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Evaluating and Selecting a Supplier in a Healthcare Supply Chain Using the Technique for Order Performance by Similarity to Ideal Solution Under Intuitionistic Fuzzy Environment

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Abstract

Supplier selection is an important aspect of effective supply chain management (SCM) and has implications in risk mitigation, profitability, and cultivating robust supplier-buyer relationships. In this dynamic and competitive landscape, it is essential to implement multi-criteria decision-making (MCDM) methods. Therefore, we employ the technique for order performance by similarity to ideal solution (TOPSIS), an MCDM technique, to evaluate the best supplier. Our approach incorporates fuzzy intuitionistic data and leverages the insights of decision-makers. Seven essential criteria, namely, supplier relationships, patient demand, quality, profitability, delivery time, post-delivery service, and patient cost, are integral to this assessment. This methodology is particularly valuable in situations that require swift supplier selection and those that cater to the urgent supplier needs of pharmacists. While our focus was on a specific context, the adaptability of this approach enables researchers to customize it for their respective fields by incorporating pertinent criteria based on expert inputs. Supplier evaluation within the healthcare sector, focusing on sector-specific metrics such as antibiotic drug selection, remains a relatively unexplored area. To address this issue, we present a comprehensive framework to select antibiotic drug suppliers.

Keywords: Multiple criteria analysis, Fuzzy, Crisp, TOPSIS, SCM

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1. Introduction

In recent decades, business management has evolved significantly and supply chain management (SCM) has emerged as a vital and continually evolving approach driven by global changes such as increased competition, higher customer expectations, technological advancements, and geopolitical factors. Although many SCM strategies rely on probability distributions derived from historical data, there are situations where historical data are unavailable. In such cases, the fuzzy set theory proves useful in addressing SCM uncertainties, particularly in the healthcare sector.

Various researchers have explored SCM in the healthcare field. Fernie and Rees [1] assessed the NHS supply services from multiple perspectives, whereas McKone-Sweet et al. [2] examined the barriers to SCM implementation. Kim [3] designed an integrated SCM system for pharmaceutical products. Callender noted the progress in healthcare SCM; however, limitations remain. Toba [4] discussed the current issues in hospital SCM and their solutions. Shou [5] highlighted the potential of healthcare SCM in developing countries, whereas Kavitha and Nanduri [6] focused on healthcare impacts, RFID technology, and cost reductions. Onder and Kabadayi [7] resolved supplier selection issues using an analytical network process.

When dealing with complex scenarios in which both membership and non-membership functions are challenging to ascertain simultaneously, the intuitionistic fuzzy set (IFS) theory is more suitable. Atanassov [8] introduced the IFS concept and generalized fuzzy sets. Szmidt and Kacprzyk [9] explored IFS for decision-making in ambiguous environments. Zhao et al. [10] modified the VIKOR method for supplier evaluation using intuitionistic fuzzy data.

In the realm of multi-standard determination, the technique for order performance by similarity to ideal solution (TOPSIS) is a classic multi-criteria decision-making (MCDM) method. It prioritizes the alternatives closest to the optimistic solution (OS) while minimizing proximity to the pessimistic solution (PS). SCM has evolved in response to the changing business landscapes. In healthcare, the adoption of IFS theory and MCDM methods such as TOPSIS offers valuable tools for addressing uncertainty and making informed decisions.

Singh et al. [11] explored the key factors contributing to women empowerment. To address the complexity of the criteria involved, this study employs an innovative research approach called the multi-criteria futuristic fuzzy decision hierarchy methodology, which combines fuzzy logic with the analytical hierarchy process (AHP).

The authors of [12] delved into a mathematical model that emphasized individuals severely afflicted by malaria transmission and examined scenarios in both precise and imprecise contexts. It considered parameters associated with situations in which the disease resurfaces. This study delves into the stability of the model in both well-defined and uncertain settings, supplementing its findings with numerical examples to confirm its validity.

