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Integrated Fermatean Fuzzy SWARA and Q-ROF-EDAS Methodology for Supplier Evaluation in the Shipyard Industry

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ABSTRACT

In recent years, increasing complexity in supply chains and the presence of high cost and risk factors in project-based industries such as shipbuilding have made supplier selection a critical decision-making problem. In this context, this study evaluates the criteria that shipyards should consider in supplier selection using an integrated multi-criteria decision-making (MCDM) approach based on Fermatean Fuzzy SWARA (FF-SWARA) and q-Rung Orthopair Fuzzy Set-based EDAS (q-ROF EDAS) methods. In the first stage of the study, the importance weights of twelve supplier selection criteria—gathered under two main categories based on expert opinions and literature review—were determined using the FF-SWARA method. In the second stage, supplier alternatives were ranked using the q-ROF EDAS method. A sensitivity analysis was also conducted in the study, and rankings generated under 100 different scenarios were evaluated. The results obtained demonstrate the practical applicability of the proposed method and its capability to address uncertainty in the decision-making process, contributing to more consistent and informed decisions in the shipyard and shipbuilding sectors.

1. Introduction

Supplier selection, a strategic component of supply chain management, is a multi-criteria decision problem that has a direct impact on the operational success of businesses. This is especially true in project-based production areas such as the shipyard industry, where high risk and cost elements are evident. In such cases, the selection of appropriate suppliers is of great importance in terms of optimizing performance criteria such as quality, cost, delivery time and flexibility. This process frequently exhibits a multifaceted structure, wherein quantitative and qualitative criteria are evaluated in conjunction, with uncertainty and decision-maker subjectivity being paramount considerations.

In this context, in recent years, multi-criteria decision making (MCDM) methods have been used intensively to provide systematic and analytical solution approaches to supplier selection problems. However, the inadequacy of traditional MCDM methods in modeling the uncertain and inconsistent

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evaluations of decision makers has directed researchers in this field to more flexible and powerful mathematical structures. In this direction, the q-rung orthopair fuzzy sets (q-ROFs) theory, developed as an extended form of intuitionistic and Pythagorean fuzzy sets, allows decision maker opinions to express both membership and opposite membership degrees in a wider space. Q-ROFs has become an effective tool that increases decision quality in multi-dimensional decision problems such as supplier selection.

This study aims to present a q-ROF based MCDM approach to a supplier selection problem specific to the shipyard industry. In the study, the weighting of decision criteria was performed with the Fermatean Fuzzy SWARA (FF-SWARA) method; and the evaluation of alternatives was performed with the q-ROFS based Evaluation based on Distance from Average Solution (EDAS) method. For this purpose, 12 evaluation criteria were defined based on literature and expert opinions, and the model was tested within the framework of a case study.

The main contributions of the study in this context can be summarized as follows:

(i) The integration of q-ROFs theory with the EDAS method on a supplier selection problem specific to the shipyard industry is provided,

(ii) The application of the FF-SWARA method in criteria weighting has been shown to contribute to the diversification of methodological approaches within the relevant literature,

(iii) The proposed integrated model has been subjected to empirical testing using real data, thereby providing a robust demonstration of its application validity.

The study is divided into six sections. In the subsequent section, the existing literature on q-ROFS-based supplier selection is critically evaluated. In the third section, the problem definition is made, and the determined criteria are presented in detail. In the fourth section, the IFS, FFS, FF-SWARA, q-ROFs and EDAS methods utilized in the study are elucidated within a methodological framework. In the fifth section, the case analysis is presented; in the sixth section, the analysis results and findings are discussed.

2. Literature Review

Supplier selection is a multi-criteria decision problem where many qualitative and quantitative criteria are taken into consideration and decision makers are faced with uncertainty and subjective judgments. Choosing the right supplier is of strategic importance, especially in industrial areas where project-based production processes such as shipyards become more complex. In this context, MCDM methods provide a systematic and rational evaluation ground in the supplier selection process.

However, classical MCDM methods may be insufficient to adequately reflect the uncertain evaluations of decision makers and the contradictions in expert opinions. For this reason, fuzzy logic approaches and their advanced versions have found a wide place in the literature, especially in recent years, to provide solutions to these problems. Q-ROFSs, which stand out among these approaches, offer a structure that can model uncertainty in a more flexible and detailed way, thanks to the ability of decision makers to express both membership and opposing membership degrees separately. Q-ROFS, as a generalized form of intuitionistic and Pythagorean fuzzy sets, provides more expressive power and decision support.

In recent years, studies on the application of q-ROFs based decision making approaches to the supplier selection problem have been increasing, and this method contributes to more reliable and realistic decisions by being used both in the weighting of supply criteria and in the evaluation of alternatives. In this article, a q-ROFs based MCDM approach is used to evaluate the supplier selection problem in the shipyard industry and it is aimed to contribute to the existing literature.

In the study conducted to determine the most suitable offshore wind farm installation locations within the maritime jurisdiction areas of Türkiye in the Aegean Sea, three alternatives (Ayvalık, Bozcaada, Gökçeada) were modelled with q-ROFs and evaluated with the COPRAS method. Twelve criteria determined as a result of the literature review were classified under four main headings as technical, strategic, social and environmental and weighted in line with expert opinions. Criteria are wind speed, wave height and period, investment cost, water depth, proximity to shore, proximity to power transmission grid, ship traffic density, proximity to military operation area, distance from fishing areas, distance from coastal touristic areas, distance from cables and pipelines, impact on fisheries. As a result of the applied method, it was determined that the most suitable alternative was off the coast of Bozcaada, and this result was confirmed by comparisons made with q-ROF TOPSIS and q-ROF WASPAS methods. In addition, the sensitivity analysis showed that the COPRAS method gave more stable results against changes in q values [1].

Another important contribution to this field was developed by Bisht and Pal [2], who presented an integrated q-ROFs decision-making framework that takes into account trust relationships and psychological behaviours among experts. For the analysing of green supplier selection problem, delivery speed, green design practices, product quality and service, total cost and energy and resource consumption are selected as criteria.

Erdebilli and Sıcakyüz [3] developed an innovative decision-making model that uses q-ROF TOPSIS and q-ROF VIKOR methods in an integrated manner to be used in the selection of supply chain management strategies. Within the scope of the proposed model, the authors evaluated the decision-maker weights and criteria importance levels via q-ROF numbers, then normalized the criteria weights and ranked the alternatives. The ten criteria used for sustainable supplier selection in the study are: cost, innovation ability, quality, service capacity, long-term cooperation, environmental management system, pollution reduction, green image, social responsibility and employment practices. In the study, five alternative suppliers were evaluated through a real industrial organization example, and similar ranking results were obtained in the analyses made with both q-ROF TOPSIS and q-ROF VIKOR methods, demonstrating the consistency of the method.

Saqlain *et al.,* [4] emphasize that the selection of energy suppliers within the scope of sustainable energy management plays a critical role in reducing environmental impacts and optimizing resources with sustainable practices. In this context, a multi-attribute decision-making system was developed in the study, which aims to determine energy suppliers by evaluating them within the framework of various features and sub-parameters. The authors introduced the interval-valued q-ROF hypersoft sets (IVq-ROFHSS) structure to manage uncertain situations and created two new aggregation operators, IVq-ROFHSEWA and IVq-ROFHSEWG, using Einstein operational laws on this structure. The evaluation criteria are reliability and service quality, sustainability and environmental impact, contract terms and flexibility, pricing and cost structures, and reputation and track record.

Supplier selection is important process, especially for companies operating in strategic sectors. In this context, Güneri and Deveci [5] structured the decision-making process with fuzzy-based MCDM methods in their study aiming to evaluate the selection criteria of supplier companies operating in the defence industry. In their study, supplier selection criteria were determined as a result of the systematic review of numerous studies published between 1966 and 2019; these criteria were clarified based on expert opinions with the Delphi method and weighted with the Analytical Hierarchy Process (AHP) method. In the evaluation phase, q-ROFS based EDAS method was used and sensitivity analyses were performed. According to the findings, while the main criterion that affects the decision process the most is performance, it was observed that sub-criteria such as product performance, quality, price, sustainability and operational controls stood out in expert evaluations.

In the studies of Khan *et al.,* [6] both the uncertainty in decision-maker opinions and the fuzziness of the evaluated criteria at the sub-attribute level were successfully modelled using the q-ROFHS structure. In addition, the q-ROFHOWG (ordered weighted geometric) aggregation operator was defined and the effect of the proposed method on increasing consensus among decision-makers was emphasized. In the real-life example carried out to demonstrate the applicability of the model, the green supplier selection problem was addressed. Green supplier selection is a complex decision-making problem that requires consideration of a large number of criteria in the context of supply chain applications that support environmental sustainability goals. In one of the studies conducted in this context, manufacturing companies assigned a group of experts to select suitable green suppliers and evaluations were made in line with three main criteria: product performance, supplier development potential and pollution control.

As a solution to the environmental problems caused by abandoned bicycles, Xu [7] proposed a two-stage MCDM method based on interval-valued q-ROF (IVq-ROF) for selecting a bicycle recycling supplier. In the first stage, evaluation information was combined with IVq-ROF Einstein operators, and in the second stage, the most suitable supplier was determined by the TOPSIS method. The criteria evaluated in the study are green image, recycling capacity and financial capacity.

Fetanat and Tayebi [8], proposed an innovative decision support system for the evaluation of industrial filtration technologies that can be used to control pollutants generated in natural gas processing plants in line with the principles of sustainability and sustainable maintenance. The study developed a q-ROFS-based version of the MAIRCA (Multi-Attributive Ideal-Real Comparative Analysis) method based on the q-ROFs theory, which has been proven to be effective in modelling decision environments containing uncertainty. In this context, five different filtration technologies (Backwash, Gravity Separator, Cyclone Separator, Basket Strainer and Cyclo-Filter) that can be applied in natural gas processing plants in the Behbahan region of Iran were evaluated and the most suitable technology was determined as Cyclo-Filter. The methodology used in the study offers a systematic MCDM approach that includes decision-maker evaluations based on linguistic variables, criterion weights and normalization steps in the q-ROFS environment.

