T.C.
İSTANBUL KÜLTÜR UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

SUSTAINABLE ALTERNATIVES TO POLYETHYLENE (PE) FOR MEDICAL APPLICATIONS: A FUZZY MULTI-CRITERIA DECISION-MAKING APPROACH

Master Thesis

Soulayma El Hallab

1900004734

Department: Industrial Engineering

Program: Engineering Management

Supervisor: Asst. Prof. Duygun Fatih Demirel

June 2025

T.C.
İSTANBUL KÜLTÜR UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

SUSTAINABLE ALTERNATIVES TO POLYETHYLENE (PE) FOR MEDICAL APPLICATIONS: A FUZZY MULTI-CRITERIA DECISION-MAKING APPROACH

Master Thesis

Soulayma El Hallab

1900004734

Supervisor and Chairperson:	**Assist. Prof. Duygun Fatih Demirel**
Members of Examining Committee:	**Assist. Prof. Eylül Damla Gönül-Sezer**
	Assist. Prof. İlayda Ülkü

June 2025

ACKNOWLEDGEMENT

I want to convey my thanks to everyone who provided me with the opportunity to finish this study. I would like to express my gratitude to my supervisor, Asst. Prof. Duygun Fatih Demirel, for his outstanding guidance, steadfast support, and continuous encouragement during this research journey. His deep knowledge, constructive criticism, and sincere faith in my abilities have not only influenced this thesis but have also motivated me to seek greater academic achievement. I am profoundly grateful to him for inspiring within me the confidence and enthusiasm that have driven my choice to pursue doctoral studies, aiming to become a distinguished scholar and mentor like him. I am profoundly thankful to my family, particularly my parents, whose constant support, patience, and motivation have been my foundation during my educational journey. To my siblings, I appreciate your encouragement and for always having faith in me. Your faith in my skills has inspired me to continue pushing through tough periods. I would also like to express my gratitude to the industry experts who contributed to this research and provided their valuable knowledge and insights regarding sustainable materials in medical applications. Their input was crucial for the successful achievement of this research. My heartfelt gratitude goes to my cherished friend and colleague, Lama Massoud, who has consistently provided support, encouragement, and priceless feedback during this academic journey. Her companionship and insightful contributions have greatly enhanced both this research and my time at the university. I am equally grateful to my friends who have stood by me, providing motivation and fostering a supportive atmosphere that made this difficult journey more pleasant. Lastly, I appreciate Istanbul Kültür University and the Department of Industrial Engineering for providing the resources and setting favorable for my research.

June 2025 Soulayma El Hallab

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

$\tilde{a}_{ji}$ Fuzzy triangular comparison value of criterion i over criterion j

$\tilde{d}_{ij}$ k^{th} decision maker's preference of i^{th} criterion over j^{th} criterion via fuzzy triangular number

$\tilde{r}_i$ Geometric means of fuzzy comparison values of criterion i

$\tilde{w}_i$ Fuzzy weight of criterion i

M_i Defuzzified value of criterion i

N_i Normalized weight of criterion i

a_{ij} Minimum value of first place

b_{ij} Average value at the middle

c_{ij} Maximum value of last place

$\bar{r}ij$ Normalized fuzzy value

c_j^* Maximum value for criterion j (benefit criteria)

$\bar{a}_j$ Minimum value for criterion j (cost criteria)

$\bar{p}_{ij}$ Weighted normalized fuzzy value

A^+ Fuzzy Positive Ideal Solution (FPIS)

A^- Fuzzy Negative Ideal Solution (FNIS)

$p^+{}_j$ Maximum component for criterion j in FPIS

$p^-{}_j$ Minimum component for criterion j in FNIS

$d\left(\bar{a}, \bar{b}\ \right)$ Distance between triangular fuzzy numbers

d_{i^+} Distance of alternative i from FPIS

d_{i^-} Distance of alternative i from FNIS

CC_i Closeness Coefficient of alternative i

Üniversite	**: İstanbul Kültür Üniversitesi**
Enstitü	**: Lisansüstü Eğitim Enstitüsü**
Anabilim Dalı	**: Endüstri Mühendisliği**
Programı	**: Mühendislik Yönetimi**
Tez Danışmanı	**Asst. Prof. Duygun Fatih Demirel**
Tez Türü ve Tarihi	**: Yüksek Lisans – Haziran 2025**

ÖZET

Tıbbi Uygulamalar için Polietilene (PE) Sürdürülebilir Alternatifler: Bulanık Çok Kriterli Karar Verme Yaklaşımı

Soulayma El Hallab

Bu araştırma, sürdürülebilir alternatifler için kapsamlı bir değerlendirme çerçevesi oluşturarak sağlık ortamlarında polietilen (PE) plastiklerin yarattığı önemli çevresel sorunları ele almaktadır. PE yaygın olarak tıbbi ambalaj ve cihazlarda kullanılmasına rağmen (tıbbi plastiklerin %25-30'u), petrol kökenli olması ve düşük geri dönüştürülebilirliği önemli çevresel zararlara yol açmaktadır. Bulanık çok kriterli karar verme yaklaşımını kullanan çalışma, dört olası seçeneği değerlendirmiştir: Bio-PE, PLA, PBS ve PHA. Bu değerlendirme, altı temel kritere dayanmaktadır: çevresel etki, maliyet, kalite, erişilebilirlik, düzenleyici koşullar ve performans uyumu. Çerçeve, uzman değerlendirmelerinden kriter ağırlıklarını belirlemek için Bulanık Analitik Hiyerarşi Süreci (F-AHP) ve alternatifleri sıralamak için İdeal Çözüme Benzerlik Bakımından Sıralama için Bulanık Teknik (F-TOPSIS) yöntemlerini birleştirmiştir. Bulgular, Bio-PE'nin 0.517 yakınlık katsayısı ile en iyi seçenek olduğunu, bunu PLA (0.495), PBS (0.433) ve PHA'nın (0.372) izlediğini göstermiştir. Bio-PE, geleneksel PE'ye benzer mükemmel düzenleyici uyum, yüksek kalite özellikleri ve teknik yetenekler sergilerken, aynı zamanda karbon ayak izinde %75'e varan bir azalma sağlamıştır. Duyarlılık analizi, bu sonuçların farklı önceliklendirme senaryolarındaki güvenilirliğini doğrulamıştır. Gelecekteki çalışmalar, değerlendirme çerçevesini daha fazla ortaya çıkan biyomalzemeleri kapsayacak şekilde genişletmeye, seçilen alternatiflerin belirli tıbbi uygulamalarda fiziksel testlerini ve klinik denemelerini gerçekleştirmeye ve bölgesel sağlık sistemleri boyunca toplam çevresel etkiyi yansıtan gelişmiş yaşam döngüsü değerlendirme modelleri oluşturmaya odaklanabilir.

Anahtar Kelimeler: Sürdürülebilir plastikler, sağlık hizmetlerinde sürdürülebilirlik, bulanık ÇKKV, malzeme seçimi, biyo-bazlı polimerler

Bilim Dalı Sayısal Kodu: 90602

University	**: İstanbul Kültür University**
Instittute	**: Institute of Graduate Studies**
Department	**: Industrial Engineering**
Program	**: Engineering Management**
Supervisor	**: Asst. Prof. Duygun Fatih Demirel**
Degree Awarded and Date	**: MS – June, 2025**

ABSTRACT

Sustainable Alternatives to Polyethylene for Medical Applications: A Fuzzy Multi-Criteria Decision-Making Approach

Soulayma El Hallab

This research tackles the major environmental issues presented by polyethylene (PE) plastics in healthcare settings by creating a thorough assessment framework for sustainable substitutes. Although PE is commonly used in medical packaging and devices (25-30% of medical plastics), its origin from petroleum and low recyclability lead to significant environmental harm. Employing a fuzzy multi-criteria decision-making approach, the study assessed four possible options: Bio-PE, PLA, PBS, and PHA, based on six essential criteria: environmental influence, expense, quality, accessibility, regulatory conditions, and performance alignment. The framework incorporated Fuzzy Analytic Hierarchy Process (F-AHP) for assessing criteria weights from expert evaluations and employed Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) for ranking the alternatives. Findings showed Bio-PE to be the best option with a closeness coefficient of 0.517, succeeded by PLA (0.495), PBS (0.433), and PHA (0.372). Bio-PE exhibited outstanding overall performance thanks to its excellent regulatory adherence, high-quality attributes, and technical capabilities like traditional PE, while providing a reduction in carbon footprint of up to 75%. Sensitivity analysis validated the strength of these results in different prioritization scenarios. Future studies may concentrate on broadening the assessment

framework to encompass more emerging biomaterials, performing physical tests and clinical trials of the selected alternatives in particular medical applications, and creating advanced cycle assessment models that reflect the total environmental impact throughout regional healthcare systems.

Keywords: Sustainable plastics, healthcare sustainability, fuzzy MCDM, material selection, bio-based polymers

Science Code: 90602

1. INTRODUCTION

In the fast-changing environment of healthcare and pharmaceutical sectors, plastic materials have turned into essential elements for medical packaging, devices, and single-use equipment. Polyethylene (PE), polypropylene (PP), and polyvinyl chloride (PVC) lead the medical plastic industry, together making up 70-85% of the plastic materials utilized in medical practices. PE by itself accounts for about 25-30% of this sector, mainly used in packaging, bottles, bags, and tubing. Although these traditional plastics provide various benefits such as strength, adaptability, cleanliness, and affordability, they present considerable environmental issues due to their petroleum-derived sources and role in contributing to global plastic pollution. While PE is technically recyclable, the recycling rates for medical-grade PE are notably low due to the contamination issues, biohazard dangers, regulatory limitations, and the intricate multi-layer design of various medical packaging items. The recycling of medical PE requires a lot of energy and is frequently not cost-effective, leading to the incineration or landfilling of most medical PE waste, which can last for hundreds of years. The increasing worry about environmental sustainability has led researchers and industry participants to investigate eco-friendly options that can substitute conventional plastic materials while maintaining quality, performance, and economic feasibility. This thesis tackles this significant issue by concentrating on pinpointing sustainable substitutes for PE in medical practices via sophisticated decision-making approaches. The aim of this study is to explore, assess, and apply Multi-Criteria Decision Making (MCDM) approaches to determine and select the most appropriate eco-friendly alternatives to substitute PE plastic in pharmaceutical and medical uses. To accomplish this goal, it is necessary to achieve the subsequent research objectives: (1) investigating different MCDM methods and their uses in material selection; (2) pinpointing essential criteria for assessing alternative materials for medical purposes; (3) Implementing fuzzy AHP and fuzzy TOPSIS techniques to prioritize potential PE replacement alternatives; and (4) confirming the results through comparative analysis and sensitivity assessment to guarantee the robustness and dependability of the suggested solutions. This study addresses the following research questions: Q1: What are the most effective MCDM methods for selecting materials in medical applications? Q2: What are the key factors that affect the choice of sustainable options to substitute PE in healthcare applications? Q3: In what ways can merging fuzzy logic with conventional MCDM techniques improve the precision and dependability of material selection choices in uncertain conditions? The initial question elucidates the methodological basis of the study, whereas the subsequent question defines the assessment framework required for thorough evaluation. The third question investigates how well fuzzy MCDM methods address the intrinsic uncertainties linked to material selection processes. This study makes a notable contribution to both academic literature and industry practices by formulating a structured framework for assessing and choosing sustainable options to traditional PE plastic in the healthcare sector. In contrast to earlier studies that examined environmental impacts or material performance separately, this research combines various aspects of sustainability, encompassing environmental, economic, technical, and social elements, into an all-inclusive decision-making framework.

The study tackles the inherent uncertainties and subjective assessments in material evaluation processes by incorporating fuzzy logic into conventional MCDM methods, leading to more dependable and stronger results. Moreover, the research connects theoretical frameworks with practical application by offering specific suggestions for material replacement in actual medical uses. This study concentrates on discovering sustainable substitutes for PE plastic in medical packaging and containment uses, a major segment of plastic consumption in the healthcare sector. The research focuses on assessing biodegradable polymers, bio-based plastics, and other novel materials that might serve as alternatives to PE; thus, it does not include other plastic varieties like PP or PVC, nor does it explore wider waste management approaches. To accomplish the primary goal of the research, guarantee the completion of the following objectives, and address the research questions, the thesis report is organized into five key chapters: The Introduction offers an overview of the topic covered in the research, outlines the aims and objectives of the study, formulates the research questions, and illustrates the importance of the study along with its scope. The Literature Review explores earlier studies on MCDM uses in material selection, sustainability evaluation, product and technology selection, supply chain management, and process enhancement, focusing specifically on research related to plastic substitutes in medical applications. The methodology outlines the research framework, which encompasses the choice of fuzzy AHP and fuzzy TOPSIS methods, criteria identification, the process for selecting alternatives, and methods for collecting data. Implementation and Results showcases the outcomes of the fuzzy MCDM analysis, featuring the assessment of alternatives based on the defined criteria, sensitivity analysis, and a comparative evaluation of the results. The conclusion highlights the main results, examines the impact on the healthcare sector, acknowledges the study's limitations, and offers suggestions for future investigations and practical application.

2. LITERATURE REVIEW

The studies on Multi-Criteria Decision Making (MCDM) applications in disciplines such as raw material selection, sustainability assessment, product and technology selection, supply chain and lean management, and process optimization are extensively reviewed in this section. It investigates how MCDM approaches improve decision-making across a range of operational challenges, from selecting ideal materials to improving sustainability, through an in-depth review of the literature. It also summarizes findings to highlight MCDM's contribution to industry competitiveness, sustainability, and efficiency.

2.1. Material Selection

Singh et al. (2020) examine the use of Multiple Criteria Decision Making (MCDM) approaches, including TOPSIS, FTOPSIS, and MTOPSIS, to optimize fibrous raw material selection in the pulp and paper industry. The study focuses on pulp and paper mills in India. The process of selection is informed by an organized method that considers several variables such as the chemical, morphological, and physical properties of fibers. Notably, sensitivity analysis was conducted to evaluate the effect of eliminating certain carbohydrate properties to prioritize the manufacturing of high-quality paper and evaluate the findings on outcomes. Fuzzy theory has been established to be effective in managing uncertainties in performance evaluation. FTOPSIS proved to be very resilient, showing consistent outcomes without rank reversal even when the number of criteria was decreased. According to the results, Jute and Kenaf came out as the top non-wood fibers, demonstrating their compatibility with the demands of the company, while Acacia and Subabul appeared as the top wood fibers. (Singh et al., 2020)

Wang et al. (2020) examine with a primary objective of enhancing competitiveness and enabling more efficient decision-making, the study explores the development of a detailed fuzzy Multiple Criteria Decision-Making framework designed especially for the raw material supplier selection process in the plastics industry. By combining approaches like the fuzzy analytic network process (FANP), the VIKOR model, and the SCOR model, the methodology seeks to thoroughly assess and identify suppliers.

Notably, the structure of the FANP model is carefully constructed using the SCOR model's criteria, highlighting the relationships and connections between criteria and using certain formulae to calculate the matrix's weights and maximum private values. The outcome of the integrated FANP-VIKOR model allows stakeholders to understand how different factors affect their final decision-making process and provides valuable details on supplier evaluation and selection. It also provides results that are understandable and simple. This comprehensive approach not only enhances the reliability of supplier selection but also offers a methodical framework for managing the complexity that characterizes the supply chain of the plastics field, eventually leading to increased efficiency and competitiveness. (Wang et al., 2019)

Chaurasiya et al. (2023) presents an approach that uses the Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methodologies for selecting materials for engineering projects. This method includes using AHP to determine the weights of the criteria and TOPSIS to rank the alternatives. The evaluation of consistency ratios, the normalization of decision matrices, and their subsequent weighting are crucial processes. Interestingly, Composite Material C2 proved to be the best option for engineering projects. Additionally, the research expands its use to identify the best material for brake pads using both AHP and TOPSIS methods, with Special Ceramic Brake Alloy (SCBA) exhibiting advantageous characteristics. The study aims to optimize both functionality and life expectancy in design applications; by highlighting the importance of choosing the most appropriate brake pad material to improve performance and durability, it highlights the study's significance in engineering decision-making processes. Overall, the study's significance lies in its practical applicability as well as methodological improvement, providing practical recommendations for improving design processes and product performance across a range of engineering fields. (Chaurasiya et al., 2023)

Multiple multi-criteria decision-making methods were used also by Thinh et al. (2023) to evaluate and select cutting oils, including the PIV method with three different weight procedures and the CURLI method. An entirely comparative study was performed using iterative applications of the PIV approach with various weight schemes, as well as the CURLI method. Unexpectedly despite the methodological variations, a universal consensus emerged, showing the same optimum cutting oil for all procedures. The findings indicate the durability and reliability of the methods used, offering useful insights into industrial decision-making processes. Notably, the study's support of the CURLI approach for scenarios in which criteria weighing and data normalization are unneeded highlights its practicality and efficiency in decision-making contexts. This research shows the effectiveness of multi-criteria decision-making methods in selecting cutting oils and providing practical suggestions for methodology selection in similarly industrial decision-making problems. (Thinh et al., 2023). Multi-Criteria Decision Making (MCDM) approaches were extensively utilized by Sharma et al. (2022) when selecting lightweight materials for railway automobiles, including approaches such as PROMETHEE, TOPSIS, VIKOR, and the Weighted Aggregated Sum Product Assessment Method. Compared to other materials, TWIP steel displayed higher strength and ductility. Porous Al, on the other hand, had a lower ranking due to reduced yield and tensile strength, limiting its applicability as a structural material for railway applications. Notably, the TOPSIS ranking approach revealed Aluminum Al 6082-T6 as the best option for light wagon railway construction due to its low weight, cost, and improved corrosion resistance. This comprehensive examination emphasizes the significance of using MCDM approaches in material selection processes, allowing for informed decisions that optimize performance and cost related to railway vehicle design and construction. (Sharma et al., 2022)

To create the canting stamps that are necessary for batik production, Setiawan et al. (2023) examined new materials and methods. It recommended applying additive manufacturing and electroforming processes to adopt Conductive ABS-Electroformed by Copper (CABS-EBC). The research evaluated multiple alternatives using Multi-Criteria Decision Making (MCDM) approaches such as Simple Additive Weighting (SAW), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Preference Ranking Hierarchical Method of Enrichment Evaluation (PROMETHEE). The multi-criteria decision-making approach benefitted from the distinctive advantages that each method used (SAW, TOPSIS, and PROMETHEE) brought to the discussion. These methods provided detailed perspectives on the feasibility of materials and technology for canting stamp manufacture. Remarkably, according to the assessment criteria and methods used, copper was the most suitable material for canting stamps, followed by CABS-EBC, ABS, acrylic, and wood. This comprehensive evaluation not only improves batik manufacturing processes advancement but also illustrates how important it is to consider a wide range of components into account when choosing materials and technologies to maximize the performance and quality of traditional labor. (Setiawan et al., 2023). The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach is used in the investigation of biomass-based carbon electrode materials for super capacitors to determine the best synthesis routes. 21 alternatives are carefully compared using a range of parameters including the physiological properties and capacitive effectiveness of activated carbons (ACs). The requirements include the gravimetric capacitance of AC electrodes, their microstructure characteristics, and their heteroatom content. To identify the ideal synthesis conditions for ACs, the study systematically ranks activating agent ratios, activation temperatures, and heating rates using the TOPSIS approach. The study focuses on a variety of synthesis procedures and highlights the effectiveness of artificial doping, 6M HCl purification, and two-step hydrothermally supported synthesis using the most effective practices. The conclusion that alkali-based activating agents with a 4:1 ratio perform effectively in terms of the microstructure properties of ACs is extremely important. Rahimi et al. (2023) also determined the optimal amounts of pre-carbonization conditions, heating rates, chemical agent ratios, and activation temperatures which are critical for producing high-quality ACs. Through the methodical evaluation of synthesis routes with the TOPSIS approach and the clarification of important factors affecting the synthesis process, the research provides a significant contribution to the development of carbon electrode materials derived from biomass for super capacitors, promoting efforts to find sustainable energy storage solutions. (Rahimi et al., 2023). Also, Chai and Zhou (2022) offered a new hybrid Multi-Criteria Decision Making (MCDM) methodology designed to handle uncertainty and take decision-makers preferred risk into account when choosing sustainable alternative aviation fuels. The approach combines cumulative prospect theory, IVTFN-AHP, and IVTFN-TOPSIS to assess alternative aviation fuels' (AAFs') sustainability performance in uncertain scenarios. To verify the robustness and applicability of the methodology, sensitivity analysis is performed on parameters a and b, as well as on the weight of each criterion. The rating of alternative aviation fuels is A1, A3, A2, and A4, with algal-based fuel being the most environmentally friendly choice, according to the suggested methodology. The proposed approach's flexibility and logic is shown by a comparative comparison with other approaches, which also highlights how well it works in handling difficult decision-making situations when choosing environmentally friendly airplane fuels. (Chai & Zhou, 2022). In another article, Ordu and Der (2023) explores the process of selecting polymeric materials that are necessary for producing flexible vibrating heat pipes using a hybrid Multi-Criteria Decision Making (MCDM) methodology. This study assesses several polymeric materials using three hybrid MCDM approaches (AHP-GRA, AHP-CoCoSo, and AHP-VIKOR) using fourteen criteria and twelve alternatives. Of these, PTFE is found to be the best material to use in the manufacturing of flexible vibrating heat pipes; PE and PP have been recommended as substitutes. This comprehensive review not only assists in identifying appropriate materials but also provides illumination on the selection procedure, improving knowledge of the variables affecting material choice and how they affect flexible pulsating heat pipe systems' performance. (Ordu & Der, 2023). The procedures of selecting materials for mechanical components are an essential and complicated one that requires an objective evaluation approach and the utilization of mathematical methods to get a useful material evaluation. In this regard Chatterjee and Chakraborty (2021) provides a distinctive Multi-Criteria Decision Making (MCDM) methodology for material ranking which uses the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to clarify the interrelationships among various criteria. The study outlines the criteria relationships using weighted matrices and causal diagrams after developing an initial decision matrix that has been normalized for gear material selection. The DEMATEL-MABAC approach is subsequently utilized for selecting the gear material by considering an array of factors and their interactions. Influential criteria are determined by calculating the Significance Rank (SR), Causality Coefficient (SC), and the sum of the SR-SC values. This allows us to clarify their significance by applying causal diagrams. Spearman's rank correlation coefficient is used, providing comparisons with previous research to verify the method's effectiveness. As a result, the study contributes to the advancement of systematic material selection procedures in mechanical engineering by determining factors for gear material selection and providing insights into their subsequent influence. (Chatterjee & Chakraborty, 2021). Furthermore, when it comes to Multi-Criteria Decision Making (MCDM), material selection difficulties provide challenging obstacles that frequently require the use of multiple methods to achieve results that are reliable and accurate. Considering an extensive examination of more than sixty publications published between 2010 and 2016, COPRAS and TOPSIS were shown to be the most effective methodologies for selecting materials. Although it was recognized that Data Envelopment Analysis (DEA) was not an ideal substitute for MCDM in this field of study, it continued to be thought of as an MCDM tool. To handle material selection issues, Mousavi-Nasab and Sotoudeh-Anvari (2017) combines COPRAS, TOPSIS, and DEA, employing the advantages of each method. The TOPSIS approach is particularly remarkable since it is generally recognized as successful in material selection, and appropriate for a range of decision-making situations. DEA is criticized for its complicated weight restriction methods and excessive weight allocation, even though it provides flexibility in weight assignments. High correlations are found in comparative rankings of material selection methods like DEA, TOPSIS, and COPRAS, confirming the validity of DEA as an MCDM tool in certain circumstances. Applying multiple methodologies to material selection problems DEA, COPRAS, and TOPSIS, provides a range of rankings and insights that are essential for accurate decision-making processes. This extensive approach advances material science and engineering by enhancing the understanding of material selection processes and providing practitioners with useful knowledge in selecting the best materials for a variety of applications. (Mousavi-Nasab & Sotoudeh-Anvari, 2017)

