Annals of Healthcare Systems Engineering

www.ahse.reapress.com

Ann. Healthc. Syst. Eng. Vol. 2, No. 3 (2025) 159–173.

Paper Type: Original Article

Presenting a New Approach to Selecting the Best Supplier Using the Failure Mode and Effects Analysis Technique and Fuzzy Hierarchy Process Analysis: A Case Study of a Pharmaceutical Company

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Citation:

Received: 03 January 2025 *Revised: 27 April 2025* *Accepted: 12 June 2025*	Fallahi Arezodar, E., Ahmadipour Rudposht, M., & Foroud, A. M. (2025). Presenting a new approach to selecting the best supplier using the failure mode and effects analysis technique and fuzzy hierarchy process analysis: A case study of a pharmaceutical company. *Annals of healthcare systems engineering,* 2(3), 159-173.

Abstract

Supplier selection has long been regarded as one of the most challenging issues in supply chain optimization, and a firm's success largely depends on choosing an appropriate supplier. The supplier selection process is a highly complex, multi-person, group decision-making problem that can benefit from systematic, rational approaches to improve the evaluation of priorities. This process typically relies on collective input from individuals across different functional areas within an organization. This study demonstrates how the Fuzzy Analytic Hierarchy Process (F-AHP) can be effectively integrated with the Failure Mode and Effects Analysis (FMEA) approach to select the best supplier in a supply chain risk environment. The F-AHP method is employed to determine the relative weight of each criterion, while the FMEA technique is used to calculate the Risk Priority Number (RPN) for each criterion and its associated sub-criteria in the supplier selection problem. Sobhan Pharmaceutical company is selected as a case study to implement the proposed approach, and the results indicate improvements in performance across various criteria.

Keywords: Supplier selection, Fuzzy analytic hierarchy process, Failure mode and effects analysis.

1 | Introduction

Modern global markets are characterized by numerous factors, among which globalization, rising customer value expectations, expanding regulatory compliance requirements, the global economic crisis, and intense competitive pressure are of paramount importance [1]. Consequently, in response to these factors,

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https://doi.org/10.22105/ahse.v2i3.46

manufacturing companies must first select and then retain their key suppliers. Selecting an appropriate supplier can significantly reduce an organization's purchasing costs, enhance market competitiveness, and increase end-user satisfaction. Therefore, the purchasing and procurement unit plays a critical role in an organization's efficiency and effectiveness. The performance of this unit directly impacts cost reduction, profitability, and organizational flexibility [2]. Undoubtedly, the most important and sensitive stage in any organization's purchasing process is supplier evaluation and selection [3].

The importance of supplier selection stems from the fact that suppliers commit to providing resources while simultaneously influencing activities such as inventory management, production planning and control, cash flow requirements, and product quality. As the importance of purchasing increases, purchasing decisions become more critical; moreover, as companies grow increasingly dependent on their suppliers, the direct and indirect consequences of poor decision-making in this area become more apparent [4].

In the supplier selection process, evaluation is conducted by assessing various criteria and supplier attributes. Numerous studies have been conducted on supplier selection, in most of which supplier selection is treated as a Multi-Criteria Decision-Making (MCDM) process [5]. Accordingly, various MCDM methods have been employed to address the supplier selection problem. The main limitation of MCDM approaches is their inability to manage risks throughout the decision-making process effectively. However, in risk environments, decision-makers always seek to manage risk; thus, in such contexts, conventional MCDM approaches are ineffective for risk management [6].

Risk can be appropriately managed using the Failure Mode and Effects Analysis (FMEA) method. FMEA is a systematic process for identifying potential failures and is applied during the design and implementation stages of a process before failures occur. The objective of this method is to eliminate or reduce potential failures [7]. Essentially, FMEA is a reliable evaluation technique used to identify failure modes that may reduce a system's overall reliability. Functional analyses are used as inputs to determine valid failure modes across all system levels. FMEA is applied to reduce risk generation (by decreasing the severity of failure effects), reduce the likelihood of failure, or achieve both objectives [8]. Fundamentally, FMEA is an inductive analysis technique.

Nevertheless, the probability of failure can only be determined or reduced through an understanding of failure occurrence mechanisms. Ideally, by eliminating the causes (roots) of failure, the probability of occurrence can be reduced to a level approaching "impossible." Therefore, in FMEA, extensive information regarding failure causes (deductive analysis) must be prepared [9].

However, the primary limitation of the FMEA technique lies in its inability to assign weights to decision criteria. In real-world problems, each criterion and sub-criterion carries a different weight. If the weights of decision criteria are not calculated accurately, the decision-maker may be led toward incorrect conclusions. Hence, precise measurement of the weights of criteria and sub-criteria in the decision-making process is unavoidable. In traditional FMEA, different combinations of severity, detectability, and occurrence can yield identical Risk Priority Numbers (RPNs), even though the actual risk consequences may differ. As a result, when multiple identical RPN values are generated from different criteria, decision-making becomes extremely difficult. Therefore, based on existing studies, the use of traditional FMEA and conventional MCDM methods for supplier selection in a risk environment is not sufficiently effective. In such environments, both the risk associated with decision criteria and their relative weights must be accurately calculated.