Kamacı and Petchimuthu [9], developed the “interval-valued bipolar q-ROFs” (IVBq-ROFs) approach to support the decision-making process in uncertain and complex evaluation environments. The study offers solutions to supplier evaluation and selection problems by proposing new similarity measures that can holistically address both quantitative and qualitative evaluations. The proposed decision-making algorithm is based on three basic criteria in the context of supplier selection: price, quality, and reputation. Each criterion was evaluated from both positive (like) and negative (dislike) perspectives; thus, the evaluations of decision makers were modelled more realistically.

Liu *et al.,* [10] developed a decision-making model based on regular q-rung orthopair fuzzy numbers (q-RONFNs) and the QUALIFLEX method for the Green Supplier Selection problem. The criteria evaluated in the study were considered as multi-faceted attributes covering economic, technological, environmental and social dimensions. However, the method was expanded within the framework of QUALIFLEX, specifically for GSS problems where the number of alternatives is less than the criteria.

Mishra *et al.,* [11] developed a new Combined Compromise Solution (CoCoSo) method based on q-ROFs to model evaluations under uncertainty for the sustainable reverse logistics provider (S3PRLP) selection problem. The study used a total of 14 criteria based on economic, environmental and social sustainability dimensions in the evaluation process. These criteria are: pollution control, green product and eco-design, green warehouse management, green R&D and innovation, environmental management system, cost, flexibility, quality, delivery time, technology competence, occupational health and safety practices, social responsibility, educational infrastructure and employment practices.

Pınar *et al.,* [12] developed a q-ROF based TOPSIS method to evaluate the green supplier selection problem in an uncertain environment. In the study, comparative analyses were made with classical

TOPSIS and intuitionistic fuzzy TOPSIS methods; it was seen that the proposed q-ROF TOPSIS method managed uncertainty better and made a clearer distinction between alternatives. The model evaluated four suppliers operating in Türkiye based on ten criteria determined by three expert decision makers. This study offers a new decision support approach that allows companies to make more accurate decisions in green supplier selection today, where environmental awareness has increased. The criteria are quality, cost, service and delivery, sustainability, technology, green production system, green supplier image, cooperation, green practices, environmental management and audit.

Saha *et al.,* [13] developed new aggregation operators in the multi-attribute decision making (MADM) process by focusing on q-ROFs and q-ROF numbers (q-ROFN), which allow for more precise and balanced expression of uncertain information. In order to provide a fair and proportional approach to membership and non-membership degrees, the authors defined q-ROF weighted fair aggregation operator (qROFWFA) and sequential weighted fair aggregation operator with new neutral transaction laws. The evaluation criteria considered within the scope of the study were determined as product quality, relationship closeness, delivery performance and price.

Krishankumar *et al.,* [14] proposed a new decision-making framework based on q-ROFs to solve the green supplier selection problem in group decision-making environments where uncertainty and fuzziness are intense. The study extended the evidence-based Bayesian approach and statistical variance (SV) method in the context of q-ROFS to provide systematic determination of decision-maker weights and criteria weights, respectively. Four green suppliers evaluated within the scope of empirical application were compared in terms of five basic criteria: product delivery speed, design in accordance with green standards, product quality and service level, total cost, and energy and resource usage.

Pınar and Boran [15] proposed a new distance criterion developed on the basis of q-ROFs in order to model uncertainties more effectively in MCDM problems such as supplier selection. In this context, both q-ROF TOPSIS and q-ROF ELECTRE methods were adapted and used in a group decision-making environment for the first time in the literature. In the study, the proposed distance criterion was both theoretically proven and its superiority was demonstrated by comparing it with other methods. Within the scope of the application, a case study was conducted for selecting the most suitable supplier for a construction company and the reliability of the obtained results was supported by comparative analyzes. The selected criteria were quality, delivery time, cost/price, service, technological level, financial position, flexibility, reliability, reputation and cooperation level.

In their study, Gao *et al.,* [16] proposed the q-RIVOF-based VIKOR model by combining the traditional VIKOR method with the q-RIVOFS theory. In the new model, the attributes in multi-attribute group decision-making (MAGDM) problems are represented by q-rung interval-valued orthopair fuzzy numbers (q-RIVOFNs) to provide a richer set of information. In the study, the basic concepts and aggregation operators of q-RIVOFNs are first introduced, and then the VIKOR method is adapted to the q-RIVOFS environment and the calculation steps are presented. In order to demonstrate the proposed method in the study, an example is presented for medical consumable supplier selection using q-RIVOF information. Five potential medical consumable suppliers were ranked. Experts determined four attributes to evaluate five possible suppliers. These four attributes are environmental improvement quality, transportation convenience of suppliers, ease of transportation of the supplier, green image, environmental competencies.

Riaz *et al.,* [17] developed new prioritized aggregation operators based on q-ROFs in order to effectively manage uncertainties in the green supplier selection process. In their study, supplier evaluation within the scope of GSCM was considered as a multi-criteria group decision-making (MCGDM) problem and decision makers were enabled to express their evaluations under uncertain environmental conditions more precisely. The criteria considered in green supplier selection were determined as quality, cost, delivery, service, environmental factors and corporate social responsibility.

Tian *et al.,* [18] developed an innovative TODIM method based on q-ROFs that takes into account the psychological states of decision makers and the uncertainty in their evaluation information in order to make green supplier selection more effective. In their study, the TODIM method was integrated with the expectation theory and the risk tendencies and perceptual awareness of decision makers were integrated into the model. In this context, a new distance measure reflecting the herd mentality was defined and it was aimed to reflect the perceptual differences of decision makers more accurately. In addition, a four-dimensional criteria set called PCEM was created in order to systematize the supplier evaluation process: product, cooperation ability, environment and market. The sub-criteria used in this context are; interest level (P_1), quality (P_2) and service (P_3) for product; management capability (C_1), innovation (C_2) and technology level (C_3) for cooperation ability; environmentally friendly design (E_1), environmental competencies (E_2) and green image (E_3) for environmental factors; and for market size, financial performance (M_1) and green market share (M_2) were determined.

Several of the criteria identified through studies conducted within the specified period are presented in Table 1.

Table 1
Several of the criteria were identified through research conducted between 2020 and 2025

Criteria / Reference	[2]	[3]	[4]	[5]	[6]	[7]	[9]	[11]	[18]	[12]	[13]	[16]	[14]	[15]	[17]	Criteria Type
Price	x	x	x	x		x	x	x	x	x	x		x	x	x	Cost
Delivery Time	x						x	x			x		x	x	x	Benefit
Quality	x	x	x	x	x			x	x	x	x		x	x	x	Benefit
Technology		x		x				x	x	x				x		Benefit
Transportation										x	x					Benefit
Flexibility								x						x		Benefit
Capacity																Benefit
After Sales Service		x	x	x					x	x			x	x	x	Benefit
Reliability			x		x		x							x		Benefit
Communication									x			x				Benefit
Location																Benefit
Green Packaging	x	x	x		x	x		x	x	x		x	x		x	Benefit

3. Problem Definition

This paper aims to evaluate the supplier selection criteria that shipyards—an essential part of the maritime industry—should consider in their procurement processes, using MCDM methods. To conduct this evaluation, a sample shipyard was selected, and common assessments were made based on the procurement activities carried out within this shipyard. During the evaluation process, twelve different criteria gathered from prior studies were submitted to six decision-makers in order to determine their respective weights. Using Saaty's a 1–9 scale [19], the decision-makers were asked to assess the criteria based on their perceived level of importance. After the weighting of the criteria, three different alternatives were identified to implement the EDAS method based on q-ROFs. The decision-makers were then asked to evaluate these alternatives according to how well they satisfy the specified criteria, using the same assessment approach. With this study, it is intended to provide guidance to various companies operating in the maritime sector regarding the extent to which they should consider specific criteria in their supplier selection processes. Accordingly, Figure 1 represents the hierarchical structure of the decision problem, while Figure 2 illustrates the methodological framework employed in the study.