The degrading of the Indian environment because of urbanization and globalization emphasizes how urgent it is to use sustainable building strategies. Employing sustainable materials for buildings is essential to reduce the depletion of resources in the construction sector. A comprehensive three-phase methodology is suggested as a solution to this problem. The method begins with the identification of criteria and sub-criteria, then moves on to the Best Worst Methodology (BWM) for weight calculation and the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for material ranking. This research provides an important contribution to sustainable construction practices by facilitating the development of an evaluation model for the selection of sustainable building materials. I involved a thorough literature study and expert consultations to establish the selection criteria. Phase II concentrated on applying the BWM methodology to determine the weights and scores of criteria, with a particular focus on the environment, economy, and social aspects of sustainability (TBL). The approach aims to deliver practical insights through numerical illustration based on expert panel discussions and industry relationships. The significance of sustainability in the construction industry is shown by the findings of the research, which are tabulated to emphasize the three primary criteria for sustainability in construction: the environment, economy, and social (TBL). The calculation of consistency ratios and main criteria weights demonstrates the significance of implementing sustainable practices in the building industry. This comprehensive method not only helps with material selection but also provides the foundation for sustainable growth in the Indian construction sector, supporting responsible urbanization and addressing environmental issues on a global scale (Mathiyazhagan et al., 2019).

2.2. Sustainability Performance

Kibria et al. (2023) examined the complicated problems related to managing plastic garbage, highlighting the significant impact it has on the ecosystem and examining the several waste-to-energy approaches that are currently being used. The authors have been engaged in the research, participating in all phases from ideation and data analysis to paper creation, editing, and review. Through exploring the complicated process of managing plastic garbage, the study indicates a variety of obstacles and prospects. These include the need for strong infrastructure development, the investigation of substitute materials, the execution of efficient waste management programs, and the critical responsibility of increasing awareness among people. Besides these significant characteristics, the research emphasizes the need for multidisciplinary methodologies that incorporate policy frameworks, technology developments, and community involvement strategies. These comprehensive approaches are crucial for addressing the various problems surrounding the management of plastic waste and developing sustainable solutions that reduce damage to the environment while increasing social development. The research makes a substantial contribution to the current discussion on plastic waste management by directing stakeholders towards more efficient and sustainable approaches through its comprehensive evaluation and practical suggestions. (Kibria et al., 2023) Additionally, Ahsan et al. (2024) examine how to reduce carbon emissions in the petrochemical sector by using decision-making methods in the novel Complex Multi-Fuzzy Hyper Soft Set (CMFHSS) framework. By employing a strict methodology, the study explores basic ideas such as fuzzy and soft sets and incorporates several methods of decision-making into the CMFHSS framework to identify effective strategies for reducing carbon emissions. The findings section provides a detailed examination of datasets and characteristics, carefully assessing how the suggested tactics work to reduce carbon emissions in the petrochemical industry. Via the utilization of advanced methods and comprehensive data analysis, the research contributes to the continuous initiatives aimed at accomplishing sustainability objectives and reducing the environmental impact of the petrochemical sector. Also, the study offers insightful information on how to apply complicated frameworks for decision-making to critical sustainability problems, highlighting the significance of multiple approaches in promoting sustainable practices in industrial sectors. (Ahsan et al., 2024)

Ersoy and Taslak (2022) emphasizes the economic, social, and environmental aspects of corporate sustainability and presents an extensive approach that evaluates the energy industry. By using hybrid multiple-criteria decision-making (MCDM) approaches, the study provides a complicated evaluation. These techniques include the Entropy method for criteria weighting and a wide range of approaches such as Proximity Indexed Value (PIV), Range of Value (ROV), Grey Relational Analysis (GRA), Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) for ranking alternatives. Significantly, research indicates that energy businesses in Asia are more sustainable than those in Europe, with certain companies outperforming others in terms of social, environmental, and economic aspects. This multifaceted approach highlights the significance of considering a variety of components when evaluating corporate sustainability within the energy sector, in addition to providing insights into the differences in sustainability performances between regions. Additionally, the study improves knowledge of sustainable practices in the global energy sector and encourages implementation, which helps to make responsible choices and promotes a higher level of social and environmental responsibility. (Ersoy & Taslak, 2022)

Keleş and Pekkaya (2023) uses Multiple Criteria Decision Making (MCDM) approaches to evaluate logistics center (LC) sites in Turkey with a concentration on sustainability. The PROMETHEE approach is used to rank alternatives, while the Entropy and CRITIC methods are applied to generate criteria weights. Sensitivity analysis is also performed to evaluate the validity of the results. According to the Turkish LC location rankings, Kayseri, Konya, and Zonguldak are the top three locations because of their high performance in economic variables, foreign commerce, and accessibility to transportation networks. However, sensitivity analysis shows that while it affects certain intermediate ranks, changing preference threshold values has little impact on the top and bottom rankings of alternatives. This comprehensive evaluation highlights the critical importance of taking sustainability factors into account when making decisions, along with offering insights on Turkey's best sites for logistics centers. Additionally, the study aims to improve the effectiveness and efficiency of logistics operations in Turkey, which eventually supports the sector's long-term development in the transportation and logistics industry. (Keleş & Pekkaya, 2023)

Moradi et al. (2022) conduct a comprehensive assessment of sustainable management in the transportation industry, with a particular focus on passenger rail corporations. Using the Fuzzy-TOPSIS method together with system dynamics modeling, the study explores the complicated dynamics of sustainability indicators and causal loops in transportation companies. Relationships within the transport company are seriously modeled using system dynamics methods, providing an understanding of important sustainability issues. Moreover, the Fuzzy-TOPSIS methodology is applied to identify the most effective scenarios to enhance sustainability in passenger rail transportation companies. The findings of this research are notable because they demonstrate the possible benefits to profitability and customer satisfaction that come with expanding the number of new wagons and locomotives in corporations such as Raja. In addition, a range of scenarios have been set up to enhance the sustainable management strategies used by passenger rail companies. These scenarios include improvements to road transport tolls and a reduction in operating expenses. In along with offering knowledge about the complicated issues of sustainability management in the transportation industry, this comprehensive study gives practical recommendations to enhance passenger rail operations' profitability, efficiency, and environmental responsibility. The study provides an important contribution to the advancement of sustainable practices in the transportation sector through its multidisciplinary approach and practical implications, leading to a future that is both ecologically friendly and economically acceptable. (Moradi et al., 2022)

Đurić et al. (2019) provide fuzzy risk management approach applies fuzzy set theory to handle uncertainties and provides a comprehensive structure to evaluate social and economic risks in supply chains. The identification of risk levels that are particularly applicable to the supply chains in the automobile sector becomes easier by the determination of the relative relevance of risk variables using fuzzy comparison matrices. The model includes fuzzy IF-THEN rules to determine each supply chain's risk level and fuzzy Analytic Hierarchy Process (AHP) to determine weights for risk factors. Remarkably, authors recommend utilizing Fuzzy AHP (FAHP) to calculate risk factor weights, considering its ease of use compared to other approaches. In the process of providing alternatives for strategic management initiatives aimed at improving the social and economic sustainability of supply chains, this method of management assists in identifying and reducing risks. In addition, the study recommends developing user-friendly software based on the model to facilitate greater acceptance and implementation in everyday scenarios and advocates for more research to increase the examination of risk levels across various automotive sector supply chains. The model provides a significant contribution to the advancement of risk management methods in supply chain operations through its practical recommendations and comprehensive approach, resulting in promoting resilience and sustainability in automotive manufacturing. (Đurić et al., 2019). The increasing shortage of water highlights the urgent need for efficient water management plans, which may be greatly improved by incorporating Internet of Things (IoT) technological advances. Narang et al. (2024) use the Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach and Principal Component Analysis (PCA) to examine the potential of IoT as a facilitator for effective water management. Through an examination of IoT enablers, including data mobility, IoT network establishment, and ecosystems, the study pinpoints critical elements required for effective integration into the open-loop Water Value Chain. This research provides important insights into the intricate dynamics and interdependencies influencing IoT integration in water-related activities, in addition to highlighting the critical role that IoT has played in transforming water management approaches. The study also emphasizes how critical it is to use advanced analytical techniques to evaluate IoT potential as a transformative in solving water shortages and advancing global initiatives for sustainable water resource management. (Narang et al., 2024). In the structure of Industry 4.0, the article offers a novel approach to sustainable product design that combines Six Sigma, Multi-Criteria Decision Making (MCDM), and Quality Function Deployment (QFD). Kar and Rai (2024) use a Neutrosophic Decision Making Trial and Evaluation Laboratory-Analytic Network Process (DEMATEL-ANP) methodology to assess the weights assigned to customer requirements. The weights assigned to engineering attributes are then determined by applying a QFD matrix. For design evaluation, Six Sigma principles are also applied. A mix of literature reviews and expert brainstorming sessions is used to identify the Critical Requirements (CRs) and Engineering Characteristics (ECs). To show how the integrated approach succeeds effectively in accomplishing sustainable product design objectives, an example is given. This strategy not only improves the subject of sustainable product design, but it also emphasizes how crucial it is to incorporate many approaches to effectively handle complicated issues that Industry 4.0 presents. In the context of modern manufacturing technology, the suggested strategy gives a comprehensive framework for fulfilling evolving demands from customers, improving sustainability, and optimizing product design processes by combining QFD, MCDM, and Six Sigma. (Kar & Rai, 2024). It is impossible to overestimate the necessity of renewable energy sources like wind and solar electricity considering Turkey's growing energy demands. Using Geographic Information Systems (GIS) and Multi-Criteria Decision Making (MCDM), a thorough analysis was carried out by Genç and Karipoğlu (2021) to identify areas that would be ideal for the deployment of wind-solar systems in Kayseri. After a thorough evaluation that included environmental impact data from Copernicus with data from sources such as the Global Wind Atlas and Global Solar Atlas, 12.3% of the area was determined to be appropriate for these types of systems. The study effectively identified sites appropriate for the development of wind-solar power plants in Kayseri by a comprehensive review of wind speed and sun irradiance values, highlighting the potential for sustainable energy generation in the region. (Genç & Karipoğlu, 2021). In another study Bhardwaj and Garg (2023) examines the critical problem of air pollution's negative impacts on human health, which have raised death rates throughout the world. A novel model called DMCTM is presented to evaluate the health impacts of air pollution by integrating CRITIC and TOPSIS methodologies using a Multi-Criteria Decision-Making (MCDM) approach. Based on a case study conducted in China, Xinxiang is the most polluted city. This is generally because of SO2 emissions, although variations in the pollution levels were between 2016 and 2022. The methodology of the study is divided into three stages: Alternative ranking, Weight Evaluation, and Data Collection and Analysis. Reliable data on air pollutants, the Air Quality Index (AQI), and the Air Quality Life Index (AQLI) are gathered in the first phase. These data are then classified into positive (AQLI), and negative (pollutants, AQI) categories based on their effects on public health and the environment. The modified TOPSIS approach is used in the third phase to rank alternatives according to the weighted criteria, while the modified CRITIC method is used in the second phase to determine weights. The study additionally examines the relationship between life expectancy and air pollution levels, recognizing slight modifications throughout the duration of the study. The research enhances activities to improve air quality and public health by giving insights into the health impacts of air pollution and a systematic strategy for evaluation and mitigation (Bhardwaj & Garg, 2023). Moreover, Chung and Chang (2022) address the difficulties associated with multi-criteria decision-making (MCDM) in the field of hydrogen energy by presenting an innovative approach based on applicable data envelopment analysis (DEA) in a fuzzy environment. To effectively handle MCDM challenges, this innovative approach combines the DEA, analytic hierarchy process (AHP), hesitant fuzzy linguistic term set (HFLTS), and soft set methods. The methodology has enhanced efficacy in ranking hydrogen energy significant developments and numerically verifies its superiority over traditional DEA, AHP/DEA, and fuzzy AHP/DEA methods. The consistency ratio (CR) computation guarantees the uniformity of expert judgments, while the Centre of Area (COA) approach is used to fuzzily Triangular Fuzzy Numbers (TFN). By evaluating decision-making units (DMUs) according to their relative efficiency ratings, the suggested DEA-based method efficiently provides information on the performance of each unit. Furthermore, the evaluation of criteria weights (EI, BP, IA, TD) is computed, with EI obtaining the highest weight value. When all factors are considered, the suggested DEA-based method improves conventional computation methods and provides insightful information to decision-makers in the hydrogen energy sector by processing MCDM challenges within a fuzzy version. (Chung & Chang, 2022)

2.3. Products and Technology Selection

To address the essential concern of food loss and waste (FLW), which has significant implications for sustainability, Görçün et al., (2024) used a decision-making model that has been presented for selecting refrigerated vehicles within Food Cold Supply Chains (FCSCs). This model tries to reduce FLW by making it easier to select the best vehicle. Sensitivity analysis has demonstrated the model's resilience, highlighting its dependability in navigating the uncertainties inherent in FCSC decision-making. Previous research has mostly focused on FLW reduction through a variety of ways, including educational campaigns, regulatory interventions, technical developments, and logistical improvements. These studies have highlighted the difficulties and uncertainties that exist in decision-making processes in food logistics. Recognizing the critical role of selecting appropriate refrigerated vehicles in mitigating FLW and supporting the achievement of UN Sustainable Development Goals (SDGs), it is important to note that not all refrigerated vehicles adhere to standard technical conditions, which may have an impact on food safety. As a result, incorporating technical compliance and safety factors into vehicle selection procedures is critical for developing long-term FCSCs and effectively dealing with FLW problems. (Görçün et al., 2024). In another article, Kang et al. (2023) used a novel technique called the Probabilistic Hesitant Fuzzy Set-based COPRAS method, the study explores the meticulous procedure of choosing a biodegradable dynamic plastic product. This approach successfully handles the uncertainty included in the selection process while also offering an organized structure for decision-making. Further improving the accuracy and dependability of the decision-making process, especially when managing uncertainty challenges during the study's implementation of the Critical approach for weight determination. The results of the research demonstrate the encouraging possibilities of using thermoplastic starches made from corn and rice in packaging applications. These biodegradable materials provide an effective replacement for typical plastics, making a substantial contribution to sustainability initiatives and resolving increasing worries about plastic pollution. Furthermore, the investigation of dynamic plastic items in the study highlights the significance of innovation in developing sustainable solutions that give equal weight to functional efficiency and environmental preservation. The research makes a substantial contribution to the discussion on sustainable packaging practices by utilizing an extensive approach and insightful results. This provides opportunities for the utilization of eco-friendly materials in a variety of industrial applications. (Kang et al., 2023). Moreover, an extensive evaluation approach is provided for sustainable manufacturing programs by Ocampo and Clark (2014) that apply the Analytic Network Process (ANP), supported by a real case study conducted in a Philippine technology company. The framework's main objective is to evaluate how well Lean Six Sigma initiatives, energy-efficient merchandise, and cleaner manufacturing techniques contribute to the implementation of sustainability objectives. The Consistency Ratio (CR) and Consistency Index (CI) are used to ensure decision consistency. Environmental, economic, and social factors are arranged in a hierarchical framework, and a super matrix filled with local priority vectors is converted into a column stochastic matrix. The study provides a higher priority on improving society and economic development in sustainable manufacturing projects. Important components such as income, profit, community development, and customer satisfaction are the major goals. However, cleaner manufacturing methods aim to satisfy customer demands while simultaneously encouraging community development. Furthermore, the framework provides useful guidance for decision-makers in the semiconductor industry and other sectors by focusing on the synergistic connections between the environmental, economic, and cultural aspects of sustainability. The study additionally demonstrates the importance of incorporating feedback from stakeholders and local context in sustainability evaluations to encourage more significant and efficient manufacturing practices. The framework enhances sustainable manufacturing practices and comprehensive approaches to corporate sustainability through its theoretical contributions and practical implementation. (Ocampo & Clark, 2014). To classify DGA-based failures in power transformers, Saroja et al. (2023) employed Machine Learning (ML) approaches. A variety of models are used in this research, including QDA, GB, ET, LGBM, RF, KNN, NB, DT, AB, LR, LDA, RC, and SVM-Linear Kernel. Using Analytic

Hierarchy Process (AHP) and Multi-Objective Optimization by Ratio Analysis (MOORA) approaches, the best-performing classifier was finally found to be QDA, with an exceptional accuracy of 99.29%. The performance of thirteen machine learning models was evaluated using a variety of measures, such as accuracy, AUC, recall, precision, F1-measure, kappa, MCC, and time-taken. Building pairwise matrices provided comparison simpler, while MCDM methods like AHP and MOORA helped to rank the classifiers according to their effectiveness. Due to QDA's capability to reliably identify and classify faults, it became the model of choice for classifiers used in transformer fault classification. This study not only improves fault detection strategies in power systems but also emphasizes how crucial it is to use effective machine learning techniques together with exacting evaluation structures to improve transformer operations' reliability as well as effectiveness. The study also emphasizes how important it is to use the best classifier model to maximize efficiency and improve problem identification procedures in power infrastructure maintenance and management. (Saroja et al., 2023). Furthermore, Hosouli et al. (2024) the objective of the project is to apply Multiple Criteria Decision Making (MCDM) methodologies to optimize the selection process of Photovoltaic Thermal (PVT) collectors. The methodology consists of many important processes, such as determining market alternatives, establishing necessary criteria, creating a weight matrix, and using MCDM techniques including VIKOR, TOPSIS, EDAS, and PROMETHEE II for ranking. The study's findings illustrate how well the suggested methods work to improve PVT collector selection, which improves the decision-making processes. Additionally, the research indicates that these approaches might be adapted for use in applications other than PVT collector selection, indicating their potential for wider use in other situations involving decision-making. The study enhances decision-making procedures in renewable energy technologies by providing more information and permitting more informed and optimized choices in the field of photovoltaic thermal systems. This is made possible by its rigorous approach and insightful conclusions. (Hosouli et al., 2024).