Buckley's Fuzzy Analytic Hierarchy Process (F-AHP) is a powerful and flexible method for solving MCDM problems under uncertainty [10]. This method offers several advantages, including flexibility, the ability to address uncertainty, and the capability to integrate knowledge from multiple stakeholders. Nevertheless, Buckley's F-AHP also has limitations, such as computational complexity and the need for specialized software. F-AHP can assist in selecting the best supplier by considering quality, price, and reliability in a fuzzy context.

In this study, the authors employ an integrated FMEA approach that addresses the existing limitations. The main objective of this research is to address research gaps in integrating FMEA and MCDM methods. Unexpected downtime in production lines, frequent failures of critical equipment, sudden declines in sales, and disruptions to work processes are undesirable events that can cause serious, and sometimes irreparable, damage to an organization. Senior managers are constantly seeking techniques that can deliver optimal results in the shortest possible time, enabling them to predict high-risk events before they cause severe losses and to take corrective actions accordingly. The purpose of applying the FMEA method is to take appropriate and effective actions to eliminate or reduce failures based on their priority. Moreover, analyzing failure modes can document the current status of activities and their failure probabilities, providing valuable records for future processes.

2 | Literature Review

Fuzzy set theory was introduced by Zadeh [11] to eliminate and neutralize the imprecision inherent in human judgments. The F-AHP can systematically solve selection problems that utilize concepts from fuzzy set theory [12]. Applications of F-AHP have been reported in various fields, including the selection of energy alternatives [13], job selection, optimal maintenance strategy selection, selection of online taxi companies, and others. Bowles and Peláez [14] introduced a new technique based on fuzzy logic for prioritizing failures for corrective actions within Failure Mode, Effects, and Criticality Analysis (FMECA). In their study, the authors represented Severity (S), Detectability (D), and Occurrence rate (O) as fuzzy sets to evaluate failure modes in FMECA. Subsequently, defuzzification is performed using the maximum weighted mean method to assess failure risk. Ravi Sankar and Prabhu [15] proposed a new Risk-Priority Ranking (RPR) technique that uses a rating scale from 1 to 1000 to represent increasing risk levels for combinations of S, O, and D parameters. They also argued that conventional FMEA attempts to determine risk without adequately quantifying the contributing factors; therefore, the RPN can be misleading. Pillay and Wang [16] introduced Evidential Reasoning (ER) using a fuzzy rule base and grey relational theory to compute the risk priority score, thereby overcoming shortcomings of the traditional FMEA approach. Seyed-Hosseini et al. [17] employed the DEMATEL decision-making method to reprioritize failure modes in FMEA based on severity (impact) and the direct and indirect relationships among them.

The integration of FMEA with the F-AHP has proven to be a powerful approach for addressing the complexities of supplier selection by combining systematic risk assessment with MCDM. This integrated method, particularly when dealing with vague or subjective criteria, enables more accurate evaluations. Empirical studies across industries such as automotive, electronics, and construction have confirmed the positive impact of this hybrid approach on the accuracy and transparency of decision-making processes. For example, Fattahi et al. [18] demonstrated that the use of FMEA–F-AHP can effectively reduce supply chain risks. Similarly, Altubaishe and Desai [19] emphasized that this method yields superior results compared to traditional techniques in dynamic and complex environments. The integration of FMEA with the F-AHP has become a cornerstone of supplier selection, effectively addressing complex MCDM challenges. This hybrid approach combines detailed risk analysis with subjective judgment, making it ideal for applications across various industries. Previous studies, such as Başaran and Ighagbon [20], have shown the applicability of this hybrid approach in complex evaluation scenarios, including risk assessment and quality evaluation of mobile learning platforms. Their findings highlight the unique advantage of integrating these methods to provide a robust decision-making framework. Moreover, the integration of FMEA and F-AHP has been successfully implemented in industrial settings. For instance, Parmar et al. [21] evaluated failure modes in hydraulic direct drive systems using a combination of F-AHP and TOPSIS, highlighting its application in supply chain risk management. This hybrid method has also found relevance in the healthcare sector. Golrizgashti and Keshmiri [22] applied an AHP–FMEA model to assess patient safety and emphasized the adaptability of these techniques across industries.

