Sustainable Supplier Evaluation and Ranking in Nanopharmaceutical Supply Chains

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Abstract
Supplier selection is a strategic decision in the nanopharmaceutical supply chain due to strict quality requirements, product sensitivity, and sustainability concerns. This study proposes a sustainability-oriented framework for evaluating and ranking suppliers in the nanopharmaceutical industry. Evaluation criteria were identified through a literature review and expert opinions, and their relative importance was determined using the Analytic Hierarchy Process (AHP). Supplier performance was then assessed and ranked using the Fuzzy ELECTOR method. The results identified 46 evaluation criteria grouped into 11 categories. Among these, Quality and Compliance, Technical Capability and Innovation, and Specialized Nanopharmaceutical Features were the most influential categories. Compliance with GMP and regulatory requirements, the ability to produce complex nanostructures such as liposomes, polymers, and dendrimers, and product unit price emerged as the most critical criteria. The proposed framework successfully ranked candidate suppliers and identified the best-performing alternatives. The main contribution of this study is the development of a comprehensive 46-criteria framework for supplier selection in the pharmaceutical industry and the novel application of the Fuzzy ELECTOR method in supplier evaluation.

Keywords: Multi-Criteria Decision-Making; Supply chain; Supplier selection; AHP; ELECTOR; fuzzy logic.

1. Introduction

In recent decades, the development of nanotechnology has led to significant transformations across various industries, particularly the pharmaceutical sector. Nanopharmaceuticals, as one of the most important achievements of nanotechnology in the healthcare domain, have attracted considerable global attention due to their unique capabilities such as enhancing drug efficacy, enabling targeted therapy, reducing side effects, and improving pharmacokinetic properties [1]. The rapid growth of the nanopharmaceutical market and increasing investment in this field have highlighted the necessity of efficient supply chain management for these products [2].

Since the quality, safety, and effectiveness of nanopharmaceuticals are strongly influenced by the quality of raw materials, equipment, and supplied services, selecting appropriate suppliers has become a strategic and critical decision in this industry's supply chain [3]. This importance becomes even more pronounced considering that nanotechnology-based drugs possess specific characteristics such as complex structures, the need for advanced equipment, high sensitivity to storage conditions, and strict regulatory requirements [4]. Therefore, supplier selection and evaluation in this field is not only an economic and industrial necessity but also directly affects patient health and public trust in the healthcare system [5]. Inefficient supplier selection may lead to increased costs, delays in drug production and distribution, and even risks to consumer health. Accordingly, designing and applying scientific and accurate approaches for prioritizing suppliers in the nanopharmaceutical supply chain is a valuable opportunity for applied research [6, 7].

In today's competitive environment, organizations evaluate suppliers not only based on economic criteria but also on environmental, social, technological, and quality standards [8]. Sustainability has become a key concept in supply chain management, requiring a balance between economic, environmental, and social objectives [9]. This issue is particularly important in the nanopharmaceutical industry, where the production and use of nanomaterials may pose potential risks to human health and the environment [10].

Despite these challenges, previous supplier selection studies in the pharmaceutical industry have mainly focused on traditional economic and operational factors, with limited attention given to integrating sustainability, supply chain resilience, and nanopharmaceutical-specific requirements into a comprehensive evaluation framework [3, 4]. On the other hand, the multi-criteria nature of supplier selection and the presence of uncertainty in evaluating criteria necessitate the use of multi-criteria decision-making (MCDM) methods. Therefore, developing models that can simultaneously evaluate diverse sustainability criteria under uncertainty is of significant importance.

Accordingly, the present study aims to develop a comprehensive framework for evaluating and ranking suppliers in the nanopharmaceutical industry by considering sustainability aspects. In this research, the criteria affecting supplier selection are first identified through an extensive review of the relevant literature and by collecting expert opinions. Then, the relative importance of each criterion is determined using the Analytical Hierarchy Process (AHP). Subsequently, supplier performance is evaluated based on the

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identified criteria, and finally, supplier ranking is carried out using the Fuzzy ELECTOR method. The use of a fuzzy approach enables the modeling of uncertainty and the subjective judgments of decision-makers, thereby improving the accuracy and realism of the results.
This study has several innovative aspects. First, it proposes a comprehensive supplier evaluation framework for the nanopharmaceutical industry by integrating 46 criteria across 11 dimensions, including quality and compliance, technical capability and innovation, safety and risk, cost, logistics, sustainability, scalability, relationships, reputation, nanopharmaceutical-specific characteristics, and supply chain resilience. This enables a holistic and sustainability-oriented assessment of suppliers. Compared with existing studies, the proposed framework incorporates a broader range of criteria, particularly those related to nanopharmaceutical-specific requirements, sustainability, and supply chain resilience. Second, the Fuzzy ELECTOR method is applied for the first time to the supplier selection problem. This method integrates the perspectives of the ELECTRE and VIKOR methods, forming a new multi-criteria decision-making approach. The combination of these two methods enhances the reliability of supplier ranking results.

1.1. Research questions

In line with the research objectives, the main research question is formulated as follows:
How can suppliers in the nanopharmaceutical industry be evaluated and ranked considering sustainability criteria?
To address this main question, the following sub-questions are proposed:

- What are the most important criteria influencing supplier selection in the nanopharmaceutical industry?
- What are the weights and relative importance of the identified criteria?
- How do the candidate suppliers perform with respect to the identified criteria?
- What is the final ranking of suppliers using the Fuzzy ELECTOR method?

1.2. Review of Previous Studies

A large number of studies have addressed supplier ranking in the pharmaceutical sector, which are reviewed in this section.
Pourghahreman and Ghatari [11] investigated the supplier selection problem in an agent-based pharmaceutical supply chain. Using expert opinions, they identified ten quantitative and qualitative criteria for supplier evaluation and applied two multi-criteria decision-making methods, TOPSIS and PROMETHEE II, for ranking suppliers. The results showed that qualitative criteria play a more significant role in the supplier selection process in the pharmaceutical industry, particularly under specific conditions in Iran.
Forghani, Sadjadi [12] examined the supplier selection problem in the pharmaceutical supply chain and proposed a hybrid approach to improve this process. They first reduced the supplier selection criteria using Principal Component Analysis (PCA), and then evaluated the importance and reliability of each supplier using Z-number-based TOPSIS. Finally, mixed-integer linear programming was used to determine supplier selection and optimal order allocation. The results demonstrated the high efficiency and accuracy of the proposed model.
Manivel and Ranganathan [13] studied the supplier selection problem in hospital pharmacies and proposed an approach to handle uncertainty in this process, considering criteria such as cost, delivery time, and flexibility. They used two multi-criteria decision-making methods, fuzzy AHPand fuzzy TOPSIS, to analyze criteria and evaluate suppliers. The comparison of the two methods showed that the proposed model can support optimal supplier selection and improve pharmacy efficiency.
Tavana, Nazari-Shirkouhi [14] investigated the selection of medical equipment suppliers and proposed an integrated framework based on quality engineering and resilience using Data Envelopment Analysis (DEA) and Z-numbers. They considered criteria such as flexibility, compliance with standards, excess capacity, cost, quality certification, and delivery time to evaluate supplier performance. The case study results in a cardiac hospital showed that the integrated framework provides more comprehensive information and higher efficiency in supplier selection compared to approaches focusing solely on quality or resilience. Alamroshan, La'li [15] examined the supplier selection problem in the medical equipment industry using a hybrid green and agile criteria approach. They applied fuzzy DEMATEL, fuzzy Best-Worst Method (BWM), fuzzy Analytic Network Process (ANP), and fuzzy VIKOR to analyze interrelationships among criteria, determine weights, and rank suppliers. The results indicated that criteria such as price and environmental indicators are among the most important factors in supplier selection.
Modibbo, Hassan [5] investigated the supplier selection problem in the pharmaceutical industry and proposed a multi-criteria decision-making model based on mixed-integer linear programming combined with the fuzzy TOPSIS method. They used PCA and triangular fuzzy numbers to determine the importance of criteria and rank suppliers. The results showed that the proposed model is capable of supporting objective and efficient decisions for selecting the best pharmaceutical supplier in real-world environments. Chakraborty, Raut [16] studied the supplier selection problem in the healthcare supply chain and proposed an integrated approach based on grey system theory and a new multi-criteria decision-making tool called MACONT. They evaluated six qualitative criteria, including cost, quality, delivery performance, reliability, responsiveness, and flexibility, and identified the best pharmaceutical supplier. The results indicated that this approach can accurately and robustly handle supplier selection in group decision-making environments under uncertainty. Chakraborty, Raut [17] also examined the supplier selection problem for medical equipment and pharmaceuticals in the healthcare sector. They applied the MABAC multi-criteria decision-making method under seven different fuzzy environments to identify the best supplier considering conflicting criteria. The results showed that all fuzzy variants of the MABAC method produced a consistent set of best and worst suppliers and were effective in handling uncertainty and differing decision-makers' judgments.
Chakraborty, Raut [18] investigated healthcare supplier selection under uncertainty and in an intuitionistic fuzzy environment. They proposed a two-stage approach in which Data Envelopment Analysis (DEA) was first used to shortlist the top four suppliers from 25 candidates. In the second stage, three multi-criteria decision-making methods—WASPAS, CODAS, and CoCoSo—were applied in an intuitionistic fuzzy environment to determine the best supplier. The results showed that all three methods produced similar rankings of the top supplier, and sensitivity analysis confirmed the stability of the methods. Bhosale and Umap [19] examined the supplier selection problem in the healthcare supply chain and used the fuzzy TOPSIS multi-criteria decision-making method in an intuitionistic fuzzy environment to evaluate the best supplier. They considered seven key criteria, including quality, delivery time, patient cost, and after-sales service. The results demonstrated that the proposed framework can be highly effective in fast and accurate supplier selection, particularly for antibiotic drug supply, and is also generalizable to other domains.
Sheykhizadeh, Ghasemi [4] investigated the supplier selection problem in the pharmaceutical supply chain and analyzed the role of lean manufacturing, agile manufacturing, resilience, and green criteria in preventing supply chain disruptions. Using a hybrid multi-criteria decision-making approach, including the BWM and ARAS, they evaluated the weights of criteria and ranked suppliers before and after the COVID-19 outbreak. The results showed that selecting suppliers based on quality, collaboration, safety stock, and environmental criteria can improve responsiveness to market needs and enhance disruption management. Chakraborty, Raut [6] studied the supplier selection problem in healthcare units and introduced a Dynamic Grey Relational Analysis approach to evaluate the performance of 25 pharmaceutical suppliers based on financial criteria. Using this method, suppliers were classified into three categories: reliable, moderate, and unreliable, and the best alternatives for order allocation