To improve network performance and efficiently optimize resource utilization Bouakouk et al. (2022) uses a Multi-Criteria Decision Making (MCDM) method to handle the complex routing needs within networks. It is primarily concerned with developing a mathematical framework for routing decisions that are based on constraints on metrics. A case study is included to highlight the benefits of this approach. Using normalized data, metric weights, and the degree of constraint satisfaction, the approach computes the Euclidean distance between routes and the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). This methodology uses the MCDM method to allow routing decisions with complex criteria, including threshold constraints (either hard or soft) on weighted metrics. This MCDM-based approach provides an acceptable alternative for handling complex routing situations by allowing compromise decisions between route performances and user application needs. The study also presents the ISOCOV method to handle threshold values in MCDM-based routing solutions and underlines the need to incorporate complicated user application requirements in decisions regarding routing. The study enhances routing processes for network management using its comprehensive methodology and innovative approach, providing up the opportunity for more efficient and adaptable solutions to challenging routing problems in current network environments. (Bouakouk et al., 2022). Garg et al. (2023) examines the complex procedure of choosing industrial robots created for the automotive manufacturing industry, navigating the complex nature of decision-making using a fuzzy Multi-Criteria Decision Making (MCDM) approach. The main objective of the research is to improve the accuracy of decision-making in this field by creating a fuzzy integrated model that combines the fuzzy SWARA (F-SWARA'B) and fuzzy CoCoSo (F-CoCoSo'B) methods with a modification of the Bonferroni function. After careful consideration of linguistic evaluations for both decision alternatives and selection criteria, A8 was determined to be the best option. The F-SWARA'B approach was used to establish critical criteria, such as Reaching Distance and Working Accuracy. This revealed the significance of these elements in the selection process. The study additionally highlights the importance of Reaching Distance, Performance, and Working Accuracy as the most important factors, confirming A8's ability to satisfy the exacting requirements of the automobile sector. Using advanced fuzzy MCDM approaches and concentration on important selection factors, the study provides insightful information about how to accelerate the industrial robot selection process, which will increase productivity and efficiency in the automotive manufacturing sector. Future studies might also combine predictive analytics with real-world performance data to further improve the selection process and customize robotic systems to changing industrial requirements. (Garg et al., 2023)

Javaid et al. (2022) in this research focuses on the challenges and solutions related to the integration of modern technology in the industrial sector, identifying 22 barriers and suggesting 14 solutions. By a systematic three-phase process that includes expert views, a study of literature, and Multi-Criteria Decision Making (MCDM) methods, the research seeks to provide thorough insights into improving technology integration in the manufacturing industry. The Best-Worst Method (BWM) is used to prioritize challenges, and this helps to emphasize the importance of management-related barriers in determining the outcome of technology adoption programs. By employing a methodical methodology, the research offers significant recommendations to industry participants and policymakers that aim to overcome challenges and utilize contemporary technology to stimulate innovation and competitiveness in the manufacturing sector. (Javaid et al., 2022). Similarly, Domaschka et al. (2020) employed Hathi which is a novel MCDM-based system that offers automated analyses based on user-specified preferences and aims to optimize capacity planning procedures in cloud-hosted Database Management Systems (DBMS). Hathi makes it easier to provide target-specific scores for different deployment alternatives by automating evaluation-driven capacity planning models and optimization objectives. It identifies ideal configurations that are compatible with certain optimization goals by carrying out three case studies with increasing configuration points. The results highlight Hathi's ability to handle extensive testing scenarios with a range of variables, including multiple DBMS, cluster sizes, cloud providers, and offers. This allows recommendations for deployment based on a variety of aspects to be derived. The evaluation also emphasizes the variety of high-performing configurations adapted to various optimization goals, highlighting the significant influence of configuration points on deployment quality. This comprehensive method not only improves cloud-hosted DBMS capacity planning efficiency but also provides insightful advice on how to best deploy methods for a range of operational requirements and situations. (Domaschka et al., 2020). Modern supply chains depend significantly on effective Information and Operations Integration Systems (IOIS), which highlight the importance of decision-making components in their implementation. To choose the best IOIS option, Deepuand and Ravi (2021) used MCDM to develop a strong model that considers several factors, including application suitability, operational efficiency, innovation potential, and technical improvements. The creation of an integrated AHP-TOPSIS approach was made possible by the identification of important decision-making criteria affecting IOIS selection by an extensive review of the literature. This methodological approach made it easier to create an extensive decision-making model that is specific to choosing the best options for IOIS. A case study within electronics supply chain was carried out to evaluate the effectiveness of the model, giving priority to variables affecting IOIS selection and filling in knowledge gaps in the literature on supply chain integration. The proposed method provides an important contribution in enhancing operational efficiency and encouraging seamless integration across diverse supply chain components by supporting the effective digitalization and management of supply networks. (Deepu & Ravi, 2021)

Roy et al. (2018) provides an innovative hybrid model for expedited automobile selection procedures that combines the PROMETHEE II and Fuzzy Analytic Hierarchy Process (AHP) approaches. By responding to customer preferences and expectations, this hybrid technique aims to support the expansion of the automotive industry. Combining PROMETHEE II and Fuzzy AHP, the model emphasizes how crucial it is to consider an array of factors while making decisions. The implementation of fuzzy AHP helps to create pairwise comparison matrices that provide weight vectors, which will be utilized in PROMETHEE II to determine the net outrank of all alternatives. Additionally, fuzzy synthetic extent analysis and the AHP approach are used to create the weight matrix, which improves the decision-making process significantly before the selection of an automobile. Customers are given an effective framework for choosing car models with this suggested hybrid model, allowing the use of PROMETHEE II and Fuzzy AHP approaches to support decision-making in the automotive sector. Through the incorporation of these methods, the model facilitates the assessment and selection of automotive alternatives according to consumer preferences, while also increasing consumer satisfaction and supporting industry expansion (Roy et al., 2018).

2.4. Lean and Supply Chain Management

Companies use green supply chain management (GSCM) as a framework to solve environmental issues by implementing eco-efficient strategies into practice. To manage the complicated and frequently contradictory features included in GSCM, Jaiswal et al. (2023) employ several Multi-Criteria Decision Making (MCDM) machine methodologies. These approaches, which include mathematical modeling, ANP, TOPSIS, VIKOR, and others, provide flexibility for handling various GSCM features. When dealing with situations involving uncertain preferences, VIKOR is extremely useful in offering reliable responses to problems involving decision-making in GSCM. However, ANP is particularly good at handling complicated and interconnected problems in GSCM, enabling thorough analysis and decision-making. In the meanwhile, TOPSIS is used to prioritize sustainable solutions by separating choices according to environmental perspectives. Moreover, complicated GSCM problems are solved by applying mathematical modeling methods, such as linear programming and advanced models, which provide reliable and optimal answers. The main areas of focus for researchers include green design and manufacturing, green procurement, and green supplier selection. MCDM tools are used to promote environmental responsibility and drive sustainability activities in supply chain operations. By combining these approaches, GSCM aims to accomplish operational effectiveness and environmental sustainability, which advances the larger objective of sustainable development in businesses and society. (Jaiswal et al., 2023). Through the application of an integrated Quality Function Deployment (QFD) and Multi-Criteria Decision Making (MCDM) framework, Hsu et al. (2024) explore the mitigation of risks associated with hazardous material road transportation. It focuses on identifying critical factors necessary for Industry 5.0 (I5.0) to improve supply chain resilience and reduce transportation risks. The approach handles the transportation potential risks associated with unsafe substances comprehensively by combining a variety of FDM-DEMATEL-ANP-EWM approaches inside the QFD framework. This provides practical solutions for companies that operate in this field. The research comprehensive review identifies the main causes of the risks associated with the transportation of hazardous materials, as well as supply chain resilience indicators and Industry 5.0 enablers. These findings offer practitioners significant novel knowledge about how to improve methods for risk management and transform to the constantly shifting industrial technology circumstances. The study provides practical recommendations for achieving greater resilience and efficiency in supply chain operations during the transition to Industry 5.0. It improves the understanding of risk reduction in unsafe material transportation by integrating multiple approaches and employing a holistic approach. (Hsu et al., 2024)

Lean management methods are essential for reducing waste and improving operational efficiency in the health industry. Yücenur et al. (2024) used the Weighted Sum Model and Weighted Product Model to compute the combined optimality value for each alternative, and the SWARA approach to estimate the important weights of criteria to evaluate the effectiveness of various lean approaches. Applying SWARA and WASPAS methodologies, the study established a multi-criteria model with 24 decision criteria and five alternatives for dealing with difficult decision-making scenarios. Kanban, Value Stream Mapping, 5S, Six Sigma, and Kaizen were the methods of lean manufacturing that were found to be the best appropriate for waste prevention in the healthcare sector. This comprehensive investigation underlines the value of lean management in the healthcare industry as well as the necessity of identifying the best lean tools for certain operational situations. The study provides significant insights for healthcare practitioners who aim to enhance overall efficiency in healthcare delivery, eliminate waste, and optimize procedures by using advanced decision-making methodologies. In addition, more studies in this field may examine the long-term effects and practical use of lean methods in various healthcare situations, ultimately advancing global healthcare system development. (Yücenur et al., 2024). Torkabadi et al. (2018) aims to identify and evaluate barriers to the implementation of sustainable production and consumption, and SPC, initiatives, with a focus on supply chains. It provides a comprehensive approach that uses a fuzzy Analytical Network Process to evaluate significant challenges divided into the supply chain, customer, organizational structure, and regulatory aspects. Internal challenges are found to be more important than external ones, with the organization dimension coming initially and being followed by the supply chain, customers, and regulations. The framework systematically evaluates supply chain challenges by applying Chang's (1992, 1996) extent analysis approach with Triangular Fuzzy Numbers (TFNs) to evaluate objectives over each objective. It highlights the internal (supply chain, organization) as well as the outside (regulatory, customer) aspects. It indicates that internal barriers have a greater impact on SPC adoption than external barriers, indicating a better possibility of repairing internal challenges to meet SPC goals. In particular, the company dimension is shown to contain the most significant challenges, highlighting the need for intra-organizational collaboration for the adoption of novel methods and technologies for resource optimization. The study provides a thorough understanding of the challenges to SPC implementation, which helps facilitate strategic planning and decision-making for the development of sustainability initiatives in supply chains (Torkabadi et al., 2018).

2.5. Process Optimization

Bimetallic billets are created via a complicated thermo-mechanical forming method called multi-material co-extrusion, which requires exact process parameters to be feasible. To examine several multi-criteria decision-making (MCDM) approaches, Fernández et al. (2022) used DEFORM 3D software. Its criteria were limited damage, extrusion force, tool wear, and maximum grain size reduction. Firstly, software was used to simulate the multi-material co-extrusion process. Several MCDM and weighting approaches were then used to determine the ideal process parameters. By multiplying the normalized value of N by its weight factor—which was found using methods like AHP, standard deviation, and entropy the weight factor matrix (W) was calculated. Several simulations have been conducted using various extrusion process parameters, including temperature, friction values, ram speeds, die semi-angles, and extrusion ratios. The findings of these simulations were used to assess and compare the effectiveness of various MCDM and weighting approaches for determining the most effective set of process parameters. By improving our understanding of multi-material co-extrusion processes, this comprehensive study provides the opportunity to create bimetallic billets that have enhanced quality and efficiency. (Fernández et al., 2022). Additionally, Ghaleb et al. (2020) examines the multifaceted issue of manufacturing process selection using Multi criteria Decision-making (MCDM) approaches including TOPSIS, AHP, and VIKOR. To evaluate these approaches, an entirely novel approach has been set up that considers significant factors such as computational complexity, decision-making agility, and suitability for group decision support. Criteria covering productivity, accuracy, complexity, flexibility, utilization of materials, quality, and operating cost were thoroughly evaluated to rank manufacturing processes, with sand casting that appear as the best alternative. Using this methodology, MCDM methods were thoroughly evaluated while considering variables like criterion flexibility, number of options and criteria, computational complexity, decision-making agility, and group decision support. The effectiveness of several manufacturing approaches was evaluated using significant criteria through a real-world case study, which finally resulted in the conclusion that sand casting was the best choice. Notably, AHP, TOPSIS, and VIKOR approaches were used in the ranking; VIKOR displayed superiority in terms of computational complexity, decision-making agility, and support over group decisions. This comprehensive study offers an adequate basis for decision-making in manufacturing contexts and assists in the selection of manufacturing processes as well as delivering valuable information about the relative effectiveness of different MCDM approaches. (Ghaleb et al., 2020)

Table 1. Literature review summary

References	MCDM	Analysis	References	MCDM	Analysis
Singh et al. (2020)	FTOPSIS, MTOPSIS, H	Sensitivity	Kar & Rai (2024)	DEMATEL, ANP, QFD	Sensitivity
Wang et al. (2020)	FANP, VIKOR		Hsu et al. (2024)	QFD, FDM, DEMATEL, ANP	
Chaurasiya et al. (2023)	AHP, TOPSIS, BWM		Yücenur et al. (2024)	SWARA, WASPAS	
Thinh et al. (2023)	PIV, CURLI, ROC, IS, Equal		Rahimi et al. (2023)	TOPSIS	
Görçün et al., (2024)	MCGDM	Sensitivity	Garg et al. (2023)	FSWARA, FCOCOSO	Sensitivity
Sharma et al. (2022)	TOPSIS, VIKOR, PROMETHEE, WASPAS		Javaid et al. (2022)	BWM, COCOSO	
Setiawan et al. (2023)	SAW, TOPSIS, PROMETHEE		Chai & Zhou (2022)	IVTFN, AHP, TOPSIS	Sensitivity
Kang et al. (2023)	PHFS, COPRAS, CRITIC	Sensitivity	Genç & Karipoğlu (2021)	GIS	
Kibria et al. (2023)		Comprehensive	Domaschka et al. (2020)	Hathi	
Ahsan et al.(2024)	TOPSIS, CMFHSS, H, SM	Comparative	Ordu & Der (2023)	AHP, GRA, AHP-COCOSO, AHP-VIKOR	
Ersoy & Taslak (2022)	PIV, MARCOS, ROV	GRA, Sensitivity	Deepuand & Ravi (2021)	AHP, TOPSIS, BWM	
Keleş& Pekkaya (2023)	CRITIC, PROMETHEE, H	Sensitivity	Chatterjee & Chakraborty (2021)	DEMATEL, MABAC	
Moradi et al. (2022)	FTOSIS,	SD	Roy et al. (2018)	FAHP, PROMETHEE	
Đurić et al. (2019)	FAHP, FIF-THEN		Fernández et al. (2022)	AHP, H, SD, TOSIS, ARAS, VIKOR, COPRA	
Ocampo& Clark (2014)	ANP		Torkabadi et al. (2018)	TFNS, FANP	
Saroja et al. (2023)	AHP, MOORA		Bhardwaj & Garg (2023)	CRITIC, TOPSIS	
Jaiswal et al. (2023)	VIKOR, ANP, TOPSIS	SWOT	Mousavi & Sotoudeh (2017)	DEA, COPRA, TOPSIS, VIKOR	
Hosouli et al.	PROMETHEE, TOPSIS, VIKOR, EDAS		Chung and Chang (2022)	DEA, TFN, FAHP	
Narang et al. (2024)	FDEMATEL	PCA	Mathiyazhagan et al. (2019)	BWM, FTOPSIS	
Bouakouk et al. (2022)	ISOCOV		Ghaleb et al. (2020)	AHP, TOPSIS, VIKOR	

3. METHODOLOGY

This section outlines the extensive methodological framework used to discover and assess sustainable substitutes for PE plastic in medical uses. The research methodology combines fuzzy set theory with conventional Multi-Criteria Decision Making (MCDM) techniques to tackle the fundamental uncertainties and complexities involved in material selection processes. Figure 1 depicts the methodology flowchart, which details the organized process adhered to in this research. The approach starts with defining the problem and determining the scope, then moves on to identifying and choosing evaluation criteria through literature review and expert advice. To identify possible substitutes for PE plastic, a thorough investigation into eco-friendly materials was performed, and then feedbacks from two subject matter experts was sought to confirm the choice of suitable options. The phase of data collection applies fuzzy scaling methods to measure qualitative assessments and manage the uncertainty in expert evaluations, instead of relying on traditional questionnaires or technical databases. The primary analytical framework integrates Fuzzy Analytic Hierarchy Process (F-AHP) to establish criteria weights and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) to prioritize alternatives. Ultimately, a sensitivity analysis is conducted to confirm the strength of the results and guarantee the dependability of the suggested options. Every element of this methodological framework is discussed in the following sections to provide a comprehensive insight into the research process.

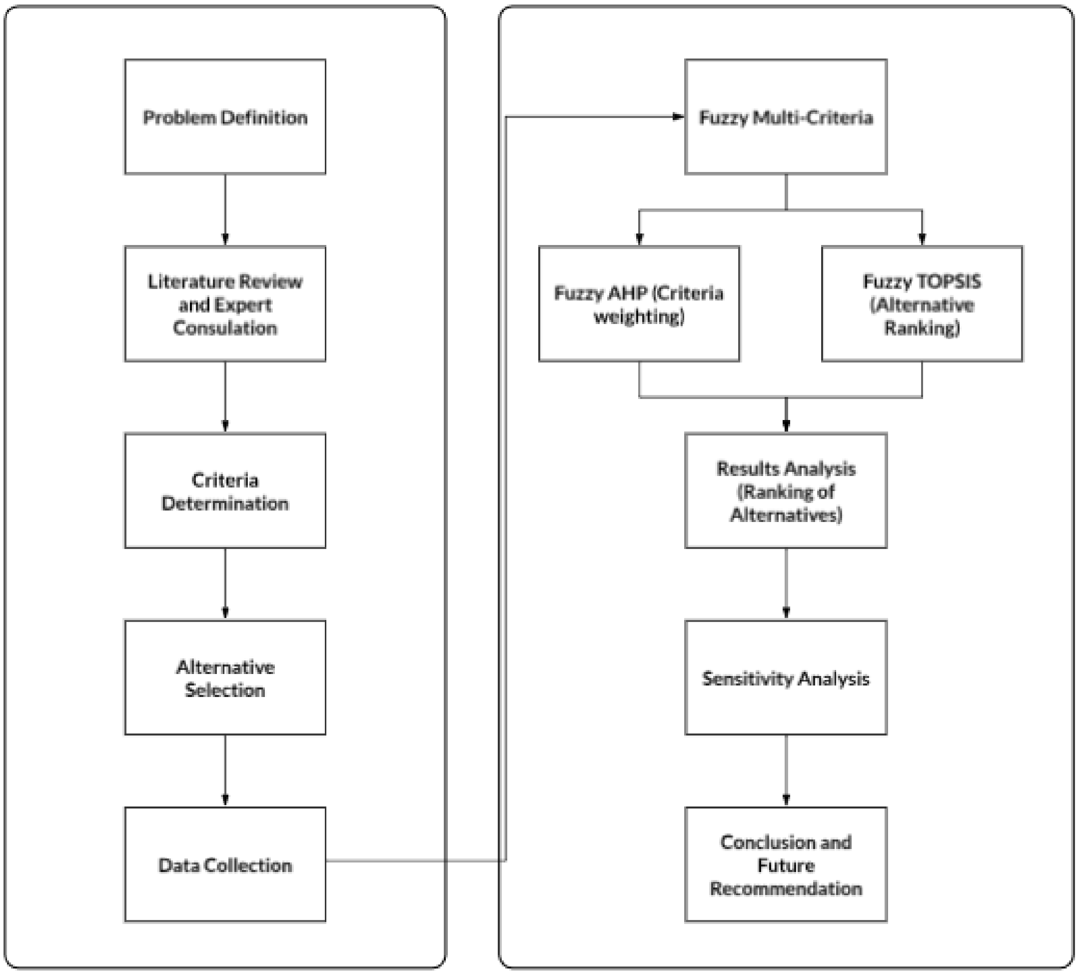

Figure 1. Flow Chart Diagram

3.1. Problem Definition

This study tackles the significant environmental issues presented by polyethylene (PE) plastic in healthcare applications. PE makes up around 25-30% of the medical plastic sector and is widely utilized in packaging, bottles, bags, and tubing. Although PE has beneficial characteristics for medical applications, it presents considerable environmental hazards during its entire lifecycle. Producing PE demands around 2 kg of oil equivalent for each 1 kg of PE created, significantly impacting the depletion of fossil fuels (Geyer et al., 2017). While producing PE, it is estimated that 6 kg of CO_2 equivalent are emitted for each kilogram of resin manufactured, contributing to increased greenhouse gas emissions (Plastics Europe, 2023). In addition, medical PE items generally possess very brief usage durations, with around 85% turning into waste within a year of their manufacture (World Economic Forum, 2016). While technically recyclable, medical PE encounters significant recycling obstacles such as biohazard contamination issues, regulatory limitations, and multi-layer composite designs that hinder processing. As a result, global recycling rates for medical polyethylene are still under 5%, with most of the waste being either incinerated or sent to landfills (Healthcare Plastics Recycling Council, 2022). When discarded in landfills, PE remains for 500-1000 years, releasing possibly harmful additives into the soil and groundwater (Barnes et al., 2009). In ocean settings, PE breaks down into microplastics (particles <5mm), which have been found in marine organisms, drinking water, and human blood samples, raising serious health worries (Ragusa et al., 2021). Moreover, healthcare facilities in the United States generate roughly 14,000 tons of PE waste each year, mainly from packaging and disposable items (Practice Greenhealth, 2023).