Chen [23] introduced a modified FMEA that evaluates the interdependencies among corrective actions using Interpretive Structural Modeling (ISM). In this research, the author calculated the weight of corrective actions through the Analytic Network Process (ANP) and successfully combined them with utility priority numbers to support decision-making on FMEA improvement priorities. Wang et al. [24] proposed Fuzzy Risk Priority Numbers (FRPNs) that account for the imprecision of human judgments. These FRPNs overcome the limitations of conventional RPNs. They are subsequently defuzzified using the centroid method, in which a new centroid-based fuzzification formula derived from α-level sets is employed. Sachdeva et al. [25] applied FMECA to maintenance problems and noted that FMECA does not account for interdependencies among failure modes and effects. To address this limitation, they employed Shannon entropy to assign objective weights to maintenance parameters and the TOPSIS method to determine the maintenance criticality index. Sellappan and Palanikumar [26] proposed a modified FMEA in which the risk-priority-number prioritization method is revised. Their study highlighted a major limitation of conventional RPNs: different combinations of severity, detectability, and occurrence can yield identical RPN values while leading to completely different risk consequences.

Arabsheybani et al. [27] proposed an integrated fuzzy MOORA–FMEA method for evaluating sustainable supplier risks, accounting for quantity discounts, and highlighted its suitability for multidimensional decision-making scenarios. An integrated Fault Tree Analysis (FTA) and F-AHP approach for green supply chain risk assessment demonstrated the capability of hybrid methods to enhance sustainability [28]. Yazdani et al. [29] examined supplier selection using DEMATEL, FMEA, and EDAS, highlighting its effectiveness in risk management and in strengthening strategic decision-making for environmentally focused projects. Tavana et al. [30] developed an integrated AHP and MULTIMOORA framework that advanced the analysis of supply chain risks and benefits, particularly for supplier prioritization. In another study, researchers integrated AHP–PROMETHEE with FMEA for supply chain management, expanding its application within hybrid decision-making frameworks [19].

Growing interest in this approach is evident across various studies, with researchers supporting its application in diverse domains, ranging from rail transportation systems [31] to optimization of digital twin systems [32]. Despite its widespread application, certain challenges remain. As noted by Gul [33], researchers need to refine these integrated methods to address evolving decision-making scenarios, including adapting datasets and increasingly complex decision hierarchies. In supplier selection criteria, supplier risk depends on the type and magnitude of risk. Supplier-induced failures pose a hazard to manufacturers, who strive to assess and score each failure's impact. The aggregate score reflects the level of supplier risk; thus, the preferred supplier selection method is effectively equivalent to selecting the supplier with the lowest risk. Although many researchers have studied supplier evaluation and selection problems, only a limited number have examined them in terms of supplier or supply chain risk. In any decision-making problem, not all criteria have equal influence, and decision criteria play a critical role in the decision system. However, a review of the literature reveals that most researchers focus on efficiently prioritizing conventional RPNs in FMEA, while only a few concentrate on the relative weights of decision criteria. Integrated FMEA can overcome this limitation. Therefore, the present study focuses on the supplier evaluation problem using an integrated FMEA approach. Consequently, the integrated FMEA–F-AHP framework can be regarded as a versatile tool for supplier selection, offering a systematic and consistent approach to MCDM. The potential for future advancements lies in integrating advanced algorithms and expanding applications within dynamic supply chain environments.

3 | Research Methodology

In the supplier selection process, the decision-making criteria relevant to the system must be identified and considered first. Subsequently, potential failure modes should be recognized. The effective implementation steps for this research are presented in a flowchart (*Fig. 1*). Briefly, based on expert opinions and previous studies, the main criteria and sub-criteria for supplier evaluation are initially selected. In the next stage, the weights of the criteria must be assessed. For this purpose, the F-AHP is employed to minimize the influence of human judgment. To account for risk and uncertainty in the problem, the integrated FMEA technique is used as a key step in this study. Accordingly, the RPN is calculated based on experts' opinions and combined with the F-AHP-derived weights, yielding the final weights for criteria and sub-criteria for different suppliers. Based on these calculations, the most desirable supplier is identified according to the selected criteria.

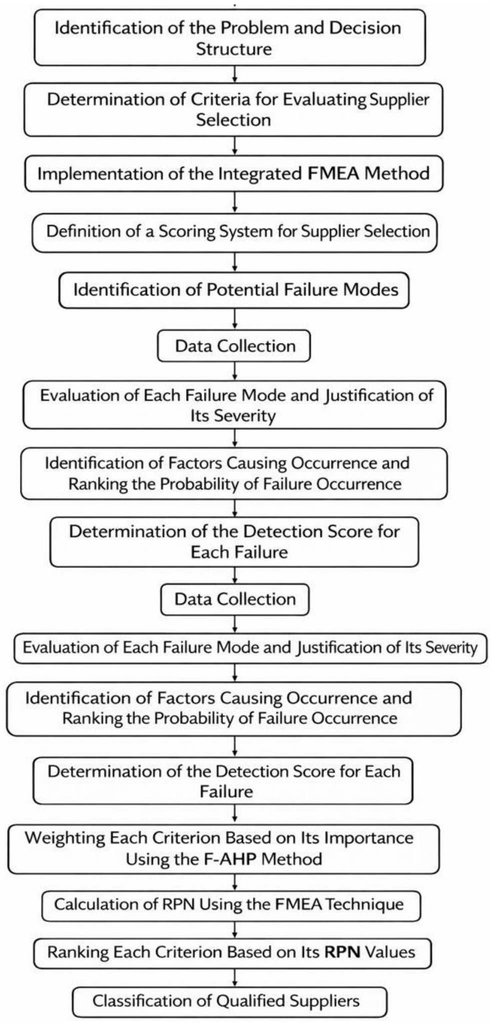

Fig. 1. Framework for the research implementation process.

