Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 10s (2025)

Comparison of Fuzzy Multi Criteria Decision Making Approaches for Supplier Selection

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Article History:

Received 05-08-2025

Revised 01-09-2025

Accepted 12-10-2025

Abstract:

In supply chain management, selecting a supplier is a fundamental challenge because companies need to choose suppliers who can provide quality, reasonable price, reliable delivery and good service at the same time. In this paper, I model supplier selection as a fuzzy multi-criteria decision-making problem, which incorporates both numerical and human factors and evaluations involve degrees of uncertainty. Five main criteria are chosen: Price and quality of products, transportation cost, delivery time and after-sales service. I use four fuzzy MCDM methods to find the most preferable of the relevant suppliers: fuzzy Analytic Hierarchy Process (FAHP), fuzzy Step-wise Weight Assessment Ratio Analysis (SWARA), fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and two hybrid methods which are fuzzy TOPSIS and FAHP and fuzzy TOPSIS and fuzzy SWARA. A numerical illustration of a real case of supplier selection problem for mechanical components is presented for demonstration of all computational steps and illustration of the methods in practice. First, the importance weights of the criteria are found by FAHP and fuzzy SWARA, which combine the opinions of several decision makers. Then, based on their distance to the ideal and the worst solutions for each weight vectors, suppliers are ranked by fuzzy TOPSIS. Given supply ranks for all four suppliers with all four methods point to same suppliers being ranked the same (i.e., A3, A4, A2, A1), all four methods suffice for small supplier selection tasks. The study demonstrates the usefulness of fuzzy MCDM methods for managers, since, through the incorporation of ambiguous linguistic evaluative input, the methods enhance group decision certitude, and offer an clarity and consistency to supplier selection processes in practical supply chains and e-retailing.

Keywords:Supplier Selection, Multi-Criteria Decision Making, Fuzzy AHP, Fuzzy SWARA, Fuzzy TOPSIS

1. INTRODUCTION

Supplier selection is the most vital choice in supply chain management as it impacts total cost, service level, and customer satisfaction. Nowadays, companies need to select suppliers in the context of growing e-shopping who can simultaneously offer high quality, delivered on time, provide good after-sale service, and offer reasonable prices. Finally, poor supplier selection is going to increase inventory level, create delays, and reduces customer confidence. On the contrary, having the right supplier base is going to support the long term competitiveness of your business. SCM is no more an operational issue, as stated by Chen and Paulraj, whereas it was previously the case. Instead, it provides strategic advantage to the business. David and Billington also provide examples of how major companies such as Hewlitt Packard transformed their supply chain to cope with new global market challenges. One of the most important things in the context of SCM is coordinating decisions between various actors participating in the chain. This is what led Chiang and Monahan to study inventory management in a two-echelon dual-channel supply chain. The purpose of the suppliers' selection – also referred to as a multi –Criteria Decision Making, is to provide an organized, logical, and simple explanation where suppliers can be assessed on criteria such as price, delivery time, quality of service, the level of risk, as well as sustainability.

Tabar and Charkhgard [1] demonstrated the use of ANP and fuzzy TOPSIS while underscoring the shortcomings of classical single-criterion approaches. D. Kumar, Singh, and Singh [16] implemented a decision support system based on fuzzy logic aimed at supplier evaluation while demonstrating that experts' subjective estimates are linguistically vague and uncertain. Liang and Cheng [18] incorporated fuzzy logic into the manufacturing and distribution planning of supply chains and claimed that fuzzy modelling offers assistance to managers whenever there are missing data. Uygun and Dede [2] combined fuzzy AHP and TOPSIS to assess the performance of a green supply chain and provided a systematic method for companies that wish to adopt an environmentally oriented approach. Shahroudi and Tonekaboni [14] applied the TOPSIS method to select suppliers in the Iranian auto industry and demonstrated that MCDM tools are viable in practice in industry. Collectively, these studies argue that the adoption of MCDM, and particularly its fuzzy form, be used for supplier selection problems.

Many methods have been developed to tackle MCDM issues, as well as to be adapted for fuzzy scenarios. Although Van Laarhoven and Pedrycz [27,31] gave a fuzzy extension of priority theory, Ruoning and Zhang [24] engaged with developments of AHP in fuzzy settings. AHP has been widely adopted in many fields, including defense and engineering, with numerous software applications as well. Chang developed the fuzzy AHP extension and its widespread popularity. Cheng [9] embraced it to assess naval missile system AHP applications. For instance, Cheng, Yang, and Hwang [10] demonstrated flexible application of the method in defense and engineering settings, besides the use of AHP with linguistic weights to evaluate attack helicopters. Fuzzy AHP was employed to determine service company technologies, as noted by Petkovic et al. [22]. M. Moayeri et al. [19] analyzed fuzzy AHP and fuzzy TOPSIS concerning selecting mathematics teachers, outlining their methods' relations and deviations. Integrated methods offering more robust results were exemplified by T. Min Wu [21], who suggested a combined TOPSIS-AHP simulation model for use in supply chain management.

Similarly, with respect to sequential alternatives, C. A. P. Santos [19], adapted TOPSIS to sequential order by proposing a hybrid method to rank logical steps for decision hierarchy in supplier selection for a case in agricultural companies. A similar case was developed in Torres and Santiago [23], who also proposed a hybrid model combining Analytical Hierarchy Process (AHP) and TOPSIS for supplier selection in the construction sector. Collazo et al. [21] also proposed a model based on hybrid AHP and TOPSIS but focused on the selection of suppliers for the automotive sector. TOPSIS method was also applied by Bosio et al. [22] for evaluating the performance of the suppliers in the bakery sector. Zavadskas et al. [24] developed a model integrating AHP, TOPSIS and Multi-Attributive Utility Theory, to select suppliers in the construction sector, and wan to apply Multi-Attributive Decision Making (MADM) to supplier selection in construction. C. Hu et al. [17] proposed a modern perspective on supplier selection and evaluation, in which a heterogeneous group of candidates is considered and AHP used. In Tekin et al [16], a total of 24 articles published between 2004 to 2019, methodology in 10 of the articles were based on TOPSIS, concluding that TOPSIS is the most applied method in the field of Multi-Attribute Decision Making (MADM) for supplier selection.

Celebi and Bayraktar [11,12] developed a combined use of a neural network and data envelopment analysis (DEA) for model evaluation of a supplier even when information was incomplete, and thereby demonstrated that intelligent methods can indeed accompany efficiency analysis of old school methods. Gumus and Guneri [13] built a multi-echelon stochastic and fuzzy inventory framework for supply chains, which illustrates that uncertainty should indeed be taken into account at a number of levels. Tolga, Demircan and Kahraman [26] used fuzzy replacement analysis and AHP for selection of an operating system, while Kumar, Singh and Singh [16] designed a fuzzy logic decision support system which shows that fuzzy MCDM is useful for much more than supplier issues, Singh, Garg and Agarwal [23] proposed an integrated fuzzy AHP and fuzzy TOPSIS model for coordination of supply chains and this provides a link for coordination of decisions and multi-criteria evaluation to Singh, Garg and Agarwal [23]. Mavi, Goh and Zarbakhshnia [20] and Uygun and Dede [2] also pointed out that the supplier criteria should include a focus on the sustainability and green performance.

Lee and Billington [17] portrayed the development of supply chain models at Hewlett Packard and how the models adapted to the evolving business needs. This, and the work of Chiang and Monahan [29], regarding the inventory decisions of dual-channel supply chains, exemplified the indissoluble nature of the supplier decision and the supply chain strategy as a whole.

Drawn from the abovementioned works, the need to evaluate competing fuzzy MCDM methods for supplier selection of the same and single context must be established. The use of fuzzy AHP was reported by a multitude of authors [5,9,10,19,22,23,24,27,30,31], as was fuzzy TOPSIS [1,6,7,14,19,21,23,25], fuzzy SWARA [15,20,28], and as well other tools of a fuzzy nature and even stochastic [13,18,20,26]. Managers of e-shopping agencies and other related organizations, however, have very practical concerns, particularly with which of the fuzzy methods is the most straightforward, which one is most conclusive, and whether the same suppliers would be chosen by the different methods. A supplier selection problem of mechanical components is the focus of the current study, wherein four methods, fuzzy AHP, fuzzy TOPSIS, fuzzy AHP with fuzzy TOPSIS, and fuzzy SWARA with TOPSIS, are used so that the results be compared to ease the suppliers' selection process for the practitioners who demand it within the ample uncertainties of a competitive supply chain.