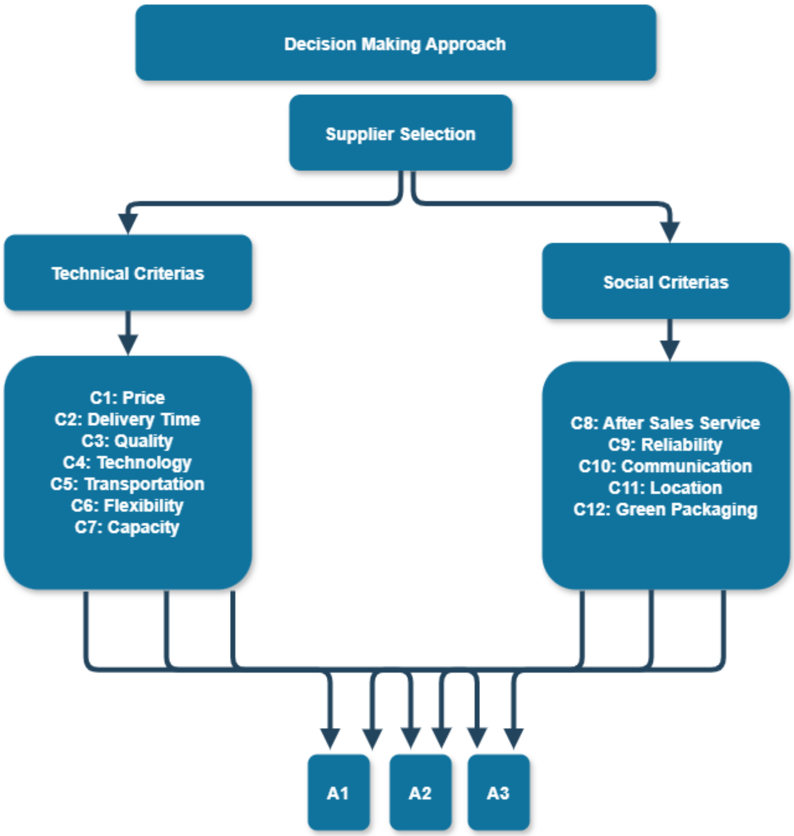

Fig. 1. The hierarchical structure of the decision problem

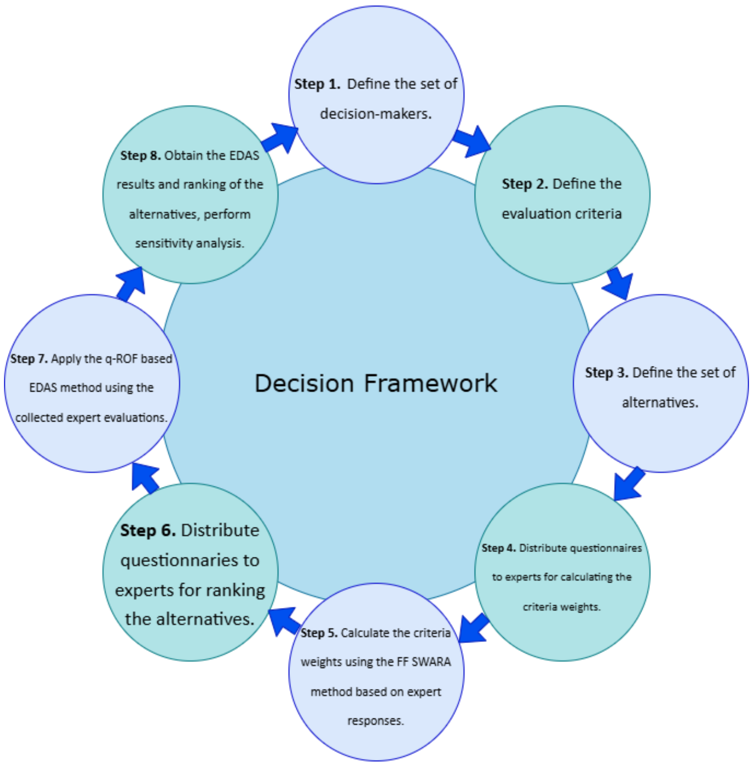

Fig. 2. Methodological framework of the study

3.1. Definition of alternatives

The alternatives encompass companies mainly engaged in the defense, maritime, and manufacturing industries within Türkiye. The firms selected for analysis are engaged in areas such as supplying materials and various services to shipyards, providing fire and damage control equipment, submarine batteries, spare parts for construction machinery, maritime supplies, marine outfitting equipment, and steel construction. The definition of alternatives is explained in the following:

A_1: This firm operates in the sale and import of spare parts for construction machinery. Focused on customer satisfaction, it offers fast and cost-effective solutions to its clients by leveraging its many years of experience and expert team. The company's goal is to meet the needs and demands of a wide range of customers by providing the best service at affordable prices, while establishing and maintaining long-term business relationships. The company is located in the İzmir region.

A_2: The company's vision is to deliver long-lasting maritime outfitting, equipment, steel construction, and repair/maintenance services in the international maritime sector. It is committed to maintaining the highest standards of safety for operations, human life, property, and the environment, all in full alignment with global industry standards and carried out by a skilled professional team.

The mission is to ensure sustainable growth by embracing continuous improvement, operational efficiency, and productivity. The company aims to meet the evolving needs of the maritime industry with a modern, safety-focused approach, supported by qualified personnel and state-of-the-art equipment. Guided by its vision, it seeks to build a profitable and forward-looking future for both its employees and business partners. The company operates in the Istanbul region.

A_3: The firm was founded in 2000 with the aim of producing products that are not manufactured domestically, particularly Fire and Damage Control systems and submarine battery components. It aims to develop high-performance, advanced technology products and to stand out in international markets through innovations in design and material engineering. The company has the technology, human resources, knowledge, and experience in advanced industrial applications of non-ferrous metals and composite materials, in compliance with ISO 9001:2015 Quality Management System requirements.

3.2. Definition of criteria

Technical Criteria:

C_1: Price (cost): In a competitive market environment, it has become essential for suppliers to offer their products or services with a competitive pricing strategy. But a competitive price does not always imply providing the cheapest option. When the cost of a good or service is high, it can have a direct impact on the procurement process. Especially in cases where budget constraints exist, companies may be compelled to consider alternative products or turn to different suppliers [5]. Additionally, aligning pricing strategies with sustainability goals enhances supply chain efficiency and serves as a crucial criterion in selecting green suppliers [20]. In this study, the price criterion is included as a cost-type criterion.

C_2: Delivery time (benefit): The delivery time criterion encompasses factors such as the supplier's quality of service, delivery capability, and flexibility in adapting to new conditions [12]. This criterion evaluates the supplier's ability to deliver products or services accurately and on time. Ensuring that products are delivered to the end user within the requested and specified timeframe is of critical importance. In this study, the delivery time criterion is considered as a benefit-type factor.

C_3: Quality (benefit): The quality criterion refers to the supplier's ability to consistently deliver products or services in accordance with established standards and customer expectations. This criterion includes elements such as compliance with quality standards, rejection rates due to quality issues, commitment to maintaining high-quality levels, and the implementation of formal quality management systems [12]. In this study, the quality criterion is included as a benefit-type criterion.

C_4: Technology (benefit): The technology criterion in supplier selection refers to the extent to which the company's goods and services are compatible with current technological advancements and their ability to adapt to innovations. Systems such as automation, artificial intelligence, and augmented reality are considered when evaluating this criterion [5]. In this study, the technology criterion has been included as a benefit type.

C_5: Transportation (benefit): This criterion reflects the efficiency of the supplier in delivering goods or services to the customer. In general, the transportation criterion covers many logistics activities, ensuring that the required goods and services reach the requesting units on time, accurately, and in a secure, undamaged condition. In this study, this criterion has been considered as a benefit type.

C_6: Flexibility (benefit): Supplier flexibility refers to the supplier's ability to quickly adapt to changing conditions and respond flexibly to varying demands. This criterion is said to enhance the overall flexibility of the supply chain, providing a competitive advantage in uncertain and dynamic market environments. Developing supply chain flexibility is especially important for creating an agile supply chain in uncertain market conditions [21]. In this study, the capacity criterion is considered as a benefit-type factor.

C_7: Capacity (benefit): This criterion covers the supplier’s technical capabilities, production competencies, and the maximum quantity of goods or services they can produce or deliver within a certain timeframe. It encompasses the supplier’s technical infrastructure, production capacity, and potential to meet demand. In this context, it reflects the supplier’s ability to respond to current and future needs. In this study, the capacity criterion is considered as a benefit-type factor.

Social Criteria:

C_8: After sales service (benefit): After-sales service refers to activities provided during the warranty period, including field technical support, spare parts distribution, customer care, and accessory sales. These services are considered important for supporting customers and enhancing the value of the product [22]. It is also evaluated that good after-sales services can lead to long-term relationships with suppliers. In this study, the after-sales service criterion is used as a benefit type.

C_9: Reliability (benefit): In business-to-business research, supplier reliability is emphasized as a critical factor in the evaluation and selection processes of buying firms [23]. Research highlights the importance of a supplier’s ability to deliver goods or services promptly and in line with agreed specifications. In cases where a single supplier is used scenarios, product reliability tends to be the most critical factor influencing purchasing decisions [24]. In this study, the reliability criterion is considered as a benefit-type criterion.

C_{10}: Communication (benefit): This criterion represents the communication with the supplier. It refers to the ability to reach the supplier when needed, including in cases of quantity or order changes. The better the communication between the requester and the supplier, the higher the likelihood that the need will be met effectively. In this study, the communication criterion is considered as a *benefit-type* criterion.

C_{11}: Location (benefit): The location criterion refers to the geographical position of the supplier. It can be stated that the prompt fulfillment of the requested goods/services is directly related to the supplier’s location. A distant supplier location may lead to delays in orders. In this study, the location criterion is considered as a benefit-type criterion.

C_{12}: Green packaging (benefit): Green packaging can be defined as a sub-criterion that reflects the supplier’s commitment to environmental sustainability. This includes the use of recyclable or reusable packaging materials. Such packaging practices contribute to the reduction of harmful environmental impacts and enhance the company's environmentally responsible image. In this study, the green packaging criterion is considered as a benefit-type criterion.

4. Methodology

4.1. Intuitionistic Fuzzy Sets

Intuitionistic fuzzy sets (IFS) were developed by Atanassov in 1986 as an extension of classical fuzzy sets. Traditional fuzzy sets are defined as a membership function that determines only one membership degree for each element. The IFS is comprised of three functions: the membership function μ(a), the non-membership function υ(a), and the hesitation function π(a) for each element. Given IFS's approach of integrating membership and non-membership degrees of sets, it enables the articulation of uncertainty and ambivalence in decision-making processes. Eq. (1) delineates the definition of IFS.

$$IFS = \{[a, \mu(a), \nu(a)]: a \in A\} \tag{1}$$

The membership function of the Intuitive Fuzzy Set assigns a membership degree to each element. This figure indicates the extent to which the element is associated with the set. The non-membership function is employed to display the non-membership degree for each element, thereby illustrating the extent to which the element does not belong to the set. Eq. (2) delineates the necessary conditions for membership and non-membership functions.

$$0 \leq \mu(a) + \nu(a) \leq 1 \tag{2}$$

The IFS hesitation function is used to model uncertainty about the degree of membership or non-membership of an element. The degree of hesitation is calculated using Eq. (3).

$$\pi(a) = 1 - \mu(a) - \nu(a) \tag{3}$$

Korucuk *et al.,* [25] explains that the use of three different functions in IFS — membership, non-membership, and hesitation — represents uncertainty and fuzziness in a more flexible and detailed way.