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were identified. Raveena and Umamaheswari [20] examined sustainable supplier selection in the pharmaceutical industry and proposed innovative evaluation criteria. They developed a hybrid framework based on fuzzy TOPSIS, grey relational analysis, and support vector regression to handle data uncertainty and accurately determine criteria weights. The results indicated that this approach enables comprehensive supplier evaluation and improves pharmaceutical inventory management while adhering to sustainability principles.

Arunyanart and Khumpang [21] investigated the evaluation and selection of medical equipment suppliers under uncertainty. They proposed a hybrid framework combining the Ordinal Priority Approach (OPA) and fuzzy AHP to weight key criteria and rank suppliers. The case study results in a hospital showed that the method improves group decision-making and enhances the efficiency of medical equipment procurement.

1.3. Research Gap Analysis

A review of the literature indicates that although several studies have addressed the supplier selection problem in the pharmaceutical industry, no comprehensive research has specifically focused on supplier selection in the nanopharmaceutical domain. In this study, an attempt has been made to identify the key criteria affecting supplier evaluation in the nanopharmaceutical supply chain.

Furthermore, 46 criteria have been considered for evaluating suppliers in the nanopharmaceutical industry, a level of comprehensiveness that has not been observed in previous studies. The list of criteria considered is presented in Figure 1. The criteria used for the first time in this study are highlighted in grey. As shown in Figure 1, the comprehensiveness of the criteria in this study is greater compared to previous research, including 14 new criteria in the scopes of sustainability, nanopharmaceutical-specific attributes, and supply chain resilience. Moreover, the proposed Fuzzy ELECTOR method, as an innovative approach, integrates the perspectives of the ELECTRE and VIKOR methods and has not previously been applied to the supplier selection problem.

Figure 1 – The criteria considered in the study and their classification

2. Research Methodology

In this section, the research methodology is presented. First, the research steps of the study are described, followed by a discussion of data gathering methods. Finally, the MCDM methods used in the study are explained.

2.1. Research Scope and Framework

The proposed framework is designed as a general approach for supplier evaluation and ranking in nanopharmaceutical supply chains rather than being restricted to a specific country or company. To empirically validate its applicability and feasibility, the proposed framework was implemented in a real-world case study involving an Iranian nanopharmaceutical supply chain.

The research steps are as follows:

Step 1 – Criteria Identification: Extraction of key criteria influencing nanopharmaceutical supplier selection based on the literature review and expert opinions.

Step 2 – Criteria Weighting: The AHP is used to determine the relative importance of each criterion. First, the weights of the criteria are evaluated through a pairwise comparison matrix questionnaire. In this questionnaire, response options are defined based on a standardized numerical scale, such that Equal Importance is assigned the value of 1, Very Weak Preference 3, Weak Preference 5, Strong Preference 7, and Very Strong Preference 9. In addition, the values 2, 4, 6, and 8 are used to represent intermediate judgments. After completing the questionnaires by experts, the geometric mean of their responses is calculated to obtain the final pairwise comparison matrix. Finally, the criteria weights are derived using the Analytical Hierarchy Process.

Step 3 –Evaluation of Suppliers Across Criteria: In this step, the scores of each alternative (supplier) under each criterion are determined using a decision matrix questionnaire. Linguistic variables are employed to assess these scores, and corresponding triangular fuzzy numbers are assigned to each linguistic term. The linguistic terms used in this questionnaire include Very Poor with the fuzzy number (0,1,2), Poor (1,2,3), Fairly Poor (2,3.5,5), Fair (4,5,6), Fairly Good (5,6.5,8), Good (7,8,9), and Very Good (8,9,10). After completing the questionnaires by experts, the arithmetic mean of their responses is calculated and considered as the final decision matrix.

Step 4 – Final Ranking: Application of the Fuzzy ELECTOR method to rank the suppliers and analyze the results.

2.2. Data gathering

To collect the required data in this study, an in-depth interview and two types of questionnaires were used. All of these instruments were administered to a group of experts. The expert sample was selected using a purposive sampling method to ensure the participation of individuals with relevant experience and specialized knowledge in the field of nanopharmaceuticals and its supply chain in the criteria evaluation process. The criteria for selecting the experts were as follows: (1) at least 8 years of work experience in the pharmaceutical or nanopharmaceutical industry; (2) a university degree in one of the related fields, including pharmaceutical sciences, medicinal chemistry, chemical engineering, nanotechnology, biotechnology, or industrial engineering; (3) holding managerial, research, or consulting positions in industry or academia. Based on these criteria, 12 qualified experts were selected as the expert sample.

The in-depth interview was conducted to identify and determine the evaluation criteria in Step 1. Two questionnaires were used in this study. The first was the Pairwise Comparison Questionnaire, which was employed to determine the weights of the criteria using the Analytic Hierarchy Process (AHP) and to collect experts' judgments regarding the relative importance of each criterion, corresponding to Step 2 of the research process. The second was the Decision Matrix Questionnaire, which was used to assign scores to each alternative (supplier) with respect to each criterion, corresponding to Step 3 of the study. In the second questionnaire, fuzzy numbers were used to assess the suppliers with respect to the considered criteria. The fuzzy numbers used in this study were adopted from the seven-point Likert fuzzy scale proposed in [22]. The fuzzy approach was selected because several supplier evaluation criteria are qualitative and their assessment relies primarily on subjective expert judgments, for which precise numerical information is unavailable or difficult to obtain.

Both questionnaires are standard and their validity has been confirmed in previous studies [23]. The reliability of the pairwise comparison questionnaire was confirmed with the inconsistency ratio. In this study, 11 main criteria were considered for supplier evaluation, each comprising a number of sub-criteria. Therefore, 12 pairwise comparison matrices were used to determine the criterion weights: one matrix was used to determine the weights of the main criteria, while the remaining 11 matrices were used to determine the weights of the sub-criteria within their respective categories. To calculate the inconsistency ratio, the experts' responses in the pairwise comparison questionnaire were first aggregated using the geometric mean method, after which the consistency ratio of each matrix was calculated. The maximum inconsistency ratio obtained across all pairwise comparison matrices was 0.03, indicating that there was no significant inconsistency among the experts' judgments. The inconsistency ratio for the main criteria was 0.015. The inconsistency ratios for the sub-criteria within each category are also reported in Table 1. Moreover, the reliability of the decision matrix questionnaire was confirmed with a Cronbach's alpha coefficient of 0.92.

The empirical case study was conducted in the Iranian nanopharmaceutical supply chain, focusing on the supplier evaluation and selection process of a company operating in this field. The

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company commenced its operations in 2015 with the aim of producing chemical and herbal nanomedicines at a quality level consistent with international standards. It offers its products through three production lines: nanocarriers, chemical nanomedicines, and herbal nanomedicines. The case was selected because supplier performance in this context needs to be assessed not only in terms of conventional procurement factors, such as price and delivery, but also with regard to quality and regulatory compliance, advanced technical capabilities, nanopharmaceutical-specific requirements, sustainability, and supply chain resilience.
Eight suppliers were selected as the decision alternatives. Given the relatively limited number of suppliers in Iran with established capabilities and relevant experience in nanopharmaceutical technologies, these suppliers represented the most relevant and practically available alternatives for the company. Their selection was based on the company's actual procurement context and its knowledge of the Iranian nanopharmaceutical market.
The evaluation framework comprised 46 criteria. The criteria were identified through a literature review and in-depth expert interviews, while their relative importance was determined using the AHP pairwise comparison questionnaire. The performance of the eight suppliers across the 46 criteria was assessed by 12 experts using the Decision Matrix Questionnaire and a seven-point linguistic scale. Each linguistic judgment was converted into the corresponding triangular fuzzy number, and the arithmetic mean of the experts' assessments was used to construct the aggregated fuzzy decision matrix. Accordingly, the values reported in Table 2 represent aggregated primary data based on expert judgments.
The data collection period covered April 2025 to April 2026. Although the empirical application was conducted in Iran, the proposed evaluation criteria are not inherently restricted to the Iranian context and may provide a basis for supplier evaluation in other nanopharmaceutical supply chains, subject to contextual adaptation.