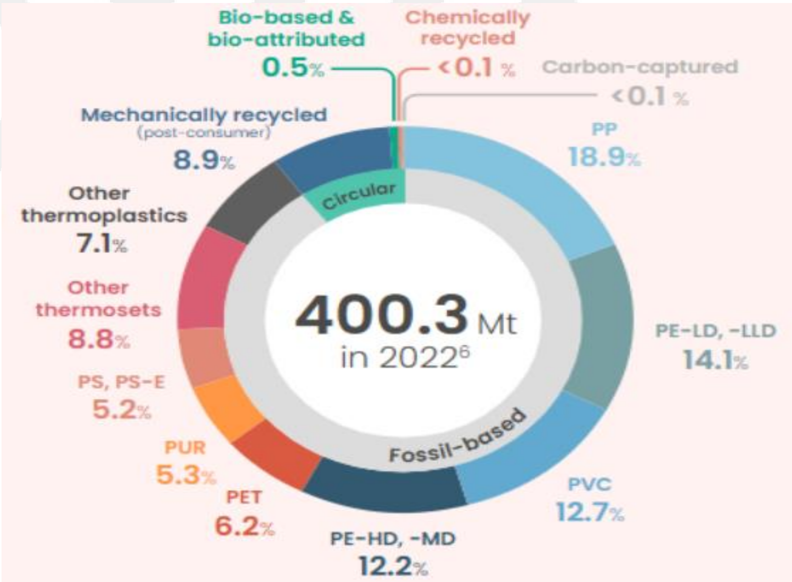

Figure 2. Global Plastic Production by Polymer (Plastics Europe, 2023)

As illustrated in Figure 2, in the worldwide plastic production scenario of 400.3 Mt in 2022, PE-HD and PE-MD collectively represent 12.2% of total production, with other significant polymers comprising PP (18.9%), PVC (12.7%), and PE-LD/LLD (14.1%). The circular segment identified as "Bio-based & bio-attributed" accounts for just 0.5% of total production, emphasizing the significant prevalence of fossil-based materials.

Figure 3. World Plastics Production (Plastics Europe, 2023)

Figure 3 further exemplifies this gap by monitoring production trends from 2018 to 2022, indicating that although total plastic production rose to 400.3 Mt, the share of fossil-based plastics continued to dominate at 90.6%, while bio-based alternatives and recycled materials showed limited advancement despite increasing environmental worries. The growing environmental consciousness in the medical field requires the discovery of sustainable substitutes for PE that preserve crucial performance traits while lessening environmental effects. This research utilizes Fuzzy Multi-Criteria Decision-Making techniques to assess and identify eco-friendly substitutes for PE in medical uses, ensuring that quality is maintained and costs are not significantly raised, thus advancing sustainable practices within the healthcare sector.

3.2. Criteria Determination

Selecting the appropriate evaluation criteria is essential for a thorough and strong assessment of possible PE plastic substitutes in medical uses. Through a thorough examination of existing literature on sustainable material selection frameworks and discussions with two industry professionals in medical plastic manufacturing and sustainability, six crucial criteria were recognized as vital for any organization contemplating material substitution in the medical industry. These experts indicate that effective material replacement must weigh environmental advantages against feasible business factors to be realistically applied. The specialists highlighted that "although environmental effects are becoming more significant for corporate sustainability objectives and adherence to regulations, businesses must also account for cost ramifications, material effectiveness, quality benchmarks, market accessibility, and regulatory endorsement status to guarantee successful implementation." As a result, the following six criteria were set for this research: (1) Environmental Impact, assessing the ecological footprint across the material's lifecycle; (2) Cost, taking into account both the direct costs of materials and any potential adjustments to manufacturing processes; (3) Quality, evaluating the material's consistency, purity, and capability to satisfy medical-grade standards; (4) Availability, scrutinizing supply chain dependability and production scalability; (5) Regulatory Status, considering adherence to relevant medical regulations and certification necessities; and (6) Performance Match, determining how closely the alternative can replicate PE's functional characteristics in medical applications. This extensive collection of standards allows for a thorough assessment of possible options that cater to both sustainability goals and practical implementation issues, mirroring the complex decision-making journey that organizations must make when evaluating material replacement for medical uses.

3.3. Alternative Selecting

The search for feasible alternatives to traditional PE in medical uses was carried out via a systematic approach that integrated thorough literature review and expert advice. After an extensive evaluation of sustainable polymers suitable for the medical field, discussions took place with two industry experts: the proprietor of a water bottle production firm knowledgeable in medical-grade packaging and a senior materials engineer from a prominent plastic manufacturing company in Italy. Two specialists independently verified that four materials demonstrate the greatest potential for substituting PE in medical uses: Bio-based Polyethylene (Bio-PE), Polylactic Acid (PLA), Polybutylene Succinate (PBS), and Polyhydroxyalkanoates (PHA). Bio-PE was emphasized for its similar chemical composition to traditional PE, yet it is sourced from renewable materials, mainly sugarcane. This option provides a reduction in carbon footprint by as much as 70-75% in comparison to traditional PE (Braz et al., 2021), since each ton of Bio-PE generated can capture up to 2.5 tons of CO_2 while the feedstock plants are growing. Although Bio-PE is not biodegradable, it is entirely recyclable via current PE recycling channels, providing a circular economy benefit without the need for new infrastructure. PLA shows considerable environmental advantages, with greenhouse gas emissions about 65% less than standard PE and a decrease in energy use of 35-45% in the production process (European Bioplastics, 2023). PLA can decompose in industrial composting settings in 3-6 months; unlike the centuries it takes for standard PE to degrade. PBS provides a 40-50% decrease in fossil resource usage throughout its lifecycle and is capable of biodegradation in both industrial composting sites and soil settings within 12-24 months (Xu & Guo, 2021). Moreover, PBS production results in about 60% of the greenhouse gas emissions relative to traditional PE manufacturing. PHA offers possibly the most eco-friendly profile, showcasing an 80% reduction in carbon footprint compared to fossil-derived PE and the capacity to biodegrade in various environments, including marine settings where it can decompose by 90% in just 6 months. PHA production via bacterial fermentation can also make use of agricultural waste streams as feedstock, redirecting approximately 0.8-1.2 tons of organic waste for each ton of PHA created. The Italian plastics specialist specifically highlighted that "these four materials embody the present edge of bio-based options, possessing the essential mix of technical characteristics, market accessibility, and regulatory possibilities needed for medical uses." This expert-led selection procedure guaranteed that the alternatives picked for assessment are practical substitutes that harmonize environmental advantages with the rigorous demands of medical uses, rather than just theoretical choices.

3.4. Data Collection

In the report, a thorough data gathering strategy was used to capture the intrinsic uncertainties and personal assessments related to the assessment of different materials for medical uses. Instead of depending exclusively on conventional quantitative metrics or binary evaluations, this research employed fuzzy scaling methods to accurately depict the uncertainty and ambiguity inherent in real decision-making processes regarding material selection.

Fuzzy set theory, originally presented by Zadeh in 1965, offers a mathematical structure for managing vague and uncertain information. In contrast to classical set theory, which states that an element is either part of a set or not, fuzzy set theory permits partial membership, facilitating a more detailed portrayal of qualitative assessments and linguistic variables. This method is especially useful in material selection, where numerous criteria may not be easily measured or where decisions may involve intrinsic uncertainty. The initial data gathering included creating linguistic scales, which were subsequently converted into triangular fuzzy numbers (TFNs). To achieve this, a seven-point linguistic scale was utilized, with verbal descriptors spanning from "Very Poor" to "Very Good" for assessing alternatives, and from "Very Low Importance" to "Very High Importance" for ranking criteria, which were transformed into their respective TFNs. Every TFN is characterized by three parameters (l, m, u), with l denoting the lower limit, m representing the most probable value, and u indicating the upper limit of the potential values.

3.5. Multi Criteria Decision Making

Multi-Criteria Decision Making (MCDM) is a subfield of operations research that addresses decision challenges featuring various, frequently opposing criteria. MCDM methods offer organized frameworks for assessing options according to various criteria, allowing decision-makers to make well-informed decisions in intricate situations where a straightforward single-criterion method would be inadequate. MCDM methods are especially useful in scenarios that necessitate the weighing of economic, technical, environmental, and social factors. These approaches assist decision-makers in methodically assessing trade-offs among conflicting goals and pinpointing solutions that optimally meet various needs at once. The core idea of MCDM is that actual decisions rarely optimize a single criterion maximize one criterion but instead aim to find acceptable trade-offs across multiple performance aspects. In relation to sustainable material selection, as discussed in this study, MCDM methods provide a structured approach to evaluate standard materials against eco-friendly options while considering various factors like cost, performance, ecological impact, and adherence to regulations.

3.5.1. Fuzzy AHP

Fuzzy Analytic Hierarchy Process (Fuzzy AHP) enhances the conventional AHP method by incorporating fuzzy set theory to tackle the uncertainty and vagueness in decision-makers' assessments. Developed as an enhancement to Saaty's original AHP, Fuzzy AHP replaces precise numerical values with fuzzy numbers, commonly triangular fuzzy numbers (TFNs), to better reflect the uncertainty in human thought and verbal assessments. This approach allows decision-makers to articulate their preferences using linguistic terms rather than exact figures, more accurately representing the uncertainty and subjectivity inherent in pairwise comparisons. The Fuzzy AHP method maintains the hierarchical structure of traditional AHP while integrating fuzziness into the pairwise comparison process. By employing fuzzy numbers, this method not only determines the most likely value in comparison but also includes the possible range of values, thereby considering the uncertainty in expert evaluations. This is particularly beneficial in cases where decision-makers cannot provide precise numerical ratings due to a lack of information, the natural vagueness of evaluation criteria, or the subjective nature of the assessment.

Table 2 displays the linguistic terms alongside their associated triangular fuzzy numbers utilized in the Fuzzy AHP scaling method. These fuzzy numbers symbolize the comparative significance of one criterion against another and form the basis for creating the fuzzy comparison matrices, which are later analyzed to establish criteria weights.

Table 2. Linguistic Terms and the Corresponding Triangular Fuzzy Numbers

Saaty Scale	Definition	Fuzzy Triangular Scale
1	Equally Important (Eq. Imp.)	(1, 1, 1)
3	Weakly Important (W. Imp.)	(2, 3, 4)
5	Fairly Important (F. Imp.)	(4, 5, 6)
7	Strongly Important (S. Imp.)	(6, 7, 8)
9	Absolutely Important (A. Imp.)	(9, 9, 9)
2	The intermittent values between two adjacent scales	(1, 2, 3)
4		(3, 4, 5)
6		(5, 6, 7)
8		(7, 8, 9)

Parameters:

$\tilde{a}_{ji}$: Fuzzy triangular comparison value of criterion i over criterion j

$\tilde{d}_{ij}$ **:** k^{th} decision maker's preference of i^{th} criterion over j^{th} criterion via fuzzy triangular number

$\tilde{r}_i$ **:** Geometric mean of fuzzy comparison values of criterion i

$\widetilde{w}_i$: Fuzzy weight of criterion i

M_i : Defuzzified value of criterion i

N_i : Normalized weight of criterion i

$$\widetilde{\boldsymbol{a}}_{\boldsymbol{ji}} = (\mathbf{1}\ /\boldsymbol{u}_{\boldsymbol{ij}}\ , \mathbf{1}\ /\boldsymbol{m}_{\boldsymbol{ij}}\ , \mathbf{1}\ /\boldsymbol{l}_{\boldsymbol{ij}}\ ) \tag{1}$$

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

$$\tilde{\boldsymbol{r}}_{\boldsymbol{i}} = \left(\prod_{j=1}^{n} \widetilde{\boldsymbol{d}}_{\boldsymbol{ij}}\right)^{1/n}, \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots\ldots, \boldsymbol{n} \tag{3}$$

The formulas (1), (2), and (3) signify essential mathematical functions in the Fuzzy Analytic Hierarchy Process. Equation (1) illustrates the transformation of a fuzzy triangular comparison value into its reciprocal, involving the inversion of each part of the triangular fuzzy number and the reversal of their sequence. Equation (2) computes the total fuzzy comparison value by averaging the preferences of K decision-makers, enabling the integration of various expert assessments into one comparative evaluation. Equation (3) calculates the geometric mean of all fuzzy comparison values for criterion i across all criteria j, serving as the foundation for assessing the relative significance of each criterion in the decision hierarchy. This series of computations lays the mathematical groundwork for determining the fuzzy weights applied in ranking evaluation criteria.

$$\widetilde{\boldsymbol{w}}_{\boldsymbol{i}} = \tilde{\boldsymbol{r}}_{\boldsymbol{i}} \otimes (\tilde{\boldsymbol{r}}_{\mathbf{1}} \oplus \tilde{\boldsymbol{r}}_{\mathbf{2}} \oplus \ldots.\ \oplus \tilde{\boldsymbol{r}}_{\boldsymbol{n}})^{-\mathbf{1}} = (\boldsymbol{lw}_{\boldsymbol{i}}, \boldsymbol{mw}_{\boldsymbol{i}}, \boldsymbol{uw}_{\boldsymbol{i}}) \tag{4}$$

$$\boldsymbol{M}_{\boldsymbol{i}} = \frac{\boldsymbol{lw}_{\boldsymbol{i}} + \boldsymbol{mw}_{\boldsymbol{i}} + \boldsymbol{uw}_{\boldsymbol{i}}}{\mathbf{3}} \tag{5}$$

$$\boldsymbol{N}_{\boldsymbol{i}} = \frac{\boldsymbol{M}_{\boldsymbol{i}}}{\sum_{i=1}^{n} \boldsymbol{M}_{\boldsymbol{i}}} \tag{6}$$

Equation (4) calculates the fuzzy weight of criterion i by multiplying its geometric mean by the inverse of the sum of all geometric means, resulting in a triangular fuzzy number with lower, middle, and upper values (lw_i, mw_i, uw_i). This operation ensures proportional distribution of importance across all criteria. Equation (5) performs defuzzification by computing the crisp value M_i as the arithmetic mean of the three components of the fuzzy weight, converting the triangular fuzzy number into a single representative value. Finally, Equation (6) normalizes these defuzzified weights by dividing each criterion's defuzzified value by the sum of all defuzzified values, ensuring that the final normalized weights N_i sum to one and properly represent the relative importance of each criterion in the decision hierarchy.

3.5.2. FUZZY TOPSIS

Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) is a variant of the traditional TOPSIS approach that integrates fuzzy set theory to tackle uncertainty and vagueness in multi-criteria decision-making scenarios. Conventional TOPSIS assesses alternatives by measuring their geometric distances from ideal and anti-ideal solutions using precise values, whereas Fuzzy TOPSIS utilizes fuzzy numbers, generally triangular fuzzy numbers (TFNs), to portray linguistic evaluations and uncertain judgments. The Fuzzy TOPSIS method adopts a systematic procedure that starts with creating a fuzzy decision matrix which includes the performance evaluations of options relative to different criteria. These assessments are represented as fuzzy numbers instead of precise figures, enabling decision-makers to utilize terms like "good," "moderate," or "poor" for evaluating options when exact numerical evaluations are hard to achieve. The approach subsequently normalizes the fuzzy decision matrix, implements criteria weights, and computes the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS). The ultimate ranking of options is established by their proximity to the FPIS and their distance from the FNIS. This method is especially useful in practical decision-making situations marked by uncertainty, personal opinions, or insufficient data, since it offers a mathematical structure for addressing the uncertainty present in human evaluations while preserving the intuitive distance-based assessment principle of conventional TOPSIS. Employing fuzzy numbers in Fuzzy TOPSIS enables a more accurate representation of decision-making issues and results in stronger rankings that more effectively capture the uncertainties involved in the assessment process.

Table 3 displays the linguistic terms alongside their respective triangular fuzzy numbers utilized in the Fuzzy TOPSIS rating scale. These imprecise figures allow for the conversion of qualitative assessments into a format appropriate for mathematical analysis, thus aiding the organized assessment of options across various criteria amid uncertain conditions.

Table 3. Fuzzy Rating for Linguistic Variables

Fuzzy Number	Alternative Assessment	Criteria Assessment
(1, 1, 3)	Very Poor (VP)	Very Low (VL)
(1, 3, 5)	Poor (P)	Low (L)
(3, 5, 7)	Fair (F)	Medium (M)
(5, 7, 9)	Good (G)	High (H)
(7, 9, 9)	Very Good (VG)	Very High (VH)

Parameters:

a_{ij} : minimum value of first place

b_{ij} : average value at the middle

c_{ij} : maximum value of last place

$\bar{r}ij$: Normalized fuzzy value

c_j^* : Maximum value for criterion j (benefit criteria)

$\bar{a}_j$: Minimum value for criterion j (cost criteria)

$\bar{p}_{ij}$: Weighted normalized fuzzy value

A^+ : Fuzzy Positive Ideal Solution (FPIS)

A^- : Fuzzy Negative Ideal Solution (FNIS)

${p^+}_j$: Maximum component for criterion j in FPIS

${p^-}_j$: Minimum component for criterion j in FNIS

$d\left(\bar{a}, \bar{b}\ \right)$: Distance between triangular fuzzy numbers

d_{i^+} : Distance of alternative i from FPIS

d_{i^-} : Distance of alternative i from FNIS

CC_i : Closeness Coefficient of alternative i

$$a_{ij} = min\{a^{k_{ij}}\} \tag{1}$$

$$b_{ij} = 1/K \sum_{k=1}^{k} b^{k_{ij}} \tag{2}$$

$$c_{ij} = max\{c^{k_{ij}}\} \tag{3}$$

Equations (1) to (3) illustrate the essential aggregation method for merging various expert assessments into one triangular fuzzy number within the Fuzzy TOPSIS approach. Equation (1) determines the minimum value (a_{ij}) from all expert evaluations for a specific alternative-criterion combination, setting the lower limit of the triangular fuzzy number. Equation (2) calculates the middle value (b_{ij}) by averaging all expert evaluations, yielding a measure of central tendency that reflects the consensus opinion. Equation (3) determines the highest value (c_{ij}) among all expert evaluations, establishing the upper limit of the triangular fuzzy number. Combined, these three equations convert potentially conflicting expert views into an all-encompassing fuzzy score that reflects both the shared assessment and the intrinsic uncertainty of the evaluation procedure, establishing a solid basis for future multi-criteria analysis.

$$\bar{r}_{ij} = \left(a_{ij}/c^*{}_j\, , b_{ij}/c^*{}_j\ , c_{ij}/c^*{}_j\right) and \tag{4}$$

$$c_j^* = \max c_{ij}\ (benefit\ Criteria\ )$$

$$\bar{r}ij = \left(\bar{a}_j/c_{ij}\, , \bar{a}_j/b_{ij}\, , \bar{a}_j/a_{ij}\ \right) and \tag{5}$$

$$\bar{a}_j = \min a_{ij}\ (cost\ Criteria\ )$$

Equations (4) and (5) define the normalization procedure for triangular fuzzy numbers within the Fuzzy TOPSIS approach, tailored to various types of criteria. Equation (4) focuses on benefit criteria (with higher values being favored), normalizing each triangular fuzzy number by dividing its elements (a_{ij}, b_{ij}, c_{ij}) by the highest upper value (c^*_j) from all alternatives for that specific criterion. This change establishes a uniform scale in which the most preferred option for each benefit criterion reaches a maximum normalized upper value of 1. In contrast, Equation (5) addresses cost criteria (favoring smaller values) by applying an inverse normalization method, which involves dividing the minimum lower value ($\bar{a}_j$) by every element of the triangular fuzzy number. This reverse function guarantees that smaller initial ratings for cost factors result in larger normalized figures, preserving uniformity in preference orientation across all criterion types and allowing for significant comparison between options across varied measurement scales.

$$\bar{p}_{ij} = \bar{r}_{ij} \times \bar{w}_j \tag{6}$$

Equation (6) illustrates the essential weighting process in the Fuzzy TOPSIS method, where the normalized fuzzy values are modified based on their significance in the decision-making context. This formula determines the weighted normalized fuzzy value ($\bar{p}_{ij}$) by multiplying each normalized fuzzy rating ($\bar{r}_{ij}$) with its respective criterion weight ($\bar{w}_j$), with both represented as triangular fuzzy numbers. By employing this fuzzy multiplication process, the equation incorporates the importance of criteria established through Fuzzy AHP into the performance evaluation matrix, guaranteeing that alternatives' performance in more critical criteria has a greater impact on their ultimate ranking. This weighted normalization phase converts the standardized performance ratings into figures that indicate both relative performance and the decision-maker's preference framework, laying the groundwork for determining the distances from ideal solutions in later stages of the Fuzzy TOPSIS process.