In 2023, Alzahrani et al. [13] performed a study focusing on selecting suitable sites for women's universities in the underdeveloped areas of West Bengal, India. This study addressed the uncertainty in the site selection process by considering 10 critical criteria. To handle this uncertainty, they integrated trapezoidal neutrosophic numbers and determined criteria weights using AHP. Subsequently, TOPSIS and complex proportional assessment (COPRAS) were used to rank the sites. Additionally, they performed comparative and sensitivity analyses to evaluate the robustness of the proposed methods.

Jana et al. [14] introduced a novel approach for addressing Pythagorean fuzzy multiple-attribute decision-making problems. Their approach leveraged Pythagorean fuzzy positive deviation weighted averaging (PFPDWA) and Pythagorean fuzzy positive deviation weighted geometric (PFPDWG) operators to develop an algorithm tailored for this purpose. Simultaneously, they introduced an innovative method to design a comparison approach that involved multiple attribute border approximation areas by utilizing Pythagorean fuzzy numbers, to demonstrate the practicality of their proposed approach. To gauge the effectiveness of their method, they performed a comparative analysis with the existing operators, and demonstrated its efficiency.

Palanikumar et al. [15] explored novel approaches for resolving multiple-attribute decision-making challenges using a framework of spherical vague normal sets. In addition, we performed a comparative analysis of our proposed method against previously established approaches to highlight the superior performance of our method.

Jana et al. [16] introduced innovative logarithmic operations for bipolar fuzzy numbers. They devised new operators based on these operations, namely, logarithmic bipolar fuzzy weighted averaging (L-BFWA), logarithmic bipolar fuzzy ordered weighted averaging (L-BFOWA), logarithmic bipolar fuzzy weighted geometric (L-BFWG), and logarithmic bipolar fuzzy ordered weighted geometric (L-BFOWG) operators. Additionally, we have developed a model for multi-attribute group decision-making, which is based on L-BFWA and L-BFWG.

Jana et al. [17] presented a method for dynamic multiple-attribute decision-making using complex q-rung orthopair fuzzy data. To assess its practicality and effectiveness, they performed a thorough comparative evaluation using a numerical example as a test case.

Chen [18] introduced a supplier-selection procedure in a fuzzy environment based on TOPSIS. This approach is applied to make conclusive decisions in various domains employing fuzzy decision systems. In this study, we extend the use of TOPSIS to intuitionistic fuzzy data, elaborated in the following sections.

2. Intuitionistic Fuzzy Model

IFSs are generalized fuzzy sets, which are beneficial situations in which the problem through the (fuzzy) linguistic variable, given only as a membership function, appears vague. These include decision-making problems particularly in clinical diagnosis, income analysis, marketing of new products, and economic services. While evaluating an unknown object, there is a possibility that a non-null hesitation may occur at any time.

The parameters within the healthcare sector SCM are typically characterized by their inherent uncertainty. In practical scenarios, these parameters tend to exhibit imprecision and vagueness. This imprecision can be effectively addressed using fuzzy set theory.

The intuitionistic fuzzy model (IFM) is an expansion of the conventional fuzzy set theory and offers a more comprehensive representation of uncertainty and ambiguity in decision-making and problem-solving processes. Pioneered by Atanassov [8] in 1986, IFM extends its scope beyond simply evaluating the degree of membership to encompass aspects such as the degree of non-membership and hesitancy. This model is particularly beneficial in situations in which decision makers possess limited information or are uncertain about the membership of an element in a set. The key components of IFM are as follows:

i. **Intuitionistic fuzzy sets (IFS):** IFSs generalize fuzzy sets by introducing a third parameter known as hesitancy. Every element 'x' is defined by three distinct membership functions: μ(x) and ν(x) signify the degree of membership and non-membership, respectively, and λ(x) portrays hesitancy, which indicates the uncertainty in assigning a specific membership value.

ii. **Membership dunction**: The membership function, μ(x), expresses the extent to which an element 'x' belongs to the IFS. It varies between zero and one, where zero denotes no membership and one signifies complete membership.

