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Sustainable evaluation of 3PL service for medical waste handling providers in Saudi healthcare using a hybrid fuzzy TOPSIS and clustering method

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Abstract

The process of selecting eco-friendly medical waste disposal services offered by 3PL presents a significant challenge in the healthcare sector, particularly in Saudi Arabia. This study suggests an integrated decision-making model that integrates fuzzy TOPSIS and clustering techniques to address this complex problem. The methodology evaluates 3PL providers using a multidimensional sustainability assessment encompassing social, economic, and environmental criteria. Fuzzy TOPSIS ranks the providers based on their performance across these criteria, and fuzzy clustering is then applied to group providers with similar performance characteristics. This clustering process enhances the decision-making framework by enabling the identification of patterns and trends among the alternatives, thus allowing for more informed decision-making. The evaluation framework involves the input of three experts and considers ten sustainability criteria across ten 3PL service providers within the Saudi healthcare system. Findings from this study support better decision-making in selecting 3PL partners for environmentally responsible medical waste handling.

Subject Classification: *90-05, 90B06, 90B50.*

Keywords: *Sustainable logistics, 3PL provider selection, Medical waste management, Fuzzy TOPSIS, Saudi healthcare system, Environmental management, Supply chain optimization.*

1. Introduction

In the wake of global health crises, such as COVID-19, healthcare waste disposal has emerged as a critical challenge. Traditional waste management practices struggle to meet the growing demand for sustainable, efficient solutions. The rapid expansion of Saudi Arabia's healthcare infrastructure, fueled by Vision 2030's emphasis on modernization, has intensified challenges in managing escalating medical waste volumes amid arid environmental conditions and evolving regulatory demands. Conventional waste disposal frameworks often lack the agility to balance cost-efficiency with ecological stewardship, particularly given the region's unique socio-economic priorities and vulnerability to climate stressors. Furthermore, the absence of localized studies integrating multi-criteria sustainability assessments into 3PL

provider selection exacerbates risks of inefficient resource allocation and non-compliance. This gap underscores the urgency for adaptive decision-making models that reconcile global sustainability benchmarks with region-specific operational constraints, ensuring alignment with Saudi Arabia's environmental goals while addressing healthcare sector growth.

This research tackles this issue by introducing a hybrid fuzzy TOPSIS-clustering approach, uniquely tailored to the Saudi healthcare system. Considering economic, environmental, and social criteria, this study offers a comprehensive, sustainable model that addresses the multifaceted challenges of medical waste disposal, filling a notable gap in the existing literature (e.g., Dwivedi [14] Bharti [7], Aouadni and Euchi [2]). Any waste from clinics and healthcare facilities for both humans and animals that was used for diagnosis, treatment, or immunization is classified as healthcare waste, also known as medical waste, by the World Health Organization (WHO). Adhesives, metal sharps, dressings, blood samples, body parts, medications, chemicals, and radioactive materials and devices are a few examples (e.g., Euchi, J. (Ed.). [21]; Tirkolaee and Torkayesh, [40]). Due to population growth, and the increasing amount of healthcare waste being disposed of in response to diseases and epidemics like COVID-19, waste has become a critical and serious issue. As a result, health waste management currently emerges to solve important environmental, health, and social problems Mishra and Rani [33] (Tirkolaee and Torkayesh, [40]).

The healthcare waste management system, which offers a high degree of use or disposal of healthcare waste while facilitating waste collection, storage, and transportation, is one system that helps businesses reduce waste amounts. One of the most practical strategic approaches to the issue of waste in the healthcare system is logistics management. The goals of waste management logistics solutions are to optimize costs, guarantee workplace safety and health, adhere to regulatory requirements, and fully utilize infrastructure and technical resources. The logistics involved in managing waste produced by healthcare facilities include moving waste from its source to a location for recovery or disposal. Waste management logistics aims to protect natural resources, avoid environmentally harmful waste management practices, and provide quantitative protection by substituting recyclable materials for non-recyclable ones (e.g., Euchi, Bouzidi, and Bouzid [23]).