$$A^{+} = \left(p^{+}{}_{1}, p^{+}{}_{2}, \ldots., p^{+}{}_{n}\right) Where \tag{7}$$

$$p^{+}{}_{j} = max\{p_{ij3}\}, i = 1, 2, \ldots, m; j = 1, 2, \ldots., n$$

$$A^{-} = \left(p^{-}{}_{1}, p^{-}{}_{2}, \ldots., p^{-}{}_{n}\right) Where \tag{8}$$

$$p^{-}{}_{j} = min\{p_{ij}1\}, i = 1, 2, \ldots, m; j = 1, 2, \ldots., n$$

Equations (7) and (8) establish the reference points used to assess all options in the Fuzzy TOPSIS approach. Equation (7) defines the Fuzzy Positive Ideal Solution (FPIS), represented as A^{+}, which symbolizes an imagined ideal option that attains the optimal performance across every criterion. For every criterion j, the component p^{+}_{j} is established by choosing the highest third element (upper value) of the weighted normalized fuzzy evaluations among all alternatives, forming an ideal benchmark. In addition, Equation (8) describes the Fuzzy Negative Ideal Solution (FNIS), represented as A^{-}, which reflects the least favorable option exhibiting the lowest performance across all criteria. For every criterion j, the component p^{-}_{j} is determined by choosing the lowest first element (smallest value) of the weighted normalized fuzzy ratings among all options. The two reference points: A^{+} and A^{-}, act as the conceptual limits of performance within the decision space, facilitating the later computation of relative closeness coefficients used to establish the ultimate ranking of alternatives.

$$d\left(\bar{a},\bar{b}\right) = \sqrt{1/3\,[(a1-b1)^2 + (a2-b2)^2 + (a3-b3)^2]} \qquad (9)$$

Equation (9) establishes the mathematical basis for calculating the distance between two triangular fuzzy numbers within the Fuzzy TOPSIS approach. This formula determines the Euclidean distance d ($\bar{a}$, $\bar{b}$) between triangular fuzzy numbers $\bar{a}$ = (a1, a2, a3) and $\bar{b}$ = (b1, b2, b3) by finding the square root of the average of the squared differences between their respective components. The formula calculates the total of squared discrepancies between the lower limits $(a1\text{-}b1)^2$, middle points $(a2\text{-}b2)^2$, and upper limits $(a3\text{-}b3)^2$, multiplies by 1/3 to indicate an average, and then finds the square root of this result. This vertex approach for distance measurement encompasses the total divergence among fuzzy numbers, considering their three-dimensional characteristics. The generated precise distance value is crucial for measuring the distance of each alternative from the Fuzzy Positive Ideal Solution and the Fuzzy Negative Ideal Solution, establishing the foundation for the ultimate ranking in the decision-making process.

$$d_{i^+} = \sum_{j=1}^{n} d(\bar{p}_{ij}, p_{j^+}) \qquad (10)$$

$$d_{i^-} = \sum_{j=1}^{n} d(\bar{p}_{ij}, p_{j^-}) \qquad (11)$$

Equations (10) and (11) outline the computation of overall separation metrics for each option from the ideal solutions in the Fuzzy TOPSIS approach. Equation (10) calculates the overall distance $d_{(i}^{+})$ of alternative i from the Fuzzy Positive Ideal Solution by aggregating the individual distances d ($\bar{p}_{ij}$, p^{+}_{j}) across all n criteria, where $\bar{p}_{ij}$ denotes the weighted normalized fuzzy score of alternatives i for criterion j, and p^{+}_{j} is the relevant part of the positive ideal solution. In a comparable manner, Equation (11) calculates the overall distance $d_{(i}^{-})$ of alternative i from the Fuzzy Negative Ideal Solution by aggregating the distinct distances d ($\bar{p}_{ij}$, p^{-}_{j}) for all criteria, with p^{-}_{j} denoting the relevant part of the negative ideal solution. These combined distance metrics offer thorough evaluations of how each option stands relative to both the optimal and the least favorable theoretical solutions, considering performance across all criteria at once. These values act as the basis for computing the ultimate closeness coefficients that establish the ranking of options.

$$CC_i = d^{-}{}_i/(d^{-}{}_i + d^{+}{}_i)\ , i = 1, 2, \ldots, m \qquad (12)$$

Equation (12) denotes the final computation in the Fuzzy TOPSIS approach, calculating the Closeness Coefficient (CC_i) for every alternative i. This coefficient assesses how close each alternative is to both the ideal and anti-ideal solutions at the same time. The calculation for CC_i is derived by taking the ratio of the distance to the Fuzzy Negative Ideal Solution (d^{-}_{i}) compared to the total distances from both the Fuzzy Negative and Positive Ideal Solutions ($d^{-}_{i} + d^{+}_{i}$). The resulting value consistently lies within the interval [0,1], where a higher coefficient signifies closer proximity to the optimal solution and a greater distance from the non-optimal solution. An option with CC_i nearing 1 is viewed as nearest to the optimal solution, whereas a value close to 0 suggests closeness to the worst solution. These proximity coefficients serve as the ultimate foundation for ordering the options, where higher coefficients indicate more favored alternatives. The ultimate ranking derived from these coefficients embodies a thorough assessment of options across all weighted criteria, considering both effectiveness and the preference framework of the decision-maker.

3.6. Results Analysis

The results analysis phase will involve a comprehensive examination of the findings obtained from the Fuzzy AHP and Fuzzy TOPSIS methodologies. We will analyze the criteria derived from Fuzzy AHP to understand the relative importance of each criterion in the decision-making process. The performance rankings generated by Fuzzy TOPSIS will be scrutinized to determine which sustainable alternative (Bio-PE, PLA, PBS, or PHA) emerges as the most suitable replacement for conventional PE in medical applications.

3.7. Sensitivity Analysis

An extensive sensitivity analysis will be performed to assess the reliability of the ranking results and pinpoint the key decision factors that affect material selection results. This examination will methodically adjust the weights given to each criterion, generating different decision scenarios that reflect diverse stakeholder priorities and organizational limitations. Four primary sensitivity models will be created: an environmentally oriented model with increased emphasis on the Environmental Impact, a cost-oriented model prioritizing economic factors, a compliance-focused model highlighting regulatory requirements, and a balanced model distributing equal importance across all criteria. In every scenario, the complete Fuzzy TOPSIS calculation will be reiterated using the modified weights, producing new closeness coefficients and alternative rankings. By evaluating these outcomes alongside the baseline ranking, we can assess the consistency of our recommendations across various decision scenarios and pinpoint threshold values where ranking shifts happen. This method will supply healthcare decision-makers with critical insights into how well each alternative material performs across different operational priorities and regulatory settings, enabling more informed and flexible material selection strategies that remain relevant as organizational goals change.

4. IMPLEMENTATION AND RESULTS

The Implementation and Results section offers an in-depth examination of sustainable substitutes for polyethylene in medical applications through the Fuzzy Multi-Criteria Decision-Making approach described earlier. This part illustrates the real-world use of Fuzzy AHP to establish criteria weights based on expert assessments, which is succeeded by Fuzzy TOPSIS to evaluate the alternatives based on their performance across all criteria. The analysis includes evaluations from two industry specialists, whose opinions were transformed into triangular fuzzy numbers to address the natural uncertainty in qualitative assessments. The findings present a distinct order of preferences among the four options: Bio-PE, PLA, PBS, and PHA, along with comprehensive performance data across environmental, economic, technical, and regulatory aspects. An ensuing sensitivity analysis confirms the reliability of these results across different prioritization scenarios, providing essential insights for healthcare decision-makers aiming for sustainable material solutions.

Table 4. Linguistic Terms for the First Expert

	FIRST EXPERT					
	Environmental Impact	**Cost**	**Quality**	**Availability**	**Regulatory Status**	**Performance Match**
Environmental Impact	Equally Important	Weakly Important	Equally Important	Weakly Important	Inverse of Absolutely Important	Weakly Important
Cost	Inverse of Weakly Important	Equally Important	Inverse of Fairly Important	Inverse Strongly Important	Inverse of Fairly Important	Inverse of Weakly Important
Quality	Equally Important	Fairly Important	Equally Important	Weakly Important	Equally Important	Fairly Important
Availability	Inverse of Weakly Important	Strongly Important	Inverse of Weakly Important	Equally Important	Inverse of Weakly Important	Inverse of Weakly Important
Regulatory Status	Absolutely Important	Fairly Important	Equally Important	Weakly Important	Equally Important	Fairly Important
Performance Match	Inverse of weakly Important	Weakly Important	Inverse of Fairly Important	Weakly Important	Inverse of Fairly Important	Equally Important

Table 4 displays the triangular fuzzy assessing correspondences for the initial expert's linguistic evaluations within the Fuzzy AHP framework. It converts qualitative significance phrases (ranging from "Equally Important" to "Absolutely Important") into exact three-parameter fuzzy values, like (4, 5, 6) for "Fairly Important." This transformation allows for mathematical analysis of the initial expert's subjective assessments while acknowledging the uncertainty present in their evaluations, creating a basis for determining criteria weights grounded in their unique expertise and viewpoint.

Table 5. Corresponding Triangular Fuzzy Numbers for the First Expert

	FIRST EXPERT					
	Environmental Impact	**Cost**	**Quality**	**Availability**	**Regulatory Status**	**Performance Match**
Environmental Impact	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(2, 3, 4)	(1/9, 1/9, 1/9)	(2, 3, 4)
Cost	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)
Quality	(1, 1, 1)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(4, 5, 6)
Availability	(1/4, 1/3, 1/2)	(6, 7, 8)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)
Regulatory Status	(9, 9, 9)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(4, 5, 6)
Performance Match	(1/4, 1/3, 1/2)	(2, 3, 4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/6, 1/5, 1/4)	(1, 1, 1)

Table 5 converts the qualitative evaluations of the first expert into a mathematical form by employing triangular fuzzy numbers. This matrix for pairwise comparisons quantifies the expert's assessments regarding the relative significance of each criterion, transforming verbal evaluations into exact numerical values. The matrix underscores the expert's significant inclination towards Regulatory Status rather than Environmental Impact (9, 9, 9), while Cost is viewed with comparatively less importance. This numerical conversion is essential for handling the expert's subjective assessments in the Fuzzy AHP framework to determine objective criteria weights for selecting sustainable materials.

Table 6. Linguistic Terms for the Second Expert

	SECOND EXPERT					
	Environmental Impact	**Cost**	**Quality**	**Availability**	**Regulatory Status**	**Performance Match**
Environmental Impact	Equally Important	Weakly Important	Strongly Important	Weakly Important	Inverse of Absolutely Important	Weakly Important
Cost	Inverse of Weakly Important	Equally Important	Inverse of Fairly Important	Inverse Absolutely Important	Inverse of Fairly Important	Inverse of Weakly Important
Quality	Inverse of Strongly Important	Fairly Important	Equally Important	Weakly Important	Equally Important	Fairly Important
Availability	Inverse of Weakly Important	Absolutely Important	Inverse of Weakly Important	Equally Important	Weakly Important	Inverse of Weakly Important
Regulatory Status	Absolutely Important	Fairly Important	Equally Important	Inverse of Weakly Important	Equally Important	Inverse of Fairly Important
Performance Match	Inverse of weakly Important	Weakly Important	Inverse of Fairly Important	Weakly Important	Fairly Important	Equally Important

Table 6 shows the pairwise linguistic comparisons conducted by the second expert to assess the six criteria. This table displays the expert's qualitative evaluations prior to numerical conversion, revealing marked disparities from the initial expert's judgments. Significantly, this specialist values Environmental Impact as "Highly Important" in relation to Quality, whereas Availability is deemed "Extremely Important" in comparison to Cost. Like the initial expert, Regulatory Status is deemed "Absolutely Important" in relation to Environmental Impact, suggesting agreement on this specific connection. These linguistic assessments offer raw insights into the prioritization framework of the second expert prior to conversion into triangular fuzzy numbers, emphasizing their distinct viewpoint on the factors that should influence sustainable material choice in medical applications.

Table 7. Corresponding Triangular Fuzzy Numbers for the Second Expert

	SECOND EXPERT					
	Environmental Impact	**Cost**	**Quality**	**Availability**	**Regulatory Status**	**Performance Match**
Environmental Impact	(1, 1, 1)	(2, 3, 4)	(6, 7, 8)	(2, 3, 4)	(1/9, 1/9, 1/9)	(2, 3, 4)
Cost	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/9, 1/9, 1/9)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)
Quality	(1/8, 1/7, 1/6)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(4, 5, 6)
Availability	(1/4, 1/3, 1/2)	(9, 9, 9)	(1/4, 1/3, 1/2)	(1, 1, 1)	(2, 3, 4)	(1/4, 1/3, 1/2)
Regulatory Status	(9, 9, 9)	(4, 5, 6)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/6, 1/5, 1/4)
Performance Match	(1/4, 1/3, 1/2)	(2, 3, 4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(4, 5, 6)	(1, 1, 1)

Table 7 converts the linguistic evaluations of the second expert into triangular fuzzy numbers for further mathematical analysis. This conversion matrix shows unique prioritization trends in contrast to the initial expert. These numerical values reflect the uncertainty in the expert's assessments and will be utilized to determine the fuzzy weights based on their viewpoint, supplying crucial information for the combined criteria weights in the ultimate decision model.

Table 8. Alternative Assessment

Criteria	**A1**		**A2**		**A3**		**A4**	
	DM1	**DM2**	**DM1**	**DM2**	**DM1**	**DM2**	**DM1**	**DM2**
C1	Good	Good	Very Good	Very Good	Good	Fair	Very Good	Very Good
C2	Fair	Good	Poor	Fair	Fair	Poor	Poor	Very Poor
C3	Very Good	Very Good	Good	Good	Fair	Good	Fair	Poor
C4	Very Good	Good	Good	Fair	Fair	Poor	Poor	Very Poor

C5	Very Good	Good	Good	Fair	Fair	Poor	Poor	Poor
C6	Very Good	Very Good	Good	Fair	Fair	Good	Fair	Poor

Table 8 displays the language evaluations of both decision-makers (DM1 and DM2) for each option (A1-A4) across all six criteria (C1-C6). This matrix displays the experts' assessments prior to numerical transformation, highlighting significant trends in their evaluations. Alternative A1 (Bio-PE) consistently achieves high scores, especially for criteria C3-C6, as both experts rated it "Very Good" across several criteria. Alternative A2 (PLA) demonstrates robust results for Environmental Impact (C1) with "Very Good" evaluations from each expert, whereas Alternatives A3 (PBS) and A4 (PHA) exhibit gradually diminishing ratings across most criteria. The table emphasizes key areas of consensus among experts (like A2's environmental advantages) and disparities (such as differing evaluations of A3's effectiveness), laying the qualitative groundwork for the fuzzy TOPSIS method that will transform these verbal assessments into quantifiable ratings for alternative ranking.

Table 9. Corresponding Triangular Fuzzy Numbers for the Alternatives

Criteria	A1		A2		A3		A4	
	DM1	DM2	DM1	DM2	DM1	DM2	DM1	DM2
C1	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)
C2	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C3	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)
C4	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C5	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
C6	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)

Table 9 transforms the linguistic evaluations of both decision-makers into triangular fuzzy numbers for every alternative across all criteria. This numerical conversion allows for mathematical operations within the Fuzzy TOPSIS model. The table shows distinct preference patterns: Alternative A1 (Bio-PE) consistently achieves high fuzzy ratings, especially for criteria C3-C6 where numerous evaluations (7, 9, 9) suggest exceptional performance. Alternative A2 (PLA) demonstrates outstanding environmental performance (C1) with (7, 9, 9) evaluations from both experts, though it has moderate ratings for other criteria. Alternatives A3 and A4 exhibit steadily decreasing fuzzy values, with A4 notably garnering very low scores (1, 1, 3) across multiple categories.

4.1. Implementation of F-AHP Method

Table 10. Geometric Mean Calculation for the First Expert

Criteria	ri		
Environmental Impact	0.98	1.2	1.39
Cost	0.245	0.293	0.371
Quality	1.78	2.05	2.29
Availability	0.535	0.665	0.891
Regulatory Status	2.57	2.96	3.3
Performance Match	0.55	0.702	0.891
Total	6.66	7.87	9.133
Reverse (power of -1)	0.15	0.13	0.11
Increasing order	0.11	0.13	0.15

Table 10 displays the computed geometric means (ri) from the initial expert's pairwise comparisons applying Fuzzy AHP. Every row displays the triangular fuzzy elements (lower, middle, upper) of the geometric mean for a particular criterion. The table shows that Regulatory Status (C5) has the highest geometric mean values (2.57, 2.96, 3.3), next is Quality (C3) with values (1.78, 2.05, 2.29), suggesting these criteria are deemed most significant by the first expert. On the other hand, Cost (C2) exhibits the lowest values (0.245, 0.293, 0.371), indicating it is considered the least important. The table additionally features row totals, their reciprocals (essential for the subsequent calculation step), and an arrangement of the reciprocals in ascending order. These geometric means form the basis for determining the fuzzy weights of every criterion in accordance with equation (4) in the methodology.

Table 11. Fuzzy Weight Values for Each Criterion of First Expert's Assessment

Criteria	Wi		
Environmental Impact	0.107	0.152	0.209
Cost	0.027	0.037	0.056
Quality	0.195	0.260	0.344
Availability	0.059	0.084	0.134
Regulatory Status	0.281	0.376	0.495
Performance Match	0.060	0.089	0.134

Table 11 displays the computed fuzzy weights (Wi) for each criterion obtained from the initial expert's pairwise comparisons. Every weight is represented as a triangular fuzzy number that includes lower, middle, and upper values. The findings clearly show that Regulatory Status holds the greatest significance with weights (0.281, 0.376, 0.495), followed by Quality (0.195, 0.260, 0.344). Environmental Impact is placed third (0.107, 0.152, 0.209), whereas Cost displays the least relative significance (0.027, 0.037, 0.056). These fuzzy weights reflect the pattern of prioritization by the expert, encompassing both the average of their judgment and the uncertainty in their assessment. These values will subsequently be defuzzified and normalized to derive precise criteria weights for the decision-making process.

Table 12. Geometric Mean Calculation for the Second Expert

Criteria	ri		
Environmental Impact	1.32	1.66	1.96
Cost	0.24	0.281	0.347
Quality	1.256	1.485	1.698
Availability	0.809	1	1.285
Regulatory Status	1.067	1.201	1.375
Performance Match	0.935	1.201	1.513

Total	5.627	6.828	8.178
Reverse (power of -1)	0.18	0.15	0.12
Increasing order	0.12	0.15	0.18

Table 12 presents the geometric mean computations (ri) for the pairwise comparisons made by the second expert. In contrast to the initial expert, the second expert places the greatest emphasis on Environmental Impact with values (1.32, 1.66, 1.96), closely followed by Quality (1.256, 1.485, 1.698) and Regulatory Status/Performance Match (both sharing a middle value of 1.201). This indicates a more equitable allocation of significance among criteria in contrast to the first expert's evaluation. Costs continue to be the least weighted criterion (0.24, 0.281, 0.347), indicating that experts concur with their comparative significance. The table additionally features row totals, reciprocals, and an arrangement in ascending order needed for later weight computations. These geometric means establish the foundation for calculating the fuzzy weights based on the second expert's evaluation, emphasizing the distinct prioritization pattern relative to the first expert's analysis in Table 6.

Table 13. Fuzzy Weight Values for Each Criterion of Second Expert's

Criteria	Wi		
Environmental Impact	0.161	0.243	0.348
Cost	0.029	0.041	0.062
Quality	0.154	0.217	0.302
Availability	0.099	0.146	0.228
Regulatory Status	0.130	0.176	0.244
Performance Match	0.114	0.176	0.269

Table 13 displays the triangular fuzzy weights (Wi) derived from the pairwise comparisons made by the second expert. In contrast to the first expert, the second expert emphasizes Environmental Impact with the highest weight values (0.161, 0.243, 0.348), with Quality following (0.154, 0.217, 0.302). Significantly, Regulatory Status (0.130, 0.176, 0.244) and Performance Match (0.114, 0.176, 0.269) possess the same median values, signifying equivalent significance in the assessment of the expert. Cost continues to be the least significant criterion (0.029, 0.041, 0.062), aligning with the evaluation of the first expert. This weight allocation shows a distinct prioritization pattern in contrast to the initial expert, highlighting a more balanced significance across various criteria and a greater focus on environmental factors. These imprecise weights represent the expert's evaluation pattern and will aid in forming the combined criteria weights for the ultimate decision model.

4.2. Implementation of F-TOPSIS

Table 14. Aggregated Fuzzy Decision Matrix Combining Both Experts' Assessments

Criteria	A1	A2	A3	A4
C1	(5, 7, 9)	(7, 9, 9)	(3, 6, 9)	(7, 9, 9)
C2	(3, 6, 9)	(1, 4, 7)	(1, 4, 7)	(1, 2, 5)
C3	(7, 9, 9)	(5, 7, 9)	(3, 6, 9)	(1, 4, 7)
C4	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 2, 5)
C5	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 3, 5)
C6	(7, 9, 9)	(3, 6, 9)	(3, 6, 9)	(1, 4, 7)

Table 14 displays the consolidated fuzzy decision matrix that integrates the assessments from both experts for each option across all criteria. This compilation adheres to the specified approach in equations (1-3) of Fuzzy TOPSIS, where the lowest value signifies the minimum evaluation, the middle value represents the average, and the highest value denotes the maximum evaluation between the two experts. The matrix shows that Alternative A1 (Bio-PE) consistently achieves strong ratings for most criteria, especially for C3 (Quality) and C6 (Performance Match) with values of (7, 9, 9). Alternative A2 (PLA) shows outstanding environmental performance (C1) with scores of (7, 9, 9) but average ratings for additional criteria. Options A3 and A4 exhibit increasingly lower ratings, with A4 especially receiving unfavorable assessments for criteria C2, C4, and C5.