iii. **Non-membership function**: The non-membership function, ν(x), exhibits the degree to which an element 'x' lacks membership in the IFS. Its values also range from 0 to 1, where 0 indicates a lack of nonmembership and 1 indicates complete nonmembership.

iv. **Hesitancy function**: The hesitancy function, λ(x), quantifies the level of uncertainty or hesitancy in assigning a precise membership value to an element 'x.' It ranges from 0 (indicating no hesitancy) to 1 (representing maximum hesitancy).

v. **Intuitionistic fuzzy operations**: Similar to classical fuzzy sets, IFSs can undergo union, intersection, and complementation operations considering all the three parameters: membership, non-membership, and hesitancy.

vi. **Intuitionistic fuzzy decision-making**: IFM finds applications in decision-making and pattern recognition problems, where decision makers can express their uncertainty and hesitancy using IFSs. This enables a more realistic and nuanced representation of the incomplete information.

IFM is a valuable tool for handling situations involving hesitancy, ambiguity, and incomplete information. It facilitates informed choices in complex and uncertain environments by providing decision makers with a more expressive framework. IFM is used in fields such as decision analysis, expert systems, MCDM, and pattern recognition, where capturing and modeling uncertainty play a vital role in obtaining accurate and reliable results.

3. Applying TOPSIS to Intuitionistic Fuzzy Sets

Intuitionistic fuzzy TOPSIS is a decision-making technique that extends the traditional TOPSIS method to handle uncertain and imprecise information using IFSs.

Intuitionistic fuzzy numbers are used to express the degree of membership, non-membership, and hesitancy of each alternative regarding both the ideal and negative ideal solutions. The intuitionistic fuzzy TOPSIS method computes the relative closeness scores based on the intuitionistic fuzzy distances to ideal solutions.

The method involves the following steps:

Step 1: Recognize and list the criteria and alternatives.

Step 2: Convert the crisp data into intuitionistic fuzzy numbers to represent membership, non-membership, and hesitancy.

Step 3: Establish the intuitionistic fuzzy ideal and intuitionistic fuzzy negative ideal solutions.

Step 4: Compute the intuitionistic fuzzy distances from each alternative to the intuitionistic fuzzy ideal solutions.

Step 5: Compute the relative closeness scores for each alternative and rank them accordingly.

These procedures equip decision makers with valuable tools to manage uncertainty and ambiguity in MCDM, enabling them to make informed and robust choices in complex real-world scenarios.

It is particularly useful in situations where decision makers have difficulty expressing their preferences in precise terms or when there is ambiguity in the data. There are some real-world applications of intuitionistic fuzzy TOPSIS–such as supplier selection, financial portfolio management, medical diagnosis, environmental impact assessment, smart city planning, personnel selection, project management, agricultural crop selection, energy resource selection, and transportation planning. These applications demonstrate that intuitionistic fuzzy TOPSIS can be useful in various fields where decision-making involves uncertainty, vagueness, and imprecision, and where multiple criteria need to be considered to make informed choices.

Many researchers have dedicated significant efforts to efficiently apply IFS to scenarios involving uncertainty, which led to its usefulness in diverse areas such as clinical diagnosis, decision-making, sample recognition, and fuzzy optimization [19]. Researchers [20-23] have also explored the application of IFS in uncertain dynamic intuitionistic fuzzy MCDM for assessing order fulfilment performance in firms. Aydin and Kahraman [24] endorsed this method as a valuable tool for solving MCDM problems in an intuitionistic fuzzy (IF) environment.

4. Numerical Example

Here, we select the best supplier for an antibiotic drug based on seven criteria: (1) supplier relationship (C1), (2) patient demand (C2), (3) quality (C3), (4) associated profit (C4), (5) delivery time (C5), (6) post-delivery service (C6), and (7) cost to the patient (C7). Five suppliers (A1, A2, A3, A4, and A5) were considered.