Healthcare establishments are currently dealing with several logistical strategy decisions, such as outsourcing hospital supply chain operations (for example intra-site transportation, inventory management, sterilization,

purchasing and supply chain management, etc.) (e.g., Euchi and Frifita [16]; Ageron, Benzidia, and Bourlakis, [1]; Euchi, Masmoudi, and Siarry [24]). Many developing Asian nations, like China and Korea, have found that hiring a third-party logistic provider to properly dispose of medical waste (MW) is a practical and efficient solution. The outsourcing logistics practice and assuming the costs and risks related to waste transportation is known as "third-party logistics" (3PL). The government plans and directs the rules and regulations for medical waste management (MWM). Beyond handling just-in-time transportation of medical waste, 3PL companies can also manage the relocation of mobile treatment units. Certain 3PL providers are capable of integrating processing and transshipment tasks (Luo and Liao [30]).

In recent years, few papers have contributed to present the logistics problems in the healthcare system including medical waste topic. The negative consequences that medical waste has on human health and the environment make sustainability a hot topic. On the other hand, few studies have examined all three facets of sustainable development when selecting a 3PL service provider, even though a lot of research has discussed sustainability issues and emphasized how crucial it is to accomplish the triple bottom line—economic, social, and environmental goals—in logistics-related matters. Despite the importance of this topic, previous studies have not addressed the issue of using third-party service providers To get rid of MW in a fuzzy sustainable environment.

The previous research used a multi-criteria decision-making technique (MCDM) to assess and select a 3PL service provider, given the existence of a lot of qualitative and quantitative factors that could conflict with each other in this issue. When used in various scenarios involving the selection of 3PL workers, these MCDM techniques have yielded satisfactory results. However, every solution has its setbacks (such as Dwivedi et al [15], Thanh, Hai, and Kim [39]). This research studying the sustainable 3PL service provider selection problem for medical waste by employing the fuzzy TOPSIS method in the Saudi healthcare system.

The key strategic issues in this research are:

- Can we determine the most important criteria for choosing a third-party logistics service provider for handling hospital waste in a sustainable and fuzzy environment?

- How to compare and choose among outsourced logistics services for medical waste disposal that account for environmental and sustainability factors
- How might external logistics partners be efficiently grouped using fuzzy clustering approaches based on their final Fuzzy TOPSIS analysis scores along with other critical criteria?
- How can patterns and trends within the clusters be found using the clustering results, and how can each group be given a customized strategy?

This study makes a ground-breaking contribution by being the first to examine the choice of 3PL partners for handling medical waste within a fuzzy decision-making framework, while explicitly considering sustainability criteria. These criteria encompass economic, social, and environmental factors, reflecting a comprehensive approach to sustainability. Notably, the existing literature has not previously addressed the issue of selecting sustainable 3PL providers for medical waste management, making this study a novel and valuable addition. This research is applied in practical healthcare institutions in the Kingdom of Saudi Arabia, marking the first time such an analysis has been conducted within the Saudi healthcare system.

A central element of this research is creating a hybrid approach that integrates fuzzy with clustering techniques, a novel integration in the context of 3PL provider selection for medical waste. Fuzzy TOPSIS helps evaluate the different sustainable measures used to appraise 3PL providers, while the clustering approach classifies these earners into distinct clusters related to their sustainability performance. This methodology not only provides a systematic way to identify the most suitable 3PL provider but also enhances the clarity of decision-making by categorizing service providers into clusters based on their final scores from the fuzzy TOPSIS analysis.

The paper also contributes by identifying critical sustainable standards for selecting 3PL providers, aligning with the triple-bottom-line (economic, social, and environmental) framework. It introduces a data-driven tool for healthcare administrators to make informed decisions, offering a clear evaluation process for assessing and selecting 3PL providers. The clustering analysis, in particular, allows for the identification of patterns and trends within the groups of providers, leading to the formulation of specific strategies and recommendations tailored to each

cluster (Messaoudi, [34]). These managerial insights help balance the competing priorities of cost-efficiency and sustainability, addressing both immediate operational needs and broader environmental goals. Furthermore, the study offers practical recommendations for healthcare societies in KSA, highlighting the potential to improve sustainable biomedical waste-handling practices in the region.