4.2. Fermatean Fuzzy Sets

Senapati and Yager, [26] introduced Fermatean fuzzy sets (FFS) for use in MCDM methods. FFS ensure that membership values are more independent for decision-makers and take hesitation effects into account more efficiently. The FFS, an extension of the IFS, is defined by Eq. (4).

$$FFS = \{[a, \mu_F(a), \nu_F(a)\ ]: a \in A\}$$
$$0 \leq \mu(a) + \nu(a) \leq 1 \tag{4}$$

In FFS, functions $\mu_F(a): A \rightarrow [0,1]$ and $\nu_F(a) : A \rightarrow [0,1]$ must satisfy the inequality in Eq. (5).

$$0 \leq \mu_F(a)^{\ 3} + \nu_F(a)^3 \leq 1 \tag{5}$$

In the FF set, the degree of hesitation is calculated by Eq. (6),

$$\pi_F(a) = \sqrt[3]{1 - \mu_F(a)^{\ 3} - \nu_F(a)^3} \tag{6}$$

The most obvious difference between IFS and FFS lies in how they model uncertainty. In FFS, it is modeled using the Fermat function. This mathematical function defines the degree to which an element belongs to a set. It is expressed with certain parameters. These parameters are adjusted to reflect the degree of uncertainty or fuzziness of the problem. The hesitation function is not explicitly defined in FFS sets. However, in their study, Senapati and Yager [26] defined the degree of hesitation for FFS decision-making problems.

FFSs may be more advantageous than IFSs in terms of computation because uncertainty is defined with only a single function. Senapati and Yager [26] compared the algebraic and topological properties of IFS and FFS spaces, showing that the FFS includes the IFS space as a subspace when the hesitation function is zero.

$x = (\mu_x, \nu_x)$, $\mu_x, \nu_x \in [0,1]$ ve $0 \le \mu_x(a)^{\ 3} + \nu_x(a)^3 \le 1$, $x = (\mu_x, \nu_x)$, $x_1 = (\mu_{x_1}, \nu_{x_1})$ $ve\ x_2 = (\mu_{x_2}, \nu_{x_2})$ Let's say there are three FFNs. The following statements regarding FFN are shown:

I. $\lambda x = \left(\sqrt[3]{1-(1-\mu_x^3)^\lambda},\ (\nu_x)^\lambda\right), \lambda > 0;$

II. $x^\lambda = \left((\mu_x)^\lambda, \sqrt[3]{1-(1-\nu_x^3)^\lambda}\right), \lambda > 0;$

III. $x_1 \cap x_2 = \left(min\{\mu_{x_1}, \mu_{x_2}\}, max\{\nu_{x_1}, \nu_{x_2}\}\right);$

IV. $y_1 \cup y_2 = \left(max\{\mu_{y_1}, \mu_{y_2}\}, min\{\nu_{y_1}, \nu_{y_2}\}\right);$

V. $y_1 \oplus y_2 = \left(\sqrt[3]{\mu_{y_1}^3 + \mu_{y_2}^3 - \mu_{y_1}^3\mu_{y_2}^3}, \nu_{y_1}, \nu_{y_2}\right);$

VI. $y_1 \otimes y_2 = \left(\mu_{y_1}, \mu_{y_2}, \sqrt[3]{\nu_{y_1}^3 + \nu_{y_2}^3 - \nu_{y_1}^3\nu_{y_2}^3}\right);$

VII. $y^C = (\nu_y, \mu_y).$

$y = (\mu_y, \nu_y)$ FFN score value is written as Eq. (7):

$$S(y) = \mu_y^{\ 3} - \nu_y^{\ 3}, -1 \le S(y) \le 1 \tag{7}$$

$y = (\mu_y, \nu_y)$ FFN score positive value is calculated as Eq. (8):

$$S^+(y) = 1 + S(y) = 1 + \mu_y^{\ 3} - \nu_y^{\ 3} \tag{8}$$

The FFN accuracy value $y = (\mu_y, \nu_y)$, is calculated by $A(y) = \mu_y^{\ 3} + \nu_y^{\ 3}$ with $0 \le A(y) \le 1$.

To compare two FFNs, $y_1 = (\mu_{y_1}, \nu_{y_1})\ and\ y_2 = (\mu_{y_2}, \nu_{y_2})$, In decision-making problems, alternatives or criteria must be compared. Here, this comparison is made via the "score function," $S(y)$, and the "accuracy function," $A(y)$.

- If $S(y_1) > S(y_2), then\ y_1 > y_2$, that is, the first number has a higher score, then that number is better.
- If $S(y_1) < S(y_2), then\ y_1 < y_2$, that is, the first number has a lower score, then that number is worse.
- If $S(y_1) = S(y_2)$, then:
  - If $A(y_1) > A(y_2), then\ y_1 > y_2$
  - If $A(y_1) < A(y_2)$, then $y_1 < y_2$
  - $A(y_1) = A(y_2)$, then $y_1 = y_2$

It was developed to establish a stable and logical order among numbers in multi-criteria decision-making problems involving uncertainty and fuzziness [27].

4.3. Fermatean Fuzzy SWARA Approach

SWARA, which stands for Subjective Weight Allocation and Ranking Approach, is a method proposed by Kersulienė and her colleagues that is based on subjective criterion weighting. It is an MCDM method. With the SWARA method, decision-makers or experts can determine their own priorities by considering the current conditions. Figure 1 shows the detailed flowchart of the FF-SWARA method. The FF-SWARA procedure is defined as follows:

I. First, create a decision matrix by considering the decision makers' evaluations of each influencing factor. These values are assigned using the linguistic terms in Table 2.

While determining the importance levels of the criteria, the nine-point scale developed by Saaty was used. After the experts scored the criteria, they were asked to evaluate three different alternatives based on the criteria obtained from the literature. The linguistic terms used in the study are presented in Table 2.

Table 2
Linguistic terms

Linguistic Terms	m	u
Extremely High (EH)	0,95	0,15
Very High (VH)	0,85	0,25
High (H)	0,75	0,35
Medium High (MH)	0,65	0,45
Medium (M)	0,55	0,55
Medium Low (ML)	0,45	0,65
Low (L)	0,35	0,75
Very Low (VL)	0,25	0,85
Extremely Low (EL)	0,15	0,95

II. The evaluations of the decision makers regarding the criteria are combined using the Fermatean Fuzzy Weighted Average (FFWA) operator in Eq. (9). This process takes into account the weight (ω_k) of each decision maker. In this study, all decision makers are given equal weight [28].

$$z_j = z(\mu_j, \nu_j) = \left(\sqrt[3]{1 - \prod_{i=1}^{n}\left(1-\mu_{ji}^3\right)^{(\omega_k)}}, \sqrt[3]{\prod_{i=1}^{n}\left(\nu_{ji}\right)^{(\omega_k)}}\right) \text{ j=1, 2, …m} \tag{9}$$

Eq. (9) allows decision makers to convert their evaluations of each criterion into a common Fermatean fuzzy number (FFN) [27-28].

III. The positive score value ($S^+(j)$) for each criterion is calculated according to the formula in Eq. (10):

$$S^+(j) = 1 + \mu_j{}^3 - \nu_j{}^3 \tag{10}$$

IV. It is sorted in decreasing order according to the calculated positive score values.

V. The relative importance of each criterion (cs_j) is determined by the second-highest preference. In other words, the difference between the positive score value of a criterion and that of the previous criterion is considered.

VI. The comparative coefficient *(cc_j)* for each criterion is calculated according to the rule of Eq. (11):

$$If\ j = 1, then\ cc_j = 1 \tag{11}$$

$$j > 1,\ then\ cc_j = \mathrm{S}^+(\mathrm{j}) + 1$$

VII. The recalculated weights *(rw_j)*are calculated using Eq. (12):

$$rw_j = \begin{Bmatrix} 1, \ j = 1 \\ \frac{rw_{j-1}}{cc_j} \ , \ i > 1 \end{Bmatrix} \tag{12}$$

VIII. Final critical weight calculation is calculated using Eq. (13):

$$w_j = \frac{rw_j}{\sum_{j=1}^{m} rw_j} \tag{13}$$

4.4. Q-Rung Orthopair fuzzy sets

Intuitionistic fuzzy sets are characterized by degree of membership and non-membership functions, with the condition that the sum of these degrees is less than or equal to 1. However, the prevailing evidence suggests that the applicable region of IFSs is triangular, and access is limited as can be seen in Figure 3. To illustrate, when decision-makers present their evaluation for the degree of membership of the element with 0.4 and degree of non-membership of the element with 0.90, IFSs cannot be effective because the sum of these two values (0.4+0.90=1.30) is greater than 1.