A committee of four decision-makers (DM1, DM2, DM3, and DM4) was formed to make this decision. Intuitionistic fuzzy TOPSIS was employed to determine the most suitable supplier of the antibiotic drug.

Step 1: Determine the weights of decision makers.

Table 1 lists the linguistic terms used to obtain the weights of decision makers.

Step 2: Convert the decision-makers' evaluation of alternatives into the intuitionistic fuzzy decision matrix.

Here, a triangular membership function is used to represent the linguistic terms with fuzzy numbers. Typically, decision-makers evaluate suppliers based on various criteria; however, here, we have a group decision-making process involving four decision-makers (Table 2).

To perform the calculations, it is necessary to create a consolidated decision matrix that combines information from the four individual decision matrices presented in Tables 3–6.

Step 3: Calculate the weights of criteria.

Weightage can be converted into an intuitionistic fuzzy number.

Although single weighting was applied to the intuitionistic fuzzy numbers, there is an alternative method. Each decision maker can assign individual weights to the criteria, and the combined weighting can be calculated using the traditional procedure (Tables 7, 8).

Step 4: Construct the aggregated weighted intuitionistic

Table 1. Linguistic terms for rating the importance of criteria and decision makers

Term	Intuitionistic fuzzy number
Very low (VL)	0.1, 0.9, 0
Low (L)	0.3, 0.6, 0.1
Average (A)	0.5, 0.45, 0.05
High (H)	0.7, 0.2, 0.1
Very high (VH)	0.85, 0.1, 0.05

Table 2. Importance scale of decision makers (DM) with corresponding weights

DM 1	DM 2	DM 3	DM 4
0.276	0.277	0.189	0.258

Table 3. Supplier ratings of DM 1 under the seven criteria

	A_1	A_2	A_3	A_4	A_5
C_1	VH	VH	A	H	H
C_2	VH	H	A	A	A
C_3	VH	H	H	A	H
C_4	VH	H	H	VH	VH
C_5	VH	VH	H	VH	VH
C_6	VH	H	VH	H	VH
C_7	VH	VH	VH	VH	VH

Table 4. Supplier ratings of DM 2 under the seven criteria

	A_1	A_2	A_3	A_4	A_5
C_1	VH	H	VH	VH	VH
C_2	VH	H	H	VH	VH
C_3	VH	VH	VH	VH	H
C_4	A	A	H	A	A
C_5	VH	VH	VH	VH	VH
C_6	H	H	H	H	H
C_7	H	VH	H	H	H

Table 5. Supplier ratings of DM 3 under the seven criteria

	A_1	A_2	A_3	A_4	A_5
C_1	VH	VH	A	L	A
C_2	VH	A	L	A	L
C_3	VH	A	L	A	L
C_4	VH	A	A	A	L
C_5	VH	A	A	A	L
C_6	VL	VL	VL	VL	VL
C_7	VH	H	A	A	L

Table 6. Supplier ratings of DM 4 under the seven criteria

	A_1	A_2	A_3	A_4	A_5
C_1	VH	H	H	H	VH
C_2	H	A	H	H	H
C_3	VH	H	VH	VH	VH
C_4	H	H	H	H	H
C_5	H	A	H	H	H
C_6	VH	A	H	A	H
C_7	VH	H	H	H	H

fuzzy decision matrix (Tables 9, 10).

Using the weights in Table 9, an aggregated weighted intuitionistic fuzzy decision matrix is formed using the product operator.

Now we calculate A^* and A^- as intuitionistic fuzzy positive-ideal and intuitionistic fuzzy negative-ideal solutions, respectively.

Step 5: Calculate the intuitionistic fuzzy positive-ideal and intuitionistic fuzzy negative-ideal solutions (Tables 11, 12). Here, C_1 to C_6 are the benefit criteria and C_7 is the cost criterion.

Step 6: Calculate positive and negative separation measures.

Next, we compute positive and negative separation measures (Tables 13, 14).