3.1 | Problem Structure and Identification of Decision Criteria

Most organizations procure raw materials and/or components from vendors (suppliers), among whom there are several competing suppliers with different capacities, pricing schemes, cost structures, service levels, and quality standards. The cost of raw materials and components accounts for a significant share of total costs in many industries. Therefore, purchasing decisions play a key role in an organization's overall efficiency and effectiveness. One of the most important decisions in purchasing operations is supplier evaluation and selection.

The supplier selection problem is an MCDM problem that is typically formulated as a mathematical model. Under conditions of risk, supplier selection is usually determined based on a set of criteria. According to previous studies, quality, on-time delivery, cost, service level, communication, experience and reputation, geographical location, and flexibility are among the most important criteria in supplier selection.

In this study, based on the existing literature and interviews with the purchasing and procurement department of the organization under study, the main criteria and sub-criteria for supplier evaluation were identified and selected. In total, eight criteria, including cost, quality, delivery capability, relationships, geographical location, experience, flexibility, and service, along with 22 sub-criteria (as shown in *Table 1*), were selected. The selected set of criteria and sub-criteria forms the basis for supplier evaluation using the integrated FMEA and F-AHP approach.

Table 1. Selected criteria and sub-criteria for supplier evaluation.

No.	Criterion	Sub-Criterion
1	Cost	Price
		Transportation cost
		Price reduction program
2	Quality	Production capability
		Quality control
		Incoming failure rate
		Customer complaint rate
3	Delivery capability	On-time delivery
		Lead time
		Production cycle time
4	Relationships	Communication system
		Long-term cooperation
		Reputation
5	Geographic location	Location
		Unexpected events
6	Experience	Past performance
		Management system
7	Flexibility	Responsiveness to demand changes
		Short lead time for action
		Conflict resolution
8	Service	Demand responsiveness
		Discount strategy

3.2 | Failure Mode and Effects Analysis Technique

The FMEA method can be considered a flexible yet powerful tool for predicting unexpected events. Risk assessment using FMEA was first introduced in the 1940s by the U.S. military. However, its application expanded significantly with the advent of human-crewed space missions in the 1960s. Subsequently, FMEA was adopted as a risk reduction method in many industries, including automotive, aerospace, power generation, petrochemical, and software, to the extent that specific standards were developed to ensure that relevant risks are properly identified and their control is feasible. Studies conducted across various industries, along with interviews with experts in this field, indicate that 46% of experts have utilized the FMEA technique and RPNs to assess risk and failure severity in their organizational decision-making processes.

The first step in FMEA is forming an evaluation team. In this study, the expert team consists of managers and specialists from the company under investigation. A non-probabilistic sampling method is employed, and the selected individuals are chosen purposefully based on their expertise and predefined expert criteria. According to existing recommendations, a team of 4 to 6 experts is sufficient for this purpose. The primary criterion for selecting experts is their work experience and familiarity with FMEA. The risk management and assessment process using FMEA consists of two general stages: the first involves completing the FMEA form, and the second involves integrating its results into project implementation. The first stage comprises three main steps, each involving completing different columns of the FMEA form.

Step 1. Severity assessment (S)

At this stage, all potential failure modes are evaluated against the eight main criteria listed in the FMEA table, and a Severity rating (S) is assigned to each failure mode. For this purpose, a four-level scale is defined for evaluation based on the main criteria. For example, under the cost criterion, if a supplier provides low-cost raw materials, a score of 1 is assigned; if the supplier provides very high-cost raw materials, a score of 4 is assigned. The same scoring approach is applied to all other criteria.

Step 2. Estimation of the Occurrence probability of each risk (O)

Step 2 involves identifying the causes of risks and their likelihood of occurrence. A four-level scale is also used for evaluation based on the main criteria. For instance, under the quality criterion, if the supplier rarely delivers defective raw materials, a score of 1 is assigned; if the supplier frequently delivers defective raw materials, a score of 4 is assigned. This valuation approach is similarly applied across all criteria.

Step 3. Determination of the detection rating (D)

Ensuring the possibility of early detection is critically important, as it refers to the likelihood that a failure will be detected before its effects occur. For this purpose, based on the expert team's opinions, values from 1 to 4 are used, where 1 indicates a strong likelihood of detection, and 4 indicates a weak likelihood of detection.