2. RELATED RESEARCH

Numerous authors have been utilizing various quantitative and heuristic approaches to address conflicting criteria as documented in the field of supplier selection and supply chain decision making. Tabar and Charkhgard [1] claimed supplier selection as a multiple criteria problem and employed ANP with fuzzy TOPSIS to interlink criteria and rank suppliers in a more efficacious manner. Uygun and Dede [2] demonstrated how firms can obtain a clear and methodical assessment of green supply chains using the combination of fuzzy AHP and fuzzy TOPSIS. Arikan [3] suggested a fuzzy multi-objective model wherein the selection of suppliers needs to be done by taking into account multiple objectives at once including cost and quality. Global supply chains also involve some level of risk and should be incorporated into the decision-making process as stated by Chan and Kumar [4] where a fuzzy extended AHP was used to include such risks in supplier development. Chang [5] presented the widely accepted extent analysis technique for fuzzy AHP used in numerous subsequent research to determine fuzzy weights in complex decisions.

Different researchers have also worked on combining fuzzy logic with TOPSIS. For instance, Chen [6] extended TOPSIS to group decision making in fuzzy environments and demonstrated how experts' evaluations could be captured with triangular fuzzy numbers. Chen, Lin and Huang [7] showed how supplier evaluation and selection could be addressed with a fuzzy TOPSIS-type approach and argued that fuzzy linguistic terms mirror human cognition more accurately when making supply chain decisions. An influential contribution toward building a framework for supply chain management in which supplier concerns are fundamental to strategic performance was made by Chen and Paulraj [8]. Studies such as Cheng [9], who evaluated naval missile systems with fuzzy AHP, and Cheng, Yang and Hwang [10] with AHP and linguistic weights in the evaluation of attack helicopters, demonstrated how fuzzy AHP is to various engineering and selection problems including suppliers.

Celebi and Bayraktar [11], [12] first synthesized the use of neural networks and data envelopment analysis (DEA) for supplier evaluation under conditions of data scarcity and posited the usefulness of this hybrid model for the understanding of efficiency and patterns that are invisible to the managers. Gumus and Guneri [13] incorporated in their multi-echelon inventory framework for stochastic and fuzzy supply chains the assertion that uncertainty permeates the entire system and is not the exclusive domain of the supplier. Shahroudi and Tonekaboni [14] demonstrated the TOPSIS method in the Iranian auto supply chain and demonstrated that real industries can be served with simple MCDM tools, which in this case is the TOPSIS method. Kersuliene, Zavadskas and Turskis [15] demonstrated the SWARA method for step-wise weight assessment and showed the importance of expert judgment in the allocation of clear criterion weights, which is crucial in reaching a consensus among managers on the hierarchy of importance of the supplier evaluation criteria.

Other researchers have centered their studies on the use of fuzzy logic and data mining while building decision support systems. One of such authors, Kumar, Singh and Singh [16] constructed a fuzzy logic based decision support system for supplier evaluation and stated that the systems have the capacity to deal with intricate rules and system evaluations. Lee and Billington [17] discussed changes that were implemented to the supply chain models used at Hewlett-Packard and demonstrated the importance of ensuring supplier decisions align with the overall supply chain strategy. With a focus on multi-period, multi-product cases, Liang and Cheng [18] applied fuzzy sets to the planning of manufacturing and distribution and claimed that a fuzzy approach to modeling was justified when the data related to demand and some other variables was uncertain. Moayeri et al. [19] discussed the use of fuzzy AHP and fuzzy TOPSIS for the problem of selection of mathematics teachers, where the authors provided a comparison, analysis of both methods, and the results of the study illustrated the importance of method selection on the outcome of ranking in any selection problem.

Over the past few years, sustainability as well as reverse logistics have received a lot of attention. In the plastic sector, Mavi, Goh, and Zarbakhshnia [20] explored the use of fuzzy SWARA and fuzzy MOORA and demonstrated how environmental and social aspects can be blended with conventional cost and service components, focusing on the sustainable selection of third party reverse logistics providers. Wu [21] demonstrated the efficiencies of simulation merging with MCDM by a combined pc of TOPSIS and AHP to demonstrate supply chain management. In a service company, Petkovic et al. [22] used fuzzy AHP to select a technology and determined that fuzzy AHP is a better approach when the decision involves a mix of qualitative and quantitative factors. Singh, Garg, and Agarwal [23] applied fuzzy AHP along with fuzzy TOPSIS to model the coordination of the supply chain; they concluded that the integrated fuzzy MCDM tools can facilitate better supply chain coordination.

On a theoretical level, Ruoning and Zhang [24] have engaged with AHP extensions in fuzzy contexts, while Van Laarhoven and Pedrycz [27, 31] contributed a pioneering fuzzy extension of Saaty's priority theory and illustrated means of capturing uncertain preferences using fuzzy numbers. The "Study in a Gear motor company" [25], which employed TOPSIS for supplier selection, validated this method within the mechanical industry. Tolga, Demircan and Kahraman [26] applied fuzzy replacement analysis and AHP to the selection of an operating system and demonstrated that fuzzy MCDM goes beyond the field of supply chains. This versatility of MCDM in different decision contexts is also evident in Vesković et al. [28], who, using DELPHI, SWARA, and MABAC, evaluated a model for railway management, and demonstrated that SWARA-based weighting is appropriate for complex public infrastructure decisions. Chiang and Monahan [29] examined a two-echelon dual-channel supply chain from the perspective of inventory management and emphasized the necessity of aligned decision-making, which illustrates the importance of suppliers. Finally, Saaty [30] presented what would eventually be known as the original AHP, which has been supplemented through many of the fuzzy and hybrid methods mentioned.

Literature has shown that many researchers have deployed various forms of MCDM tools—AHP, ANP, DEA, TOPSIS, neural networks, fuzzy logic, SWARA, MOORA—and hybrid models to address supplier selection and associated supply chain problems [1-31]. In these works, researchers unanimously agree that supplier selection represents a complicated multi-criteria problem and that there exists a degree of uncertainty within the domain of experts' opinions. They recommended the use of fuzzy MCDM approaches, and these studies have adopted fuzzy AHP, fuzzy TOPSIS, fuzzy SWARA, and other combinations, which are also the focus of the present research.

3. RESEARCH METHODOLOGY

3.1. Objectives

- To apply fuzzy AHP, fuzzy SWARA, and fuzzy TOPSIS methods for supplier selection, using both numerical data and linguistic evaluations from decision makers in an uncertain and competitive supply chain environment.
- To compare the results of different fuzzy MCDM methods and the hybrid model, in order to identify the approach that gives the most consistent, practical, and easy-to-understand ranking of suppliers for real managerial use.
- To improve overall quality and service level by selecting suppliers who can offer acceptable prices together with reliable delivery, better product quality, and effective after-sales service, so that customer satisfaction and long-term relationships can be strengthened.

Fuzzy TOPSIS and fuzzy multi-criteria decision-making methods have been utilized for supplier selection problems, since they can tackle the imprecision, incompleteness, and subjectivity effectively, according to previous studies. In the context of this literature, I develop a research methodology whereby I apply fuzzy AHP, fuzzy TOPSIS, fuzzy SWARA, and a hybrid model of fuzzy AHP and fuzzy TOPSIS to the same supplier selection problem. In the first step, the relative importance (weights) of the criteria of supplier evaluation is determined by applying fuzzy AHP and fuzzy SWARA separately, where experts do pairwise comparison and ordered preference, and the data is represented in fuzzy format. In the second step, fuzzy TOPSIS is utilized to obtain the supplier's rank with each of the sets of weights where the distance to the ideal best and ideal worst supplier is calculated. The rankings of the suppliers from the four methods are compared for the final rank and the transparency of the decision-making process. By examining the degree of concordance and disparity in the rankings, I intend to ascertain which of the fuzzy MCDM methods, along with their possible combinations, provides a more dependable and understandable analytical approach to decision-making for managers tasked with supplier selection and enhancing their supply chain system.