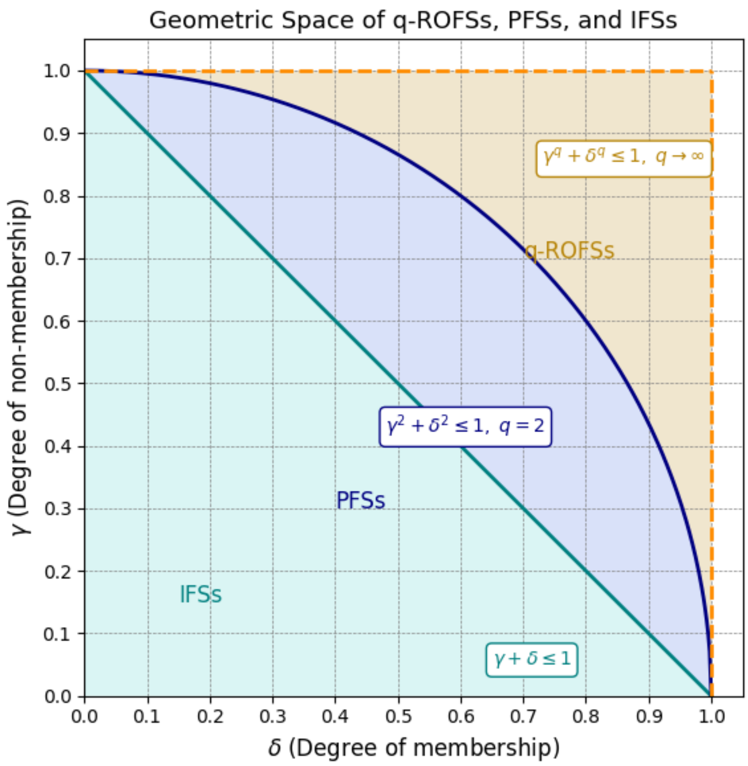

Fig. 3. The representation of geometric space intervals of q-ROFs, PFSs and IFSs

In order to surmount this issue and extend the search space, Yager and Abbasov [29] introduced the notion of Pythagorean fuzzy sets (PFSs), which are general forms of the IFSs. These are characterized by the degree of membership and non-membership functions, with the condition that the sum of these degrees is less than or equal to 1 [30]. For instance, an expert evaluation (0.8, 0.5) can be managed with PFSs as 0.82 + 0.52 = 0.89. While this scenario is not feasible with IFS as 0.8 +0.5 > 1, PFSs effectively address this limitation as can be seen in Figure 3.

Recently, Yager [23] introduced q-ROFs, which serve as an extension of IFSs and PFSs. As illustrated in Figure 3, the geometric interpretations of the space of IFSs, PFSs, and q-ROFSs are demonstrated. The sum of the qth powers of the membership and non-membership degrees of q-ROFSs is constrained to one [31]. As the rung q increases, the allowable area of the orthopyres escalates, and, therefore, more orthopyres meet the constraints. Consequently, q-ROF numbers provide a flexible means of expressing a broader scope of fuzzy information [15]. Recently, there has been an uptick in the interest surrounding q-ROFSs, as evidenced by the works of [32,33]. Consequently, we have opted to utilize q-ROFSs in this study, a decision that is informed by the advantageous nature of the freedom to choose the power degree. The present study puts forth a q-ROFS-based integrated full consistency method (FUCOM) and combined approach.

In this section, we introduce some fundamental definitions of q-ROFs.

$x = (\mu_x, \nu_x)$ be a q-ROFN, the score function S(x) of x can be expressed in Eq. (14) by Wei *et al.,* [34]:

$$S(x) = \frac{1}{2}(1 + \mu_x^q + \nu_x^q) \tag{14}$$

Peng and Dai [35] defined the score function differently as shown in Eq. (15):

$$S(x) = \frac{1}{3}\left(\mu_x^q - 2 * \nu_x^q - 1\right) + \frac{\lambda}{3}\left(\mu_x^q + \nu_x^q + 2\right) \tag{15}$$

Let $x_i = (\mu_{x_i}, \nu_{x_i})$ $i = 1,2, \dots, n$ be set of q-ROFNs and $w = (w_1, w_2, \dots, w_n)^T$ be weight vector of x_i with $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0,1]$. Q-rung orthopair fuzzy weighted average (q-ROFWA) and q-rung orthopair weighted geometric (q-ROFWG) operators can be expressed by Liu and Wang [36], as illustrated in Eq. (16) and Eq. (17):

$$\text{q-ROFWA}\ (x_1, x_2, \dots, x_n) = \left(1 - \left(\prod_{i=1}^{n}\left(1 - \mu_{x_i}^q\right)^{w_i}\right)^{\frac{1}{q}}, \prod_{i=1}^{n} \nu_{x_i}^{W_i}\right) \tag{16}$$

$$\text{q-ROFWG}\ (x_1, x_2, \dots, x_n) = \left(\prod_{i=1}^{n} \gamma_{Q_i}^{w_i}, \left(1 - \prod_{i=1}^{n}\left(1 - \delta_{Q_i}^q\right)^{w_i}\right)^{\frac{1}{q}}\right) \tag{17}$$

The decision matrix based on q-ROFs, which is to be created as a result of expert evaluations, is given in Table 3, and the aggregated q-ROFs decision matrix is provided in Table 4.

Table 3
The expert evaluation based on q-ROFs

Criteria	Alternatives			
	Z_1	Z_2	…	Z_b
C_1	$([\gamma_{11l}\ \delta_{11l}])$	$([\gamma_{12l}\ \delta_{12l}])$	…	$([\gamma_{1bl}\ \delta_{1bl}])$
C_2	$([\gamma_{21l}\ \delta_{21l}])$	$([\gamma_{22l}\ \delta_{22l}])$	…	$([\gamma_{2bl}\ \delta_{2bl}])$
…	…	…	…	…
C_a	$([\gamma_{a1l}\ \delta_{a1l}])$	$([\gamma_{a2l}\ \delta_{a2l}])$	…	$([\gamma_{abl}\ \delta_{abl}])$

Table 4
The aggregated q-ROF desicion matrix

Criteria	Alternatives			
	Z_1	Z_2	…	Z_b
C_1	$([\gamma_{11}\ \delta_{11}])$	$([\gamma_{12}\ \delta_{12}])$	…	$([\gamma_{1b}\ \delta_{1b}])$
C_2	$([\gamma_{21}\ \delta_{21}])$	$([\gamma_{22}\ \delta_{22}])$	…	$([\gamma_{2b}\ \delta_{2b}])$
…	…	…	…	…
C_a	$([\gamma_{a1}\ \delta_{a1}])$	$([\gamma_{a2}\ \delta_{a2}])$	…	$([\gamma_{ab}\ \delta_{ab}])$

4.5. EDAS method

In 2015, EDAS method was introduced into the literature by Keshavarz Ghorabaee *et al.,* [37]. Despite being a relatively new approach, the EDAS method has been widely applied in the literature as part of hybrid models to solve various decision-making problems. The first step in the EDAS method involves the construction of the decision matrix (x), which is presented in Eq. (18). In the decision matrix, x_{ij} represents the performance of alternative i with respect to criterion j. The steps of the proposed model are described as follows [38]:

$$Y = [Y_{ij}]_{axb} = \begin{bmatrix} y_{11}\, y_{12} \cdots y_{1b} \\ y_{11}\, y_{12} \cdots y_{1b} \\ \cdots \; \cdots \; \cdots \; \cdots \\ y_{i1}\, y_{i2} \cdots y_{ib} \\ \cdots \; \cdots \; \cdots \; \cdots \\ y_{a1}\, y_{a2} \cdots y_{ab} \end{bmatrix} \tag{18}$$

Subsequently, the mean solution is calculated based on all the specified criteria. The following assertion is made:

The determination of the mean solutions is presented in Eq. (19) and Eq. (20).

$$AV_j = \frac{\sum_i^m Y_{ij}}{m} \tag{19}$$

$$AV = [AV_j]_{1xb} \tag{20}$$

In the subsequent step, a positive distance matrix (PDA) from the mean given in Eq. (21) and a negative distance matrix (NDA) from the mean given in Eq. (22) are designed for each criterion. In the event that the criteria are expressed in terms of utility, the PDA and NDA matrices are formed by the following Eq. (23) and Eq. (24), respectively. In the event that cost is the primary criterion, the PDA and NDA matrices are calculated using Eq. (25) and Eq. (26), respectively.

$$PDA = [PDA_{ij}]_{axb} \tag{21}$$

$$NDA = [NDA_{ij}]_{axb} \tag{22}$$

$$PDA_{ij} = \frac{\max(0,(Y_{ij} - AV_j))}{AV_j} \tag{23}$$

$$NDA_{ij} = \frac{\max(0,(AV_j - y_{ij}))}{AV_j} \tag{24}$$

$$PDA_{ij} = \frac{\max(0,(AV_j - y_{ij}))}{AV_j} \tag{25}$$

$$NDA_{ij} = \frac{max\,(0,(y_{ij} - AV_j))}{AV_j} \tag{26}$$

Subsequently, the weighted total PDA Eq. (27) and NDA Eq. (28) for each alternative are calculated. v_j, "j" indicates the weight of the measure.

$$SP_i = \sum_{j=1}^{n} v_j PDA_{ij} \tag{27}$$

$$SN_i = \sum_{j=1}^{n} v_j NDA_{ij} \tag{28}$$

For each of the aforementioned alternatives, the SP and SN values are normalized using the following Eq. (29) and Eq. (30).

$$NSP_i = \frac{SP_i}{max_i(SP_i)} \quad (29)$$

$$NSN_i = 1 - \frac{SN_i}{max_i(SN_i)} \quad (30)$$

The evaluation score (ES) is calculated using Eq. (31) for each alternative.

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \quad (31)$$

It is imperative that the AS_i value satisfy the condition of 0 ≤AS_i≤1. The final step in the evaluation process involves ranking the alternatives in descending order of their evaluation score. The first-ranked alternative is regarded as the optimal choice, while the last-ranked alternative is designated as the least favorable option.

5. Case Study

One of the key stages of this study is the expert selection process. The experts involved in the study consist of six individuals who actively work in procurement and purchasing departments and have more than 10 years of professional experience. Interviews were conducted with the experts individually and via telephone to determine the weights of the criteria.

A total of 12 different criteria identified through a literature review were grouped under 2 main criteria categories. In the next stage, experts were asked to assess the importance levels of these 12 sub-criteria grouped under the 2 main criteria.

5.1. Proposed Methodology Results

This section introduces a novel MCDM approach. The subsequent discourse delves into the interplay between Fermatean fuzzy and SWARA methodologies, drawing parallels with earlier research. Subsequently, the q-ROFs EDAS method for multi-criteria selection is elucidated in detail. The primary flow of the Fermatean SWARA method for determining criteria weights and the q-ROFs EDAS method for selecting the optimal alternative among options is hereby presented. This approach will provide a ranking of three alternatives from best to worst.