2.3. Multi-Criteria Decision-Making Methods Used

2.3.1. Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) is one of the most widely used methods in multi-criteria decision-making. In this study, AHP is employed to determine the weights of the criteria.
The steps of the AHP method are as follows [24]:
Step 1- Construction of the pairwise comparison matrix: If there are n criteria and the numerical value of the comparison between criteria i and j is denoted by a_{ij}, then the pairwise comparison matrix is defined as an $n \times n$matrix as follows:

$$A = [a_{ij}]_{n\times n}, a_{ij} = \frac{1}{a_{ji}}, i, j = 1,2, \dots, n \quad (1)$$

Step 2- Normalization of the pairwise comparison matrix: Using the following equation, the pairwise comparison matrix is normalized, where a^*_{ij} represents the normalized value of a_{ij}.

$$a^*_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (2)$$

Step 3- Calculation of final weights: The final weight of each criterion is obtained using the following relation, where W_i represents the final weight of criterion i.

$$W_i = \sum_{i=1}^{n} \frac{a^*_{ij}}{n} \; i.j = 1.2. \dots .n \quad (3)$$

2.3.2. Fuzzy ELECTOR Method

The proposed ELECTOR method integrates the perspectives of both the VIKOR and ELECTRE methods to provide a more efficient and reliable ranking approach [25]. The VIKOR method considers a Positive Ideal Solution (PIS) and prioritizes an alternative that has a lower overall relative distance from the PIS, represented by the Utility Index, and a lower distance from the PIS for each criterion, represented by the Regret Index [26].
The ELECTRE method compares alternatives pairwise for each criterion. In these comparisons, the alternative with better performance is considered the winner, while the other alternative is considered the loser. ELECTRE prioritizes an alternative that wins in a greater number of criteria or in more important criteria, i.e., an alternative with a higher Pure Concordance Index. In addition, the ELECTRE method considers the intensity of winning and losing in the ranking process. It therefore prioritizes an alternative with stronger wins and weaker losses compared with other alternatives, i.e., an alternative with a higher Pure Discordance Index [27].
Although ELECTRE is effective in identifying pairwise outranking relationships and determining the relative intensity of wins and losses among alternatives, its ranking perspective does not explicitly consider the overall distance of an alternative from the Positive Ideal Solution (PIS), represented by the Utility Index, or its maximum deviation from the ideal solution at the criterion level, represented by the Regret Index. Consequently, an alternative may have strong outranking relationships with other alternatives without necessarily having the best overall proximity to the ideal solution.
On the other hand, VIKOR is effective in identifying compromise solutions based on overall utility and regret. However, its ranking logic does not explicitly capture the pairwise outranking structure among alternatives or indicate the extent to which an alternative outperforms other alternatives across a larger number of criteria or more important criteria. Therefore, two alternatives with similar performance in terms of utility and regret may not be sufficiently differentiated based on the Pure Concordance and Pure Discordance Indices.
The proposed ELECTOR method attempts to overcome the complementary limitations of VIKOR and ELECTRE by considering all four indices simultaneously. Accordingly, it prioritizes alternatives with lower Utility and Regret Indices, and higher Pure Concordance and Pure Discordance Indices.
The ELECTOR method reduces the likelihood that the final ranking is determined solely from a single perspective of alternative performance by simultaneously considering these four indices. This is particularly important in nanopharmaceutical supplier selection, as an alternative should not only demonstrate satisfactory overall performance but also avoid critical weaknesses and demonstrate stable and reliable superiority over competing suppliers. Therefore, the proposed approach is not merely a mechanical combination of the two methods; rather, it integrates the complementary decision-making perspectives of these two methods into a unified ranking logic.
This method takes the decision matrix and criteria weights as inputs. Let n be the number of criteria and m the number of alternatives. The decision matrix is defined as follows, where $\tilde{x}_{ij}$represents the score of alternative i under criterion j. Also, letting $w_j$denote the weight of criterion j, the weight vector is defined as:

$$\tilde{x} = [\tilde{x}_{ij}]_{m\times n} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & . & . & . & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & . & . & . & \tilde{x}_{2n} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & . & . & . & \tilde{x}_{mn} \end{bmatrix} \quad (4)$$

If two triangular fuzzy numbers $\tilde{A}=(a_1,a_2,a_3)$and $\tilde{B}=(b_1,b_2,b_3)$are given, their arithmetic operations are defined as follows:

$$\tilde{A}+\tilde{B}=(a_1+b_1, a_2+b_2, a_3+b_3) \quad (5)$$

$$\tilde{A}-\tilde{B}=(a_1-b_3, a_2-b_2, a_3-b_1) \quad (6)$$

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$$\tilde{A}\times\tilde{B}=(\min(a_1b_1,a_1b_3,a_3b_1,a_3b_3),a_2b_2,\max(a_1b_1,a_1b_3,a_3b_1,a_3b_3)) \quad (7)$$

$$\tilde{A}\div\tilde{B}=(\min\left(\frac{a_1}{b_1},\frac{a_1}{b_3},\frac{a_3}{b_1},\frac{a_3}{b_3}\right),\frac{a_2}{b_2},\max\left(\frac{a_1}{b_1},\frac{a_1}{b_3},\frac{a_3}{b_1},\frac{a_3}{b_3}\right)) \quad (8)$$

To defuzzify a triangular fuzzy number $\tilde{B}=(b_1,b_2,b_3)$, the Graded Mean Integration Representation (GMIR) method is used, as given by the following equation:

$$D(\tilde{B})=\frac{b_1+4b_2+b_3}{6} \quad (9)$$

Unlike the conventional centroid/Center of Area approach for a triangular fuzzy number, which is commonly expressed as ((a+b+c)/3), the GMIR method assigns greater importance to the modal value while retaining information from both the lower and upper bounds. This is appropriate for the present study because the fuzzy assessments are generated from linguistic judgments of experts, and the modal value represents the most representative assessment while the lower and upper values reflect the uncertainty associated with the judgment.

The steps of the ELECTOR method are presented in three phases:

Phase 1 – Calculation of Utility and Regret Indices

Step 1: Determination of the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS):

$FPIS=[\widetilde{fpis}_j=(l_j^+,m_j^+,u_j^+)]_{1\times n}$,

$$\widetilde{fpis}_j=\begin{cases}\max_i \tilde{x}_{ij} & \text{For the profit criterion j}\\ \min_i \tilde{x}_{ij} & \text{For the cost criterion j}\end{cases} \quad (10)$$

$FNIS=[\widetilde{fnis}_j=(l_j^-,m_j^-,u_j^-)]_{1\times n}$,

$$\widetilde{fnis}_j=\begin{cases}\min_i \tilde{x}_{ij} & \text{For the profit criterion j}\\ \max_i \tilde{x}_{ij} & \text{"For the cost criterion j}\end{cases} \quad (11)$$

where FPIS and FNIS are determined based on benefit and cost criteria, respectively.

Step 2: Computation of the normalized distance matrix from FPIS ($\tilde{D}=[\tilde{d}_{ij}]_{m\times n}$):

$$\tilde{d}_{ij}=\begin{cases}(\widetilde{fpis}_j-\tilde{x}_{ij})/(u_j^+-l_j^-) & \text{For the profit criterion j}\\ (\tilde{x}_{ij}-\widetilde{fpis}_j)/(u_j^--l_j^+) & \text{For the cost criterion j}\end{cases} \quad (12)$$

Step 3: Calculation of overall utility $\tilde{S}_i$and regret $\tilde{R}_i$:

$$\tilde{S}_i=\sum_{j=1}^{m}(w_j\times\tilde{d}_{ij}) \quad (13)$$

$$\tilde{R}_i=\max_j(w_j\times\tilde{d}_{ij}) \quad (14)$$

Phase 2 – Computation of Concordance and Discordance Indices

Step 4: Normalized decision matrix ($\tilde{Z}=[z_{ij}]_{m\times n}$):

$$\tilde{z}_{ij}=\frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^{m}\tilde{x}_{ij}^2}} \quad (15)$$

Step 5: Weighted normalized matrix ($\tilde{V}=[\tilde{v}_{ij}]_{m\times n}$):

$$\tilde{v}_{ij}=\tilde{w}_j\times\tilde{z}_{ij} \quad (16)$$

Step 6 – For each pair of alternatives $k$and l, the set of criteria is divided into two subsets: the concordance set and the discordance set. Since the weighted score of each alternative under each criterion $(\tilde{v}_{ij}=(v_{ij}^L,v_{ij}^M,v_{ij}^U))$is represented by a triangular fuzzy number and consists of three values, three concordance sets are defined for each pair of alternatives $k$and l, denoted by $CSET_{kl}^L$, $CSET_{kl}^M$, and $CSET_{kl}^U$, respectively.