3.2. Fuzzy analytic hierarchy process (FAHP)

I harness the fuzzy analytic hierarchy process in this study to handle the uncertainty that may accompany the evaluation of suppliers. Classical analytic hierarchy process (AHP), suggested by Saaty, is a very effective method in the analysis of multi criteria decision making. It provides the decision maker with a way to simplify a complex problem step by step into a hierarchy of goal, criteria and alternatives and then assign priorities by pairwise comparison. This is not the case, however, in real supplier selection problems. The degree of these judgments is not a real number. Some criteria, like service quality, flexibility or reliability are expressed in words for instance, and even experts find it extremely difficult to say that one of the criteria is 'exactly three times' more important than the other. Van Laarhoven and Pedrycz introduced fuzzy AHP to tackle this weakness of AHP. In fuzzy AHP, pairwise comparisons are made using fuzzy ratios, usually of the type triangular fuzzy numbers. The extent analysis method, introduced by Chang, is perhaps the most well-known method of fuzzy AHP and it is systematic in that it computes the fuzzy weights and then defuzzifies these to usable values of priority. In my work, FAHP serves to establish the weights of the criteria of supplier selection before the ranking methods are applied.

Step 1: I first identify the evaluation goal, the main criteria and, if needed, sub-criteria, and arrange them in a hierarchical structure. After the hierarchy is clear, each decision maker compares the criteria (or alternatives) pairwise by using linguistic terms such as "equally important", "moderately more important" or "extremely more important". These verbal judgments are then translated into corresponding triangular fuzzy numbers according to the predefined linguistic scale table, so that the qualitative preferences of experts can be captured in a quantitative fuzzy form and used in the later computational steps of the FAHP method.

Table 1. Linguistic Variables for Importance Weight of Each Criterion

Linguistic term	Code	TFN – lower	TFN – middle	TFN – upper	Reciprocal TFN – lower	Reciprocal TFN – middle	Reciprocal TFN – upper	Response scale – lower	Response scale – middle	Response scale – upper
Much less important	MuL	7/2	4	9/2	2/9	1/4	2/7	0.22	0.25	0.29
Very less important	VL	5/2	3	7/2	2/7	1/3	2/5	0.29	0.33	0.40
Less important	L	3/2	2	5/2	2/5	1/2	2/3	0.40	0.50	0.67
Moderately less important	ML	2/3	1	3/2	2/3	1	3/2	0.67	1.00	1.50

Equal important	E	1	1	1	1	1	1	1.00	1.00	1.00

In this way, Table 1 acts as a bridge between qualitative language and quantitative analysis. Instead of forcing experts to give exact numerical values, they only choose the phrase that best describes the importance of each criterion. The assigned triangular fuzzy numbers then capture the natural vagueness of these phrases and make it possible to perform fuzzy AHP, fuzzy SWARA, and fuzzy TOPSIS calculations. Thus, Table 1 is an essential element for transforming human judgments into a structured fuzzy decision-making framework.

Table 2: Linguistic variables for Pair Wise Comparisons of Alternatives of Criteria

Linguistic variables	**Response Scale**
Less	(0.25,0.50,0.75)
Moderately less	(0.50,0.75,1.00)
Equal	(1.00,1.00,1.00)
Moderately greater	(1.00,1.25,1.50)
Greater	(1.25,1.50,1.75)

Table 2 outlines the linguistic variables employed for pairwise comparisons of alternatives with respect to each criterion, expressed through associated triangular fuzzy response scales. This representation enables the incorporation of imprecise human judgments into the decision-making process.

Using fuzzy triangular numbers, the pairwise comparisons matrices appear in (1), where $\tilde{d}_{ij}^{k}$ suggests that the k[th] decision maker favored the i[th] criterion over j[th] criterion. In this instance, "tilde" stood for the triangular number demonstration, and , $\tilde{d}_{12}^{1}$ for the first decision maker's preference for the first criterion over the second.

$$\tilde{A}^{k} = \begin{bmatrix} \tilde{d}_{11}^{k} & \tilde{d}_{12}^{k} & \dots & \tilde{d}_{1n}^{k} \\ \tilde{d}_{21}^{k} & \tilde{d}_{22}^{k} & \dots & \tilde{d}_{2n}^{k} \\ \dots & \dots & \dots & \dots \\ \tilde{d}_{n1}^{k} & \tilde{d}_{n2}^{k} & \dots & \tilde{d}_{nn}^{k} \end{bmatrix} \tag{1}$$

Step 2: In this step, the opinions of all decision makers are first collected separately, so that each expert can express his or her own judgment on the importance of criteria and the performance of suppliers without being influenced by others. For every supplier–criterion pair by using the arithmetic mean (equation (2)), which treats all decision makers as equally important.

$$\tilde{d}_{ij} = \frac{\sum_{k=1}^{K} \tilde{d}_{ij}^{k}}{K} \tag{2}$$

Step 3: The pairwise comparison matrices, reconstructed using the averaged preferences, are provided below.

$$\widetilde{A} = \begin{bmatrix} \tilde{d}_{11} & \tilde{d}_{12} & \dots & \tilde{d}_{1n} \\ \tilde{d}_{21} & \tilde{d}_{22} & \dots & \tilde{d}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{d}_{n1} & \tilde{d}_{n2} & \dots & \tilde{d}_{nn} \end{bmatrix} \quad (3)$$

Step 4: Equation (4) was used to determine the geometric mean of the fuzzy comparing values for each criterion, which is also shown as triangular fuzzy values.

$$\tilde{g}_i = \left(\prod_{j=1}^{n} \tilde{d}_{ij}\right)^{\frac{1}{n}}, \quad i = 1, 2, \dots, n \quad (4)$$

Step 5: Determination of fuzzy weights for each criterion

- **Summation of fuzzy geometric means**

  In the first stage, I add all fuzzy geometric mean values across the criteria to obtain a single fuzzy summation vector. This vector represents the total "strength" of all criteria together and is needed to bring the individual fuzzy numbers onto a common scale before weighting.

- **Construction of the reversed fuzzy vector**

  Next, I calculate the inverse of this summation vector. After finding the inverse, I arrange the resulting triangular fuzzy numbers in increasing order of their values. This reordered inverse vector serves as a normalizing factor that will later convert the fuzzy geometric means into comparable fuzzy weights.

- **Computation of fuzzy criterion weights**

  Finally, I derive the fuzzy weight of each criterion by multiplying its fuzzy geometric mean by the reversed summation vector. This operation is performed for all criteria, giving a set of fuzzy weights whose relative sizes show the importance of each criterion in the decision-making process. Through this three-step procedure—summation, inversion and reordering, and multiplication—I obtain normalized fuzzy weights that are consistent with the original expert judgments and ready to be used in the subsequent stages of the fuzzy MCDM analysis.

$$\widetilde{w}_i = \tilde{g}_i * (\tilde{g}_1 * \tilde{g}_2 * \dots * \tilde{g}_n)^{-1} = (lw_i, mw_i, uw_i) \quad (5)$$

Step 6: Since $\widetilde{w}_i$ are represented as fuzzy triangular numbers, they must be defuzzified using the Centre of Area (COA) method, as proposed by Chou and Chang, through the application of equation (6).

$$M_i = \frac{(lw_i + mw_i + uw_i)}{3} \quad (6)$$

Step 7: M_i is a non-fuzzy number; however, it requires normalization according to the procedure specified in equation (7).

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \quad (7)$$

For my research, I focus on a defined seven-step methodology for obtaining normalized weights for the criteria and the supplier alternatives. At every step, the fuzzy values for each supplier are incorporated, and the values are aggregated and normalized. This way all criteria, a supplier's performance and weights are measured in the same metric. I derive a final score for every supplier based on the final normalized weights. In the simplest form, the score for a given supplier for a particular criterion is computed by multiplying performance score for the criterion by the weight of the criterion assigned to him, and the final score is the summation of all weighted scores. As a result, the supplier is ranked based on the aggregated score. Subsequently, the supplier is ranked based on the aggregated score. In addition to being practicable, I also provide a step-by-step numerical example for supplier ranking.

3.3 Numerical Example of FAHP

In this subsection, I present a small numerical illustration to show how the fuzzy AHP method is applied in my study. The company under consideration wants to select one supplier from four candidates, denoted as A1, A2, A3 and A4. Since the purchasing manager believes that several issues must be evaluated at the same time, five main criteria are taken into account: product quality, product price, after-sales service, transportation cost and delivery time. First, I ask a group of decision makers to compare these criteria with each other by using linguistic terms such as "equally important", "moderately more important" and "strongly more important". These verbal judgments are then converted into triangular fuzzy numbers and arranged in a fuzzy pairwise comparison matrix for the criteria. Using the FAHP procedure, I calculate the fuzzy weights of each criterion and defuzzify them to obtain crisp priority values. The same process is repeated for each criterion with respect to the four suppliers, producing local preference weights for A1–A4. Finally, the global scores of the suppliers are obtained by combining the criteria weights with the supplier weights, which allows me to identify the most suitable supplier according to the FAHP approach.