Initially, it is imperative to ascertain the pertinent evaluation criteria for the problem at hand. In this study, twelve key criteria have been identified: The factors to be considered in the analysis include price, delivery time, quality, technology, transportation, flexibility, capacity, after-sales service, reliability, communication, location, and green packaging. Subsequent to the identification of these criteria, experts will be consulted to assess the importance of each criterion. Concurrently, the individual weights for each expert (E_1, E_2, ..., E_k) will be calculated.

The determination of criteria weights is a critical phase, relying heavily on expert judgment. Table 5 presents the initial linguistic assessments provided by experts for each criterion. These qualitative linguistic expressions are subsequently transformed into quantitative fuzzy numbers, as detailed in Table 6, to facilitate the calculation of evaluation criteria weights.

Table 5
With using linguistic terms criteria evaluating results

Experts	Criteria											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Expert 1 (E_1)	EH	EH	EH	VH	M	H	ML	M	M	VH	H	ML
Expert 2 (E_2)	VH	VH	EH	VH	VH	EH	H	H	VH	EH	M	H
Expert 3 (E_3)	EH	VH	VH	VH	H	H	M	M	H	M	M	M
Expert 4 (E_4)	EH	EH	EH	EH	H	EH	H	MH	H	VH	MH	M
Expert 5 (E_5)	VH	VH	EH	EH	VH	EH	VH	H	H	VH	H	H
Expert 6 (E_6)	EH	EH	VH	VH	VH	VH	MH	MH	VH	EH	M	MH

Table 6
Results presentation using the q-ROF number framework

Experts	Criteria											
	C_1		C_2		C_3		C_4		C_5		C_6	
E_1	0.95	0.15	0.95	0.15	0.95	0.15	0.85	0.25	0.55	0.55	0.75	0.35
E_2	0.85	0.25	0.85	0.25	0.95	0.15	0.85	0.25	0.85	0.25	0.95	0.15
E_3	0.95	0.15	0.85	0.25	0.85	0.25	0.85	0.25	0.75	0.35	0.75	0.35
E_4	0.95	0.15	0.95	0.15	0.95	0.15	0.95	0.15	0.75	0.35	0.95	0.15
E_5	0.85	0.25	0.85	0.25	0.95	0.15	0.95	0.15	0.85	0.25	0.95	0.15
E_6	0.95	0.15	0.95	0.15	0.85	0.25	0.85	0.25	0.85	0.25	0.85	0.25

Experts	Criteria												
		C_7		C_8		C_9		C_{10}		C_{11}		C_{12}	
E_1	0.35	0.45	0.65	0.55	0.55	0.55	0.55	0.85	0.25	0.75	0.35	0.45	0.65
E_2	0.15	0.75	0.35	0.75	0.35	0.85	0.25	0.95	0.15	0.55	0.55	0.75	0.35
E_3	0.35	0.55	0.55	0.55	0.55	0.75	0.35	0.55	0.55	0.55	0.55	0.55	0.55
E_4	0.15	0.75	0.35	0.65	0.45	0.75	0.35	0.85	0.25	0.65	0.45	0.55	0.55
E_5	0.15	0.85	0.25	0.75	0.35	0.75	0.35	0.85	0.25	0.75	0.35	0.75	0.35
E_6	0.25	0.65	0.45	0.65	0.45	0.85	0.25	0.95	0.15	0.55	0.55	0.65	0.45

In this phase, a consolidated decision matrix is created for each criterion evaluated by the experts. The elements of this matrix are derived using the Fermatean fuzzy method depending on the specific application. The belonging and non-belonging values used in this method are presented in Table 7. Based on these values and the expression in Eq. (9), the final values shown in Table 8 are calculated to express each criterion as a single variable.

Table 7
Fermatean Fuzzy Weighted Average (FFWA) operator

Main Criterias	Sub Criterias	μ					
Technical	Price	0.722824	0.853246	0.722824	0.722824	0.853246	0.722824
	Delivery time	0.722824	0.853246	0.853246	0.722824	0.853246	0.722824
	Quality	0.722824	0.722824	0.853246	0.722824	0.722824	0.853246
	Technology	0.853246	0.853246	0.853246	0.722824	0.722824	0.853246
	Transportation	0.970127	0.853246	0.912719	0.912719	0.853246	0.853246
	Flexibility	0.912719	0.722824	0.912719	0.722824	0.722824	0.853246
Social	Capacity	0.984202	0.912719	0.970127	0.912719	0.853246	0.947895
	After sales service	0.970127	0.912719	0.970127	0.947895	0.912719	0.947895
	Reliability	0.970127	0.853246	0.912719	0.912719	0.912719	0.853246
	Communication	0.853246	0.722824	0.970127	0.853246	0.853246	0.722824
	Location	0.912719	0.970127	0.970127	0.947895	0.912719	0.970127
	Green Packaging	0.984202	0.912719	0.970127	0.970127	0.912719	0.947895

The positive score values for each criterion are calculated using the formula in Eq. (10), resulting in the data presented in Table 9. Subsequently, these obtained values are ranked in descending order. For each criterion, its importance degree (cs_j value) is calculated. Since the values defined in Table 10 are derived starting with the first criterion, for subsequent criteria, we consider the difference between the positive score value of the current criterion and that of the preceding criterion.

Table 7
Continued

Main Criterias	Sub Criterias	ν					
Technical	Price	0.762603	0.820335	0.762603	0.762603	0.820335	0.762603
	Delivery time	0.762603	0.820335	0.820335	0.762603	0.820335	0.762603
	Quality	0.762603	0.762603	0.820335	0.762603	0.762603	0.820335
	Technology	0.820335	0.820335	0.820335	0.762603	0.762603	0.820335
	Transportation	0.91814	0.820335	0.86073	0.86073	0.820335	0.820335
	Flexibility	0.86073	0.762603	0.86073	0.762603	0.762603	0.820335
	Capacity	0.940315	0.86073	0.91814	0.86073	0.820335	0.892193
Social	After sales service	0.91814	0.86073	0.91814	0.892193	0.86073	0.892193
	Reliability	0.91814	0.820335	0.86073	0.86073	0.86073	0.820335
	Communication	0.820335	0.762603	0.91814	0.820335	0.820335	0.762603
	Location	0.86073	0.91814	0.91814	0.892193	0.86073	0.91814
	Green Packaging	0.940315	0.86073	0.91814	0.91814	0.86073	0.892193

Table 8
Fermatean fuzzy number (FFN)

μ	ν
0.4164	0.6106
0.3833	0.6256
0.4164	0.6106
0.3482	0.6410
0.2052	0.7214
0.3549	0.6460
0.1367	0.7765
0.1102	0.7922
0.1872	0.7331
0.3197	0.6655
0.1033	0.7998
0.0990	0.8062

Table 9
Ranking of positive score value

Main Criterias	Sub Criterias	Positive Score S+
Tehnical	Price	0.8446
	Delivery time	0.8115
	Quality	0.8446
	Technology	0.7788
	Transportation	0.6331
	Flexibility	0.7752
	Capacity	0.5344
Social	After sales service	0.5042
	Reliability	0.6126
	Communication	0.7379
	Location	0.4895
	Green Packaging	0.4770

Table 10
The relative importance of each criterion

Criteria	cs_j
Quality	-
Price	0
Delivery time	0.0332
Technology	0.0326
Flexibility	0.0037
Communication	0.0373
Transportation	0.1048
Reliability	0.0206
Capacity	0.0781
After sales service	0.0302
Location	0.0147
Green Packaging	0.0125

For the comparative coefficient (cc_j), if $j = 1$, the comparative coefficient is 1. In other cases, it's calculated as the sum of the score value defined in Eq. (11) and the previous comparative coefficient value in Table 11.

Table 11
The comparative coefficient (cc_j) for each criterion

Criteria	cc_j
Quality	1
Price	1.8446
Delivery time	1.8115
Technology	1.7788
Flexibility	1.7752
Communication	1.7379
Transportation	1.6331
Reliability	1.6126
Capacity	1.5344
After sales service	1.5042
Location	1.4895
Green Packaging	1.4770

Using Eq. (12), If $j = 1$, the criterion's weight is set to 1. Otherwise, it's calculated by dividing the previously computed weight by the criterion's comparative coefficient value, which then yields the values in Table 12.

Finally, to calculate the final criterion weights, Eq. (13) is utilized. Each criterion's weight is proportioned to the total sum of all criterion weights, yielding the final criterion weights presented in Table 13.

Table 12
The recalculated weights

rw_j	
Quality	1
Price	0.5421
Delivery time	0.2993
Technology	0.1682
Flexibility	0.0948
Communication	0.0545
Transportation	0.0334
Reliability	0.0207
Capacity	0.0135
After sales service	0.009
Location	0.006
Green Packaging	0.0041
Total	2.245605

Table 13
Final critical weights

Normalized Weights	
Quality	0.4453
Price	0.2414
Delivery time	0.1333
Technology	0.0749
Flexibility	0.0422
Communication	0.0243
Transportation	0.0149
Reliability	0.0092
Capacity	0.006
After sales service	0.004
Location	0.0027
Green Packaging	0.0018

Q-ROFs are highly effective in addressing uncertainty and comprehensiveness within decision-making processes. Unlike traditional fuzzy sets, q-ROFs offer a broader range of membership degrees through their three parameters, which encompass the measurement of uncertainty and the degree of evaluation. This enhanced flexibility allows for better modeling of complex uncertain situations. Consequently, q-ROFs improve the ability to model expert opinions and preferences with greater adaptability, enabling experts to make more rational decisions and more easily consolidate their views. Table 14 presents the fuzzy linguistic terms for 12 criteria across three alternatives, as defined by five industry experts. These linguistic variables were then converted into the format shown in Table 15, utilizing the conversions specified in Table 2. Subsequently, to express the fuzzy variables from the five experts as a single variable, Table 16 was generated using Eq. (16), developed by Liu and Wang.