These sets represent the criteria for which alternative $k$is better than or equal to alternative l based on the lower, middle, and upper values of their scores in the decision matrix, respectively.

The discordance sets, which are the complements of $CSET_{kl}^L$, $CSET_{kl}^M$, and $CSET_{kl}^U$, are denoted by $DSET_{kl}^L$, $DSET_{kl}^M$, and $DSET_{kl}^U$, respectively.

These sets are obtained using the following relations.

$$CSET_{kl}^L=\left\{j\left|\begin{matrix}v_{kj}^L\geq v_{lj}^L\text{, if j is the benefit criterion}\\ \text{or}\\ v_{kj}^L\leq v_{lj}^L\text{, if j is the cost criterion}\end{matrix}\right.\right\} \quad (17)$$

$$DSET_{kl}^L=\left\{j\left|\begin{matrix}v_{kj}^L< v_{lj}^L\text{, if j is the benefit criterion}\\ \text{or}\\ v_{kj}^L> v_{lj}^L\text{, if j is the cost criterion}\end{matrix}\right.\right\} \quad (18)$$

$$CSET_{kl}^M=\left\{j\left|\begin{matrix}v_{kj}^M\geq v_{lj}^M\text{, if j is the benefit criterion}\\ \text{or}\\ v_{kj}^M\leq v_{lj}^M\text{, if j is the cost criterion}\end{matrix}\right.\right\} \quad (19)$$

$$DSET_{kl}^M=\left\{j\left|\begin{matrix}v_{kj}^M< v_{lj}^M\text{, if j is the benefit criterion}\\ \text{or}\\ v_{kj}^M> v_{lj}^M\text{, if j is the cost criterion}\end{matrix}\right.\right\} \quad (20)$$

$$CSET_{kl}^U=\left\{j\left|\begin{matrix}v_{kj}^U\geq v_{lj}^U\text{, if j is the benefit criterion}\\ \text{or}\\ v_{kj}^U\leq v_{lj}^U\text{, if j is the cost criterion}\end{matrix}\right.\right\} \quad (21)$$

$$DSET_{kl}^U=\left\{j\left|\begin{matrix}v_{kj}^U< v_{lj}^U\text{, if j is the benefit criterion}\\ \text{or}\\ v_{kj}^U> v_{lj}^U\text{, if j is the cost criterion}\end{matrix}\right.\right\} \quad (22)$$

Step 7 – Calculation of the Concordance and Discordance Matrices: These matrices are of size $m\times m$. The element (k,l)in the concordance matrix $\tilde{C}_{kl}=(c_{kl}^L,c_{kl}^M,c_{kl}^U)$ is obtained by summing the weights of the criteria belonging to the concordance sets when comparing alternatives $k$and l, as shown in the following equations:

$$c_{kl}^L=\sum w_j\text{ , } j\in CSET_{kl}^L \quad (23)$$

$$c_{kl}^M=\sum w_j\text{ , } j\in CSET_{kl}^M \quad (24)$$

$$c_{kl}^U=\sum w_j\text{ , } j\in CSET_{kl}^U \quad (25)$$

Furthermore, the element (k,l)in the discordance matrix $\tilde{D}_{kl}=(d_{kl}^L,d_{kl}^M,d_{kl}^U)$is calculated using the following equations:

$$d_{kl}^L=\frac{\sum_j\{|v_{kj}^L-v_{lj}^U|, j\in DSET_{kl}^L\}}{\sum_j\{|v_{kj}^L-v_{lj}^U|\}} \quad (26)$$

$$d_{kl}^M=\frac{\sum_j\{|v_{kj}^M-v_{lj}^M|, j\in DSET_{kl}^M\}}{\sum_j\{|v_{kj}^M-v_{lj}^M|\}} \quad (27)$$

$$d_{kl}^U=\frac{\sum_j\{|v_{kj}^U-v_{lj}^L|, j\in DSET_{kl}^U\}}{\sum_j\{|v_{kj}^U-v_{lj}^L|\}} \quad (28)$$

Step 8 – Calculation of the Net Concordance Index (PCI) and Net Discordance Index (PDI): For each alternative, the Net Concordance Index and Net Discordance Index, denoted by $\widetilde{PCI}_i$ and $\widetilde{PDI}_i$, respectively, are calculated using the following equations:

$$\widetilde{PCI}_i=\sum_{k=1}^{m}\tilde{C}_{ik}-\sum_{k=1}^{m}\tilde{C}_{ki} \quad (29)$$

$$\widetilde{PDI}_i=\sum_{k=1}^{m}\tilde{D}_{ik}-\sum_{k=1}^{m}\tilde{D}_{ki} \quad (30)$$

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Phase 3 – Ranking of Alternatives

Step 9 – Calculation of the ELECTOR Index ($\tilde{Q}_i$): The ELECTOR index for each alternative is calculated using the following equation based on the utility index $\tilde{S}_i = (S_i^L, S_i^M, S_i^U)$, regret index $\tilde{R}_i = (R_i^L, R_i^M, R_i^U)$, net concordance index $\widetilde{PCI}_i = (PCI_i^L, PCI_i^M, PCI_i^U)$, and net discordance index $\widetilde{PDI}_i = (PDI_i^L, PDI_i^M, PDI_i^U)$:

$$\tilde{Q}_i = \nu_1 \times \left[\frac{\tilde{S}_i - \tilde{S}^+}{S^{max} - S^{min}}\right] + \nu_2 \times \left[\frac{\tilde{R}_i - \tilde{R}^+}{R^{max} - R^{min}}\right] - \nu_3 \times \left[\frac{\widetilde{FPCI}_i - \widetilde{FPCI}^+}{FPCI^{max} - FPCI^{min}}\right] - \nu_4 \times \left[\frac{\widetilde{FPDI}_i - \widetilde{FPDI}^+}{FPDI^{max} - FPDI^{min}}\right] \quad (31)$$

$$(\nu_1 + \nu_2 + \nu_3 + \nu_4 = 1)$$

$$\tilde{S}^+ = \min_i \tilde{S}_i \qquad S^{max} = \max_i S_i^U \qquad S^{min} = \min_i S_i^L$$

$$\tilde{R}^+ = \min_i \tilde{R}_i \qquad R^{max} = \max_i R_i^U \qquad R^{min} = \min_i R_i^L$$

$$\widetilde{PCI^+} = \min_i \widetilde{PCI}_i \qquad PCI^{max} = \max_i PCI_i^U \qquad PCI^{min} = \min_i PCI_i^L$$

$$\widetilde{PDI^+} = \min_i \widetilde{PDI}_i \qquad PDI^{max} = \max_i PDI_i^U \qquad PDI^{min} = \min_i PDI_i^L$$

where $\nu_1, \nu_2, \nu_3, \nu_4$ are the weights of utility, regret, net concordance, and net discordance indices, respectively.

Step 10: Ranking of alternatives in ascending order of the defuzzified ELECTOR index. The best alternative is the one with the smallest ELECTOR value.

The proposed method in this study is a modified version of the ELECTRE method, referred to as ELECTOR. In the conventional ELECTRE method, the pure concordance matrix and pure discordance matrix are combined. This requires determining the concordance threshold and discordance threshold, which are then used to convert the respective matrices into binary matrices known as the dominant concordance matrix and dominant discordance matrix.

In the ELECTRE method, two indices are calculated for each alternative: the pure concordance index, which represents the total weight of the criteria on which one alternative outperforms another; a higher value indicates a higher priority for the alternative, and the pure discordance index, which reflects the intensity of losses or wins. An alternative is considered preferable when the difference between the intensity of its wins and the intensity of its losses is smaller. These two indices are calculated using Equations (29) and (30), respectively. Subsequently, these two indices are combined with the utility and regret indices, calculated using the VIKOR method, through Equation (31).

In other words, the proposed ELECTOR method eliminates the need to determine the concordance and discordance threshold values required in the conventional ELECTRE method.

The sum of the Concordance Set for alternative with respect to alternative ($CSET_{kl}$) represents the set of criteria on which alternative performs better than alternative. The sum of the weights of these criteria represents the Concordance value of alternative with respect to alternative (c_{kl}). In the fuzzy case, each element of the Weighted Normalized Matrix is a triangular fuzzy number with three values. Therefore, three values—lower, middle, and upper—are considered for the performance of each alternative under each criterion. Accordingly, a separate Concordance Set and Discordance Set are determined for each of these three values. For the lower, middle, and upper values, the corresponding Concordance Sets are denoted by $CSET_{kl}^L$, $CSET_{kl}^M$, and $CSET_{kl}^U$, respectively, and are calculated using Equations (17), (19), and (21). Similarly, for the lower, middle, and upper values, the corresponding Discordance Sets are denoted by $DSET_{kl}^L$, $DSET_{kl}^M$, and $DSET_{kl}^U$, respectively, and are calculated using Equations (18), (20), and (22). As shown in Equations (17)–(22), no alpha-cut operation is applied.

3. Results

In this section, the results obtained from the implementation of the research steps are presented.