Table 3. Criteria Comparison Matrix

Criteria	**Product Price**	**Quality**	**Transportation Cost**	**Delivery Time**	**After Sales services**
Product Price	(1.00,1.00,1.00)	(0.67,1.00,1.50)	(0.29,0.33,0.40)	(0.22,0.25,0.29)	(0.40,0.50,0.67)
Quality	(0.67,1.00,1.50)	(1.00,1.00,1.00)	(0.67,1.00,1.50)	(0.40,0.50,0.67)	(0.29,0.33,0.40)
Transportation Cost	(0.29,0.33,0.40)	(0.67,1.00,1.50)	(1.00,1.00,1.00)	(0.22,0.25,0.29)	(0.40,0.50,0.67)
Delivery Time	(0.22,0.25,0.29)	(0.40,0.50,0.67)	(0.22,0.25,0.29)	(1.00,1.00,1.00)	(0.22,0.25,0.29)
After Sales services	(0.40,0.50,0.67)	(0.29,0.33,0.40)	(0.40,0.50,0.67)	(0.22,0.25,0.29)	(1.00,1.00,1.00)

After finishing the first three stages of the procedure, I move to the fourth stage, where equation (4) is used to obtain the geometric mean of the fuzzy pairwise comparison values for every criterion. In this step, all fuzzy judgments given by the decision makers for a particular criterion are combined into a single representative fuzzy number. The geometric mean is chosen because it reflects the collective opinion of the experts while keeping the basic shape of the fuzzy numbers. The results of these calculations are summarized in Table 4, which lists the geometric mean of the fuzzy comparison values for each criterion separately. This table gives a compact view of how important each criterion is, based on the group's evaluations. In the last row of Table 4, the aggregated fuzzy numbers are reordered from the smallest to the largest value, beginning with the values from the second-to-last row. This ascending arrangement helps to clearly see which criteria are considered less important and which ones are viewed as more significant before moving on to the next step of the fuzzy AHP analysis.

Table 4. Fuzzy comparison values for all criteria using geometric means

Criteria	$\tilde{g}_i$		
Product Price	0.4432	0.5285	0.6506
Quality	0.5538	0.6974	0.9038
Transportation Cost	0.4432	0.5285	0.6506
Delivery Time	0.3356	0.3789	0.4392
After Sales services	0.3997	0.4601	0.5538
Total	2.1755	2.593577987	3.197964995
Reverse (power of -1)	0.459659021	0.385567739	0.312698857
Increasing Order	0.312698857	0.385567739	0.459659021

In the fifth step, the fuzzy weight for each criterion is calculated, while the relative non-fuzzy weight and normalized weight for each criterion are obtained through steps 7 and 8. The results are presented in Table 5.

Table 5. The averaged and normalized relative weights of the criteria, along with their corresponding relative fuzzy weights.

Criterion	wi			Mi	Ni
Product Price	0.138585371	0.203791225	0.299061562	0.213812719	0.203614494
Quality	0.173160094	0.268904133	0.415431334	0.285831854	0.272198532
Transportation Cost	0.138585371	0.203791225	0.299061562	0.213812719	0.203614494
Delivery Time	0.104952286	0.146102852	0.201878257	0.150977798	0.14377661
After Sales services	0.12500127	0.177410565	0.254540742	0.185650859	0.17679587

In the next step of the analysis, I calculate the relative weight of each alternative for every criterion. For this purpose, I repeat the pairwise comparison procedure, but now I compare the suppliers with each other instead of comparing the criteria. For every single criterion, all suppliers are evaluated two by two and their performance is expressed by fuzzy linguistic terms, which are then converted into fuzzy numbers. This means that the whole comparison process must be carried out separately for each of the five criteria used in the study. Explaining all of these repetitions in detail would make the paper very long and difficult to follow. Therefore, I present the full procedure only for one criterion, namely “Product Price,” because it is usually the first and most intuitive factor considered by decision makers. For this criterion, I build a fuzzy pairwise comparison matrix of the alternatives and then derive their fuzzy weights. The resulting matrix for “Product Price” is given in Table 6. The same calculation steps are applied in the background for the remaining criteria, and their final weights are reported directly in the following tables without repeating the full derivation.

Table 6. Pairwise comparisons of alternatives concerning the "product price" criterion.

Alternatives	A1	A2	A3	A4
A1	(1.00,1.00,1.00)	(0.50,0.75,1.00)	(1.00,1.25,1.50)	(1.00,1.25,1.50)
A2	(1.00,1.25,1.50)	(1.00,1.00,1.00)	(1.25,1.50,1.75)	(1.25,1.50,1.75)
A3	(0.50,0.75,1.00)	(0.25,0.50,0.75)	(1.00,1.00,1.00)	(1.00,1.00,1.00)
A4	(0.50,0.75,1.00)	(0.25,0.50,0.75)	(1.00,1.00,1.00)	(1.00,1.00,1.00)

Table 7 illustrates the criterion calculation process, presenting the geometric means of fuzzy comparison values along with the relative fuzzy weights of alternatives for each criterion.

Table 7. Fuzzy weights and geometric means of the alternatives in relation to the "Product Price" criterion

Criteria	$\tilde{g}_i$			$\tilde{w}_i$		
A1	0.7071	0.9157	1.1067	0.1565	0.2340	0.3413
A2	0.4204	0.6580	0.8660	0.0931	0.1681	0.2671
A3	1.0574	1.1702	1.2729	0.2340	0.2990	0.3926
A4	1.0574	1.1702	1.2729	0.2340	0.2990	0.3926
Total	3.2423	3.9141	4.5184			
Reverse (power of -1)	0.3084	0.2555	0.2213			
Increasing Order	0.2213	0.2555	0.3084			

Table 8 displays the non-fuzzy and normalized values that were determined using the center of area approach in accordance with steps 6 and 7.

Table 8. Averaged and normalized relative weights for each option in relation to the "Product Price" criterion

Alternatives	Mi	Ni
A1	0.2439	0.2352

A2	0.1761	0.1698
A3	0.3085	0.2975
A4	0.3085	0.2975

The normalized non-fuzzy relative weights of each alternative for every criterion are also determined in accordance with this rationale.

Table 9. The normalized non-fuzzy relative weights of each alternative for each criterion.

Alternatives	Product Price	Quality	Transportation Cost	Delivery Time	After Sales services
A1	0.2352	0.2686	0.1868	0.3354	0.2144
A2	0.1698	0.2314	0.2491	0.2653	0.3329
A3	0.2975	0.2416	0.2491	0.1996	0.2808
A4	0.2975	0.2583	0.3149	0.1996	0.1718

From Table 5 and Table 9, individual scores of each alternative for each criterion are tabulated.

Table 10. Summative outcomes for every option based on every criterion

Criteria	Weights	A1	A2	A3	A4
Product Price	0.2036	0.2352	0.1698	0.2975	0.2975
Quality	0.2722	0.2686	0.2314	0.2416	0.2583
Transportation Cost	0.2036	0.1868	0.2491	0.2491	0.3149
Delivery Time	0.1438	0.3354	0.2653	0.1996	0.1996

After Sales services	0.1768	0.2144	0.3329	0.2808	0.1718
		0.2452	**0.2453**	**0.2554**	**0.2541**
Ranking		**4**	**3**	**1**	**2**

The normalized values presented in the last row of Table 10 summarize the final performance of all four suppliers after applying the fuzzy TOPSIS procedure. In this step, the initial fuzzy evaluations given by the decision makers for the five criteria—price, quality, transportation cost, delivery time and after-sales service—are converted into comparable scores and combined into a single performance index for each alternative. When these indices are examined, Alternative A3 clearly obtains the largest value, which means that it is closest to the ideal supplier and farthest from the worst reference point. In other words, A3 achieves a better balance between cost and service-related factors than A1, A2 and A4. Although the other suppliers may perform well on some individual criteria, their overall normalized scores remain lower, showing that they cannot match the comprehensive performance of A3. Therefore, considering both the quantitative information and the fuzzy, linguistic judgments of the experts, I conclude that A3 should be selected as the most suitable supplier in this case. This choice is expected to support higher quality, more reliable deliveries and improved service for the purchasing company.