After completing the analysis, the second stage of the FMEA process can begin. At this stage, the RPN is calculated for each criterion. The RPN essentially prioritizes risks by their level of importance, allowing decision-makers to focus first on those with the greatest potential impact. The RPN is calculated using *Eq. (1)*.

In this study, a questionnaire was used to evaluate the RPNs. Experts rated the severity, occurrence probability, and detection level of each risk using linguistic terms ranging from very low to high on a four-point scale. Clearly, the maximum possible RPN value for each risk in the worst-case scenario is 64. Typically, if a risk's RPN is less than 32, it is considered a low-level risk. Values between 32 and 48 indicate a moderate risk level, while values greater than 48 indicate risks that require urgent and intensive management.

$$\mathrm{RPN} = \mathrm{S} \times \mathrm{O} \times \mathrm{D}. \tag{1}$$

In this study, a questionnaire was used to evaluate the RPN. Experts assessed the severity of impact, the probability of occurrence, and the detectability of each risk using a four-point scale, with values ranging from very low to high. Clearly, the maximum possible RPN for each risk in the worst-case scenario is 64. Generally, if a risk's RPN is less than 32, it is considered a low-level risk. Values between 32 and 48 indicate a moderate level of risk, whereas risks with an RPN greater than 48 require urgent and intensive management

3.3 | Fuzzy Analytic Hierarchy Process

As mentioned earlier, the objective of the present study is to identify the best supplier among the suppliers of the case company. The AHP is one of the most effective MCDM methods for similar problems. In the AHP technique, the consistency ratio is carefully examined using a scale of absolute judgments. Since the classical AHP method does not account for the ambiguity inherent in subjective judgments, its principles have been enhanced by incorporating fuzzy logic. The classical AHP technique is not capable of fully reflecting human thinking because it lacks access to precise decision-makers' requirements. Therefore, linguistic variables expressed in fuzzy numbers appear to be more appropriate for describing inputs and capturing the decision-makers' preferences.

Fuzzy theory, as opposed to classical (crisp) theory, was first introduced by Zadeh [11] to eliminate or reduce linguistic ambiguities. In this study, the output of the F-AHP method is used as an input for the FMEA approach. Accordingly, F-AHP is employed to determine the weights of all criteria.

To this end, in the first step, pairwise comparison matrices are constructed, and responses are provided based on the scale presented in *Table 2*. Similar to the classical AHP method, pairwise comparisons must be created and evaluated according to the fuzzy scale. At this stage, the inconsistency ratio of the pairwise comparisons should also be examined. If this ratio is less than 0.1, it indicates acceptable consistency and stability of the pairwise comparisons. In this study, to calculate the inconsistency ratio for fuzzy matrices, the fuzzy pairwise comparison matrix is first defuzzified, and then the inconsistency ratio is calculated crisply.

Table 2. Linguistic terms and corresponding triangular fuzzy numbers.

Saaty Scale	Linguistic Phrases for Determining Preference	Triangular Fuzzy Numbers
1	Equal preference or importance	(1, 1, 1)
3	Low preference or importance	(2, 3, 4)
5	Stronger preference or importance	(4, 5, 6)
7	Much stronger preference or importance	(6, 7, 8)
9	Complete and absolute preference	(9, 9, 9)
2, 4, 6, 8	Intermediate values between two adjacent scales	(1, 2, 3) or (3, 4, 5) or (5, 6, 7) or (7, 8, 9)

In the second step, when multiple respondents have completed the pairwise comparisons, the pairwise judgments must be aggregated. To integrate the experts' opinions, the arithmetic mean method is used to obtain an aggregated pairwise comparison matrix. *Eq. (2)* is used to calculate the average preferences of the respondents

$$\widetilde{d_{ij}} = \sum_{k=1}^{K} \widetilde{d_{ij}} \Big/ K. \tag{2}$$

After integrating the respondents' preferences, the pairwise comparison matrix will be presented as *Eq. (3)*.

$$M = \begin{bmatrix} \widetilde{d_{11}} & \cdots & \widetilde{d_{1n}} \\ \vdots & \ddots & \vdots \\ \widetilde{d_{n1}} & \cdots & \widetilde{d_{nn}} \end{bmatrix}. \tag{3}$$

The fusion of fuzzy matrices is such that the first elements of all comparisons together take the geometric mean, the second elements together take the geometric mean, and the third elements together take the geometric mean. *Eq. (4)* shows how to calculate the geometric mean of the fuzzy comparison values of each criterion.