3.1. Identified Criteria and Their Weights

In order to identify the effective criteria for evaluating and prioritizing nanopharmaceutical suppliers, both the literature review and the results of in-depth interviews with experts were used. The list of identified criteria is presented in Figure 1. The criteria used for the first time in this study are highlighted in grey. In Table 1, the weights of the criteria obtained using the Analytical Hierarchy Process (AHP) are also shown.

The results indicate that compliance with GMP and regulatory requirements (C1,1), unit product price (C4,1), and the ability to produce complex nanostructures (liposomes, polymers, dendrimers, etc.) (C2,1) have the highest weights and are therefore the most important criteria, respectively.

Table 1. Weights of supplier evaluation criteria

3.2. Suppliers and Their Evaluation

In this study, with the participation of experts, eight suppliers were considered as decision alternatives and were evaluated using a decision matrix questionnaire completed by the experts. The resulting decision matrix is presented in Table 2.

Table 2. Decision Matrix

3.3. Supplier Ranking Using the Fuzzy ELECTOR Method

The results of supplier ranking using the Fuzzy ELECTOR method are presented in Table 3. For comparison purposes, the ranking results obtained from other methods, including F-ELECTRE [28], F-VIKOR [26], F-VISIS [29], F-RVIKOR [23], F-PROMETHEE [30], F-TOPSIS [31], F-COCOSO [32], F-TOPKOR [22], and F-ARASKOR [33], are also included in this table.

Table 3. Final ranking of suppliers

To evaluate the results, Pearson correlation coefficients between each pair of methods were calculated and presented in Table 4. A higher Pearson correlation coefficient between two methods indicates a greater level of agreement and consistency between their results. In contrast, lower values indicate greater differences and inconsistencies between the outcomes of the methods [34].

The results show that the Fuzzy ELECTOR method has the highest total Pearson correlation coefficient among the different methods. This indicates that the results of the Fuzzy ELECTOR method have the highest level of agreement with other methods and provide a compromise solution among the different approaches.

Table 4. Pearson correlation coefficients between different methods

3.4. Sensitivity Analysis

To evaluate the stability of the rankings obtained from the F-ELECTOR method with respect to changes in criteria weights, two types of sensitivity analyses were performed.

In the first sensitivity analysis, the weight of each criterion was individually increased and then decreased by 30% from its original value. Accordingly, two scenarios were generated for each criterion, resulting in a total of 92 scenarios (46 × 2). In each scenario, the weights of the remaining criteria were proportionally adjusted using Equation (32) to ensure that the total sum of weights remained equal to 1 [35]. In this equation, W_i^n, W_i^o, W_j^n, and W_j^o represent the updated and original weights of criteria i and j, respectively.

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$$W_i^n = (1 - W_j^n) \times \frac{W_i^o}{(1-W_j^o)} \tag{32}$$

For each scenario, supplier rankings were recalculated using the Fuzzy ELECTOR method and compared with the baseline ranking (Scenario 0). The results of the first sensitivity analysis are presented in Figure (2.A). In this figure, S_j denotes the j-th scenario. The results indicate that changes in criteria weights do not lead to significant changes in supplier rankings (particularly for the top four suppliers), demonstrating that the results of the Fuzzy ELECTOR method are not highly sensitive to a 30% variation in criteria weights.

In the second sensitivity analysis, the most important criterion (compliance with GMP and regulatory requirements, with a weight of 0.0593) was gradually reduced in 10 steps until it reached zero. In this case, the weights of the other criteria were adjusted using Equation (32). The results of the second sensitivity analysis are presented in Figure (2.B). The results show that the first and second ranks remain unchanged across all scenarios, while only minor changes occur in the third and fourth ranks. This further confirms the robustness and low sensitivity of the Fuzzy ELECTOR results with respect to changes in the weight of the most important criterion.

Figure 2. Results of the sensitivity analyses under changes in criterion weights

Moreover, to assess the sensitivity of the results to supplier elimination, the five suppliers ranked fourth to eighth (S2, S5, S4, S1, and S6) were sequentially removed, and the rankings of the top three suppliers (S8, S3, and S7) were examined after each elimination. The results are presented in Table 5. The findings show that the elimination of any of these suppliers did not affect the rankings of the three top-ranked suppliers: S8 remained first, S3 remained second, and S7 remained third in all scenarios and no rank reversal was observed among the leading alternatives. These results provide additional empirical evidence for the robustness of the proposed ELECTOR ranking under changes in the supplier set. This stability may partly be related to the simultaneous consideration of utility, regret, concordance, and discordance information in the ELECTOR framework.

Table 5. Results of the sensitivity analysis of supplier elimination

4. Conclusion

In this study, a hybrid model based on the AHP and the Fuzzy ELECTOR methods was developed to prioritize suppliers in the nanopharmaceutical supply chain. First, through a literature review and expert interviews, 46 criteria grouped into 11 main categories were identified for supplier evaluation. Then, the weights of the criteria were determined using the AHP method. Finally, eight suppliers were evaluated based on these criteria and ranked using the Fuzzy ELECTOR method.

4.1. Discussion

The results showed that the categories of "Quality and Compliance," "Technical Capability and Innovation," and "Specialized Nanopharmaceutical Features" are the most important dimensions in supplier evaluation. Moreover, compliance with GMP and regulatory requirements (C1,1), unit product price (C4,1), and the ability to produce complex nanostructures (liposomes, polymers, dendrimers, etc.) (C2,1) were identified as the most important criteria, respectively. These findings indicate that supplier selection in nanopharmaceutical supply chains is driven not only by economic considerations but also by other aspects including regulatory, technical, and product-specific risks.

The highest weight assigned to GMP compliance can be explained by its fundamental role in ensuring product quality, safety, and manufacturing consistency. In nanopharmaceutical production, variations in raw materials and manufacturing conditions can substantially affect product characteristics and performance. Therefore, GMP compliance can be viewed as a prerequisite or threshold condition for supplier suitability rather than simply another quality criterion. Non-compliance may result in quality failures, batch rejection, production disruptions, recalls, regulatory penalties, and reputational damage. Moreover, compliance with GMP and regulatory requirements contributes to patient safety and reduces legal and regulatory risks [36]. Consistent compliance also supports production stability and reproducibility and can reduce indirect costs associated with waste, recalls, and delivery delays [37, 38]. Thus, the high weight assigned to GMP reflects its simultaneous influence on clinical, regulatory, operational, and economic risks.

"Technical Capability and Innovation" was also among the most influential dimensions. Nanopharmaceutical manufacturing requires advanced technical capabilities to control complex processes, maintain consistent product characteristics, and respond to evolving technological requirements. Strong technical capabilities can reduce process and quality failures, while supplier innovation can support new product development, improve drug performance, enhance flexibility, and strengthen supply chain resilience [36, 39].

The high importance of "Specialized Nanopharmaceutical Features," particularly nanostructure capability, is attributable to the distinctive characteristics of nanopharmaceutical products. Parameters such as nanoparticle size and size distribution, formulation stability, material biocompatibility, and process reproducibility can directly affect therapeutic effectiveness, patient safety, and regulatory acceptance [40, 41]. Consequently, the ability to reliably produce and control complex nanostructures represents a fundamental technical capability rather than merely an additional supplier advantage.

Importantly, the finding that nanostructure capability received a higher weight than cost can be interpreted from a risk-based perspective. While price primarily represents economic efficiency, nanostructure capability determines whether the supplier can technically deliver the required product with consistent quality. A lower purchase price may be outweighed by downstream costs arising from failed batches, waste, rework, production delays, quality problems, or regulatory rejection. Therefore, in nanopharmaceutical supply chains, technical feasibility and risk reduction may be more critical than short-term price savings. This finding suggests that price becomes meaningful only after suppliers satisfy the minimum technical, quality, and regulatory requirements.

Overall, the findings suggest a hierarchical logic in nanopharmaceutical supplier evaluation: regulatory and quality compliance constitute the foundation of supplier suitability, while technical and nanostructure capabilities determine the supplier's ability to reliably support advanced production. Economic factors such as price remain important but should be considered alongside these technical and risk-related dimensions. Therefore, supplier selection in nanopharmaceutical supply chains should move beyond conventional cost-oriented approaches and incorporate specialized quality, regulatory, technical, and nanotechnology-related capabilities. The proposed 46-criteria framework provides such a comprehensive basis for evaluating suppliers while accounting for the multidimensional risks and requirements of the nanopharmaceutical industry.

4.2. Research Limitations and Implications

The questionnaires used in this study were completed based on the opinions of a sample of experts in Iran. Therefore, if the number of experts changes or if their geographical scope is altered, the weighting of the criteria and, consequently, the ranking of suppliers may also change. Nevertheless, the proposed evaluation framework can be adapted to other nanopharmaceutical supply chains by incorporating context-specific expert judgments and supplier information. Moreover, the criteria considered in this research can assist managers and decision-makers in the pharmaceutical industry in selecting

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suppliers through a more comprehensive and accurate evaluation process. Considering each criterion reflects attention to a specific aspect of decision-making, and the comprehensiveness of the criteria included in this study helps decision-makers in this field take various aspects into account when making their decisions. The findings indicate that nanopharmaceutical supplier selection should not focus solely on price; rather, GMP compliance, quality, regulatory requirements, and nanostructure-related technical capabilities should be prioritized. Accordingly, managers are recommended to first screen suppliers based on essential quality and regulatory requirements and then rank the qualified alternatives using a comprehensive set of economic, technical, sustainability, and resilience criteria.

