268348	0.866185684
C_{10}	0.931418996	0.174703588	0.571463687	0.656561062	0.452656573	0.854634987

Si^-, Si^+, Ri^-, and Ri^+ values are shown in Table 9.

The values of Si, Ri, and Qi were determined through the application of formulas delineated between Equations (17)–(20). These calculated values are meticulously recorded and presented in Table 8. and Figure 2. This comprehensive analysis offers insights into the

performance and characteristics of each alternative, facilitating a deeper understanding of their respective strengths and weaknesses in the decision-making process.

Table 8. Values of *Si*, *Ri*, and *Qi*.

Alternatives	*Si*	*Ri*	*Q i(v = 0.5)*	*Rank*
A_1	0.7829	0.1188	0.7736	**4**
A_2	0.7031	0.1135	0.7008	**3**
A_3	0.8700	0.1578	1.0000	**5**
A_4	0.5500	0.1304	0.6801	**2**
A_5	0.0655	0.0445	0.0000	**1**

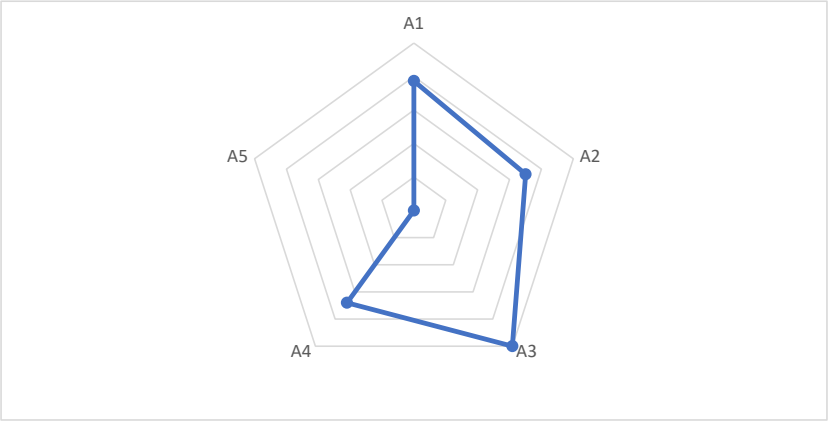


Figure 2. Values of *Si*, *Ri*, and *Q*.

Based on the Qi results, the alternatives are ranked as follows: A5 > A4 > A2 > A1 > A3. Consequently, A5 emerges as the most suitable alternative, while A3 is identified as the least favorable option. Notably, these rankings align with those obtained from the Q-ROF VIKOR method, reaffirming the consistency of the outcomes across different analytical approaches. This consistency underscores the robustness of the analysis and provides further confidence in the selection of A5 as the preferred alternative.

When assessing companies based on certain criteria, even if there are minimal discrepancies between them, certain criteria tend to hold more weight in people's preferences. Specifically, factors such as the number of examinations, brand strength, and premium suitability emerge as particularly influential. Both analytical methods indicate that the A5 alternative, occupying the top position, represents a well-established entity in the local market and enjoys greater credibility in the eyes of the public. This suggests that A5 is perceived as a more reliable option, likely due to its strong presence and reputation within the industry.

Table 9. Values of Si and Ri.

Si^-	Si^+	Ri^-	Ri^+
0.8700	0.0655	0.1578	0.0445

4.2. Selection with Q-ROF TOPSIS Method

This section outlines the procedural steps of the Q-ROF TOPSIS method by taking into account the combined weighted decision matrix. The Q-ROF Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) values presented in Table 10 were computed utilizing the equations outlined in Equations (21)–(25), with the q-value set to 3.

Table 10. Positive and Negative Ideal Solution Values.

$A^*=$	C_1	0.491	0.856	0.633	$A^-=$	C_1	0.317	0.924	0.552
	C_2	0.560	0.812	0.660		C_2	0.283	0.927	0.565
	C_3	0.555	0.820	0.652		C_3	0.330	0.913	0.587
	C_4	0.410	0.884	0.621		C_4	0.255	0.943	0.525
	C_5	0.488	0.865	0.619		C_5	0.213	0.961	0.470
	C_6	0.499	0.867	0.607		C_6	0.218	0.960	0.473
	C_7	0.540	0.831	0.644		C_7	0.272	0.935	0.545
	C_8	0.581	0.794	0.672		C_8	0.251	0.939	0.540
	C_9	0.443	0.898	0.573		C_9	0.230	0.963	0.457
	C_{10}	0.451	0.903	0.555		C_{10}	0.268	0.955	0.479

The separation measures were calculated using Equations (26) and (27). Afterward, proximity values to the ideal solution were established, guiding the determination of rankings for the alternatives. These rankings are clearly outlined in Table 11 and Figure 3 for comprehensive evaluation and comparison.