Table 14
Results of evaluations conducted using language scales.

Experts	Alternatives	Criteria											
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Expert 1	A_1	MH	MH	M	MH	H	VH	VH	VH	EH	EH	VH	M
	A_2	L	L	MH	VH	H	VH	EH	VH	MH	H	H	M
	A_3	MH	MH	MH	VH	H	VH	VH	VH	H	H	H	M
Expert 2	A_1	H	H	H	M	M	MH	M	VH	VH	EH	H	MH
	A_2	EH	H	VH	H	ML	ML	H	H	M	H	MH	H
	A_3	H	H	VH	MH	M	ML	H	VH	H	H	MH	MH
Expert 3	A_1	MH	M	H	MH	VH	VH	MH	H	M	H	H	MH
	A_2	VH	M	VH	MH	H	VH	H	H	ML	MH	H	MH
	A_3	MH	M	H	MH	H	VH	H	H	ML	H	H	MH
Expert 4	A_1	MH	H	VH	MH	H	EH	VH	EH	MH	H	VH	H
	A_2	H	MH	EH	H	MH	VH	VH	H	MH	H	H	H
	A_3	H	H	EH	H	MH	EH	VH	EH	MH	H	H	H
Expert 5	A_1	H	MH	H	H	VH	H	MH	VH	VH	EH	VH	H
	A_2	EH	MH	H	H	H	MH	H	H	MH	H	H	H
	A_3	H	H	H	H	VH	H	H	H	VH	VH	H	H

Table 15
Presentation of evaluation outcomes using the q-ROF system

Experts	Alt.	Criteria											
		C_1		C_2		C_3		C_4		C_5		C_6	
E_1	A_1	0.65	0.45	0.65	0.45	0.55	0.55	0.65	0.45	0.75	0.35	0.85	0.25
	A_2	0.35	0.75	0.35	0.75	0.65	0.45	0.85	0.25	0.75	0.35	0.85	0.25
	A_3	0.65	0.45	0.65	0.45	0.65	0.45	0.85	0.25	0.75	0.35	0.85	0.25
E_2	A_1	0.75	0.35	0.75	0.35	0.75	0.35	0.55	0.55	0.55	0.55	0.65	0.45
	A_2	0.95	0.15	0.75	0.35	0.85	0.25	0.75	0.35	0.45	0.65	0.45	0.65
	A_3	0.75	0.35	0.75	0.35	0.85	0.25	0.65	0.45	0.55	0.55	0.45	0.65
E_3	A_1	0.65	0.45	0.55	0.55	0.75	0.35	0.65	0.45	0.85	0.25	0.85	0.25
	A_2	0.85	0.25	0.55	0.55	0.85	0.25	0.65	0.45	0.75	0.35	0.85	0.25
	A_3	0.65	0.45	0.55	0.55	0.75	0.35	0.65	0.45	0.75	0.35	0.85	0.25
E_4	A_1	0.65	0.45	0.75	0.35	0.85	0.25	0.65	0.45	0.75	0.35	0.95	0.15
	A_2	0.75	0.35	0.65	0.45	0.95	0.15	0.75	0.35	0.65	0.45	0.85	0.25
	A_3	0.75	0.35	0.75	0.35	0.95	0.15	0.75	0.35	0.65	0.45	0.95	0.15
E_5	A_1	0.75	0.35	0.65	0.45	0.75	0.35	0.75	0.35	0.85	0.25	0.75	0.35
	A_2	0.95	0.15	0.65	0.45	0.75	0.35	0.75	0.35	0.75	0.35	0.65	0.45
	A_3	0.75	0.35	0.75	0.35	0.75	0.35	0.75	0.35	0.85	0.25	0.75	0.35

To consolidate the fuzzy values into a single unknown, we use Eq. (15), proposed by Peng and Dai, to generate the score matrix shown in Table 17. Following this, we apply the steps of the EDAS method, which is a MCDM technique.

First, we calculate the average for each criterion within the obtained matrix, as presented in Table 18. Subsequently, we construct a Positive Distance from Average (PDA) matrix and a Negative Distance from Average (NDA) matrix for each criterion. These are based on Eq. (21) for PDA and Eq. (22) for NDA.

Table 15
Continued

Experts	Alt.	Criteria											
		C_7		C_8		C_9		C_{10}		C_{11}		C_{12}	
	A_1	0.85	0.25	0.85	0.25	0.95	0.15	0.95	0.15	0.85	0.25	0.55	0.55
E_1	A_2	0.95	0.15	0.85	0.25	0.65	0.45	0.75	0.35	0.75	0.35	0.55	0.55
	A_3	0.85	0.25	0.85	0.25	0.75	0.35	0.75	0.35	0.75	0.35	0.55	0.55
	A_1	0.55	0.55	0.85	0.25	0.85	0.25	0.95	0.15	0.75	0.35	0.65	0.45
E_2	A_2	0.75	0.35	0.75	0.35	0.55	0.55	0.75	0.35	0.65	0.45	0.75	0.35
	A_3	0.75	0.35	0.85	0.25	0.75	0.35	0.75	0.35	0.65	0.45	0.65	0.45
	A_1	0.65	0.45	0.75	0.35	0.55	0.55	0.75	0.35	0.75	0.35	0.65	0.45
E_3	A_2	0.75	0.35	0.75	0.35	0.45	0.65	0.65	0.45	0.75	0.35	0.65	0.45
	A_3	0.75	0.35	0.75	0.35	0.45	0.65	0.75	0.35	0.75	0.35	0.65	0.45
	A_1	0.85	0.25	0.95	0.15	0.65	0.45	0.75	0.35	0.85	0.25	0.75	0.35
E_4	A_2	0.85	0.25	0.75	0.35	0.65	0.45	0.75	0.35	0.75	0.35	0.75	0.35
	A_3	0.85	0.25	0.95	0.15	0.65	0.45	0.75	0.35	0.75	0.35	0.75	0.35
	A_1	0.65	0.45	0.85	0.25	0.85	0.25	0.95	0.15	0.85	0.25	0.75	0.35
E_5	A_2	0.75	0.35	0.75	0.35	0.65	0.45	0.75	0.35	0.75	0.35	0.75	0.35
	A_3	0.75	0.35	0.75	0.35	0.85	0.25	0.85	0.25	0.75	0.35	0.75	0.35

Table 16
q-ROFWA decision matrix

	0.241		0.133		0.445		0.075		0.015		0.042	
Alternative/ Criteria	C1		C2		C3		C4		C5		C6	
A1	0.740	0.407	0.740	0.424	0.830	0.358	0.732	0.445	0.839	0.335	0.928	0.272
A2	0.937	0.272	0.732	0.493	0.928	0.272	0.830	0.344	0.744	0.417	0.844	0.340
A3	0.744	0.387	0.744	0.403	0.928	0.290	0.830	0.362	0.830	0.377	0.928	0.292
	0.006		0.004		0.009		0.024		0.003		0.002	
Alternative/ Criteria	C7		C8		C9		C10		C11		C12	
A1	0.839	0.370	0.928	0.241	0.928	0.297	0.943	0.211	0.844	0.286	0.740	0.424
A2	0.928	0.276	0.830	0.327	0.645	0.504	0.748	0.368	0.748	0.368	0.744	0.403
A3	0.839	0.306	0.928	0.258	0.830	0.389	0.830	0.327	0.748	0.368	0.740	0.424

Table 17
q-ROFs the score matrix

Alternative/ Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A1	0.2000	0.2000	0.2000	0.2000	0.2000	0.2037	0.2000	0.2037	0.2037	0.2111	0.2000	0.2000
A2	0.2074	0.2000	0.2037	0.2000	0.2000	0.2000	0.2037	0.2000	0.2000	0.2000	0.2000	0.2000
A3	0.2000	0.2000	0.2037	0.2000	0.2000	0.2037	0.2000	0.2037	0.2000	0.2000	0.2000	0.2000

Table 18
All of Criteria Average matrix

Alternative/ Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A1	0.2000	0.2000	0.2000	0.2000	0.2000	0.2037	0.2000	0.2037	0.2037	0.2111	0.2000	0.2000
A2	0.2074	0.2000	0.2037	0.2000	0.2000	0.2000	0.2037	0.2000	0.2000	0.2000	0.2000	0.2000
A3	0.2000	0.2000	0.2037	0.2000	0.2000	0.2037	0.2000	0.2037	0.2000	0.2000	0.2000	0.2000
Average	0.2025	0.2000	0.2025	0.2000	0.2000	0.2025	0.2012	0.2025	0.2012	0.2037	0.2000	0.2000

If the criteria are expressed in terms of benefit, the PDA and NDA matrices are formed using Eq. (23) and Eq. (24), respectively. Conversely, if cost is the primary criterion, the PDA and NDA matrices are calculated using Eq. (25) and Eq. (26), respectively, leading to the values in Tables 19 and 20.

Table 19
Positive distance matrix

Alternative/ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.0122	0.0000	0.0000	0.0000	0.0000	0.0061	0.0000	0.0061	0.0123	0.0362	0.0000	0.0000
A2	0.0000	0.0000	0.0061	0.0000	0.0000	0.0000	0.0123	0.0000	0.0000	0.0000	0.0000	0.0000
A3	0.0122	0.0000	0.0061	0.0000	0.0000	0.0061	0.0000	0.0061	0.0000	0.0000	0.0000	0.0000

Table 20
Negative distance matrix

Alternative/ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.0000	0.0000	0.0122	0.0000	0.0000	0.0000	0.0061	0.0000	0.0000	0.0000	0.0000	0.0000
A2	0.0244	0.0000	0.0000	0.0000	0.0000	0.0122	0.0000	0.0122	0.0062	0.0181	0.0000	0.0000
A3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0061	0.0000	0.0062	0.0181	0.0000	0.0000

The positive distance matrix and negative distance matrix are multiplied by the weights obtained in Table 13. Subsequently, for each alternative, the sum of the products of the criteria and their respective weights is calculated, resulting in the creation of Table 21 and Table 22.