3.4 Fuzzy TOPSIS method (FTOPSIS)

In this research, I apply Techniques for Order Preference by Similarity to Ideal Solution (TOPSIS) within the context of the multiple criteria nature of supplier selections - a classical technique of MCDM developed from Hwang and Yoon (1981) and further expanded into the fuzzy paradigm by Chen and Hwang (1992). Every supplier, as an alternate, is evaluated by a positive and a negative ideal as the benchmarks. Specifically, the positive ideal is the most favorable output for the criteria while the negative ideal is the least favorable.

An alternate is deemed good if, within the evaluation space, it's closest to the positive ideal and largest from the negative ideal. Considering the experts' vague assessment of the alternatives is applied to the fuzzy TOPSIS frameworks by Chen Hwang. Specifically, the five criteria selected are Quality, Product Price, After-Sales Services, Transportation Cost, and Delivery Time, evaluated by D1 to D5, the five decision makers, for each of the potential suppliers. As has been the case, fuzzy TOPSIS has been employed by Chen et al. [10] and Chen et al. [11] where suppliers were narrowed down to three alternatives. The method's calculations are detailed in the following sub-section.

Step 1: A group of decision-makers is first formed. The fuzzy evaluation of each decision maker, $D_k = (k = 1, 2, \ldots, K)$ in a decision-making committee with K members can be represented as a triangular fuzzy number, $\widetilde{R}_k = (k = 1, 2, \ldots, K)$ with a membership function of $\mu_{\widetilde{R}_k}(x)$.

Step 2: Evaluation criteria are determined.

Step 3: For assessing criteria and options, suitable linguistic variables are used.

Step 4: Weights of criteria are aggregated by Chen et al. [10].

The aggregated fuzzy rating can be found as $\widetilde{R} = a, b, c, \ (k = 1, 2, \ldots, K)$ if the fuzzy ratings of all decision-makers are represented as triangular fuzzy numbers $\widetilde{R}_k = a_k, b_k, c_k (k = 1, 2, \ldots, K)$

Here;

$$a = \min_k\{a_k\}, \quad b = \frac{1}{k}\sum_{k=1}^{K} b_k, \quad c = \max_k\{c_k\} \tag{8}$$

If the kth decision-makers fuzzy rating and importance weight are $\tilde{x}_{ij}^{k} = a_{ij}^{k}, b_{ij}^{k}, c_{ij}^{k}$ and $\tilde{w}_{ij}^{k} = w_{j1}^{k}, w_{j2}^{k}, w_{j3}^{k}, i = 1,2, \dots, m, j = 1,2, \dots n$ respectively, then the aggregated fuzzy ratings $(\tilde{x}_{ij})$of alternatives with respect to each criterion can be found as $(\tilde{x}_{ij}) = a_{ij}, b_{ij}, c_{ij}$ Here,

$$a_{ij} = \min_k\{a_{ij}^{k}\}, \quad b_{ij} = \frac{1}{k}\sum_{1}^{k} b_{ij}^{k}, \quad c_{ij} = \max_k\{c_{ij}^{k}\} \tag{9}$$

Then the aggregated fuzzy weights $(\tilde{w}_{ij})$of each criterion are calculated as:

$$(\tilde{w}_j) = (w_{j1}, w_{j2}, w_{j3}) \tag{10}$$

Here,

$$w_{j1} = \min_k\{w_{jk1}\}, \quad w_{j2} = \frac{1}{k}\sum_{k=1}^{K} w_{jk2}, \quad w_{j3} = \max_k\{w_{jk3}\} \tag{11}$$

Step 5: Then the fuzzy decision matrix is constructed as:

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix} \tag{12}$$

$$W = [\tilde{w}_1, \tilde{w}_2, \dots \tilde{w}_n]$$

Here $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}, i = 1,2, \dots, m, j = 1,2, \dots n$ can be approximated by positive triangular fuzzy numbers.

Step 6: After building the initial fuzzy decision matrix, I first bring all criteria to a comparable scale so that no criterion dominates the others simply because of its measurement unit. Instead of using the relatively complicated normalization procedure of the classical TOPSIS method, I adopt a simple linear scale transformation. For each criterion, the original fuzzy ratings of the suppliers are rescaled between the minimum and maximum fuzzy values observed in that criterion. In this way, benefit and cost criteria are both converted to dimensionless fuzzy numbers lying in the same interval, while their relative preference information is preserved. This linear transformation is easy to compute, transparent for decision makers, and suitable for implementation in real applications where time and computational effort are limited. After performing this operation for all criteria and all suppliers, I obtain the normalized fuzzy decision matrix. This matrix becomes the starting point for the subsequent TOPSIS calculations, such as determining the weighted normalized values, identifying the fuzzy positive and negative ideal solutions, and computing the distance of each supplier from these ideal points.

$$\tilde{R} = [\tilde{r}_{ij}]_{m*n} \quad i = 1,2, \dots, m, j = 1,2, \dots n \tag{13}$$

Where:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right),$$

$$c_j^* = \max_i c_{ij}$$

Step 7: The evaluation criteria's important weights are multiplied by the values in the normalized fuzzy decision matrix to obtain the weighted normalized decision matrix, which takes into account the differing significance of each criterion. $\widetilde{V}$, or the weighted normalized decision matrix, is defined as:

$$\tilde{v}_{ij} = \tilde{r}_{ij}(.)\tilde{w}_j$$

Here $\tilde{w}_j$ represents the importance weight of criterion C_j.

Normalized positive triangular fuzzy numbers may also be used to represent the items $\tilde{v}_{ij}\ \forall\ i, j$. based on the weighted normalized fuzzy decision matrix.

Step 8: The fuzzy negative ideal solution (FNIS, A^-) and fuzzy positive ideal solution (FPIS, A^+) are identified as Gumus et al. [85]:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+) \quad (14)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-) \quad (15)$$

Where,

$$\tilde{v}_j^+ = \max_i\{v_{ij3}\} \text{ and } \tilde{v}_j^- = \min_i\{v_{ij1}\}\ i = 1,2, \dots, m, j = 1,2, \dots n$$

Step 9: The distance of each alternative between FPIS and FNIS is calculated as follows:

$$d_i^+ = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^+\right), \quad i = 1,2, \dots, m \quad (16)$$

$$d_i^- = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^+\right), \quad i = 1,2, \dots, m \quad (17)$$

Where $d_v(.,.)$is the distance measurement between two fuzzy numbers.

Step 10: Each possible alternative is ranked and evaluated using a closeness coefficient (Cci). Distances to both the fuzzy positive ideal solution (A^+) and the fuzzy negative ideal solution (A^-) are simultaneously shown via the Closeness coefficient. Chen [11] calculates the closeness factor for each option:

$$Cc_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1,2, \dots, m \quad (18)$$

Step 11: The closeness coefficient can be used to rank the options. An alternate A_i would obviously be closer to FPIS and farther from FNIS as Cc_i gets closer to 1. This is evident from (18).

3.4.1 Numerical illustrations of FTOPSIS

In order to assess the options with respect to each criterion, linguistic variables are shown in Table 11.

Table 11. Linguistic variables for rating

Linguistic variables	Triangular fuzzy numbers	Attribute grade
Very Bad (VB)	(0,0,2.5)	**1**
Bad (L)	(0,2.5,5)	**2**
Medium (M)	(2.5,5,7.5)	**3**
Good (G)	(5,7.5,10)	**4**
Very Good (VG)	(7.5,10,10)	**5**

Table 12 presents the decision-makers' performance ratings for supplier selection in the form of Triangular Fuzzy Numbers (TFNs), corresponding to the criteria outlined in Table 4.11.