Step 7: Calculate the relative closeness coefficient to the intuitionistic ideal solution (Table 15).

Step 8: Rank the alternatives.

The alternative with the highest $C_i{}^*$ value is the best supplier, and the alternative with the least $C_i{}^*$ value is the least preferred supplier.

Supplier 1 (0.9263) was the first supplier to be selected, followed by suppliers 4 (0.3430), 5 (0.3053), 2 (0.2929), and 3 (0.2203).

5. Sensitivity Analysis

A sensitivity analysis was performed to assess the robustness and stability of the ranking in relation to changes in criteria weights. This helped to validate whether the priorities of the alternatives shifted when the importance of a specific criterion was adjusted. For instance, if the significance of a service criterion increases significantly, the preferred choice of antibiotic drug will also change accordingly.

Supplier rankings were derived by adjusting the weights of the criteria. For nearly all variations in the weights of the criteria, supplier 1 consistently ranked first, followed by supplier 4, supplier 5, supplier 2, and supplier 3 in the subsequent positions, respectively. This suggests that the changes in the intuitionistic fuzzy weights of the variables did not have a significant impact on the ranking of suppliers, which indicates the stability of supplier ranking (Table 16).

6. Simulation Results

After applying the same intuitionistic fuzzy TOPSIS methodology to two additional antibiotic drugs for supplier evaluation, the following results were obtained (Tables 17, 18):

Drug ii: There were four suppliers, four decision-makers, and six criteria: (1) supplier relationship (C1), (2) patient demand (C2), (3) quality (C3), (4) associated profit (C4), (5) delivery time (C5), and (6) post-delivery service (C6).

Supplier 1 (0.9829) was the best choice, followed by suppliers 2 (0.8493), 3 (0.1799), and 4 (0.1481).

Drug iii: Here, we have three suppliers, four decision-makers, and six criteria: (1) supplier relationship (C1), (2) patient demand (C2), (3) quality (C3), (4) associated profit (C4), (5) delivery time (C5), and (6) post-delivery service (C6).

Supplier 2 (0.6555) was the first supplier to be selected, followed by suppliers 1 (0.6152) and 3 (0.1542).

7. Results

Supplier selection is a critical task in healthcare pharmaceuticals because many criteria often conflict. This belongs to the MCDM category and plays a pivotal role in SCM. In this study, TOPSIS was applied with a focus on using the intuitionistic fuzzy data.

The priority ranking of suppliers was as follows: supplier 1 ranked first, followed by suppliers 4, 2, 5, and 3 at the subsequent positions, respectively, as determined through intuitionistic fuzzy TOPSIS.

Table 7. Combined decision matrix for the supplier ratings

	A_1	A_2	A_3	A_4	A_5
C_1	0.95, 0.04, 0.01	0.85, 0.1, 0.05	0.7, 0.2, 0.1	0.725, 0.15, 0.125	0.8, 0.1, 0.1
C_2	0.95, 0.04, 0.01	0.675, 0.125, 0.2	0.625, 0.25, 0.125	0.675, 0.125, 0.2	0.675, 0.125, 0.2
C_3	0.975, 0.015, 0.01	0.725, 0.15, 0.125	0.725, 0.15, 0.125	0.725, 0.15, 0.125	0.7, 0.2, 0.1
C_4	0.8, 0.1, 0.1	0.65, 0.2, 0.15	0.65, 0.2, 0.15	0.7, 0.2, 0.1	0.625, 0.25, 0.125
C_5	0.925, 0.015, 0.06	0.75, 0.2, 0.05	0.75, 0.2, 0.05	0.75, 0.2, 0.05	0.725, 0.15, 0.125
C_6	0.7, 0.2, 0.1	0.575, 0.3, 0.125	0.65, 0.2, 0.15	0.6, 0.2, 0.2	0.675, 0.125, 0.2
C_7	0.9, 0.05, 0.05	0.85, 0.1, 0.05	0.775, 0.1, 0.125	0.725, 0.15, 0.125	0.725, 0.15, 0.125

Table 8. Fuzzy weightage for the criteria

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Weightage	H	VH	VH	VH	H	H	A

Although there are numerous studies on supplier assessment, selecting and assessing suppliers by specific criteria for antibiotic drugs has received relatively less attention. This study aimed to bridge this gap. The proposed methodology can also be adapted to make decisions related to production planning, product development, order production, logistics management, and site selection.