$$\tilde{r_i} = \left(\prod_{j=1}^{n} \tilde{d}_{ij}\right)^{1/n} \quad \text{and} \quad i = 1,2,\dots,n, \tag{4}$$

where r_i represents triangular values. In the third step, the fuzzy weights of the criteria must be calculated. The fuzzy weights for each criterion can be determined by combining the following three steps: 1) the vector sum of each r_i should be computed, 2) the inverse of the vector sum is computed, and the triangular fuzzy numbers are then arranged in ascending order, and 3) to find the fuzzy weight of the i[th] criterion $\tilde{w}_i$ each r_i is multiplied by the inverse vector. *Eq. (5)* shows the calculation method.

$$\tilde{w}_i = \tilde{r_i} \times (\tilde{r}_1 + \tilde{r}_2 + \cdots + \tilde{r}_n)^{-1} = (lw_i, mw_i, uw_i). \tag{5}$$

Since the value $\tilde{w}_i$ in *Eq. (5)* is still a fuzzy number, *Eq. (6)* is used to defuzzify it.

$$M_i = \frac{lw_i + mw_i + uw_i}{3}, \tag{6}$$

where the value of M_i is a non-fuzzy number and can be normalized through *Eq. (7)*.

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

4 | Results and Data Analysis

Sobhan Darou company (Public Joint Stock) was originally designed and established in 1976 under the name Sooiran Cosmetics and Hygiene company (Private Joint Stock). The factory was launched in 1981 and renamed Sobhan Pharmaceutical company in 1985. Following the establishment of the factory and new production lines in 2004, it was registered as Sobhan Darou company (Private Joint Stock). In 2005, the company changed from a private joint-stock to a public joint-stock company. In 2010, its name was listed on the Securities and Exchange Organization under the symbol "DSobhan".

The expert team consists of marketing, sales, and commercial managers; industry specialists with several years of experience in the pharmaceutical sector; quality assurance experts; and academic members, all of whom are tasked with validating the criteria extracted by the research team based on previous studies. The industrial/academic experts were asked to rank the main drivers of the integrated FMEA model by their impact on various selection criteria for the best supplier, including social, sustainable quality, and economic factors.

Generally, economic criteria are defined in terms of costs and profits. In the production context, the economic aspect of sustainability is described in terms of its impact on shareholder economic welfare and local and national economic strategies [34]. The economic dimension covers all economic indicators, including conventional criteria related to financial accounting and intangible assets that are not typically reflected in financial reports [34]. However, the economic aspect is inherently aligned with both social aspects and sustainable quality. The social and sustainable quality dimension is based on empowerment or access to resources, employment generation, loyalty, transparency, and formal stability. It considers community cohesion and its capacity to work toward mutual goals while meeting individual needs such as worker health and safety, nutrition, shelter, education, and cultural expression. In this study, three main suppliers of the organization were evaluated.

A hybrid approach was adopted to identify relevant criteria and key drivers, drawing on a literature review and expert opinions. As the first step, studies by Kirytopoulos et al. [35] and Ishizaka et al. [36] were used as a source to select 14 criteria for triple sourcing in terms of economic, sustainable quality, and social criteria in the raw materials supply sector. In addition, 42 key sub-criteria were selected from the most important sub-criteria identified in previous sources for the integrated top-supplier model. Subsequently, 15 experts were contacted via email, phone, and in-person interviews; 12 (80%) agreed to respond. The experts were then asked (via a designed questionnaire) to confirm and prioritize the 14 selected criteria and 42 key sub-criteria regarding the supplier selection approach and overall impact on sustainability. The response time frame was from October 3, 2024 (questionnaires sent) to November 8, 2024 (responses received).

In some cases, in-person and telephone discussions were conducted for clarification. After receiving all responses, the researchers analyzed the questionnaires. They ultimately selected eight criteria and 22 sub-criteria as the basis for evaluating suppliers using the integrated FMEA and fuzzy hierarchical analysis method.

4.1 | Fuzzy Analytic Hierarchy Process Using Bowley's Method

A pairwise comparison questionnaire was designed for the eight selected criteria and 22 sub-criteria and distributed to the expert team for evaluation. A total of 15 questionnaires were completed and used for analysis. The matrix in *Table 3* presents the respondents' average opinions on the pairwise comparisons of the criteria. Expert Choice™ software was used to analyze the pairwise comparison matrices. The matrix's inconsistency ratio was calculated and found to be less than 0.1, indicating the consistency of respondents' preferences.

Table 3. Pairwise comparison matrix of criteria.