The results also emphasize the need for multidimensional supplier evaluation and the use of ranking results to develop and improve lower-performing suppliers. The sensitivity analysis further showed that the rankings remained relatively stable under substantial changes in criterion weights. Therefore, the results can provide a reliable basis for managerial decision-making, while criterion weights should be periodically reviewed and updated in response to changes in technology, regulations, market conditions, and supply chain risks.

4.3. Future Research Directions

There are several avenues for future research development and extension. One of the most important is the generalization of the study to other related fields in the pharmaceutical industry, such as biopharmaceuticals and advanced vaccines, which share similar levels of sensitivity and complexity with nanopharmaceuticals. Additionally, other multi-criteria decision-making methods can be employed in future studies. The use of type-2 fuzzy numbers may also represent another promising direction for future research.

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Table 1. Weights of supplier evaluation criteria

Category	Weight	Inconsistency rate	Criterion	Type	Weight in Category	Final Weight
Quality and Compliance (C1)	0.1367	0.006	C1,1	Benefit	0.4335	0.0593
			C1,2	Benefit	0.205	0.028
			C1,3	Cost	0.2176	0.0297
			C1,4	Benefit	0.1438	0.0197
Technical Capability and Innovation (C2)	0.1141	0.012	C2,1	Benefit	0.2902	0.0331
			C2,2	Benefit	0.2689	0.0307
			C2,3	Benefit	0.2438	0.0278
			C2,4	Benefit	0.1972	0.0225
Safety and Risk (C3)	0.1014	0.003	C3,1	Benefit	0.2868	0.0291
			C3,2	Benefit	0.263	0.0267
			C3,3	Benefit	0.2381	0.0242
			C3,4	Benefit	0.2122	0.0215
Cost (C4)	0.1014	0.033	C4,1	Cost	0.3773	0.0383
			C4,2	Cost	0.2582	0.0262
			C4,3	Benefit	0.1915	0.0194
			C4,4	Benefit	0.173	0.0175
Delivery and Logistics (C5)	0.0808	0.004	C5,1	Cost	0.2947	0.0238
			C5,2	Benefit	0.2657	0.0215
			C5,3	Benefit	0.2308	0.0187
			C5,4	Benefit	0.2087	0.0169
Sustainability (C6)	0.1045	0.007	C6,1	Benefit	0.1524	0.0159
			C6,2	Benefit	0.1429	0.0149
			C6,3	Benefit	0.1357	0.0142

Category	Weight	Inconsistency rate	Criterion	Type	Weight in category	Final Weight
Sustainability (C6)	0.1045	0.007	C6,4	Cost	0.1311	0.0137
			C6,5	Cost	0.1172	0.0122
			C6,6	Cost	0.1094	0.0114
			C6,7	Benefit	0.1095	0.0114
			C6,8	Benefit	0.1019	0.0106
Capacity and Scalability (C7)	0.0776	0.012	C7,1	Benefit	0.3996	0.031
			C7,2	Benefit	0.3175	0.0246
			C7,3	Benefit	0.283	0.022
Relationships (C8)	0.0534	0.001	C8,1	Benefit	0.3863	0.0206
			C8,2	Benefit	0.3187	0.017
			C8,3	Benefit	0.2951	0.0158
Reputation and Track Record (C9)	0.0514	0.000	C9,1	Benefit	0.3788	0.0195
			C9,2	Benefit	0.3375	0.0173
			C9,3	Benefit	0.2838	0.0146
Specialized Nanodrug Features (C10)	0.1119	0.006	C10,1	Benefit	0.2655	0.0297
			C10,2	Benefit	0.25	0.028
			C10,3	Benefit	0.1849	0.0207
			C10,4	Benefit	0.1571	0.0176
			C10,5	Benefit	0.1425	0.0159
Supply Chain Resilience (C11)	0.0668	0.01	C11,1	Benefit	0.2942	0.0197
			C11,2	Benefit	0.2809	0.0188
			C11,3	Benefit	0.2254	0.0151
			C11,4	Benefit	0.1995	0.0133