Table 11. Proximity values and ranking of alternatives.

	S^*	S^-	Ci^*	*Rank*
A_1	0.101	0.037	0.269	4
A_2	0.097	0.041	0.296	3
A_3	0.107	0.031	0.223	5
A_4	0.075	0.063	0.456	2
A_5	0.009	0.129	0.934	1

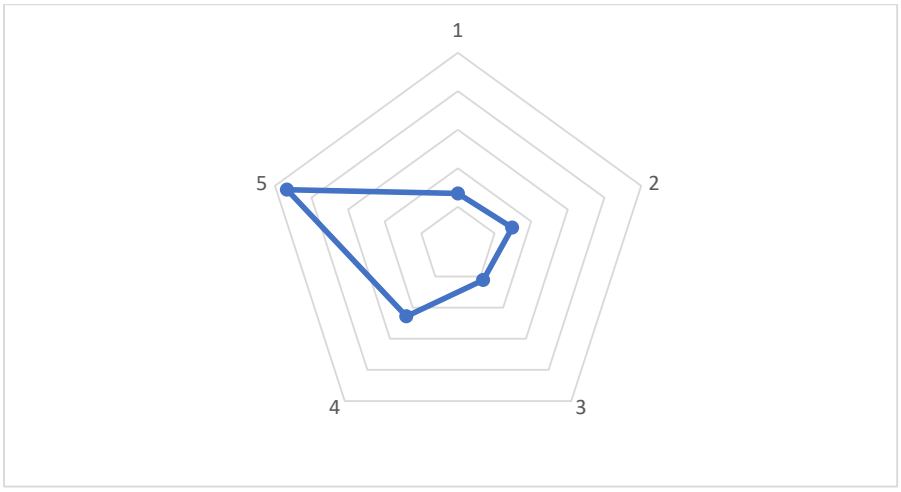


Figure 3. Proximity values and ranking of alternatives.

Comprehensive evaluation and comparison of two methods. (See Figure 4).

Following the computation of the Ci* results, the alternatives are ranked as follows: A5 > A4 > A2 > A1 > A3. Consequently, the analysis reveals that A5 stands out as the most suitable alternative, while A3 is identified as the least suitable option. This ranking provides valuable insights into the comparative effectiveness and appropriateness of each alternative, guiding decision-makers toward optimal choices in the decision-making process.

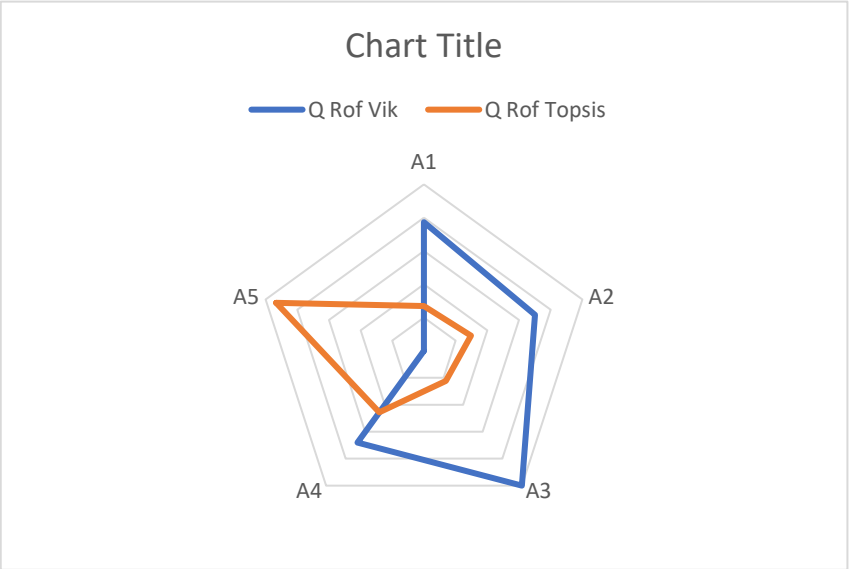


Figure 4. Proximity values and ranking of alternatives (Q-Rof VIKOR and TOPSIS).

5. Conclusions and Future Studies

Modern businesses face the significant challenge of implementing sustainable supply-chain management, with supplier selection being a crucial aspect. This is particularly pertinent in engineering and management, given that a company's supply chain involves multiple suppliers, and their qualifications significantly impact overall supply chain performance. To achieve sustainable development goals, companies must prioritize social and environmental responsibility while maximizing economic benefits. This study aims to address the objectives outlined in the introduction by evaluating the literature on sustainable suppliers, establishing a framework of environmental, social, and economic performance indicators, and formulating selection criteria for sustainable suppliers. By combining subjective and objective weights, the study creates a total weight, indicating the importance of various indicators. This approach enhances the effectiveness of ranking results by incorporating human judgment and raw data information. Moreover, supplier selection is identified as a multi-criteria decision-making (MCDM) issue, underscoring the complexity of the decision-making process in this context.