Criterion	Cost	Quality	Delivery	Relationships	Geo. Location	Experience	Flexibility	Service
Cost	(1,1,1)	(1.4, 1.3, 1.2)	(1.3, 1.2, 1)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1,1,1)
Quality	(2,3,4)	(1,1,1)	(1,2,3)	(4,5,6)	(9,9,9)	(5,6,7)	(6,7,8)	(4,5,6)
Delivery	(1,2,3)	(1.3, 1.2, 1)	(1,1,1)	(2,3,4)	(4,5,6)	(2,3,4)	(3,4,5)	(2,3,4)
Relationships	(1,1,1)	(1.6, 1.5, 1.4)	(1.4, 1.3, 1.2)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
Geo. Location	(1.3, 1.2, 1)	(1.9, 1.9, 1.9)	(1.6, 1.5, 1.4)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
Experience	(1,1,1)	(1.7, 1.6, 1.5)	(1.4, 1.3, 1.2)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
Flexibility	(1,1,1)	(1.8, 1.7, 1.6)	(1.5, 1.4, 1.3)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
Service	(1,1,1)	(1.6, 1.5, 1.4)	(1.4, 1.3, 1.2)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)

After calculating the average of the experts' opinions and forming the pairwise comparison matrix, the geometric mean of the fuzzy comparison values for each criterion is computed. Therefore, the geometric mean of the fuzzy comparison values of all criteria is shown in *Table 4*. In addition, the total and inverse values are also presented in the last row of the table, since the fuzzy triangular number must be in increasing order. The order of the numbers in the first and third columns changes.

Table 4. Geometric mean, sum, and inverse values of fuzzy values.

Criterion	R_i
Cost	0.7329, 0.8716, 1.0519
Quality	3.1050, 3.9282, 4.6477
Delivery capability	1.5422, 2.1955, 2.9515
Relationships	0.6721, 0.7128, 0.7711
Geographic location	0.5294, 0.5697, 0.6389
Experience	0.6593, 0.6967, 0.7498
Flexibility	0.6305, 0.6593, 0.6967
Service	0.6721, 0.7128, 0.7711
Sum	8.5435, 10.3466, 12.2887
Inverse values	0.1170, 0.0966, 0.0814
Increasing order	0.0814, 0.0966, 0.1170

In the next step, the fuzzy weights of the criteria should be calculated. In this way, all criteria are calculated, and the relative fuzzy weights, average relative weights, and normalized relative weights for each criterion are presented in *Table 5*.

Table 5. The relative fuzzy weights, average relative weights, and normalized relative weights.

Criterion	W_i	M_i	N_i
Cost	0.0596, 0.0842, 0.1231	0.089	0.0852
Quality	0.2528, 0.3795, 0.5442	0.3921	0.3755
Delivery capability	0.1255, 0.2121, 0.3455	0.2277	0.218
Relationships	0.0547, 0.0688, 0.0903	0.0712	0.0682
Geographic location	0.0431, 0.0550, 0.0748	0.0576	0.0552
Experience	0.0536, 0.0673, 0.0877	0.0696	0.0666
Flexibility	0.0513, 0.0637, 0.0815	0.0655	0.0627
Service	0.0547, 0.0688, 0.0903	0.0712	0.0682

After calculating the normalized non-fuzzy relative weights for the criteria, the same method is used to find the corresponding values for the sub-criteria with respect to each criterion. But first, the sub-criteria should be compared pairwise for each criterion. Here, the steps for calculating the pairwise comparisons of the sub-criteria are not included due to space limitations and the large number of matrices, and only the results are presented in *Table 6*.

Table 6. Weights of criteria, sub-criteria, and final weights.

Row	Criterion	Criterion Weight (W1)	Sub-Criterion	Sub-Criterion Weight (W2)	Final Sub-Criterion Weight (W1×W2)
1	Cost	0.0852	Price	0.519	0.0442
			Transportation cost	0.3079	0.0262
			Price reduction program	0.173	0.0147
2	Quality	0.3755	Manufacturability	0.4652	0.1746
			Quality control	0.2786	0.1046
			Inward failure rate	0.1642	0.0616
			Customer complaint rate	0.0919	0.3451
3	Delivery capability	0.218	On-time delivery	0.6312	0.1376
			Delivery lead time	0.1942	0.0423
			Production cycle time	0.1745	0.038
4	Relationships	0.0682	Communication system	0.6622	0.0452
			Long-term cooperation	0.2479	0.0169
			Reputation	0.0897	0.0061
5	Geographical Location	0.0552	Location	0.7423	0.0409
			Unexpected events	0.2576	0.0142
6	Experience	0.0666	Past performance	0.7423	0.0494
			Management system	0.2576	0.0171
7	Flexibility	0.0627	Responsiveness to demand changes	0.6131	0.0384
			Short lead time	0.2414	0.0151
			Conflict resolution	0.1454	0.0091
8	Service	0.0682	Demand responsiveness	0.8314	0.0567
			Discount strategy	0.1685	0.0115

4.2 | Results of Failure Mode and Effects Analysis

To calculate the RPN, the prepared questionnaire was provided to the expert team, who were asked to determine the Severity (S), Occurrence (O), and Detection (D) values according to the provided scale. For this purpose, seven managers and specialists from the purchasing, sales, and procurement departments, who were fully familiar with the subject, were selected. *Table 7* shows the average results obtained from the questionnaire.