Table 15. Calculated Weight for First and Second Expert

	Wi	
Criteria	**DM1**	**DM2**
C1	(0.107, 0.152, 0.209)	(0.161, 0.243, 0.348)

C2	(0.027, 0.037, 0.056)	(0.029, 0.041, 0.062)
C3	(0.195, 0.260, 0.344)	(0.154, 0.217, 0.302)
C4	(0.059, 0.084, 0.134)	(0.099, 0.146, 0.228)
C5	(0.281, 0.376, 0.495)	(0.130, 0.176, 0.244)
C6	(0.060, 0.089, 0.134)	(0.114, 0.176, 0.269)

Table 15 displays a comparative analysis of the fuzzy weights determined for each criterion based on the evaluations from both experts using Fuzzy AHP. This table acts as the input for the Fuzzy TOPSIS execution stage, offering the significant weights that will be utilized for the normalized decision matrix. The analysis shows notable differences in how experts prioritize factors: the first expert (DM1) emphasizes Regulatory Status (0.281, 0.376, 0.495) and Quality (0.195, 0.260, 0.344) the most, while the second expert (DM2) focuses on Environmental Impact (0.161, 0.243, 0.348) and Quality (0.154, 0.217, 0.302). The most notable variation is found in Regulatory Status, which is ranked first for DM1 but fourth for DM2. Both specialists give the least significance to Cost. These unique weight patterns will affect the following Fuzzy TOPSIS calculations, since they embody the various viewpoints on the significance of criteria that will be incorporated into the ultimate alternative rankings.

Table 16. Aggregated Fuzzy Weights for All Criteria

Criteria	Wi
C1	(0.107, 0.198, 0.348)
C2	(0.027, 0.039, 0.062)
C3	(0.154, 0.239, 0.344)
C4	(0.059, 0.115, 0.228)
C5	(0.130, 0.276, 0.495)
C6	(0.060, 0.133, 0.269)

Table 16 displays the combined fuzzy weights derived from the assessments of both experts for each criterion. These combined weights utilize a particular aggregation technique in which the lower value indicates the minimum weight, the upper value denotes the maximum weight between the two specialists, and the middle value signifies a weighted average. The table indicates that Regulatory Status (C5) retains the greatest overall weight (0.130, 0.276, 0.495), next is Quality (C3) with values of (0.154, 0.239, 0.344) and Environmental Impact (C1) at (0.107, 0.198, 0.348). Cost

(C2) continues to be the least prioritized criterion (0.027, 0.039, 0.062). The broad variations in the fuzzy numbers, especially concerning Regulatory Status, indicate considerable discrepancies in expert views about the significance of criteria. These combined weights signify the shared evaluation of the two experts and will serve to weigh the normalized decision matrix in the following stages of the Fuzzy TOPSIS method, guaranteeing that both viewpoints are included in the ultimate rankings of alternatives.

Table 17. Normalized Fuzzy Decision Matrix

rij				
Criteria	**A1**	**A2**	**A3**	**A4**
C1	(0.556, 0.778, 1)	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.778, 1, 1)
C2	(0.111, 0.167, 0.333)	(0.143, 0.25, 1)	(0.143, 0.25, 1)	(0.2, 0.5, 1)
C3	(0.778, 1, 1)	(0.556, 0.778, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)
C4	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.222, 0.556)
C5	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.333, 0.556)
C6	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)

Table 17 presents the normalized fuzzy decision matrix, a critical step in the Fuzzy TOPSIS methodology that converts the original fuzzy ratings into comparable scale-free values. This normalization follows equation (4) for benefit criteria and equation (5) for cost criteria, ensuring all values fall within the range [0,1]. For benefit criteria (C1, C3-C6), each value is divided by the maximum upper value of that criterion, while for cost criteria (C2), the minimum lower value is divided by each value (using the reciprocal operation). The normalized matrix preserves the relative performance of alternatives while making them comparable across different measurement scales. Notable patterns include Alternatives A1 and A2 showing strong normalized performance across most criteria, particularly for C1 where A2 and A4 both achieve the maximum possible normalized value (0.778, 1,1). This normalized matrix will be weighed in the next step by multiplying each value by the corresponding criteria weights to obtain the weighted normalized fuzzy decision matrix.

Table 18. Weighted Normalized Fuzzy Decision Matrix

Pij=rij*Wi				
Criteria	**A1**	**A2**	**A3**	**A4**

C1	(0.060, 0.154, 0.348)	(0.083, 0.198, 0.348)	(0.036. 0.132, 0.348)	(0.083, 0.198, 0.348)
C2	(0.003, 0.007, 0.021)	(0.004, 0.01, 0.062)	(0.004, 0.01, 0.062)	(0.005, 0.020, 0.062)
C3	(0.120, 0.239, 0.344)	(0.086, 0.186, 0.344)	(0.051, 0.159, 0.344)	(0.017, 0.106, 0.268)
C4	(0.033, 0.102,0.228)	(0.020, 0.077, 0.228)	(0.007, 0.052, 0.177)	(0.007, 0.026, 0.127)
C5	(0.072, 0.245, 0.495)	(0.043, 0.184, 0.495)	(0.014, 0.123, 0.385)	(0.014, 0.092, 0.275)
C6	(0.047, 0.133, 0.269)	(0.020, 0.089, 0.269)	(0.020, 0.089, 0.269)	(0.007, 0.059, 0.209)

Table 18 shows the weighted normalized fuzzy decision matrix, which is derived by multiplying each value in the normalized matrix (Table 17) by its respective aggregated criteria weight (Table 16) as outlined in equation (6) of the methodology. This vital stage includes the significance of each criterion in the performance evaluations of the options. The resulting matrix indicates that Alternative A1 (Bio-PE) excels notably in the high-weight criteria C3 (Quality) with values (0.120, 0.239, 0.344) and C5 (Regulatory Status) with values (0.072, 0.245, 0.495). Alternative A2 (PLA) demonstrates excellent results in Environmental Impact (C1) with figures (0.083, 0.198, 0.348). Although A4 (PHA) demonstrates outstanding environmental performance, its weighted scores for other significant criteria are considerably lower. The weighted normalized matrix clearly shows how the weights of criteria affect the overall evaluation of alternatives, with performance in criteria with higher weights having a more significant effect on the final rankings. This matrix will serve to calculate the distances of each alternative from the fuzzy positive and negative ideal solutions in the subsequent step of the Fuzzy TOPSIS approach.

Table 19. Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS)

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
A+	(0.348, 0.348, 0.348)	(0.062, 0.062, 0.062)	(0.344, 0.344, 0.344)	(0.228, 0.228, 0.228)	(0.495, 0.495, 0.495)	(0.269, 0.269, 0.269)
A-	(0.036, 0.036, 0.036)	(0.003, 0.003, 0.003)	(0.017, 0.017, 0.017)	(0.007, 0.007, 0.007)	(0.014, 0.014, 0.014)	(0.007, 0.007, 0.007)

Table 19 sets the benchmark for evaluating options in the Fuzzy TOPSIS approach. Based on equations (7) and (8), these figures are obtained from the weighted normalized decision matrix presented in Table 18. For the FPIS (A+), every value indicates the utmost achievable performance for each criterion, deriving the highest upper value from all options for that criterion and forming a consistent triangular fuzzy number (e.g., (0.348, 0.348, 0.348) for C1). Likewise, the FNIS (A-) indicates the least achievable performance by utilizing the lowest lower value for every criterion. These reference points do not signify real alternatives but rather theoretical standards of ideal and worst-case performance. In the following steps, the distance of each alternative from these ideals will be assessed to establish their relative performance ranking, where those closer to A+ and further from A- will obtain higher rankings.

Table 20. Distance Measurements from FPIS and FNIS for Each Alternative

Criteria	FPIS(A1)	FPIS(A2)	FPIS(A3)	FPIS(A4)	FNIS(A1)	FNIS(A2)	FNIS(A3)	FNIS(A4)
C1	0.200	0.176	0.219	0.176	0.193	0.205	0.188	0.205
C2	0.052	0.045	0.045	0.041	0.011	0.034	0.034	0.035
C3	0.143	0.175	0.200	0.237	0.236	0.216	0.207	0.154
C4	0.159	0.174	0.197	0.219	0.140	0.134	0.101	0.070
C5	0.284	0.317	0.357	0.384	0.310	0.295	0.223	0.157
C6	0.150	0.177	0.177	0.197	0.169	0.159	0.159	0.120

Table 20 displays the computed distances from each alternative to both the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS) for every criterion. These distances are calculated using equation (9) in the methodology, which assesses the distance between triangular fuzzy numbers. In the FPIS columns, lesser values signify superior performance (more aligned with the ideal solution), whereas in the FNIS columns, greater values are favored (further from the negative ideal solution). The outcomes indicate that Alternative A1 (Bio-PE) displays the shortest distances from FPIS for criteria C1, C3, and C5, showcasing its excellent performance in these key areas. Alternative A4 (PHA) exhibits the greatest distances from FPIS in nearly all criteria, especially for C5 (Regulatory Status). In the FNIS measurements, A1 typically exhibits greater distances, particularly for C3 and C5, signifying a significant separation from the worst-case scenario. In the following step, these distance measurements will be aggregated to establish the total distance of each alternative from the ideal solutions, which will subsequently be utilized to compute the closeness coefficients and final rankings.

Table 21. Final Closeness Coefficients and Rankings of Alternatives

	A1	A2	A3	A4
d+	0.988	1.064	1.195	1.253
d-	1.058	1.043	0.913	0.741
CCi	0.517	0.495	0.433	0.372

Table 21 displays the results of the Fuzzy TOPSIS analysis, indicating the overall distance of each option from the Fuzzy Positive Ideal Solution (d+) and the Fuzzy Negative Ideal Solution (d-), as well as the determined Closeness Coefficient (CCi). The distances are determined by adding the separate criterion distances from Table 20 in line with equations (10) and (11), and the Closeness Coefficient is derived using equation (12) as the ratio of d- to the total of d+ and d-. The findings distinctly outline a ranking sequence with Alternative A1 (Bio-PE) reaching the top CCi value (0.517), trailed by A2 (PLA) at 0.495, A3 (PBS) at 0.433, and A4 (PHA) at 0.372. This ranking shows that Bio-PE is the optimal sustainable alternative to traditional PE in medical applications, reflecting the best overall performance across all weighted criteria. The declining CCi values indicate a clear ranking among the options, with Bio-PE leading the pack mainly because of its consistent performance across the critical criteria, especially Regulatory Status, Quality, and Environmental Impact.

4.3. Results Analysis

The analysis of results shows a distinct hierarchy of sustainable options compared to traditional PE for medical uses, with Bio-PE (A1) proving to be the best choice, achieving a closeness coefficient of 0.576, followed by PLA (A2) at 0.533, PBS (A3) at 0.454, and PHA (A4) at 0.388. This tiered preference ranking demonstrates the well-rounded performance of Bio-PE across all six assessment criteria, with strength in high-weight categories like Regulatory Status, Quality, and Performance Match. Although PLA shows better environmental performance and PBS provides moderate capabilities in many areas, Bio-PE's major edge is its robust regulatory compliance and quality properties, which are essential for medical uses. The significant difference between Bio-PE and PHA (almost 0.2 points in closeness coefficient) suggests that although PHA has a remarkable biodegradability profile, its challenges in availability, regulatory approval, and technical performance render it less feasible for widespread use in medicine currently. These results are consistent with industry anticipations, since Bio-PE's chemical resemblance to traditional PE allows it to utilize current regulatory structures and production systems while providing considerable environmental advantages.

4.4. Sensitivity Analysis

A thorough sensitivity analysis was carried out to assess the reliability of our results and to investigate how changes in criteria's weighting could affect the ultimate ranking of options. This examination is vital for decision-makers in the healthcare sector who might work under varying priorities or limitations when choosing sustainable materials. Four separate sensitivity models were created, each illustrating a notable change in the significance of criteria, to assess whether the ranking would remain consistent across different stakeholder viewpoints. The comprehensive, step-by-step recalculations for every sensitivity model, which encompass modified criteria weights, normalized decision matrices, weighted normalized matrices, calculations for FPIS and FNIS, distance measurements, and ultimate closeness coefficients, are included in the **appendix** for thorough reference and validation of the sensitivity analysis outcomes. These thorough calculations guarantee total clarity in our analysis and enable stakeholders to evaluate the effects of various priority scenarios on material choice decisions.

4.4.1. Environmental Impact

In the initial sensitivity model, the significance of Environmental Impact (C1) increased, creating a scenario where ecological factors and minimizing carbon footprint are the main influences in material choice. The initial weights set by the experts were modified to give top priority to environmental factors, leading to a complete recalibration of the Fuzzy TOPSIS method. Curiously, even with this notable change in priorities, the overall ranking did not alter (A1 > A2 > A3 > A4), as Bio-PE continued to be the favored option, trailed by PLA, PBS, and PHA accordingly. This stability indicates that Bio-PE provides a strong enough environmental profile to compete effectively, even in situations where ecological factors are crucial, although the difference between Bio-PE and PLA significantly decreased in this context.

4.4.2. Cost

The second sensitivity model highlighted Cost considerations (C2), simulating decision environments with budget constraints where economic factors take precedence over other criteria. This significant change in priorities entirely rearranged the options, with PLA (A2) becoming the top choice, succeeded by PBS (A3), PHA (A4), and Bio-PE (A1) dropping to the lowest rank. This notable shift in rankings underscores Bio-PE's key vulnerability, its elevated production expenses in comparison to other options while showcasing PLA's remarkable cost efficiency in relation to its functional effectiveness. This situation would be especially pertinent for healthcare systems in resource-constrained environments where financial limitations could hinder the implementation of ideal yet more expensive options.

4.4.3. Regulatory Status

When the significance of Regulatory Status (C5) was heightened in the third sensitivity model, reflecting a highly regulated medical environment with strict compliance demands, the ranking shifted to A1 > A2 > A4 > A3, causing PBS to fall behind PHA. This change indicates the more robust regulatory system related to Bio-PE and PLA, and the relatively less advanced regulatory condition of PBS. This discovery is especially important for medical uses, where adherence to regulations is essential and materials lacking established regulatory routes encounter major hurdles to adoption, irrespective of their other benefits.

4.4.4. Balanced Criteria Weighting Scenario

In the ultimate sensitivity model, every criterion was given equal significance (1,1,1), signifying a completely balanced decision-making scenario devoid of any bias toward criteria. The resulting ranking returned to the initial sequence (A1 > A2 > A3 > A4), verifying that Bio-PE's superiority is not just a consequence of our weighting system but reflects a truly better overall performance within the entire evaluation framework. This comprehensive evaluation offers further assurance in Bio-PE as a strong endorsement for many medical uses.

5. CONCLUSION

This study investigated eco-friendly substitutes for polyethylene in healthcare applications by employing an extensive assessment framework utilizing fuzzy multi-criteria decision-making techniques. The research focused on the major environmental issues created by traditional PE plastics in healthcare, which result in nearly 14,000 tons of waste each year in the U.S., with recycling rates under 5% and degradation times of 500-1000 years. By combining fuzzy set theory with the AHP and TOPSIS methods, the research effectively assessed four viable options: Bio-PE, PLA, PBS, and PHA, based on six essential criteria covering environmental, economic, technical, and regulatory factors. The study showed a distinct ranking of sustainable options, where Bio-PE appeared as the best choice with a closeness coefficient of 0.517, followed by PLA (0.495), PBS (0.433), and PHA (0.372). The exceptional performance of Bio-PE is linked to its stringent regulatory adherence, high-quality features, and impressive technical performance comparable to traditional PE, all while delivering substantial environmental advantages with a reduction of up to 75% in carbon footprint in comparison to fossil-based options. The sensitivity analysis validated the reliability of these results across different prioritization scenarios, with Bio-PE retaining its leading status in many cases, except when cost was emphasized, where PLA became the favored choice. For healthcare organizations aiming to adopt sustainable materials, this study suggests a gradual strategy starting with Bio-PE as the main substitute for traditional PE in areas with strict regulatory standards, then introducing PLA for less critical uses where cost factors are vital. Additionally, a combined approach utilizing various materials tailored to application needs could enhance both sustainability and performance results.

Future studies ought to concentrate on broadening the assessment framework to encompass more emerging biomaterials, performing physical tests and clinical trials of the selected alternatives in particular medical applications, and creating advanced life cycle assessment models that reflect the total environmental impact throughout regional healthcare systems. Moreover, exploring the possibility of developing blended materials that harness the advantages of various alternatives could produce encouraging new solutions for medical uses that more effectively harmonize technical efficiency, regulatory adherence, and environmental sustainability.

BIBLIOGRAPHY

Ahsan, M., Tian, L., Du, R., Alhussan, A. A., & El-Kenawy, E.-S. M. (2024). Optimizing Environmental Impact: MCDM-Based Approaches for Petrochemical Industry Emission Cuts. *IEEE access, 12*, 1. doi:10.1109/access.2024.3370164

Barnes, D. K. A., Galgani, F., Thompson, R. C., & Barlaz, M. (2009). Accumulation and fragmentation of plastic debris in global environments. *Philosophical Transactions of the Royal Society B*, 364, 1985-1998. https://doi.org/10.1098/rstb.2008.0205

Braz, A., Lemos, P. V. F., Almeida, F. C., Moreira, L. M., Scheffler, T., & Wrasse-Schrage, A. (2021). Life cycle assessment of bio-based polyethylene packaging: Comparing the environmental benefits of sugarcane and corn-based resources. Sustainability, 13(5), 2863.

Bhardwaj, R., & Garg, S. (2023). An MCDM Approach to Analytically Identify the Air Pollutants' Impact on Health. *Atmosphere, 14*(6), 909. doi:10.3390/atmos14060909

Bouakouk, M. R., Abdelli, A., Mokdad, L., & Othman, J. B. (2022). Dealing with Complex Routing Requirements Using an MCDM Based Approach. *International Wireless Communications and Mobile Computing (IWCMC)*, (pp. 1256-1261). doi:10.1109/iwcmc55113.2022.9825024

Chai, N., & Zhou, W. (2022). A Novel Hybrid MCDM Approach for Selecting Sustainable Alternative Aviation Fuels in Supply Chain Management. *Fuel, 327*, 125180. doi:10.1016/j.fuel.2022.125180

Chatterjee, S., & Chakraborty, S. (2021). Material Selection of a Mechanical Component based on Criteria Relationship Evaluation and MCDM Approach. *Materials today: proceedings, 44*, 1621-1626. doi:10.1016/j.matpr.2020.11.817

Chaurasiya, P. K., Rathod, N. J., Jain, P. K., Pandey, V., Shashikant, & Lala , K. (2023). Material Selection for Optimal Design Using MultiCriteria Decision Making. *3rd International Conference on Advancement in Electronics & Communication Engineering (AECE)* (pp. 206-210). IEEE. doi:10.1109/AECE59614.2023.10428303

Chung, H.-Y., & Chang, K.-H. (2022). A Novel General Data Envelopment Analysis Based Approach for MCDM Issues of Hydrogen Energy under a Fuzzy Environment. *Systems, 10*(5), 176. doi:10.3390/systems10050176

Deepu, T., & Ravi, V. (2021). Supply Chain Digitalization: An Integrated MCDM Approach for Inter-organizational Information Systems Selection in an Electronic Supply Chain. *International journal of information management data insights, 1*(2), 100038. doi:10.1016/j.jjimei.2021.100038

Domaschka, J., Volpert, S., & Seybold, D. (2020). Hathi: An MCDM-based Approach to Capacity Planning for Cloud-hosted DBMS. *13th International Conference on Utility and Cloud Computing (UCC).* doi:10.1109/ucc48980.2020.00033

Đurić, G., Todorović, G., Đorđević, A., & Tišma, A. B. (2019). A New Fuzzy Risk Management Model for Production Supply Chain Economic and Social Sustainability. *ECONOMIC RESEARCH-EKONOMSKA ISTRAZIVANJA, 32*(1), 1697-1715. doi:10.1080/1331677x.2019.1638287

European Bioplastics. (2023). Environmental impacts of bioplastics: A comparative life cycle assessment (LCA) study of PLA and conventional plastics. Retrieved from https://www.european-bioplastics.org/publications/

Ersoy, N., & Taslak, S. (2022). Comparative Analysis of MCDM Methods for the Assessment of Corporate Sustainability Performance in Energy Sector. *EGE ACADEMIC REVIEW, 23*(3), 341-362. doi:10.21121/eab.986122

Fernández, D., Rodríguez-Prieto, Á., & Camacho, A. M. (2022). Optimal Parameters Selection in Advanced Multi-Metallic Co-Extrusion based on Independent MCDM Analytical Approaches and Numerical Simulation. *Mathematics, 10*(23), 4489. doi:10.3390/math10234489

Genç, M. S., & Karipoğlu, F. (2021). Wind-Solar Site Selection Using a GIS-MCDM-Based Approach with an Application in Kayseri Province/Turkey. *7th Iran Wind Energy Conference (IWEC).* doi:10.1109/iwec52400.2021.9467003

Ghaleb, A. M., Kaid, H., Alsamhan, A., Mian, S. H., & Hidri, L. (2020). Assessment and Comparison of Various MCDM Approaches in the Selection of Manufacturing Process. *Advances in materials science and engineering, 2020*, 1-16. doi:10.1155/2020/4039253