8. Discussion

In this study, we performed supplier evaluations of three antibiotic drugs. Selecting the right suppliers is very crucial to pharmacists. This facilitates the purchase of high-quality products at reasonable prices, prevents issues, and establishes reliable, ethical, and innovative partnerships with suppliers. This decision significantly influences the quality of medicines they provide, cost control, and the long-term success of their enterprise, making it a critical aspect of their SCM.

Gazi et al. [25] addressed the issue of ranking restaurants within a bustling metropolis like Kolkata, India. Choosing a restaurant involves considering various factors such as special occasions, budget, ambiance, geographical location, comfort, and food quality. The ranking of these dining establishments relies on intricate and sometimes conflicting qualitative characteristics. To address the imprecision and uncertainty inherent in this context, this study employed hexagonal fuzzy numbers as a suitable representation method.

Momena et al. [26] used an MCDM approach to identify illness symptoms, and diagnose possible diseases. This study considered a range of symptoms, including fever, muscle pain, tiredness, chills, difficulty in breathing, queasiness, retching, and diarrhea. This investigation demonstrated the application of a generalized dual hesitant hexagonal fuzzy number to the disease diagnosis process.

Jana et al. [?] employed novel Dombi hybrid operators, including the intuitionistic fuzzy Dombi hybrid average (IFDHWA) and intuitionistic fuzzy Dombi hybrid geometric (IFDHWG) operators. These operators exhibit a significant advantage in terms of flexibility when adapted to varying parameters. Subsequently, they provided a practical illustration of the financial performance of an enterprise and discussed the advantages and utility of the generated results.

9. Conclusion

In the current highly competitive global setting, the abundance of suppliers and the multitude of criteria to consider when selecting the ideal supplier pose significant challenges. Therefore, it is necessary to adopt a structured approach to evaluate and select the best supplier based on the respective criteria. The supplier selection process is the cornerstone of an effective SCM, making it a critical issue in the development of a robust supply chain system.

The primary objective of the supplier selection process is threefold: minimizing purchasing risks, enhancing the overall profitability of the customer, and fostering enduring and close relationships between suppliers and buyers. Owing to the diverse and sometimes conflicting nature of these criteria, supplier selection is one of the most pivotal tasks. Consequently, MCDM methods are well suited to address the intricate nature of supplier selection, as it inherently involves multiple criteria. Several techniques, such as TOPSIS, ELECTRE, PROMETHEE, DEMATEL, AHP, and ANP, have been developed to facilitate

Table 9. Intuitionistic fuzzy weightage for the criteria

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Weightage	0.7, 0.2, 0.1	0.85, 0.1, 0.05	0.85, 0.1, 0.05	0.85, 0.1, 0.05	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.5, 0.45, 0.05