Table 21
Weighted PDA matrix

	0.2414	0.1333	0.4453	0.0749	0.0149	0.0422	0.0060	0.0040	0.0092	0.0243	0.0027	0.0018
Alternative/ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.0513	0.0002	0.0000	0.0000	0.0010	0.0032	0.0000	0.0005	0.0026	0.0113	0.0003	0.0000
A2	0.0000	0.0000	0.0534	0.0031	0.0000	0.0000	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
A3	0.0485	0.0022	0.0351	0.0020	0.0000	0.0031	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000

Table 22
Weighted NDA matrix

	0.2414	0.1333	0.4453	0.0749	0.0149	0.0422	0.0060	0.0040	0.0092	0.0243	0.0027	0.0018
Alternative/ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.0000	0.0000	0.0480	0.0164	0.0000	0.0000	0.0254	0.0000	0.0000	0.0000	0.0000	0.0012
A2	0.0998	0.0023	0.0000	0.0000	0.0010	0.0063	0.0000	0.0009	0.0017	0.0064	0.0002	0.0000
A3	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0004	0.0000	0.0008	0.0049	0.0002	0.0000

For all alternatives, the S_p and S_n values are normalized using Eq. (29) and Eq (30). Subsequently, Eq. (31) is used to calculate the score values, yielding the AS_i results presented in Table 23.

Table 23
The final score values of alternatives for $q = 5$

Alternatives	NSPi	NSNi	ASi	Rank
A1	0.7716	0.2323	0.5019	2
A2	0.6306	0.0000	0.3153	3
A3	1.0000	0.9458	0.9729	1

5.2. Validition of the results

This study employs the EDAS technique for sensitivity analysis. The method assesses alternatives based on their distance from the mean solution point, typically yielding risk-averse decisions compared to extreme value-based methods. A group of five experts evaluated three alternatives as part of the analysis phase. The weights of the criteria were calculated using the Fermatean Fuzzy-SWARA technique.

In the final step of the EDAS method, each alternative was ranked based on its performance scores, resulting in a consistent ordering across most scenarios. According to the evaluation results, Alternative A_3 demonstrated the highest performance, followed by A_1 and A_2, respectively. The comparison of the results obtained using different values of the parameter q (ranging from 1 to 100) under the q-ROFs environment showed that the overall ranking remained completely stable, with no variations observed across the tested range. This clearly indicates the robustness and reliability of the proposed model.

As illustrated in Table 24, the ranking of the alternatives $A_3 > A_1 > A_2$ remained unchanged at both $q = 5$ and $q = 100$. The consistency of the results across all values of q confirms the model's stability and insensitivity to changes in the q parameter.

Table 24
Comparative analysis of outcomes for q-values 5 and 100

Alternatives	q-ROFS EDAS $q = 5$	q-ROFS EDAS $q = 100$
A_1	2	2
A_2	3	3
A_3	1	1

Moreover, Table 25 presents a summary of rankings across selected scenarios (e.g., q = 5, 14, 45, 68, and 100). It confirms that the ranking of the alternatives $A_3 > A_1 > A_2$ remains completely consistent across all examined values of the parameter q. Unlike cases where ranking shifts occur due to changes in q, the results here demonstrate that the q-ROFs framework can deliver highly stable decision outcomes. This consistent behavior highlights the robustness of the proposed model against variations in the q parameter, reinforcing its reliability in different evaluation scenarios.

Table 25
Comparison of ranking outcomes for $q = 5$ and $q = 100$.

Alternatives	Case 5 $q = 5$	Case 14 $q = 14$	Case 45 $q = 45$	Case 68 $q = 68$	Case 100 $q = 100$
A_1	2	2	2	2	2
A_2	3	3	3	3	3
A_3	1	1	1	1	1

The sensitivity analysis presented in Figure 4 visually supports the stability of the EDAS results despite variations in the q parameter. It has been observed that the ranking of the alternatives remains constant ($A_3 > A_1 > A_2$) throughout the entire range of q values, and the top-performing alternative does not change in any of the tested scenarios. This confirms the high applicability of the model to decision-making problems under conditions of uncertainty and imprecision. The findings indicate that the integration of the q-ROFs approach with the EDAS method enables highly robust and consistent supplier evaluations, particularly in complex sectors such as the shipbuilding industry.

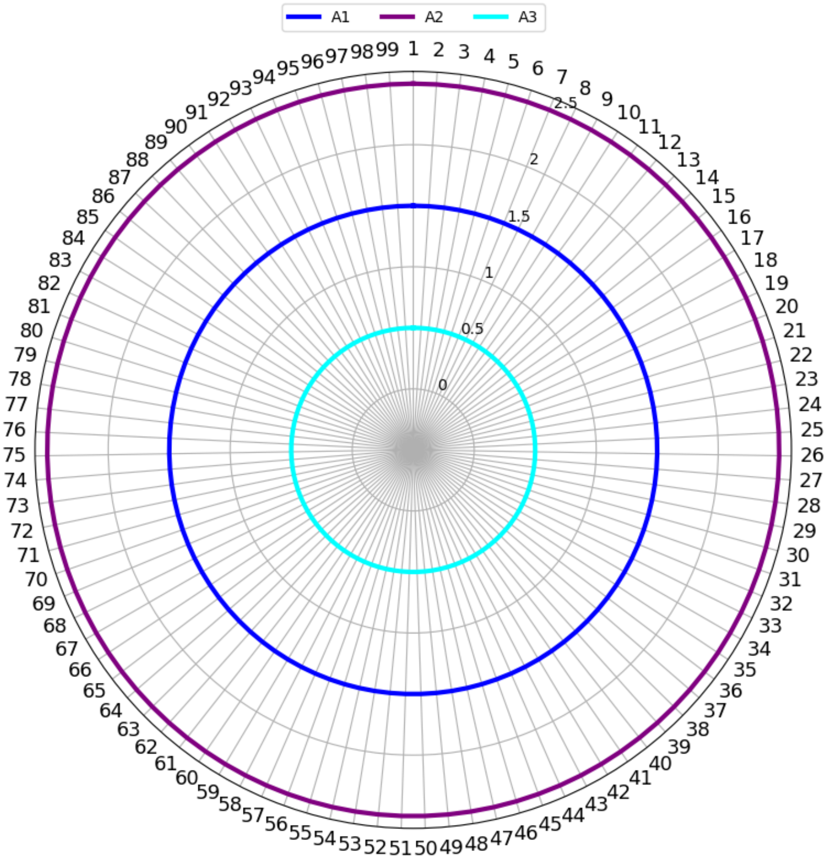

Fig. 4. Sensitivity analysis graph

6. Discussion and Conclusion

The shipbuilding industry, which is the focus of this study, is recognized as one of the strategic sectors significantly affected by global developments. Over time, the wear and aging of both military and commercial vessels require regular maintenance and repair, ensuring that this sector remains continuously active. Additionally, following the COVID-19 pandemic, maritime transportation continues to be one of the most efficient modes of transport worldwide. It is undeniable that strengthening naval forces plays a critical role in enhancing national deterrence on the international stage. In this context, shipyards and shipbuilding companies continue their operations uninterruptedly to reinforce both national defense capabilities and commercial maritime logistics.

In light of these factors, supply chain management holds great importance in procuring the goods and services needed during shipbuilding and repair processes. Optimal supplier selection, accurate identification of needs through well-defined criteria, and procurement from appropriate sources directly affect operational efficiency. Conversely, selecting the wrong supplier or materials can lead to excessive time loss and significant financial resource depletion. For these reasons, effective management of the supply chain and careful evaluation of suppliers are vital to prevent such adverse outcomes.

In this study, supplier firms operating in Türkiye's shipbuilding and repair industry were evaluated based on 12 criteria derived from a comprehensive literature review. The decision-maker experts involved in the evaluation were selected from professionals working in procurement and supply departments who had experience with the chosen suppliers. Based on expert opinions, alternatives were analyzed using a decision-making framework that incorporates FF-SWARA for criteria weighting and a q-ROFs-based EDAS method for ranking alternatives.

The results demonstrated a high degree of stability and consistency across all tested scenarios. Notably, the ranking of alternatives ($A_3 > A_1 > A_2$) remained unchanged across all values of the q parameter (ranging between $q = 1$ and $q = 100$), indicating that the proposed model exhibits strong robustness even under varying levels of uncertainty. This outcome can be considered a significant advantage, especially in a strategic sector such as shipbuilding where decision-making processes are critically important amid prevalent uncertainty.

Furthermore, the integration of q-ROFs enables decision-makers to capture and assess hesitation and uncertainty more effectively compared to traditional fuzzy approaches. The findings confirm that this approach not only provides reliable evaluations but also supports informed and resilient decision-making processes in complex supply environments.

The proposed model offers important benefits to procurement and purchasing department personnel aiming to minimize operational risks and optimize resource utilization. The use of expert opinions and real data increases the model's applicability and relevance to the sector.

For future research, the FF-SWARA and q-ROFs-based EDAS methods proposed in this study can be adapted and applied to various multi-criteria and uncertainty-involved decision-making problems. Additionally, integrating fuzzy trigonometric operators into the q-ROFs framework may provide further advantages in handling uncertainty and contribute meaningfully to the literature. Conducting comparative studies in different industries such as defense, aerospace, or energy would also be beneficial for evaluating the generalizability and flexibility of the proposed approach.

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Conflicts of Interest
The authors declare no conflicts of interest.

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