Görçün, Ö. F., Tirkolaee, E. B., Küçükönder, H., & Garg, C. P. (2024). Assessing and Selecting Sustainable Refrigerated Road Vehicles in Food Logistics using a Novel Multi-criteria Group Decision-making Model. *Information sciences, 661*, 120161. doi:10.1016/j.ins.2024.120161

Hsu, C., Yang, J., Chang, A., & Liu, G. (2024). A New Hybrid MCDM Approach for Mitigating Risks of Hazardous Material Road Transportation. *Mathematical biosciences and engineering, 21*(3), 4210-4240. doi:10.3934/mbe.2024186

Healthcare Plastics Recycling Council. (2022). *Medical plastics recycling barriers and opportunities report*. Retrieved from https://www.hprc.org/barriers-to-recycling-healthcare-plastics/

Hosouli, S., Gaikwad, N., Qamar, S. H., & Gomes, J. (2024). Optimizing Photovoltaic Thermal (PVT) Collector Selection: A Multi-criteria Decision-making (MCDM) Approach for Renewable Energy Systems. *Heliyon, 10*, e27605. doi:10.1016/j.heliyon.2024.e27605

Jaiswal , A., Negi , P., & Singh , N. (2023). MCDM Computational Approaches for Green Supply Chain Management Strategies. *6th International Conference on Information Systems and Computer Networks (ISCON)* (pp. 1-9). Mathura, India: IEEE. doi:10.1109/iscon57294.2023.10112124

Javaid, M., Khan, S., Haleem, A., & Rab, S. (2022). Adoption of Modern Technologies for Implementing Industry 4.0: an Integrated MCDM Approach. *Benchmarking, 30*(10), 3753-3790. doi:10.1108/bij-01-2021-0017

Kang, D., Jaisankar, R., Murugesan, V., Suvitha, K., Narayanamoorthy, S., Omar, A. H., Ahmadian, A. (2023). A Novel MCDM Approach to Selecting a Biodegradable Dynamic Plastic Product: a Probabilistic Hesitant Fuzzy Set-based COPRAS Method. *Journal of environmental management, 340*, 117967. doi:10.1016/j.jenvman.2023.117967

Keleş, N., & Pekkaya, M. (2023). Evaluation of Logistics Centers in Terms of Sustainability via MCDM Methods. *Journal of advances in management research, 20*(2), 291-309. doi:10.1108/jamr-04-2022-0087

Kibria, M. G., Masuk, N. I., Safayet, R., Nguyen, H. Q., & Mourshed, M. (2023). Plastic Waste: Challenges and Opportunities to Mitigate Pollution and Effective Management. *International Journal of Environmental Research, 17*(1), 20. Retrieved from https://doi.org/10.1007/s41742-023-00507-z

Kar, A., & Rai, R. N. (2024). QFD-based Hybrid Neutrosophic MCDM Approach with Six Sigma Evaluation for Sustainable Product Design in Industry 4.0. *Kybernetes*. doi:10.1108/k-09-2023-1757

Mathiyazhagan, K., Gnanavelbabu, A., & Prabhuraj, B. L. (2019). A Sustainable Assessment Model for Material Selection in Construction Industries Perspective using Hybrid MCDM Approaches. *Journal of advances in management research, 16*(2), 234-259. doi:10.1108/jamr-09-2018-0085

Moradi, S., Sierpiński, G., & Masoumi, H. (2022). System Dynamics Modeling and Fuzzy MCDM Approach as Support for Assessment of Sustainability Management on the Example of Transport Sector Company. *Energies, 15*(13), 4917. doi:10.3390/en15134917

Mousavi-Nasab, S. H., & Sotoudeh-Anvari, A. (2017). A Comprehensive MCDM-based Approach Using TOPSIS, COPRAS and DEA as an Auxiliary Tool for Material Selection Problems. *Materials & design, 121*, 237-253. doi:10.1016/j.matdes.2017.02.041

Narang, D., Madaan, J., Chan, F. T., & Chungcharoen, E. (2024). Managing Open Loop Water Resource Value Chain through LoT Focused Decision and Information Integration (DII) Modelling Using Fuzzy MCDM Approach. *Journal of environmental management, 350*, 119609. doi:10.1016/j.jenvman.2023.119609

Ocampo, L. A., & Clark, E. E. (2014). A Comprehensive Evaluation of Sustainable Manufacturing Programs Using Analytic Network Process (ANP). *Multiple Criteria Decision Making, 9*, 101-122. Retrieved from https://cejsh.icm.edu.pl/cejsh/element/bwmeta1.element.desklight-17322e9a-fb43-4ec4-be84-3c4ee4974211

Ordu, M., & Der, O. (2023). Polymeric Materials Selection for Flexible Pulsating Heat Pipe Manufacturing Using a Comparative Hybrid MCDM Approach. *Polymers, 15*(13), 2933. doi:10.3390/polym15132933

Prakash, C., Görçün, Ö. F., Kundu, P., & Küçükönder, H. (2023). An Integrated Fuzzy MCDM Approach Based on Bonferroni Functions for Selection and Evaluation of Industrial Robots for the Automobile Manufacturing Industry. *Expert systems with applications, 213*, 118863. doi:10.1016/j.eswa.2022.118863

Plastics Europe. (2023). *Plastics - the Facts 2023: An analysis of European plastics production, demand and waste data*. https://plasticseurope.org/knowledge-hub/plastics-the-fast-facts-2023/

Practice Greenhealth. (2023). *Less waste: A sustainability benchmark report for healthcare facilities*. https://practicegreenhealth.org/sites/default/files/2024-01/2023-benchmark-data.pdf

Ragusa, A., Svelato, A., Santacroce, C., Catalano, P., Notarstefano, V., Carnevali, O., Papa, F., Rongioletti, M. C. A., Baiocco, F., Draghi, S., D'Amore, E., Rinaldo, D., Matta, M., & Giorgini, E. (2021). Plasticenta: First evidence of microplastics in human placenta. *Environment International*, 146, 106274.

Roy , S., Mohanty, S., & Mohanty , S. (2018). An Efficient Hybrid MCDM Based Approach for Car Selection in Automobile Industry. *international conference on research in intelligent and computing in engineering (RICE)* (pp. 1-5). IEEE. doi:10.1109/rice.2018.8509065

Rahimi, M., Thanh, H. V., Ebrahimzade, I., Abbaspour-Fard, M. H., & Rohani, A. (2023). A Multi-Criteria Decision-Making (MCDM) Approach to Determine the Synthesizing Routes of Biomass-Based Carbon Electrode Material in Supercapacitors. *Journal of cleaner production, 397*, 136606. doi:10.1016/j.jclepro.2023.136606

Saroja, S., Haseena, S., & Madavan, R. (2023). Dissolved Gas Analysis of Transformer: An approach based on ML and MCDM. *IEEE transactions on dielectrics and electrical insulation, 30*(5), 2429-2438. doi:10.1109/tdei.2023.3271609

Setiawan, J., Sudiarso, A., Winursito, I., & Herliansyah, M. K. (2023). Selection of Material and Manufacturing Technology for Batik Canting Stamps Based on Multi-Criteria Decision-Making Methods. *Journal of Engineering and Technological Sciences, 55*(4), 434-452. doi:10.5614/j.eng.technol.sci.2023.55.4.7

Sharma, V., Zivic, F., Adamovic, D., Ljusic, P., Kotorcevic, N., Slavkovic, V., & Grujovic, N. (2022). Multi-Criteria Decision Making Methods for Selection of Lightweight Material for Railway Vehicles. *Materials, 16*(1), 368. doi:10.3390/ma16010368

Setiawan et al., J. (2023). Selection of Material and Manufacturing Technology for Batik Canting Stamps Based on Multi-Criteria Decision-Making Methods. *Journal of Engineering and Technological Sciences, 55*(4), 434-452. doi:10.5614/j.eng.technol.sci.2023.55.4.7

Singh, M., Pant, M., Godiyal, R. D., & Sharma, A. K. (2020). MCDM Approach for Selection of Raw Material in Pulp and Papermaking Industry. *Materials and Manufacturing Processes, 35*(3), 241–249. doi:10.1080/10426914.2020.1711917

Thinh, H. X., Mai, N. T., Giang, N. T., & Khiem, V. V. (2023). APPLYING MULTI-CRITERIA DECISION-MAKING METHODS FOR CUTTING OIL SELECTION. *Eastern-European Journal of Enterprise Technologies, 3*(1), 52–58. doi:10.15587/1729-4061.2023.275717

Torkabadi, A. M., Pourjavad, E., & Mayorga, R. V. (2018). An Integrated Fuzzy MCDM Approach to Improve Sustainable Consumption and Production Trends in Supply Chain. *Sustainable production and consumption, 16*, 99-109. doi:10.1016/j.spc.2018.05.008

Wang, C.-N., Nguyen, V. T., Chyou, J.-T., Lin, T.-F., & Nguyen, T. N. (2019). Fuzzy Multicriteria Decision-Making Model (MCDM) for Raw Materials Supplier Selection in Plastics Industry. *Mathematics, 7*(10), 981. doi:10.3390/math7100981

World Economic Forum. (2016). *The New Plastics Economy: Rethinking the future of plastics*. Geneva: World Economic Forum. https://www3.weforum.org/

Xu, J., & Guo, B. H. (2010). Poly (butylene succinate) and its copolymers: Research, development and industrialization. *Biotechnology journal*, *5*(11), 1149-1163.

Yücenur, G. N., Şentürk, S., & Taşpatlatanlar, E. (2024). Lean Management Approach in Health Sector: MCDM Model Proposal to Prevention of Waste. *Decision science letters, 13*(2), 427-440. doi:10.5267/j.dsl.2024.1.004

Zadeh, L. A. (1988). Fuzzy logic. *Computer*, 21(4), 83-93. https://www.scss.tcd.ie/Khurshid.Ahmad/Teaching/Lectures_on_Fuzzy_Logic/00000053.pdf

APPENDIX A – SENSITIVITY ANALYSIS RESULTS

A.1. Sensitivity Analysis 1 for Fuzzy AHP and Fuzzy TOPSIS

Table 22. First Expert Pairwise Comparison Matrix for Criteria Evaluation

	FIRST EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(6, 7, 8)	(4, 5, 6)	(6, 7, 8)	(1/6, 1/5, 1/4)	(4, 5, 6)
Cost	(1/8, 1/7, 1/6)	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)
Quality	(1/6, 1/5, 1/4)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(4, 5, 6)
Availability	(1/8, 1/7, 1/6)	(6, 7, 8)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)
Regulatory Status	(4, 5, 6)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(4, 5, 6)
Performance Match	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/6, 1/5, 1/4)	(1, 1, 1)

Table 23. Second Expert Pairwise Comparison Matrix for Criteria Evaluation

	SECOND EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(6, 7, 8)	(6, 7, 8)	(4, 5, 6)	(1/6, 1/5, 1/4)	(4, 5, 6)
Cost	(1/8, 1/7, 1/6)	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/9, 1/9, 1/9)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)
Quality	(1/8, 1/7, 1/6)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(4, 5, 6)
Availability	(1/6, 1/5, 1/4)	(9, 9, 9)	(1/4, 1/3, 1/2)	(1, 1, 1)	(2, 3, 4)	(1/4, 1/3, 1/2)
Regulatory Status	(4, 5, 6)	(4, 5, 6)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/6, 1/5, 1/4)
Performance Match	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(4, 5, 6)	(1, 1, 1)

Table 24. Geometric Mean Calculation for the First Expert

Criteria	ri		
Environmental Impact	2.140	2.501	2.884
Cost	0.218	0.255	0.309
Quality	1.322	1.57	1.817
Availability	0.477	0.577	0.742
Regulatory Status	2.245	2.685	3.086
Performance Match	0.514	0.645	0.794
Total	6.916	8.233	9.632
Reverse (power of -1)	0.145	0.121	0.104

Increasing order	0.10	0.12	0.15

Table 25. Geometric Mean Calculation for the Second Expert

Criteria	ri		
Environmental Impact	2.14	2.501	2.884
Cost	0.214	0.244	0.289
Quality	1.26	1.485	1.698
Availability	0.757	0.918	1.145
Regulatory Status	0.935	1.089	1.285
Performance Match	0.874	1.103	1.348
Total	6.18	7.34	8.649
Reverse (power of -1)	0.162	0.136	0.116
Increasing order	0.116	0.136	0.162

Table 26. Fuzzy Weight Values for Each Criterion of First Expert's Assessment

Criteria	Wi		
Environmental Impact	0.223	0.303	0.418
Cost	0.023	0.031	0.045
Quality	0.137	0.190	0.263
Availability	0.050	0.070	0.108
Regulatory Status	0.233	0.325	0.447
Performance Match	0.053	0.078	0.115

Table 27. Fuzzy Weight Values for Each Criterion of Second Expert's Assessment

Criteria	Wi		
Environmental Impact	0.248	0.340	0.467
Cost	0.025	0.033	0.047
Quality	0.146	0.202	0.275
Availability	0.088	0.125	0.185
Regulatory Status	0.108	0.148	0.208
Performance Match	0.101	0.150	0.218

Table 28. Fuzzy Decision Matrix of Criteria and Alternative Assessments for both Experts

Criteria	A1		A2		A3		A4	
	DM1	DM2	DM1	DM2	DM1	DM2	DM1	DM2
C1	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)
C2	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C3	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)
C4	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C5	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
C6	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)

Table 29. Calculated Weight for Both Experts

	Wi	
Criteria	DM1	DM2
C1	(0.223, 0.303, 0.418)	(0.248, 0.340, 0.467)
C2	(0.023, 0.031, 0.045)	(0.025, 0.033, 0.047)
C3	(0.137, 0.190, 0.263)	(0.146, 0.202, 0.275)
C4	(0.050, 0.070, 0.108)	(0.088, 0.125, 0.185)
C5	(0.233, 0.325, 0.447)	(0.108, 0.148, 0.208)
C6	(0.053, 0.078, 0.115)	(0.101, 0.150, 0.218)

Table 30. Aggregated Fuzzy Decision Matrix Combining Both Experts' Assessments

Criteria	A1	A2	A3	A4
C1	(5, 7, 9)	(7, 9, 9)	(3, 6, 9)	(7, 9, 9)
C2	(3, 6, 9)	(1, 4, 7)	(1, 4, 7)	(1, 2, 5)
C3	(7, 9, 9)	(5, 7, 9)	(3, 6, 9)	(1, 4, 7)
C4	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 2, 5)
C5	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 3, 5)
C6	(7, 9, 9)	(3, 6, 9)	(3, 6, 9)	(1, 4, 7)

Table 31. Aggregated Fuzzy Weights for All Criteria

Criteria	Wi
C1	(0.223, 0.322, 0.467)
C2	(0.023, 0.032, 0.047)
C3	(0.137, 0.196, 0.275)
C4	(0.050, 0.098, 0.185)
C5	(0.108, 0.237, 0.447)
C6	(0.053, 0.114, 0.218)

Table 32. Normalized Fuzzy Decision Matrix

rij				
Criteria	A1	A2	A3	A4
C1	(0.556, 0.778, 1)	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.778, 1, 1)
C2	(0.111, 0.167, 0.333)	(0.143, 0.25, 1)	(0.143, 0.25, 1)	(0.2, 0.5, 1)
C3	(0.778, 1, 1)	(0.556, 0.778, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)
C4	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.222, 0.556)
C5	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.333, 0.556)
C6	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)

Table 33. Weighted Normalized Fuzzy Decision Matrix

Pij=rij*Wi				
Criteria	A1	A2	A3	A4
C1	(0.124, 0.251, 0.467)	(0.173, 0.322, 0.467)	(0.074, 0.215,0.467)	(0.173, 0.322, 0.467)
C2	(0.003, 0.005, 0.016)	(0.003,0.008, 0.047)	(0.003,0.008, 0.047)	(0.005 0.016, 0.047)
C3	(0.107, 0.196, 0.275)	(0.076, 0.152, 0.275)	(0.046, 0.131, 0.275)	(0.015, 0.087, 0.214)
C4	(0.028, 0.087, 0.185)	(0.017, 0.065, 0.185)	(0.006, 0.044, 0.144)	(0.006, 0.022, 0.103)
C5	(0.06, 0.211, 0.447)	(0.036, 0.158, 0.447)	(0.012, 0.105, 0.348)	(0.012, 0.079, 0.249)
C6	(0.041, 0.114, 0.218)	(0.018, 0.076, 0.218)	(0.018, 0.076, 0.218)	(0.006, 0.051, 0.170)

Table 34. Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS)

	C1	C2	C3	C4	C5	C6
A+	(0.467, 0.467, 0.467)	(0.047, 0.047, 0.047)	(0.275, 0.275, 0.275)	(0.185, 0.185, 0.185)	(0.447, 0.447, 0.447)	(0.218, 0.218, 0.218)

A-	(0.074, 0.074, 0.074)	(0.003, 0.003, 0.003)	(0.015, 0.015, 0.015)	(0.006, 0.006, 0.006)	(0.012, 0.012, 0.012)	(0.006, 0.006, 0.006)

Table 35. Distance Measurements from FPIS and FNIS for Each Alternative

Criteria	FPIS(A1)	FPIS(A2)	FPIS(A3)	FPIS(A4)	FNIS(A1)	FNIS(A2)	FNIS(A3)	FNIS(A4)
C1	0.234	0.189	0.259	0.189	0.250	0.274	0.249	0.274
C2	0.039	0.034	0.034	0.030	0.008	0.026	0.026	0.027
C3	0.107	0.135	0.156	0.188	0.190	0.173	0.165	0.122
C4	0.107	0.119	0.134	0.147	0.114	0.109	0.083	0.057
C5	0.262	0.290	0.324	0.348	0.277	0.265	0.201	0.142
C6	0.118	0.142	0.142	0.158	0.139	0.129	0.129	0.098

Table 36. Final Closeness Coefficients and Rankings of Alternatives

	A1	A2	A3	A4
d+	0.867	0.909	1.048	1.062
d-	0.979	0.976	0.852	0.720
Cci	0.530	0.518	0.448	0.404

A.2. Sensitivity Analysis 2 for Fuzzy AHP and Fuzzy TOPSIS

Table 37. First Expert Pairwise Comparison Matrix for Criteria Evaluation

	FIRST EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(2, 3, 4)	(1/9, 1/9, 1/9)	(2, 3, 4)
Cost	(4, 5, 6)	(1, 1, 1)	(4, 5, 6)	(6, 7, 8)	(4, 5, 6)	(4, 5, 6)
Quality	(2, 3, 4)	(1/6, 1/5, 1/4)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1, 1, 1)	(4, 5, 6)
Availability	(1/4, 1/3, 1/2)	(1/8, 1/7, 1/6)	(2, 3, 4)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)
Regulatory Status	(9, 9, 9)	(1/6, 1/5, 1/4)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(4, 5, 6)
Performance Match	(1/4, 1/3, 1/2)	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/6, 1/5, 1/4)	(1, 1, 1)

Table 38. Second Expert Pairwise Comparison Matrix for Criteria Evaluation

	SECOND EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/4, 1/3, 1/2)	(1/9, 1/9, 1/9)	(1/4, 1/3, 1/2)
Cost	(4, 5, 6)	(1, 1, 1)	(4, 5, 6)	(9, 9, 9)	(4, 5, 6)	(4, 5, 6)
Quality	(1/4, 1/3, 1/2)	(1/6, 1/5, 1/4)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/4, 1/3, 1/2)
Availability	(2, 3, 4)	(1/9, 1/9, 1/9)	(2, 3, 4)	(1, 1, 1)	(2, 3, 4)	(1/4, 1/3, 1/2)
Regulatory Status	(9, 9, 9)	(1/6, 1/5, 1/4)	(1, 1, 1)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/4, 1/3, 1/2)
Performance Match	(2, 3, 4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(2, 3, 4)	(2, 3, 4)	(1, 1, 1)

Table 39. Geometric Mean Calculation for the First Expert

Criteria	ri		
Environmental Impact	0.514	0.637	0.778
Cost	3.397	4.044	4.67
Quality	0.833	1	1.201
Availability	0.397	0.501	0.661
Regulatory Status	1.513	1.732	1.944
Performance Match	0.364	0.447	0.561
Total	7.018	8.361	9.815
Reverse (power of -1)	0.142	0.120	0.102
Increasing order	0.102	0.120	0.142

Table 40. Geometric Mean Calculation for the Second Expert

Criteria	ri		
Environmental Impact	0.364	0.442	0.550
Cost	3.634	4.217	4.762
Quality	0.371	0.442	0.561
Availability	0.778	1	1.235
Regulatory Status	0.674	0.765	0.909
Performance Match	1.178	1.591	2
Total	6.999	8.457	10.017
Reverse (power of -1)	0.143	0.118	0.100
Increasing order	0.100	0.118	0.143

Table 41. Fuzzy Weight Values for Each Criterion of First Expert's Assessment

Criteria	Wi		
Environmental Impact	0.052	0.076	0.111
Cost	0.346	0.484	0.665
Quality	0.085	0.120	0.171
Availability	0.040	0.060	0.094
Regulatory Status	0.154	0.207	0.277
Performance Match	0.037	0.053	0.080