Table 10. Aggregated weighted Intuitionistic fuzzy decision matrix

	A_1	A_2	A_3	A_4	A_5
C_1	0.665, 0.232, 0.103	0.595, 0.28, 0.125	0.49, 0.36, 0.15	0.5075, 0.32, 0.1725	0.56, 0.28, 0.16
C_2	0.8075, 0.136, 0.0565	0.57375, 0.2125, 0.21375	0.53125, 0.325, 0.14375	0.57375, 0.2125, 0.21375	0.57375, 0.2125, 0.21375
C_3	0.82875, 0.1135, 0.05775	0.61625, 0.235, 0.14875	0.61625, 0.235, 0.14875	0.61625, 0.235, 0.14875	0.595, 0.28, 0.125
C_4	0.68, 0.19, 0.13	0.5525, 0.28, 0.1675	0.5525, 0.28, 0.1675	0.595, 0.28, 0.125	0.53125, 0.325, 0.14375
C_5	0.6475, 0.212, 0.1405	0.525, 0.36, 0.115	0.525, 0.36, 0.115	0.525, 0.36, 0.115	0.5075, 0.32, 0.1725
C_6	0.49, 0.36, 0.15	0.4025, 0.44, 0.1575	0.455, 0.36, 0.185	0.42, 0.36, 0.22	0.4725, 0.3, 0.2275
C_7	0.45, 0.4755, 0.0725	0.425, 0.505, 0.07	0.3875, 0.505, 0.1075	0.3625, 0.5325, 0.105	0.3625, 0.5325, 0.105

Table 11. Intuitionistic fuzzy positive ideal solution

${r_1}'^{*}$	0.665, 0.232, 0.103
${r_2}'^{*}$	0.8075, 0.136, 0.0565
${r_3}'^{*}$	0.82875, 0.1135, 0.05775
${r_4}'^{*}$	0.68, 0.19, 0.13
${r_5}'^{*}$	0.6475, 0.212, 0.1405
${r_6}'^{*}$	0.49, 0.36, 0.15
${r_7}'^{*}$	0.3625, 0.5325, 0.105

Table 12. Intuitionistic fuzzy negative ideal solution

${r_1}'^{-}$	0.49, 0.36, 0.15
${r_2}'^{-}$	0.53125, 0.325, 0.14375
${r_3}'^{-}$	0.595, 0.28, 0.125
${r_4}'^{-}$	0.53125, 0.325, 0.14375
${r_5}'^{-}$	0.5075, 0.32, 0.1725
${r_6}'^{-}$	0.4025, 0.44, 0.1575
${r_7}'^{-}$	0.45, 0.4775, 0.0725

Table 13. Positive separation measures

	$D(A_1, S^*)$	$D(A_2, S^*)$	$D(A_3, S^*)$	$D(A_4, S^*)$	$D(A_5, S^*)$
C_1	0.0000	0.0506	0.1281	0.1116	0.0743
C_2	0.0000	0.1685	0.1997	0.1685	0.1685
C_3	0.0000	0.1508	0.1508	0.1508	0.1702
C_4	0.0000	0.0927	0.0927	0.0715	0.1162
C5	0.0000	0.1119	0.1119	0.1119	0.1037
C_6	0.0000	0.0686	0.0286	0.0572	0.0575
C_7	0.0625	0.0443	0.0215	0.0000	0.0000

Table 14. Negative separation measures

	$D(A_1, S^-)$	$D(A_2, S^-)$	$D(A_3, S^-)$	$D(A_4, S^-)$	$D(A_5, S^-)$
C_1	0.1281	0.0776	0.0000	0.0284	0.0616
C_2	0.1997	0.0803	0.0000	0.0803	0.0803
C_3	0.1702	0.0318	0.0318	0.0318	0.0000
C_4	0.1162	0.0318	0.0318	0.0463	0.0000
C_5	0.1037	0.0417	0.0417	0.0417	0.0000
C_6	0.0686	0.0000	0.0575	0.0595	0.0990
C_7	0.0000	0.0215	0.0443	0.0625	0.0625

the selection of the best supplier, recognizing it as an MCDM problem. These methods provide structured approaches to assist in making informed decisions when choosing suppliers, thereby optimizing the effectiveness and efficiency of the supply chain.

This study presents a methodology to assess and rank suppliers, and focuses on selecting the best supplier based on seven key criteria including, supplier relationship, patient demand, quality, associated profitability, delivery time, post-delivery service, and costs to the patient, Using the TOPSIS method. By leveraging the judgments and inputs from decision-makers

Table 15. Closeness coefficient of each supplier

	A1	A2	A3	A4	A5
Si*	0.0625	0.6874	0.7332	0.6715	0.6905
Si-	0.7866	0.2848	0.2071	0.3506	0.3035
Si* + Si-	0.8491	0.9722	0.9404	1.0221	0.9941
CCi	0.9263	0.2929	0.2203	0.3430	0.3053

regarding various suppliers, the rankings for these suppliers are established. In intuitionistic fuzzy TOPSIS, supplier 1> supplier 4> supplier 2> supplier 5> supplier 3, were selected in decreasing order of preference.