Table 12. Triangular Fuzzy Numbers for Rating Alternative Suppliers

Criteria	Alternatives	Decision Makers				
		D1	**D2**	**D3**	**D4**	**D5**
Product Price	A1	(0,2.5,5)	(5,7.5,10)	(2.5,5,7.5)	(0,2.5,5)	(0,0,2.5)
	A2	(0,2.5,5)	(2.5,5,7.5)	(0,2.5,5)	(0,2.5,5)	(2.5,5,7.5)
	A3	(2.5,5,7.5)	(7.5,10,10)	(5,7.5,10)	(2.5,5,7.5)	(7.5,10,10)
	A4	(5,7.5,10)	(0,2.5,5)	(2.5,5,7.5)	(5,7.5,10)	(5,7.5,10)
Quality	A1	(2.5,5,7.5)	(0,2.5,5)	(2.5,5,7.5)	(5,7.5,10)	(2.5,5,7.5)
	A2	(5,7.5,10)	(2.5,5,7.5)	(5,7.5,10)	(2.5,5,7.5)	(0,2.5,5)
	A3	(7.5,10,10)	(5,7.5,10)	(5,7.5,10)	(2.5,5,7.5)	(5,7.5,10)
	A4	(2.5,5,7.5)	(7.5,10,10)	(0,2.5,5)	(5,7.5,10)	(0,2.5,5)
Transportation Cost	A1	(0,0,2.5)	(5,7.5,10)	(2.5,5,7.5)	(5,7.5,10)	(2.5,5,7.5)
	A2	(0,2.5,5)	(2.5,5,7.5)	(5,7.5,10)	(5,7.5,10)	(5,7.5,10)
	A3	(5,7.5,10)	(5,7.5,10)	(2.5,5,7.5)	(0,2.5,5)	(5,7.5,10)
	A4	(7.5,10,10)	(0,2.5,5)	(5,7.5,10)	(2.5,5,7.5)	(5,7.5,10)
Delivery Time	A1	(7.5,10,10)	(2.5,5,7.5)	(2.5,5,7.5)	(5,7.5,10)	(0,2.5,5)
	A2	(2.5,5,7.5)	(5,7.5,10)	(5,7.5,10)	(2.5,5,7.5)	(2.5,5,7.5)
	A3	(0,2.5,5)	(7.5,10,10)	(7.5,10,10)	(5,7.5,10)	(5,7.5,10)
	A4	(5,7.5,10)	(5,7.5,10)	(0,2.5,5)	(7.5,10,10)	(5,7.5,10)
After Sales services	A1	(5,7.5,10)	(0,2.5,5)	(0,2.5,5)	(2.5,5,7.5)	(0,2.5,5)

	A2	(0,2.5,5)	(2.5,5,7.5)	(2.5,5,7.5)	(0,0,2.5)	(2.5,5,7.5)
	A3	(2.5,5,7.5)	(5,7.5,10)	(5,7.5,10)	(5,7.5,10)	(7.5,10,10)
	A4	(7.5,10,10)	(2.5,5,7.5)	(2.5,5,7.5)	(0,2.5,5)	(2.5,5,7.5)

The supplier's aggregated ratings are utilized to construct the fuzzy decision matrix, following the steps outlined in the fuzzy TOPSIS algorithm. The fuzzy ratings assigned to the supplier for each criterion, represented in the fuzzy decision matrix, are presented in Table 13.

Table 13. Fuzzy decision matrix

Criteria	**A1**	**A2**	**A3**	**A4**
Product Price	(1.5,3.5,6)	(1,3.5,6)	(5,7.5,9)	(3.5,6,8.5)
Quality	(2.5,5,7.5)	(3,5.5,8)	(5,7.5,9.5)	(3,5.5,7.5)
Transportation Cost	(3,5,7.5)	(3.5,6,8.5)	(3.5,6,8.5)	(4,6.5,8.5)
Delivery Time	(3.5,6,8)	(3.5,6,8.5)	(5,7.5,9)	(4.5,7,9)
After Sales services	(1.5,4,6.5)	(1.5,3.5,6)	(5,7.5,9.5)	(3,5.5,7.5)

Table 14 displays the corresponding weight for each criterion within the context of the normalized fuzzy decision matrix, which is based on Chen's [6] technique.

Table 14. Weighted Normalized fuzzy decision matrix

Criteria	**A1**	**A2**	**A3**	**A4**	**Weight**
Product Price	(0.15,0.35,0.6)	(0.1,0.35,0.6)	(0.5,0.75,0.9)	(0.35,0.6,0.85)	(0.67,0.9,1)
Quality	(0.25,0.5,0.75)	(0.3,0.55,0.8)	(0.5,0.75,0.95)	(0.3,0.55,0.75)	(0.7,1,1)
Transportation Cost	(0.3,0.5,0.75)	(0.35,0.6,0.85)	(0.35,0.6,0.85)	(0.4,0.65,0.85)	(0.5,0.65,0.8)
Delivery Time	(0.35,0.6,0.8)	(0.35,0.6,0.85)	(0.5,0.75,0.9)	(0.45,0.7,0.9)	(0.4,0.5,0.6)

After Sales services	(0.15,0.4,0.65)	(0.15,0.35,0.6)	(0.5,0.75,0.95)	(0.3,0.55,0.75)	(0.6,0.7,0.85)

In accordance with Step 7, the weight assigned to each criterion is multiplied by the corresponding normalized observation to generate the weighted normalized fuzzy decision matrix, as presented in Table 15.

Table 15. Weighted Normalized Fuzzy Decision Matrix

Criteria	**A1**	**A2**	**A3**	**A4**
Product Price	(0.1005,0.315,0.6)	(0.067,0.315,0.6)	(0.335,0.675,0.9)	(0.2345,0.54,0.85)
Quality	(0.175,0.5,0.75)	(0.21,0.55,0.8)	(0.35,0.75,0.95)	(0.21,0.55,0.75)
Transportation Cost	(0.15,0.325,0.6)	(0.175,0.39,0.68)	(0.175,0.39,0.68)	(0.2,0.4225,0.68)
Delivery Time	(0.14,0.3,0.48)	(0.14,0.3,0.51)	(0.2,0.375,0.54)	(0.18,0.35,0.54)
After Sales services	(0.09,0.28,0.5525)	(0.09,0.245,0.51)	(0.3,0.525,0.8075)	(0.18,0.385,0.6375)

With step 8 shown in Tables 16 and 17, respectively, the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) were now computed.

Table 16. Distances between Ai (i=1, 2, 3, 4) and A+ with respect to each criterion

Criteria	**d(A1,A+)**	**d(A2,A+)**	**d(A3,A+)**	**d(A4,A+)**
Product Price	0.33	0.35	0.35	0.40
Quality	0.36	0.37	0.37	0.33
Transportation Cost	0.30	0.34	0.34	0.31
Delivery Time	0.22	0.25	0.22	0.24
After Sales services	0.31	0.29	0.34	0.30

Table 17. Distances between Ai (i=1, 2, 3,4) and A^- with respect to each criterion

Distances between Ai(i=1, 2, 3, 4) and A^- with respect to each criterion				
Criteria	**d(A1,A-)**	**d(A2,A-)**	**d(A3,A-)**	**d(A4,A-)**
Product Price	0.31	0.34	0.38	0.40
Quality	0.38	0.39	0.42	0.37
Transportation Cost	0.28	0.32	0.32	0.31
Delivery Time	0.22	0.23	0.22	0.23
After Sales services	0.29	0.26	0.32	0.29

Step 9 is used to determine each alternative's distance from FPIS and FNIS, and Step 10 is used to get the closeness coefficient.

Table 18. Computations of d_i^+; d_i^- and CC_i

	A1	A2	A3	A4
di+	1.53	1.59	1.61	1.58
di-	1.48	1.54	1.66	1.59
Cci	0.49	0.49	0.51	0.50
	3	**3**	**1**	**2**

The closeness coefficient value for each supplier alternative was given in Table 18. The closeness coefficient was 0.49 for the first and second suppliers, 0.51 for the third, and 0.50 for the fourth. This suggested that the third supplier should be given priority since they are the closest to FPIS. The supplier's priorities, as determined by closeness coefficients, were A3 > A4 > A2=A1.

1. An Integrated approach FTOPSIS with FAHP:

In my work I follow the hybrid idea used by Rajendra et al. [23], where fuzzy AHP and fuzzy TOPSIS are used together to evaluate suppliers in a structured way. First, I treat the supplier problem as a fuzzy multi-criteria decision situation with five main criteria, and I use the fuzzy AHP procedure to obtain the relative importance of each criterion. In this stage, experts compare the criteria pairwise using linguistic terms that are converted into triangular fuzzy numbers. These fuzzy judgments are then processed through the FAHP steps—building the comparison matrices, calculating the fuzzy synthetic values and finally defuzzifying them—to obtain a crisp weight for each criterion. The final weights that result from this analysis are reported in Table 10 of my study, where each value shows how strongly a particular criterion supports the overall goal of selecting the most suitable supplier.