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Table 2. Decision Matrix

	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6	Supplier 7	Supplier 8
C1,1	(2,3.25,4.5)	(1.5,2.62,3.75)	(4,5.12,6.25)	(1.17,2.25,3.33)	(3.67,4.75,5.83)	(1.25,2.38,3.5)	(6.17,7.38,8.58)	(6.33,7.5,8.67)
C1,2	(1.67,2.88,4.08)	(4.58,5.88,7.17)	(2.17,3.62,5.08)	(3.83,4.88,5.92)	(4.92,6.38,7.83)	(4.92,6.38,7.83)	(6,7.12,8.25)	(6.33,7.38,8.42)
C1,3	(3.58,4.62,5.67)	(1.5,2.62,3.75)	(5,6.38,7.75)	(6.17,7.25,8.33)	(6.25,7.38,8.5)	(3.5,4.62,5.75)	(1.75,3,4.25)	(1.42,2.5,3.58)
C1,4	(2.33,3.62,4.92)	(5.92,7,8.08)	(4.33,5.75,7.17)	(2.83,4.25,5.67)	(4.58,6,7.42)	(1.92,3,4.08)	(4.92,6,7.08)	(1.75,3,4.25)
C2,1	(2.33,3.75,5.17)	(3.42,4.5,5.58)	(5.08,6.5,7.92)	(5.83,7.12,8.42)	(1.5,2.62,3.75)	(2.25,3.62,5)	(1.33,2.5,3.67)	(6,7.25,8.5)
C2,2	(2.25,3.75,5.25)	(6.25,7.38,8.5)	(2.75,4.12,5.5)	(1.17,2.25,3.33)	(2.5,3.88,5.25)	(2.67,4,5.33)	(1.25,2.38,3.5)	(2,3.5,5)
C2,3	(1.17,2.25,3.33)	(3.92,5,6.08)	(3.92,5,6.08)	(3.67,4.75,5.83)	(2.58,3.88,5.17)	(2,3.38,4.75)	(5.75,7,8.25)	(6.33,7.5,8.67)
C2,4	(5.75,6.88,8)	(6.5,7.62,8.75)	(2.17,3.62,5.08)	(6,7.12,8.25)	(1.67,2.75,3.83)	(6.5,7.62,8.75)	(5.25,6.62,8)	(4,5.12,6.25)
C3,1	(1.5,2.5,3.5)	(2.42,3.88,5.33)	(1.92,3.38,4.83)	(6.25,7.38,8.5)	(4.25,5.38,6.5)	(4.75,6.12,7.5)	(6.17,7.25,8.33)	(1.83,3.12,4.42)
C3,2	(6.25,7.38,8.5)	(2.17,3.25,4.33)	(6,7.12,8.25)	(2.5,3.75,5)	(1.83,3,4.17)	(2.25,3.75,5.25)	(6.5,7.62,8.75)	(4.25,5.38,6.5)
C3,3	(5.25,6.62,8)	(1.25,2.38,3.5)	(6.25,7.38,8.5)	(2.17,3.5,4.83)	(6.17,7.25,8.33)	(4.83,6.25,7.67)	(2.67,4,5.33)	(1.67,2.75,3.83)
C3,4	(1.33,2.5,3.67)	(2.42,3.88,5.33)	(3.83,4.88,5.92)	(3.58,4.62,5.67)	(6.5,7.62,8.75)	(2.33,3.75,5.17)	(1.83,3.12,4.42)	(2.42,3.75,5.08)
C4,1	(1.17,2.25,3.33)	(3.92,5,6.08)	(5.92,7.12,8.33)	(2,3.38,4.75)	(2.5,3.75,5)	(4,5.25,6.5)	(5.75,7,8.25)	(3.5,4.75,6)
C4,2	(1.58,2.75,3.92)	(2,3.12,4.25)	(4.25,5.62,7)	(6.83,7.88,8.92)	(6.42,7.5,8.58)	(4.83,6.25,7.67)	(1.17,2.25,3.33)	(4.17,5.25,6.33)
C4,3	(2,3.38,4.75)	(2.25,3.5,4.75)	(5.92,7,8.08)	(6.83,7.88,8.92)	(3,4.38,5.75)	(2.42,3.75,5.08)	(2.42,3.88,5.33)	(2.92,4.38,5.83)
C4,4	(2.08,3.5,4.92)	(1.08,2.12,3.17)	(4.92,6.38,7.83)	(1.67,2.75,3.83)	(1.25,2.38,3.5)	(1.5,2.62,3.75)	(1.5,2.62,3.75)	(4.75,6.12,7.5)
C5,1	(5.17,6.38,7.58)	(4.33,5.62,6.92)	(4.42,5.62,6.83)	(5.92,7,8.08)	(1.92,3.12,4.33)	(4.83,6.12,7.42)	(5.92,7.12,8.33)	(6.17,7.25,8.33)
C5,2	(6,7,8)	(3.5,4.5,5.5)	(2.42,3.88,5.33)	(3.83,4.88,5.92)	(1.75,2.88,4)	(5.92,7.12,8.33)	(1.25,2.38,3.5)	(3.75,4.88,6)
C5,3	(1.5,2.62,3.75)	(5,6.38,7.75)	(2.08,3.5,4.92)	(4.83,6.25,7.67)	(2.17,3.62,5.08)	(1.42,2.5,3.58)	(3.17,4.5,5.83)	(6.08,7.25,8.42)
C5,4	(5.67,6.75,7.83)	(3.17,4.25,5.33)	(5.75,7,8.25)	(1.5,2.5,3.5)	(1.5,2.62,3.75)	(1.33,2.5,3.67)	(5.42,6.75,8.08)	(5.67,7,8.33)
C6,1	(1.92,3.25,4.58)	(1.83,3.25,4.67)	(4.83,6.25,7.67)	(1.08,2.12,3.17)	(1.42,2.5,3.58)	(6.5,7.5,8.5)	(1.42,2.5,3.58)	(1.92,3.12,4.33)
C6,2	(6.42,7.5,8.58)	(4.42,5.5,6.58)	(1.33,2.5,3.67)	(4.08,5.25,6.42)	(3.83,5,6.17)	(1.33,2.5,3.67)	(5.5,6.62,7.75)	(6.08,7.25,8.42)
C6,3	(4.92,6.25,7.58)	(3.58,4.75,5.92)	(1.75,2.88,4)	(3.5,4.62,5.75)	(2.08,3.25,4.42)	(1.75,2.75,3.75)	(3.08,4.5,5.92)	(4.42,5.5,6.58)
C6,4	(2.25,3.75,5.25)	(2.25,3.62,5)	(1.5,2.62,3.75)	(2.58,3.88,5.17)	(6.08,7.25,8.42)	(2.33,3.75,5.17)	(6,7.12,8.25)	(1.92,3,4.08)
C6,5	(4.33,5.75,7.17)	(4.17,5.25,6.33)	(2.33,3.75,5.17)	(1.83,2.88,3.92)	(2.67,4,5.33)	(2,3.38,4.75)	(6.42,7.5,8.58)	(2.42,3.88,5.33)
C6,6	(6.17,7.38,8.58)	(1.58,2.62,3.67)	(2.08,3.38,4.67)	(2.75,4.12,5.5)	(3.75,4.88,6)	(4.25,5.62,7)	(1.58,2.62,3.67)	(3.33,4.38,5.42)
C6,7	(4.58,5.62,6.67)	(6.33,7.5,8.67)	(4.67,6,7.33)	(6.25,7.38,8.5)	(5.25,6.62,8)	(4.75,6.12,7.5)	(6.33,7.5,8.67)	(1.33,2.5,3.67)
C6,8	(1.75,2.88,4)	(2.33,3.62,4.92)	(6.33,7.5,8.67)	(1.33,2.38,3.42)	(2.08,3.5,4.92)	(4.58,6,7.42)	(1.58,2.62,3.67)	(1.5,2.62,3.75)
C7,1	(1.83,3.25,4.67)	(6.33,7.5,8.67)	(1.67,2.88,4.08)	(1.25,2.25,3.25)	(6.08,7.12,8.17)	(2.75,4.12,5.5)	(4.5,5.88,7.25)	(6.75,7.75,8.75)
C7,2	(4.75,6.25,7.75)	(2.33,3.75,5.17)	(4.58,6,7.42)	(4.58,6,7.42)	(3.08,4.38,5.67)	(4.08,5.38,6.67)	(6.5,7.62,8.75)	(2.42,3.75,5.08)
C7,3	(4.08,5.25,6.42)	(2,3.38,4.75)	(4.75,6.12,7.5)	(1.5,2.75,4)	(6.33,7.38,8.42)	(1.5,2.62,3.75)	(6.25,7.38,8.5)	(4,5.12,6.25)
C8,1	(4.5,5.62,6.75)	(5.25,6.62,8)	(6.33,7.5,8.67)	(6.42,7.5,8.58)	(5.92,7,8.08)	(1.92,3.38,4.83)	(6.58,7.62,8.67)	(3.83,4.88,5.92)
C8,2	(2,3.25,4.5)	(5,6.25,7.5)	(5.5,6.75,8)	(2.58,4,5.42)	(4.83,6.25,7.67)	(4.83,6.25,7.67)	(3.67,4.75,5.83)	(6.33,7.5,8.67)
C8,3	(3,4.25,5.5)	(4.5,5.75,7)	(6.17,7.25,8.33)	(2.17,3.5,4.83)	(2.08,3.5,4.92)	(1.08,2.12,3.17)	(4.08,5.12,6.17)	(2.92,4.25,5.58)
C9,1	(3.33,4.5,5.67)	(5.92,7.12,8.33)	(3.92,5.12,6.33)	(4.58,5.88,7.17)	(5.08,6.38,7.67)	(4.58,5.88,7.17)	(2.33,3.62,4.92)	(3.92,5.12,6.33)
C9,2	(1.5,2.62,3.75)	(1.92,3.25,4.58)	(5.83,7,8.17)	(6.67,7.75,8.83)	(5.33,6.75,8.17)	(3.92,5,6.08)	(3.67,4.75,5.83)	(2.83,4.25,5.67)
C9,3	(1.75,2.88,4)	(3.75,4.88,6)	(1.5,2.75,4)	(2.17,3.5,4.83)	(1.83,3.25,4.67)	(5.08,6.5,7.92)	(2.25,3.62,5)	(4,5.12,6.25)
C10,1	(4.75,6.12,7.5)	(1.67,2.75,3.83)	(1.67,2.75,3.83)	(3.92,5,6.08)	(1.42,2.5,3.58)	(3.42,4.5,5.58)	(3.42,4.5,5.58)	(6,7.12,8.25)
C10,2	(1.83,3,4.17)	(2,3.38,4.75)	(6.17,7.25,8.33)	(5.58,6.75,7.92)	(1.33,2.5,3.67)	(5.17,6.5,7.83)	(5.17,6.5,7.83)	(4.92,6.25,7.58)
C10,3	(4.33,5.5,6.67)	(1.58,2.75,3.92)	(4.08,5.25,6.42)	(5.67,6.88,8.08)	(4.08,5.38,6.67)	(6.42,7.5,8.58)	(2.83,4,5.17)	(2.92,4.25,5.58)
C10,4	(3.92,5.25,6.58)	(3.67,5,6.33)	(3.42,4.75,6.08)	(4.58,5.75,6.92)	(3.17,4.5,5.83)	(5.08,6.25,7.42)	(4.17,5.5,6.83)	(1.33,2.5,3.67)
C10,5	(6.08,7.25,8.42)	(5.17,6.5,7.83)	(1.75,2.88,4)	(1.92,3.25,4.58)	(4.67,6,7.33)	(2.42,3.88,5.33)	(4.67,6.12,7.58)	(1.75,2.88,4)
C11,1	(3.5,4.62,5.75)	(3.25,4.38,5.5)	(4.25,5.38,6.5)	(6.42,7.5,8.58)	(4.83,6.25,7.67)	(2.75,4.12,5.5)	(3.75,4.88,6)	(4.75,6.12,7.5)
C11,2	(1.42,2.5,3.58)	(1.58,2.75,3.92)	(5.17,6.5,7.83)	(2.5,3.88,5.25)	(5.25,6.62,8)	(3.25,4.38,5.5)	(1.5,2.62,3.75)	(4,5.12,6.25)
C11,3	(5,6.38,7.75)	(2.33,3.62,4.92)	(2.42,3.88,5.33)	(3.83,4.88,5.92)	(1.83,3,4.17)	(2.17,3.62,5.08)	(1.17,2.25,3.33)	(1.58,2.75,3.92)
C11,4	(6.08,7.25,8.42)	(6.33,7.38,8.42)	(4.42,5.88,7.33)	(4.67,6.12,7.58)	(1.33,2.38,3.42)	(1.83,2.88,3.92)	(4.17,5.62,7.08)	(1.75,2.88,4)

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Table 3. Final ranking of suppliers

Supplier	Defuzzified ELECTOR Index	F-ELECTOR	F-ELECTRE	F-VIKOR	F-VISIS	F-RVIKOR	F-PROMETHEE	F-TOPSIS	F-COCOSO	F-TOPKOR	F-ARASKOR
Supplier 1	0.092	7	6	5	5	5	7	8	7	8	5
Supplier 2	0	4	4	6	6	6	4	7	4	7	6
Supplier 3	-0.169	2	2	3	3	3	2	1	3	2	3
Supplier 4	0.073	6	5	7	7	7	5	4	5	5	7
Supplier 5	0.06	5	7	4	4	4	6	5	6	4	4
Supplier 6	0.163	8	8	8	8	8	8	6	8	6	8
Supplier 7	-0.102	3	3	2	2	2	3	3	2	3	2
Supplier 8	-0.25	1	1	1	1	1	1	2	1	1	1