The results of the TOPSIS framework can assist decision-makers to examine the rankings of suppliers, as well as supplier strengths and weaknesses. However, the adequacy of assessment at the underlying levels relies on the precision and value of the judgment provided by decision-makers. The proposed procedure can be used for selecting elective choices connected with the planning of production, item improvement process, order production, logistics management, and site selection. This method is particularly valuable when it is necessary to choose a single supplier swiftly from multiple options. This is especially beneficial to pharmacists, as it aids in identifying the most suitable supplier capable of efficiently meeting all their requirements. This study presents a systematic method for selecting suppliers using the judgement of the decision-makers in an intuitionistic fuzzy environment.

Furthermore, researchers can apply this approach in their respective fields, which allows them to adapt and incorporate additional criteria aligned with specific research areas. They can also leverage the expertise and opinions of specialists in their field to make informed supplier selection decisions tailored to their unique needs and objectives.

10. Limitations of the Study

Intuitionistic fuzzy TOPSIS is a valuable decision-making technique for handling uncertainty and imprecision in multi-criteria decision analysis; however, it also has limitations such as complexity and computational load, subjectivity in parameter setting, data collection and validation, lack of standardization, interpretability, limited real-world applications, sensitivity to weight assignments, and limited software support. Despite these limitations, the intuitionistic fuzzy TOPSIS can be a valuable tool in situations where decision-makers need to account for uncertainty and imprecision in their decision-making processes. Careful consideration of these limitations and appropriate parameter settings can help mitigate some of the challenges associated with their use.

11. Future Research Scope

Future research on the Intuitionistic fuzzy TOPSIS method can focus on refining the algorithms, exploring hybrid approaches, handling big data and Internet-of-Things applications, expanding to multi-objective optimization, conducting real-world case studies, developing user-friendly software, and addressing various forms of uncertainty. Benchmarking studies, sensitivity analyses, and educational resources will further enhance the performance and accessibility of this method in both academic and practical contexts.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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Table 16. Cases i-iii

Case i)							
Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Weightage	0.5, 0.45, 0.05	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.85, 0.1, 0.05	0.85, 0.1, 0.05	0.7, 0.2, 0.1
Suppliers	A_1	A_2	A_3	A_4	A_5		
Ranking	0.9209	0.3041	0.2433	0.3650	0.3249		
Case ii)							
Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Weightage	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.7, 0.2, 0.1	0.7, 0.2, 0.1
Suppliers	A_1	A_2	A_3	A_4	A_5		
Ranking	0.8932	0.3130	0.2516	0.3770	0.3444		
Case iii)							
Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Weightage	0.8, 0.1, 0.1	0.85, 0.1, 0.05	0.85, 0.1, 0.05	0.85, 0.1, 0.05	0.6, 0.2, 0.2	0.6, 0.2, 0.2	0.6, 0.35, 0.05
Suppliers	A_1	A_2	A_3	A_4	A_5		
Ranking	0.9137	0.2978	0.2240	0.3488	0.3163		

Table 17. Drug ii

	A1	A2	A3	A4
Si*	0.0160	0.1480	0.7732	0.8006
Si-	0.9221	0.8338	0.1696	0.1392
Si* + Si-	0.9381	0.9817	0.9427	0.9398
CCi	0.9829	0.8493	0.1799	0.1481

Table 18. Drug iii

	A1	A2	A3
Si*	0.1046	0.2828	0.5033
Si-	0.1672	0.5381	0.0917
Si* + Si-	0.2718	0.8209	0.5950
CCi	0.6152	0.6555	0.1542

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