Once the criterion weights are available, I use them as direct input to the fuzzy TOPSIS method. Here, each supplier is rated against the five criteria using linguistic assessments, again represented by fuzzy numbers. These ratings form the initial fuzzy decision matrix, which is then normalized so that the criteria become comparable in scale. After normalization, I multiply each entry by the FAHP-derived weight for the corresponding criterion to obtain the weighted normalized fuzzy matrix. The intermediate computational steps of the fuzzy TOPSIS algorithm—construction of the normalized matrix, formation of the weighted matrix, and identification of the fuzzy positive ideal and fuzzy negative ideal solutions—are illustrated in the numerical example up to step 6, which is summarized in Table 13.

In the next stage, I calculate the distance of each supplier from the fuzzy positive ideal solution and from the fuzzy negative ideal solution using an appropriate distance measure for triangular fuzzy numbers. These distances are then used to compute the closeness coefficient of every supplier, which indicates how close that supplier is to the ideal case. Table 19 presents the normalized fuzzy matrix together with the applied criterion weights, and it serves as the basis for determining these closeness coefficients and the final ranking. By structuring the analysis in this way, I ensure that the subjective preferences captured in the FAHP stage are consistently reflected in the fuzzy TOPSIS evaluation, leading to a transparent and logically connected hybrid approach to supplier selection.

Table 19. Normalized fuzzy matrix with criteria weight

Criteria	A1	A2	A3	A4	Weight
Product Price	(0.15,0.35,0.6)	(0.1,0.35,0.6)	(0.5,0.75,0.9)	(0.35,0.6,0.85)	0.2036
Quality	(0.25,0.5,0.75)	(0.3,0.55,0.8)	(0.5,0.75,0.95)	(0.3,0.55,0.75)	0.2722
Transportation Cost	(0.3,0.5,0.75)	(0.35,0.6,0.85)	(0.35,0.6,0.85)	(0.4,0.65,0.85)	0.2036
Delivery Time	(0.35,0.6,0.8)	(0.35,0.6,0.85)	(0.5,0.75,0.9)	(0.45,0.7,0.9)	0.1438
After Sales services	(0.15,0.4,0.65)	(0.15,0.35,0.6)	(0.5,0.75,0.95)	(0.3,0.55,0.75)	0.1768

Table 20 presents the weighted normalized matrix, where each criterion's importance is integrated with the normalized performance values of the alternatives (A1–A4) using triangular fuzzy numbers. This matrix facilitates the comparison of alternatives across multiple criteria in a fuzzy multi-criteria decision-making framework.

Table 20. Weighted normalized matrix

Criteria	A1	A2	A3	A4
Product Price	(0.03,0.07,0.12)	(0.02,0.07,0.12)	(0.1,0.15,0.18)	(0.07,0.12,0.17)
Quality	(0.07,0.14,0.2)	(0.08,0.15,0.22)	(0.14,0.2,0.26)	(0.08,0.15,0.2)
Transportation Cost	(0.06,0.1,0.15)	(0.07,0.12,0.17)	(0.07,0.12,0.17)	(0.08,0.13,0.17)
Delivery Time	(0.05,0.09,0.12)	(0.05,0.09,0.12)	(0.07,0.11,0.13)	(0.06,0.1,0.13)
After Sales services	(0.03,0.07,0.11)	(0.03,0.06,0.11)	(0.09,0.13,0.17)	(0.05,0.1,0.13)

The calculated FPIS (Fuzzy Positive Ideal Solution) and FNIS (Fuzzy Negative Ideal Solution) are presented in Table 21 and Table 22, respectively.

Table 21. Distances between Ai (i=1, 2, 3,4) and A^+ with respect to each criterion

Criteria	$d(A1,A^+)$	$d(A2, A^+)$	$d(A3, A^+)$	$d(A4, A^+)$
Quality	0.0605	0.0657	0.0502	0.0657
Capacity	0.0879	0.0879	0.0774	0.0774
Cost	0.0605	0.0657	0.0657	0.0579
Delivery time	0.0409	0.0464	0.0355	0.0409
Service After Sales	0.0571	0.0525	0.0503	0.0503

Table 22. **Distances between Ai (i=1, 2, 3,4) and A^- with respect to each criterion**

Criteria	d(A1,A^-)	d(A2, A^-)	d(A3, A^-)	d(A4, A^-)
Quality	0.0579	0.0657	0.0554	0.0657
Capacity	0.0879	0.0879	0.0809	0.0809
Cost	0.0579	0.0657	0.0657	0.0605
Delivery time	0.0427	0.0464	0.0392	0.0427
Service After Sales	0.0571	0.0503	0.0525	0.0525

The distances of each alternative from the FPIS, FNIS, and the corresponding closeness coefficient were calculated and are presented in Table 23.

Table 23. Computations of d_i^+; d_i^- and Cc_i

	A1	A2	A3	A4
d_i^+	0.3068	0.3182	0.2791	0.2921
d_i^-	0.3034	0.3160	0.2938	0.3024
C*c*	0.4972	0.4982	0.5128	0.5086
	4	**3**	**1**	**2**

The closeness coefficient value for each supplier alternative was given in Table 23. The closeness coefficient was 0.4972 for the first provider, 0.4982 for the second, 0.5128 for the third, and 0.5128 for the fourth. This suggested that the third supplier should be given priority since they are the closest to FPIS. According to closeness coefficients, the supplier's preferences were A3 > A4 > A2 > A1.

2. An Integrated Approach FTOPSIS with Fuzzy SWARA.

In my study, I use the Step-wise Weight Assessment Ratio Analysis method in its fuzzy form to obtain the importance of each evaluation criterion. Kersuliene et al. [15] presented SWARA as a simple but systematic procedure that lets decision-makers express their preferences and then turns those preferences into quantitative weights. I extend this idea by using fuzzy numbers instead of crisp values so that hesitation and vagueness in expert judgments can be reflected more realistically. The fuzzy SWARA procedure in this work follows the same general phases described in the original SWARA studies and in the decision-making framework of D. Celebi et al. [11], but it is adapted to suit the supplier selection problem and to work together with the FTOPSIS method.

First, the set of evaluation criteria is discussed with the experts and then arranged from the most important to the least important according to their expected impact on supplier performance. This ordered list serves as the starting point of the fuzzy SWARA process. Rather than working with fixed scores, each expert gives a fuzzy linguistic comparison of the importance of one criterion relative to the one placed immediately before it in the ordered list. Beginning from the second criterion, the expert states how much less important or more important it is compared with the previous criterion. These assessments are expressed using the triangular fuzzy scale given in Table 3, which translates terms such as “equally important”, “slightly less important” or “much more important” into fuzzy numbers.

The fuzzy comparison values collected from all experts are then aggregated to obtain a group measure of the relative significance for each successive criterion. From these fuzzy ratios, a sequence of fuzzy coefficients is constructed, and step by step the preliminary fuzzy weights for all criteria are derived. Afterwards, a normalization process is carried out so that the final fuzzy weights sum to one and can be directly used in further analysis. These normalized fuzzy weights represent the collective view of the decision-makers on how important each criterion is in the supplier selection problem. Finally, I combine these fuzzy SWARA-derived weights with the FTOPSIS procedure to calculate the closeness of each supplier to the fuzzy ideal solution and to identify the most suitable provider among the available alternatives.

$$\bar{S}_j = (\bar{S}_{jl}, \bar{S}_{jm}, \bar{S}_{ju}) = \left(min\ (\bar{S}_{jlk}), \frac{\sum_{k=1}^{K} \bar{S}_{jmk}}{K}, max\ (\bar{S}_{juk})\right) \quad (19)$$

Step 3: Obtain coefficient $\bar{k}_j$ values, fuzzy weights $\bar{q}_j$ and final weights of criteria. Coefficient $\bar{k}_j$ value is computed as:

$$\bar{k}_j = \begin{cases} \bar{1} & ; j = 1 \\ \bar{S}_j & ; j > 1 \end{cases} \quad (20)$$

Fuzzy recalculated weights $\bar{q}_j$ as :

$$\bar{q}_j = \begin{cases} \bar{1} & ; j = 1 \\ \frac{\bar{x}_{j-1}}{\bar{k}_j} & ; j > 1 \end{cases} \quad (21)$$

Final relative weights of criteria $\bar{w}_j$ as:

$$\bar{w}_j = \frac{\bar{q}_j}{\sum_{k=1}^{K} \bar{q}_k} \quad (22)$$

Where $\bar{w}_j = (\bar{w}_{jl}, \bar{w}_{jm}, \bar{w}_{ju})$ denotes relative importance fuzzy weight of the jth criterion.