Table 4. Pearson correlation coefficients between different methods

	F-ELECTOR	F-ELECTRE	F-VIKOR	F-VISIS	F-RVIKOR	F-PROMETHEE	F-TOPSIS	F-COCOSO	F-TOPKOR	F-ARASKOR	Sum
F-ELECTOR	1	0.9286	0.8571	0.8571	0.8571	0.9762	0.7619	0.9524	0.8095	0.8571	8.8571
F-ELECTRE	0.9286	1	0.7619	0.7619	0.7619	0.9762	0.7143	0.9524	0.6905	0.7619	8.3095
F-VIKOR	0.8571	0.7619	1	1	1	0.7857	0.6429	0.8095	0.7619	1	8.619
F-VISIS	0.8571	0.7619	1	1	1	0.7857	0.6429	0.8095	0.7619	1	8.619
F-RVIKOR	0.8571	0.7619	1	1	1	0.7857	0.6429	0.8095	0.7619	1	8.619
F-PROMETHEE	0.9762	0.9762	0.7857	0.7857	0.7857	1	0.7857	0.9762	0.7857	0.7857	8.6429
F-TOPSIS	0.7619	0.7143	0.6429	0.6429	0.6429	0.7857	1	0.7381	0.9524	0.6429	7.5238
F-COCOSO	0.9524	0.9524	0.8095	0.8095	0.8095	0.9762	0.7381	1	0.7619	0.8095	8.619
F-TOPKOR	0.8095	0.6905	0.7619	0.7619	0.7619	0.7857	0.9524	0.7619	1	0.7619	8.0476
F-ARASKOR	0.8571	0.7619	1	1	1	0.7857	0.6429	0.8095	0.7619	1	8.619

Table 5. Results of the sensitivity analysis of supplier elimination

	Removing S1	Removing S2	Removing S4	Removing S5	Removing S6
Rank 1	S8	S8	S8	S8	S8
Rank 2	S3	S3	S3	S3	S3
Rank 3	S7	S7	S7	S7	S7
Rank 4	S2	S5	S2	S2	S2
Rank 5	S4	S4	S5	S1	S4
Rank 6	S5	S1	S1	S4	S5
Rank 7	S6	S6	S6	S6	S1

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Quality and Compliance (C1)	
Criterion	Code
Compliance with GMP and Regulatory Requirements	C1.1
International Certifications (ISO, FDA, EMA, ICH)	C1.2
Product Defect and Return Rate	C1.3
Traceability and Documentation	C1.4

Technical Capability and Innovation (C2)	
Criterion	Code
,Capability to Produce Complex Nanostructures (Liposomes (.Polymers, Dendrimers, etc	C2.1
Advanced Manufacturing Infrastructure and Equipment	C2.2
Research and Development (R&D) Intensity	C2.3
Patents and Proprietary Technical Knowledge	C2.4

Safety and Risk (C3)	
Criterion	Code
Safety Protocols for Handling Nanoparticles	C3.1
Toxicity Risk Management	C3.2
Contamination Control and Product Quality Assurance	C3.3
Anti-Counterfeiting and Traceability Systems	C3.4

Cost (C4)	
Criterion	Code
Unit Product Price	C4.1
Total Cost of Ownership (Purchasing , Transportation, Quality Testing)	C4.2
Payment Terms	C4.3
Supplier Financial Stability and Sustainability	C4.4

Delivery and Logistics (C5)	
Criterion	Code
Delivery Lead Time	C5.1
On-Time Delivery Rate	C5.2
Supply Capability under Emergency Conditions	C5.3
Cold Chain Management for Sensitive Pharmaceuticals	C5.4

Sustainability (C6)	
Criterion	Code
Management of Nanomaterial Waste and Expired Pharmaceuticals	C6.1
Compliance with HSE (Health, Safety, and Environment) Standards	C6.2
Commitment to Ethical Principles and Corporate Social Responsibility (CSR)	C6.3
Energy Consumption	C6.4
Water Consumption	C6.5
Greenhouse Gas Emissions	C6.6
Use of Green Raw Materials	C6.7
Clean Production Technology	C6.8

Capacity and Scalability (C7)	
Criterion	Code
Industrial Production Capacity	C7.1
Ability to Rapidly Increase Capacity During Crises	C7.2
Flexibility of Production Lines for Different Formulations	C7.3

Relationship Management (C8)	
Criterion	Code
Quality of Communication and Responsiveness	C8.1
History of Successful Collaboration	C8.2
Willingness for Long-Term Contracts	C8.3

Reputation and Track Record (C9)	
Criterion	Code
Reputation in Domestic and International Markets	C9.1
Endorsements from Scientific and Governmental Authorities	C9.2
National and International Awards and Achievements	C9.3

Nanopharmaceutical-Specific Attributes (C10)	
Criterion	Code
Control of Nanoparticle Size and Size Distribution	C10.1
Stability of Nano-Drug Formulations	C10.2
Biocompatibility of Nanomaterials	C10.3
Reproducibility of the Manufacturing Process	C10.4
,Capability to Perform Specialized Nano-Characterization Tests (DLS (TEM, SEM, Zeta Potential	C10.5

Supply Chain Resilience (C11)	
Criterion	Code
Diversity of Supply Sources	C11.1
Supply Chain Flexibility	C11.2
Recovery Capability After Disruptions	C11.3
Information Security and Formulation Confidentiality	C11.4

Figure 1 – The criteria considered in the study and their classification

In press

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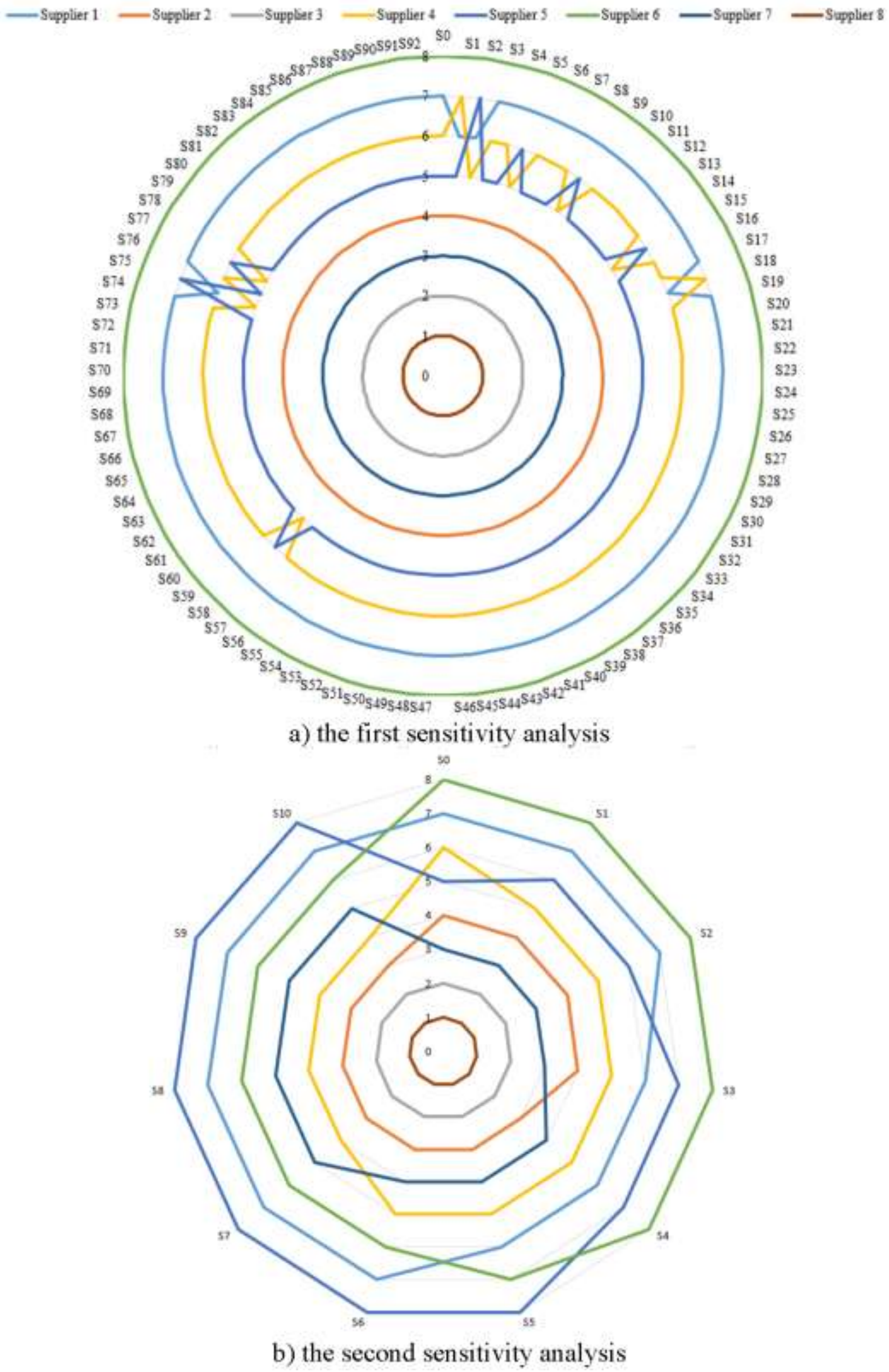

a) the first sensitivity analysis

b) the second sensitivity analysis

Figure 2. Results of the performed sensitivity analyses

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