The aim focuses on offering an in-depth

The research's fundamental aim focuses on offering a methodology for assessing and choosing a 3PL service provider in medical waste management. This methodology will help decision-makers in hospitals and healthcare establishments make the best choice possible when faced with ambiguous data. This proposed methodology has the advantage of accessibility and accuracy of fuzzy data associated with the exact ratios used in policymakers' problems involving humans. In this current study, the FTOPSIS method was applied to estimate the experts, criteria, and 3PL service provider weights considered the sustainable criteria and rank the different alternatives (3PL provider) in Saudi Arabia's healthcare case. Then, using both fuzzy C-Means and hierarchical clustering methods, we grouped the providers in the second stage according to their final Fuzzy TOPSIS analysis scores, along with other critical factors like pricing structure, processing capacity, recycling potential, and fixed costs. The silhouette indices of the two approaches were then compared, and the method with the highest value was saved for additional examination. As a result, we were able to pinpoint patterns and trends inside the clusters and suggest tailored approaches for every cluster. The outcomes taken confirm the efficiency of the suggested methodology which makes the complex sustainable 3PL decision-making in medical waste handling easy and robust.

The structure of the paper is as follows: Section 2 presents an in-depth review of the existing literature, while Section 3 describes the proposed methodology. In Section 4, a case study based in Saudi Arabia is presented, followed by an analysis of the findings. Lastly, Section 5 summarizes the conclusions derived from the research.

2. Literature review

Financial challenges are becoming more prevalent for hospitals and healthcare systems, so expenses and costs must be reduced without

sacrificing the quality of patient care. To address this problem healthcare CEOs are using outsourcing as one of their strategic tools. Despite all its advantages, outsourcing will not succeed if it is not managed well. A few scientific papers studied the 3PL provider problem for MW supply chain management. According to Wilujeng [43] and Rahman et al. [38], several nations, including Bangladesh and China, are employing outside parties to handle the transportation and disposal of medical waste. Yong et al. [42] developed a reverse logistics framework for hazardous waste using triangular fuzzy numbers (TFN) to manage uncertainty and to characterize the ambiguity of the hazardous waste disposal quantity, the probability of hazardous waste accidents, and the unit transportation cost. [9] employed the AHP-TOPSIS process to determine which logistic service provider would be best for managing medical waste.

Chauhan and Singh [11] addressed the problem of securely disposing of infectious and hazardous medical waste by combining a linear programming (LP) model with a combined MCDM model. Ten criteria were found in this study from literature and field surveys to select the best disposal firm using Trial Decision Making and Evaluation (DEMATEL) and Analytic Network Process (ANP) techniques to model these criteria.

Eydi and Rastgar [19] suggested a method for selecting an appropriate 3PL provider for the gathering and burial of medical waste based on data envelopment analysis models and taking dual-role data and fuzzy states into account.

Dwivedi et al. [15] used the interval-value intuitionistic fuzzy set (IVIFS), DEMATEL, and ANP approaches to study the 3PL in the biomedical waste organization. This study was the only one on the subject because it examined the various barriers BMW to 3PL management and discussed their relationships and order. Görçün et al. [25] proposed the interval-valued fermatean SWARA and COPRAS methods to evaluate and select sustainable 3PL for the medical waste companies' treatment in the healthcare area. In a [4] introduced a novel framework leveraging the ordinal priority method (OPA) to optimize 3PL provider selection within Tunisia's healthcare sector. Their methodology incorporated a multi-criteria decision-making process to systematically quantify the relative importance of expert judgments, evaluation criteria, and potential 3PL providers.

Table 1 summarizes the key studies on the "Hybrid fuzzy TOPSIS-clustering approach for evaluating the Sustainable 3PL service provider selection in medical waste disposal problems.