In contexts where situations are not clearly defined by crisp numbers, traditional analytical methods may fall short of providing clear insights. This is where the Q-ROF (Quality-Robustness-Operation Fuzziness) method proves invaluable, as it offers a framework for making clearer decisions amid uncertainty. Recognizing the uncertainties inherent in policy selection, this study leveraged Q-ROF-based clusters to navigate through the complexities and arrive at the most informed decisions. Five alternatives were subjected to analysis to evaluate the effectiveness of the Q-ROF method, using both the Q-ROF TOPSIS and Q-ROF VIKOR methods. These analyses were conducted through surveys administered to three decision-makers actively engaged in the sector, providing diverse perspectives on the matter. By employing different distance measures in the evaluation process, the study sought to ascertain whether varying measures would yield divergent outcomes. Interestingly, despite employing different distance measures, the results obtained from both methods exhibited remarkable similarity, indicating that the choice of distance measure had minimal impact on the outcomes.

Furthermore, a detailed parameter analysis revealed that the ranking between q-values remained consistent in the Q-ROF TOPSIS method, underscoring the robustness of this approach. However, slight variations were observed in the rankings of the last three alternatives in the Q-ROF VIKOR method, highlighting the nuanced differences in their performance. Nevertheless, across all analyses conducted using both methods,

alternatives A5 and A4 consistently emerged as the top-performing options, reaffirming their superiority in the decision-making process.

6. Research Limitation

Integrating Q-ROF with MCDM can lead to increased complexity stemming from the fusion of fuzzy logic with MCDM. This complexity can make the decision-making process more challenging to grasp and execute. Moreover, this integration may demand substantial computational resources and time, especially for sizable decision problems. Additionally, interpreting the outputs of integrated Q-ROF and MCDM approaches can be challenging, particularly for stakeholders unfamiliar with fuzzy logic or decision analysis methods.

7. Recommendations for Future Works

The limitations identified in the study provide directions for future research. This study employs Q-level fuzzy set and sensitivity analyses to evaluate alternatives, providing a comprehensive decision-support framework. Through comparisons of results at different Q-levels, the methodology offers valuable insights into the evaluation process. It tackles challenges such as analyzing criteria-alternatives relationships, handling uncertainty, assigning importance weights, and assessing diverse options. The study does have certain restrictions. Future research should consider the decision-making mechanism coefficient and any potential interactions and relationships between standards, as these elements have not been fully explored in the current study. Additionally, fuzzy sets cannot fully capture fundamental uncertainty; therefore, future research will focus on combining multi-granularity language data with support vector machines, fuzzy sets, and neutrosophic sets to create a model known as multi-criteria decision-making (MCDM).

Future research should also consider multiple directions to improve the robustness and applicability of the results. First, expanding the panel of experts is essential. Increasing the number of experts involved in the decision-making process increases the significance and reliability of the results. This can be achieved by involving a more diverse group of experts, ideally between 10 and 15, to ensure a comprehensive assessment of the criteria. Second, integrating more advanced analytical methods can provide deeper insights into the complexities of supply-chain management. Future studies should focus on combining multi-granularity speech data with support vector machines, fuzzy sets, and neutrosophical sets. This approach will more effectively address fundamental uncertainties and enable a more nuanced analysis of the decision-making process. Third, examining possible interactions and relationships between different criteria is crucial. Using advanced multi-criteria decision-making (MCDM) techniques to examine these relationships will enable a more holistic understanding of the factors that influence supply-chain management decisions. Additionally, analyzing the organization's internal processes alongside supplier selection will provide a more comprehensive view of supply-chain management. This holistic approach ensures that both internal efficiency and the performance of external suppliers are taken into account in the decision-making process. Finally, the development of dynamic decisions is required.

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Abbreviations and Notations

Multi-Criteria Decision-Making	MCDM
Group Decision-Making	MCGDM
Q-Rung Orthopair Fuzzy	Q-ROF
Supply-Chain Management	SCM
Analytic Hierarchy Process	AHP
Analytic Network Process	ANP
Technique for Order Preference by Similarity to Ideal Solution	TOPSIS
Vlsekriterijumska Optimizacija I Kompromisno Resenje	VIKOR
Decision-Making Trial and Evaluation Laboratory	DEMATEL
Simple Additive Weighting	SAW
Green Supplier Selection	GSS
Intuitionistic Fuzzy Sets	IFS
Pythagorean Fuzzy Sets	PFS
Q-Rung Orthopair Fuzzy	Q-ROF
Grey Relational Analysis	GRA

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