In this study, I used the fuzzy SWARA method to obtain the fuzzy weights of the supplier selection criteria, and all calculations were carried out according to the standard steps of this technique. First, I asked the decision makers to think about which criteria are more important for their company when choosing a supplier. After a discussion, the experts agreed on a preliminary ranking of the criteria from the most to the least important. The order that was finally accepted was: C2 (Quality) as the most important factor, followed by C1 (Product Price), C4 (Delivery Time), C5 (After Sales Services), and finally C3 (Transportation Cost). This ranking reflects the company’s policy of giving priority to product quality and then considering cost and service issues. Once the order was fixed, I moved to the next stage of the fuzzy SWARA procedure. In this step, five experts from the company’s management team—who are directly involved in purchasing, logistics, and customer service—were invited to give their opinions on how much more important each criterion is compared with the one just before it in the ranking. Their judgments were expressed using linguistic terms such as “equally important,” “slightly more important,” or “much more important,” which were then converted into corresponding triangular fuzzy numbers. These fuzzy comparison values form the basis for calculating the adjustment coefficients and the relative weights in the SWARA method. For each criterion, I computed the coefficient that reflects the change in importance from the previous criterion, and then derived the recalculated weights step by step, moving from the most important criterion to the least important one. The resulting normalized fuzzy weights show the relative influence of each criterion on the supplier selection decision and are later used as input to the fuzzy TOPSIS evaluation. The detailed expert assessments, the derived coefficients, and the intermediate calculations of the fuzzy SWARA process are summarized and reported in Table 24, which provides a clear view of how the final weights were obtained.

Table 24. Comparison of criteria relative importance by "Lagerton" Expert

	C1 to C2	C4 to C1	C5 to C4	C3 to C5
E1	(1.00,1.00,1.00)	(0.67,1.00,1.50)	(0.40,0.50,0.67)	(0.29,0.33,0.40)
E2	(0.67,1.00,1.50)	(0.40,0.50,0.67)	(0.67,1.00,1.50)	(0.40,0.50,0.67)
E3	(0.67,1.00,1.50)	(0.29,0.33,0.40)	(0.29,0.33,0.40)	(0.67,1.00,1.50)
E4	(0.40,0.50,0.67)	(0.67,1.00,1.50)	(0.40,0.50,0.67)	(0.29,0.33,0.40)
E5	(0.67,1.00,1.50)	(0.40,0.50,0.67)	(0.29,0.33,0.40)	(0.40,0.50,0.67)

Table 24 presents the comparison of criterion importance as assessed by the "Lagerton" experts. All subsequent calculations (step 3) and results are provided in Table 25. The values in the column are calculated using Equation (18-21).

Table 25. Criteria weights obtained using SWARA method

Criteria	$\bar{S}_j$	$\bar{k}_j$	$\bar{q}_j$	$\bar{w}_j$
Quality	(-,-,-)	(1.00,1.00,1.00)	(1.00,1.00,1.00)	(0.33,0.46,0.61)
Product Price	(0.4,0.9,1.5)	(1.4,1.9,2.5)	(0.4,0.53,0.71)	(0.13,0.24,0.43)
Delivery Time	(0.29,0.666,1.5)	(1.29,1.666,2.5)	(0.16,0.32,0.55)	(0.053,0.15,0.34)
After Sales services	(0.29,0.532,1.5)	(1.29,1.532,2.5)	(0.064,0.21,0.43)	(0.021,0.095,0.26)
Transportation Cost	(0.29,0.532,1.5)	(1.29,1.532,2.5)	(0.026,0.14,0.33)	(0.008,0.062,0.20)

The fuzzy TOPSIS method is utilized to assess suppliers in relation to the specified criteria within the framework of FMCDM. The values of d_i^+, d_i^- and Cc_i are presented as follows.

Table 26. Computations of d_i^+; d_i^- and Cc_i

	A1	A2	A3	A4
di+	0.84	0.88	0.98	0.93
di-	0.71	0.75	0.86	0.80
Cci	0.45785	0.45979	0.46763	0.46408
	4	**3**	**1**	**2**

Table 4.26 provided value of closeness coefficient for all alternatives of supplier. The closeness coefficient was 0.45785 for the first provider, 0.45979 for the second, 0.46763 for the third, and 0.46408 for the fourth. This suggested that the third supplier should be given priority since they are the closest to FPIS. According to closeness

coefficients, the supplier's preferences were A3 > A4 > A2 > A1. The implementation of the proposed FMCDM approaches provides a comprehensive ranking of the suppliers, as displayed in Table 27.

3. Results and Discussions

In most companies, supplier evaluations are done using simple checklists and price metrics, and even these routine methods seldom investigate the supply chain of each supplier thoroughly. From my own experience, when selecting suppliers, personal attributes, biases and expectations come into play, and other decision makers are no different. As a consequence, evaluations can become subjective, sometimes ambiguous and in some cases these evaluations are even omitted. To tackle this type of ambiguity, I have incorporated fuzzy multi-criteria decision-making tools, these tools help to combine both quantifiable variables and subjective opinions. Three fuzzy methods are most relevant to my case – fuzzy SWARA, fuzzy AHP and fuzzy TOPSIS – and I have also worked on two hybrid models that combine some of these methods. Each of the techniques derives a different type of answer. For example, with fuzzy SWARA, the first step involves experts ordering the criteria of the assessment in terms of their subjective importance and after that weights are adjusted stepwise using fuzzy numbers that represent how much more one of the criteria is in importance than another. The end result is a ranked list of the criteria based on the subjective weights provided by the experts. Contrastingly, fuzzy AHP relies on pairwise comparisons.

I consider performing criteria and sub-criteria comparisons two at a time using fuzzy scales, and order judgements to derive priority weights and a preliminary order of suppliers. Fuzzy TOPSIS takes a different approach, for it does not use pairwise comparisons; it positions every supplier with respect to an ideal best supplier and an ideal worst supplier, relying once again on fuzzy numbers to represent rating uncertainties. Closest to the positive ideal and furthest from the negative ideal is the “best” supplier. I employ fuzzy AHP, fuzzy TOPSIS, the combination of fuzzy AHP and fuzzy TOPSIS, and fuzzy SWARA with fuzzy TOPSIS to a real case of selecting suppliers of mechanical components in this research. By means of outcome comparisons, I demonstrate the ability of all four fuzzy MCDM configurations to successfully assist supplier choice when data uncertainty and a flexible, human-centric representation of judgment by decision makers must be accounted for.

Table 27. The comprehensive rankings of the suppliers, based on various FMCDM approaches, are presented as follows.

FMCDM approaches	Supplier			
	A1	A2	A3	A4
FAHP	4	3	1	2
FTOPSIS	3	3	1	2
Fuzzy AHP + Fuzzy TOPSIS	4	3	1	2
Fuzzy SWARA + Fuzzy TOPSIS	4	3	1	2

When it comes to supplier alternative priority, the results of these four fuzzy MCDM techniques are similar.

4. Conclusions

In this study, I used four fuzzy multi-criteria decision-making methods to evaluate and rank the candidate suppliers: fuzzy TOPSIS, fuzzy AHP, integrated fuzzy TOPSIS with fuzzy SWARA, and integrated fuzzy TOPSIS with fuzzy AHP. Each method followed the same basic idea: first I measured how well each supplier performed on the main criteria, and then I combined these scores to obtain an overall priority value. The criteria chosen for this work were quality, product price, after-sales service, transportation cost, and delivery time, because these factors strongly affect customer satisfaction and the total cost of the supply chain. Expert judgments on these criteria and on each supplier were expressed in fuzzy linguistic terms so that uncertainty and subjectivity could be included in a systematic way. After carrying out all the calculations for the four approaches, the same supplier, called A3, consistently emerged as the preferred option. The remaining suppliers were placed in the order A4, A2, and A1, although the exact numerical scores and small differences between them changed slightly from one method to another. These minor variations are expected, because the internal logic and calculation steps of the methods are not identical. However, the fact that all approaches pointed to A3 as the best choice and produced very similar rankings for the other suppliers suggests that the decision is robust and does not depend on a single technique. This means that for small and medium-sized supplier selection problems, it is usually enough to apply just one of these fuzzy methods, as any of them can provide a reliable ranking with reasonable effort. The results also show that fuzzy MCDM tools are flexible and can easily be adapted to other types of selection problems where several criteria must be considered at the same time, such as choosing projects, machines, software packages, employees, or business partners. In such situations, the same general procedure—identifying criteria, collecting expert opinions in fuzzy form, and applying a suitable fuzzy method—can help decision makers reach more transparent and defensible choices.

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