Table 42. Fuzzy Weight Values for Each Criterion of Second Expert's Assessment

Criteria	Wi		
Environmental Impact	0.036	0.052	0.079
Cost	0.363	0.499	0.680
Quality	0.037	0.052	0.080
Availability	0.078	0.118	0.176
Regulatory Status	0.067	0.090	0.130
Performance Match	0.118	0.188	0.286

Table 43. Fuzzy Decision Matrix of Criteria and Alternative Assessments for both Experts

Criteria	A1		A2		A3		A4	
	DM1	DM2	DM1	DM2	DM1	DM2	DM1	DM2
C1	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)
C2	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C3	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)
C4	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C5	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
C6	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)

Table 44. Calculated Weight for Both Experts

	Wi	
Criteria	DM1	DM2
C1	(0.052, 0.076, 0.111)	(0.036, 0.052, 0.079)
C2	(0.346, 0.484, 0.665)	(0.363, 0.499, 0.680)
C3	(0.085, 0.120, 0.171)	(0.037, 0.052, 0.080)
C4	(0.040, 0.060, 0.094)	(0.078, 0.118, 0.176)
C5	(0.154, 0.207, 0.277)	(0.067, 0.090, 0.130)
C6	(0.037, 0.053, 0.080)	(0.118, 0.118, 0.286)

Table 45. Aggregated Fuzzy Decision Matrix Combining Both Experts' Assessments

Criteria	A1	A2	A3	A4
C1	(5, 7, 9)	(7, 9, 9)	(3, 6, 9)	(7, 9, 9)
C2	(3, 6, 9)	(1, 4, 7)	(1, 4, 7)	(1, 2, 5)
C3	(7, 9, 9)	(5, 7, 9)	(3, 6, 9)	(1, 4, 7)
C4	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 2, 5)
C5	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 3, 5)
C6	(7, 9, 9)	(3, 6, 9)	(3, 6, 9)	(1, 4, 7)

Table 46. Aggregated Fuzzy Weights for All Criteria

Criteria	Wi
C1	(0.036, 0.064 ,0.111)
C2	(0.346, 0.492, 0.680)
C3	(0.037, 0.086, 0.171)
C4	(0.040, 0.089, 0.176)
C5	(0.067, 0.149, 0.277)
C6	(0.037, 0.086, 0.286)

Table 47. Normalized Fuzzy Decision Matrix

	rij			
Criteria	A1	A2	A3	A4
C1	(0.556, 0.778, 1)	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.778, 1, 1)
C2	(0.111, 0.167, 0.333)	(0.143, 0.25, 1)	(0.143, 0.25, 1)	(0.2, 0.5, 1)
C3	(0.778, 1, 1)	(0.556, 0.778, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)
C4	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.222, 0.556)
C5	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.333, 0.556)
C6	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)

Table 48. Weighted Normalized Fuzzy Decision Matrix

	Pij=rij*Wi			
Criteria	A1	A2	A3	A4
C1	(0.020, 0.050, 0.111)	(0.028, 0.064, 0.111)	(0.012, 0.043, 0.111)	(0.028,0.064, 0.111)
C2	(0.038, 0.082, 0.226)	(0.049, 0.123, 0.680)	(0.049, 0.123, 0.680)	(0.069, 0.246, 0.680)
C3	(0.029, 0.086, 0.171)	(0.021, 0.067, 0.171)	(0.012, 0.057, 0.171)	(0.004, 0.038, 0.133)
C4	(0.022, 0.079, 0176)	(0.0133, 0.059, 0.176)	(0.004, 0.040, 0.137)	(0.004, 0.020, 0.098)
C5	(0.037, 0.132, 0.277)	(0.022, 0.099, 0.277)	(0.007, 0.066, 0.216)	(0.007, 0.050, 0.154)
C6	(0.029, 0.086, 0.286)	(0.012, 0.057, 0.286)	(0.012, 0.057, 0.286)	(0.004, 0.038, 0.223)

Table 49. Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS)

	C1	C2	C3	C4	C5	C6
A+	(0.111, 0.111, 0.111)	(0.680, 0.680, 0.680)	(0.171, 0.171, 0.171)	(0.176, 0.176, 0.176)	(0.277, 0.277, 0.277)	(0.286, 0.286, 0.286)
A-	(0.012, 0.012, 0.012)	(0.038, 0.038, 0.038)	(0.004, 0.004, 0.004)	(0.004, 0.004, 0.004)	(0.007, 0.007, 0.007)	(0.004, 0.004, 0.004)

Table 50. Distance Measurements from FPIS and FNIS for Each Alternative

Criteria	FPIS(A1)	FPIS(A2)	FPIS(A3)	FPIS(A4)	FNIS(A1)	FNIS(A2)	FNIS(A3)	FNIS(A4)
C1	0.063	0.055	0.069	0.055	0.061	0.065	0.060	0.065
C2	0.570	0.486	0.486	0.432	0.111	0.374	0.374	0.390
C3	0.096	0.105	0.113	0.125	0.108	0.103	0.101	0.077
C4	0.105	0.116	0.129	0.141	0.109	0.104	0.080	0.055
C5	0.162	0.179	0.201	0.216	0.173	0.165	0.125	0.088
C6	0.188	0.206	0.206	0.220	0.170	0.166	0.166	0.128

Table 51. Final Closeness Coefficients and Rankings of Alternatives

	A1	A2	A3	A4
d+	1.184	1.147	1.203	1.189
d-	0.733	0.977	0.905	0.803
Cci	0.382	0.460	0.429	0.403

A.3. Sensitivity Analysis 3 for Fuzzy AHP and Fuzzy TOPSIS

Table 52 . First Expert Pairwise Comparison Matrix for Criteria Evaluation

	FIRST EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(2, 3, 4)	(1/4, 1/3, 1/2)	(2, 3, 4)	(1/9, 1/9, 1/9)	(2, 3, 4)
Cost	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)
Quality	(2, 3, 4)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1/6, 1/5, 1/4)	(4, 5, 6)
Availability	(1/4, 1/3, 1/2)	(6, 7, 8)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)
Regulatory Status	(9, 9, 9)	(6, 7, 8)	(4, 5, 6)	(6, 7, 8)	(1, 1, 1)	(6, 7, 8)
Performance Match	(1/4, 1/3, 1/2)	(2, 3, 4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/8, 1/7, 1/6)	(1, 1, 1)

Table 53. Second Expert Pairwise Comparison Matrix for Criteria Evaluation

	SECOND EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(2, 3, 4)	(6, 7, 8)	(2, 3, 4)	(1/9, 1/9, 1/9)	(2, 3, 4)
Cost	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/9, 1/9, 1/9)	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)
Quality	(1/8, 1/7, 1/6)	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(1/6, 1/5, 1/4)	(4, 5, 6)
Availability	(1/4, 1/3, 1/2)	(9, 9, 9)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)
Regulatory Status	(9, 9, 9)	(6, 7, 8)	(4, 5, 6)	(6, 7, 8)	(1, 1, 1)	(6, 7, 8)
Performance Match	(1/4, 1/3, 1/2)	(2, 3, 4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(1/8, 1/7, 1/6)	(1, 1, 1)

Table 54. Geometric Mean Calculation for the First Expert

Criteria	ri		
Environmental Impact	0.778	1.000	1.235
Cost	0.234	0.277	0.347
Quality	1.484	1.886	2.289
Availability	0.477	0.577	0.742
Regulatory Status	4.451	4.99	5.499
Performance Match	0.525	0.664	0.833
Total	7.949	9.394	10.945
Reverse (power of -1)	0.126	0.106	0.091
Increasing order	0.091	0.106	0.126

Table 55. Geometric Mean Calculation for the Second Expert

Criteria	ri		
Environmental Impact	1.322	1.661	1.961
Cost	0.229	0.266	0.324
Quality	0.935	1.135	1.348
Availability	0.51	0.602	0.757
Regulatory Status	4.45	4.99	5.499
Performance Match	0.525	0.664	0.833
Total	7.971	9.318	10.722
Reverse (power of -1)	0.125	0.107	0.093
Increasing order	0.093	0.107	0.125

Table 56. Fuzzy Weight Values for Each Criterion of First Expert's Assessment

Criteria	Wi		
Environmental Impact	0.071	0.106	0.155
Cost	0.021	0.029	0.044
Quality	0.136	0.201	0.288
Availability	0.044	0.061	0.093
Regulatory Status	0.407	0.531	0.692
Performance Match	0.048	0.071	0.105

Table 57. Fuzzy Weight Values for Each Criterion of Second Expert's Assessment

Criteria	Wi		
Environmental Impact	0.123	0.178	0.246
Cost	0.021	0.029	0.041
Quality	0.087	0.122	0.169
Availability	0.048	0.065	0.095
Regulatory Status	0.415	0.536	0.690
Performance Match	0.049	0.071	0.105

Table 58. Fuzzy Decision Matrix of Criteria and Alternative Assessments for both Experts

Criteria	A1		A2		A3		A4	
	DM1	DM2	DM1	DM2	DM1	DM2	DM1	DM2
C1	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)
C2	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C3	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)
C4	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C5	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
C6	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)

Table 59. Calculated Weight for Both Experts

	Wi	
Criteria	DM1	DM2
C1	(0.071, 0.106, 0.155)	(0.123, 0.178, 0.246)
C2	(0.021, 0.029, 0.044)	(0.021, 0.029, 0.041)
C3	(0.136, 0.201, 0.288)	(0.087, 0.122, 0.169)
C4	(0.044, 0.061, 0.093)	(0.048, 0.065, 0.095)
C5	(0.407, 0.531, 0.692)	(0.415, 0.536, 0.690)
C6	(0.048, 0.071, 0.105)	(0.049, 0.071, 0.105)

Table 60. Aggregated Fuzzy Decision Matrix Combining Both Experts' Assessments

Criteria	A1	A2	A3	A4
C1	(5, 7, 9)	(7, 9, 9)	(3, 6, 9)	(7, 9, 9)
C2	(3, 6, 9)	(1, 4, 7)	(1, 4, 7)	(1, 2, 5)
C3	(7, 9, 9)	(5, 7, 9)	(3, 6, 9)	(1, 4, 7)
C4	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 2, 5)
C5	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 3, 5)
C6	(7, 9, 9)	(3, 6, 9)	(3, 6, 9)	(1, 4, 7)

Table 61. Aggregated Fuzzy Weights for All Criteria

Criteria	Wi
C1	(0.071, 0.142, 0.246)
C2	(0.021, 0.029, 0.044)
C3	(0.087, 0.162, 0.288)
C4	(0.044, 0.063, 0.095)
C5	(0.407, 0.534, 0.692)
C6	(0.048, 0.071, 0.105)

Table 62. Normalized Fuzzy Decision Matrix

rij				
Criteria	A1	A2	A3	A4
C1	(0.556, 0.778, 1)	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.778, 1, 1)
C2	(0.111, 0.167, 0.333)	(0.143, 0.25, 1)	(0.143, 0.25, 1)	(0.2, 0.5, 1)
C3	(0.778, 1, 1)	(0.556, 0.778, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)
C4	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.222, 0.556)
C5	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.333, 0.556)
C6	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)

Table 63. Weighted Normalized Fuzzy Decision Matrix

Pij=rij*Wi				
Criteria	A1	A2	A3	A4
C1	(0.040, 0.111, 0.246)	(0.055, 0.142, 0.246)	(0.024, 0.095, 0.246)	(0.055, 0.142, 0.146)
C2	(0.002, 0.005, 0.015)	(0.003, 0.007, 0.044)	(0.003, 0.007, 0.044)	(0.004, 0.015, 0.044)
C3	(0.068, 0.162, 0.288)	(0.048, 0.126, 0.288)	(0.029, 0.108, 0.288)	(0.01, 0.172, 0.224)
C4	(0.025, 0.056, 0.095)	(0.015, 0.042, 0.095)	(0.005, 0.028, 0.074)	(0.005, 0.014, 0.053)
C5	(0.226, 0.475, 0.692)	(0.136, 0.356, 0.692)	(0.045, 0.237, 0.538)	(0.045, 0.178, 0.385)
C6	(0.038, 0.071, 0.105)	(0.0160, 0.047, 0.105)	(0.016, 0.047, 0.105)	(0.005, 0.032, 0.082)

Table 64. Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS)

	C1	C2	C3	C4	C5	C6
A+	(0.246, 0.246, 0.246)	(0.044 0.044, 0.044)	(0.288, 0.288, 0.288)	(0.095, 0.095, 0.095)	(0.692, 0.692, 0.692)	(0.105, 0.105, 0.105)
A-	(0.024, 0.024, 0.024)	(0.002, 0.002,0.002)	(0.01, 0.01,0.01)	(0.005, 0.005, 0.005)	(0.045, 0.045, 0.045)	(0.005, 0.005, 0.005)

Table 65. Distance Measurements from FPIS and FNIS for Each Alternative

Criteria	FPIS(A1)	FPIS(A2)	FPIS(A3)	FPIS(A4)	FNIS(A1)	FNIS(A2)	FNIS(A3)	FNIS(A4)
C1	0.142	0.125	0.155	0.138	0.138	0.146	0.134	0.100
C2	0.037	0.032	0.032	0.029	0.008	0.024	0.024	0.025
C3	0.146	0.167	0.182	0.178	0.186	0.175	0.170	0.155
C4	0.046	0.055	0.066	0.074	0.061	0.056	0.042	0.028
C5	0.297	0.375	0.465	0.297	0.460	0.418	0.305	0.460
C6	0.043	0.061	0.061	0.073	0.072	0.063	0.063	0.047

Table 66. Final Closeness Coefficients and Rankings of Alternatives

	A1	A2	A3	A4
d+	0.712	0.816	0.961	0.788
d-	0.924	0.883	0.740	0.815
Cci	0.565	0.520	0.435	0.509

A.4. Sensitivity Analysis 4 for Fuzzy AHP and Fuzzy TOPSIS

Table 67. First Expert Pairwise Comparison Matrix for Criteria Evaluation

	FIRST EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Cost	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Quality	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Availability	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Regulatory Status	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Performance Match	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)

Table 68. Second Expert Pairwise Comparison Matrix for Criteria Evaluation

	Second EXPERT					
	Environmental Impact	Cost	Quality	Availability	Regulatory Status	Performance Match
Environmental Impact	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Cost	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Quality	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Availability	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Regulatory Status	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Performance Match	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)

Table 69. Geometric Mean Calculation for the First Expert

Criteria	ri		
Environmental Impact	1.000	1.000	1.000
Cost	1.000	1.000	1
Quality	1	1	1
Availability	1	1	1
Regulatory Status	1	1	1
Performance Match	1	1	1
Total	6.000	6.000	6.000
Reverse (power of -1)	0.167	0.167	0.167
Increasing order	0.167	0.167	0.167

Table 70. Geometric Mean Calculation for the Second Expert

Criteria	ri		
Environmental Impact	1.000	1.000	1.000
Cost	1.000	1.000	1
Quality	1	1	1
Availability	1	1	1
Regulatory Status	1	1	1
Performance Match	1	1	1
Total	6.000	6.000	6.000
Reverse (power of -1)	0.167	0.167	0.167
Increasing order	0.167	0.167	0.167

Table 71. Fuzzy Weight Values for Each Criterion of First Expert's Assessment

Criteria	Wi		
Environmental Impact	0.167	0.167	0.167
Cost	0.167	0.167	0.167
Quality	0.167	0.167	0.167
Availability	0.167	0.167	0.167
Regulatory Status	0.167	0.167	0.167
Performance Match	0.167	0.167	0.167

Table 72. Fuzzy Weight Values for Each Criterion of Second Expert's Assessment

Criteria	Wi		
Environmental Impact	0.167	0.167	0.167
Cost	0.167	0.167	0.167
Quality	0.167	0.167	0.167
Availability	0.167	0.167	0.167
Regulatory Status	0.167	0.167	0.167
Performance Match	0.167	0.167	0.167

Table 73. Fuzzy Decision Matrix of Criteria and Alternative Assessments for both Experts

Criteria	A1		A2		A3		A4	
	DM1	DM2	DM1	DM2	DM1	DM2	DM1	DM2
C1	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)
C2	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C3	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)
C4	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 1, 3)
C5	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
C6	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)

Table 74. Calculated Weight for Both Experts

	Wi	
Criteria	DM1	DM2
C1	(0.167, 0.167, 0.167)	(0.167, 0.167, 0.167)
C2	(0.167, 0.167, 0.167)	(0.167, 0.167, 0.167)
C3	(0.167, 0.167, 0.167)	(0.167, 0.167, 0.167)
C4	(0.167, 0.167, 0.167)	(0.167, 0.167, 0.167)
C5	(0.167, 0.167, 0.167)	(0.167, 0.167, 0.167)
C6	(0.167, 0.167, 0.167)	(0.167, 0.167, 0.167)

Table 75. Aggregated Fuzzy Decision Matrix Combining Both Experts' Assessments

Criteria	A1	A2	A3	A4
C1	(5, 7, 9)	(7, 9, 9)	(3, 6, 9)	(7, 9, 9)
C2	(3, 6, 9)	(1, 4, 7)	(1, 4, 7)	(1, 2, 5)
C3	(7, 9, 9)	(5, 7, 9)	(3, 6, 9)	(1, 4, 7)
C4	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 2, 5)
C5	(5, 8, 9)	(3, 6, 9)	(1, 4, 7)	(1, 3, 5)
C6	(7, 9, 9)	(3, 6, 9)	(3, 6, 9)	(1, 4, 7)

Table 76. Aggregated Fuzzy Weights for All Criteria

Criteria	Wi
C1	(0.167, 0.167, 0.167)
C2	(0.167, 0.167, 0.167)
C3	(0.167, 0.167, 0.167)
C4	(0.167, 0.167, 0.167)
C5	(0.167, 0.167, 0.167)
C6	(0.167, 0.167, 0.167)

Table 77. Normalized Fuzzy Decision Matrix

	rij			
Criteria	A1	A2	A3	A4
C1	(0.556, 0.778, 1)	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.778, 1, 1)
C2	(0.111, 0.167, 0.333)	(0.143, 0.25, 1)	(0.143, 0.25, 1)	(0.2, 0.5, 1)
C3	(0.778, 1, 1)	(0.556, 0.778, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)
C4	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.222, 0.556)
C5	(0.556, 0.889, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)	(0.111, 0.333, 0.556)
C6	(0.778, 1, 1)	(0.333, 0.667, 1)	(0.333, 0.667, 1)	(0.111, 0.444, 0.778)

Table 78. Weighted Normalized Fuzzy Decision Matrix

	Pij=rij*Wi			
Criteria	A1	A2	A3	A4
C1	(0.093, 0.130, 0.167)	(0.130, 0.167, 0.167)	(0.056, 0.111, 0.167)	(0.130, 0.167, 0.167)
C2	(0.019, 0.028, 0.056)	(0.024, 0.042, 0.167)	(0.024, 0.042, 0.167)	(0.033, 0.084, 0.167)
C3	(0.130, 0.167, 0.167)	(0.093, 0.130, 0.167)	(0.056, 0.111, 0.167)	(0.019, 0.074, 0.130)
C4	(0.093, 0.149, 0.167)	(0.056, 0.111, 0.167)	(0.019, 0.074, 0.130)	(0.019, 0.037, 0.093)
C5	(0.093, 0.149, 0.167)	(0.056, 0.111, 0.167)	(0.019, 0.074, 0.130)	(0.019, 0.056, 0.093)
C6	(0.130, 0.167, 0.167)	(0.056, 0.111, 0.167)	(0.056, 0.111, 0.167)	(0.019, 0.074, 0.130)

Table 79. Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS)

	C1	C2	C3	C4	C5	C6
A+	(0.167,0.167, 0.167)	(0.167,0.167, 0.167)	(0.167,0.167, 0.167)	(0.167,0.167, 0.167)	(0.167,0.167, 0.167)	(0.167,0.167, 0.167)
A-	(0.056,0.056,0.056)	(0.019, 0.019,0.019)	(0.019, 0.019, 0.019)	(0.019, 0.019, 0.019)	(0.019, 0.019, 0.019)	(0.019, 0.019, 0.019)

Table 80. Distance Measurements from FPIS and FNIS for Each Alternative

Criteria	FPIS(A1)	FPIS(A2)	FPIS(A3)	FPIS(A4)	FNIS(A1)	FNIS(A2)	FNIS(A3)	FNIS(A4)
C1	0.048	0.021	0.072	0.021	0.080	0.100	0.071	0.100
C2	0.134	0.110	0.110	0.091	0.022	0.086	0.086	0.094
C3	0.021	0.048	0.072	0.103	0.137	0.115	0.103	0.071
C4	0.044	0.072	0.103	0.121	0.121	0.103	0.071	0.044
C5	0.044	0.072	0.103	0.115	0.121	0.103	0.071	0.048
C6	0.021	0.072	0.072	0.103	0.137	0.103	0.103	0.071

Table 81. Final Closeness Coefficients and Rankings of Alternatives

	A1	A2	A3	A4
d+	0.312	0.394	0.531	0.555
d-	0.618	0.610	0.507	0.428
Cci	0.665	0.608	0.488	0.436