Table 7. Risk priority number results for sub-criteria.

Row	Criterion	Sub-Criterion	Supplier 1	Supplier 2	Supplier 3
			S | O | D | RPN	S | O | D | RPN	S | O | D | RPN
1	Cost	Price	3 | 2 | 1 | 6	3 | 3 | 1 | 9	2 | 3 | 1 | 6
		Transportation cost	2 | 2 | 1 | 4	4 | 3 | 1 | 12	2 | 3 | 1 | 6
		Price reduction program	2 | 2 | 1 | 4	3 | 3 | 1 | 9	2 | 2 | 1 | 4
2	Quality	Manufacturability	2 | 2 | 1 | 4	3 | 2 | 1 | 6	2 | 2 | 1 | 4
		Quality control	1 | 2 | 1 | 2	3 | 2 | 1 | 6	2 | 1 | 1 | 2
3	Delivery	On-time delivery	3 | 1 | 1 | 3	3 | 2 | 1 | 6	1 | 2 | 1 | 2

Considering the RPNs and the fact that all values are below 32 across all sub-criteria, it can be concluded that none of the suppliers face high risk. The results indicate that, according to the cost criterion, the highest risk is associated with Supplier 2, followed by Suppliers 3 and 1. Overall, across all criteria, Supplier 2 appears to have a higher level of risk compared to the other two suppliers. To calculate the risk for each supplier based on the selected sub-criteria, multiply each sub-criterion's final weight by its RPN to obtain the weighted RPN. *Table 8* summarizes these calculations.

Table 8. Weighted risk priority number values for sub-criteria.

Row	Criterion	Sub-Criterion	Final Sub-Criterion Weight	RPN (S1, S2, S3)	Weighted RPN Value (S1, S2, S3)
1	Cost	Price	0.0442	(6, 9, 2006)	(0.2652, 0.3978, 0.2652)
2	Quality	Manufacturability	0.1746	(4, 6, 2004)	(0.6984, 1.0476, 0.6984)
Total score					(5.3896, 8.0023, 4.8259)
Average score					(0.6737, 1.0002, 0.6032)

The weighted-average RPNs for Suppliers 3, 1, and 2 are 0.6032, 0.6737, and 1.0002, respectively, indicating that Supplier 3 has the lowest risk. To analyze the RPNs of suppliers with respect to each criterion, the total scores for each criterion can be calculated, and the RPN for each criterion can be evaluated across suppliers. *Table 9* presents the results obtained from these calculations.

Table 9. Comparison of supplier risk priority numbers across different criteria.

Row	Criterion	Supplier 1	Supplier 2	Supplier 3
1	Cost	0.4288	0.8445	0.4812
2	Quality	2.4728	3.9922	2.6576
3	Delivery capability	0.7046	1.3074	0.681
4	Relationships	0.397	0.4202	0.1702
5	Geographical location	0.4533	0.167	0.2204
6	Experience	0.1672	0.266	0.1672
7	Flexibility	0.4027	0.4027	0.2322
8	Service	0.3632	0.6023	0.2161
Average Score		0.6737	1.0002	0.6032

The results indicate that Supplier 3's RPN value is higher than Supplier 1's for both cost and quality criteria. In contrast, the score for the experience criterion of Supplier 3 is equal to that of Supplier 1. Additionally, Supplier 3's score in the geographic location criterion is higher than Supplier 2. However, the average RPN across the eight criteria for Supplier 3 is lower, making it the best supplier. It indicates that collaborating with Supplier 3 enables the company under study to operate in a lower-risk supply chain environment. The advantage of the F-AHP method over AHP is that F-AHP accounts for the imprecision of human judgment during calculations. When human judgment imprecision is taken into account, the weighted RPN values change.

5 | Conclusion

In this study, the authors employed an integrated FMEA approach to select the best supplier in a supply chain risk environment. When RPNs are identical across different decision-making criteria, traditional FMEA cannot handle the situation. However, this integrated FMEA approach successfully overcomes the limitations of conventional FMEA. In this research, for confidentiality reasons, the exact names of the suppliers are not disclosed. None of the respondents raised any negative claims regarding the pairwise comparisons or risk numbers, and they were highly satisfied with the selection process. Despite the contributions, this study still has some limitations. In the F-AHP method, triangular fuzzy numbers are used to account for human judgment imprecision. To further improve judgment accuracy, trapezoidal fuzzy numbers could be utilized. This study is based on information provided by the suppliers, and the relative weight of each criterion may change when applied to a different organization. In this research, eight criteria and twenty-two sub-criteria were considered, but they may not be sufficient for other organizations. Besides F-AHP, other MCDM methods, such as Fuzzy Analytic Network Process (F-ANP) and Fuzzy TOPSIS, can also be integrated with the FMEA technique. The authors also suggest using FTA, the Delphi method, or stress testing in addition to FMEA and combining them with MCDM approaches

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