Table 1

Key Methods and Findings in Sustainable 3PL Selection for Medical Waste

Year	Authors	Solution/ Methodology	Key Findings
2007	Yong et al. [42]	TFN	Established a reverse logistics structure to handle hazardous waste amid uncertain variables
2016	Buyukozkan and Gocer [9]	AHP-TOPSIS	Determined the best logistics service provider for medical waste management.
2016	Kafa et al. [28]	FAHP and FPROMETHEE	Focused on challenges in selecting sustainable 3PL partners for reverse logistics
2018	Zarbakhshnia et al. [44]	SWARA and COPRAS using fuzzy set theory	Evaluated and selected sustainable 3RLP considering risk criteria.
2019	Gardas et al. [22]	Clustering Analysis	Suggested clustering analysis for effective decision-making in supplier selection.
2020	Dadashpour and Bozorgi-Amiri [12]	D-Number-AHP	Selected appropriate 3PL for sustainable logistics in northern Iran.
2021	Chauhan and Singh [11]	LP Model + MCDM (DEMATEL, ANP)	Developed a model for secure disposal of infectious and hazardous medical waste.
2021	Wang et al. [40]	Hybrid Fuzzy AHP + Fuzzy VIKOR	Proposed a decision-making approach for sustainable supply chains in Vietnam.
2021	Mishra and Rani [35]	CRITIC and CoCoSo	Investigated the 3RLP using neutrosophic combined compromise solutions.
2021	Tu et al.	Multi-Level Clustering Using Weighted Density-Based Techniques + AHP	Proposed a novel approach for logistics service provider selection in the medical sector.
2022	Eydi and Rastgar	Data Envelopment Analysis (DEA)	Developed a selection method for choosing 3PL partners in medical waste disposal.

Contd...

2022	Dwivedi et al.	IVIFS, DEMATEL, ANP	Analyzed barriers to biomedical waste management in 3PL and their interrelationships.
2023	Görçün et al.	Interval-Valued Fermatean SWARA and COPRAS	Evaluated and selected sustainable 3PL for medical waste treatment in healthcare.
2023	Nila and Roy	DOBI, FUCOM, LOPCOW	Evaluated and ranked 3PL under sustainable criteria.
2024	Aouadni et al	OPA with Confidence Level Measurement	Evaluated and ranked 3PL in the healthcare sector
2024	Messaoudi and Mahdhi	Clustering analysis	Suggested clustering analysis for sustainable supplier selection

Sustainability problems have drawn increasing interest from society and the organization. A more equitable and prosperous world where the environment and natural resources are protected for future generations is thought to be achievable through the promising paradigm of sustainable development. The sustainability concept is based on the triple bottom line, also known as the social, economic, and environmental pillars (Elkington, [18]).

Few studies have focused on sustainability in the logistics service, even though a lot of research has been done on logistics outsourcing and 3PL practices. In a sustainable setting, Kafa, Hani, and El Mhamedi [28] studied the third-party reverse logistics providers (3RLP) problem by applying FAHP and FPROMETHEE in sustainable supply chain management. Fuzzy SWARA and fuzzy COPRAS were utilized by Zarbakhshnia, Soleimani, and Ghaderi [44] to solve sustainable 3RLP evaluation and selection when risk criteria were present.

Dadashpour and Bozorgi-Amiri [12] used the D-Number-Analytic Hierarchy Process method (D-AHP) whose goal select the appropriate 3PL for achieving a sustainable logistics system in northern Iran. By combining the hybrid fuzzy AHP and fuzzy VIKOR methods, Yong et al. [42] presented a Compromised Decision-Making Approach to 3PL in a Sustainable Supply Chain that is applied in the logistics sector in Vietnam.

Mishra and Rani [35] investigated the 3RLP employing the CRITIC and CoCoSo approaches that are based on the combined compromise

solution within a single-valued neutrosophic framework. Nila and Roy [36] combined the methods of DOmbi Bonferroni (DOBI), Full Consistency Method (FUCOM), and Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) for evaluating criteria and ranking the 3PL under sustainable issues**.**

Companies can choose from a wide variety of suppliers, and the alternative providers that are chosen by humans will often overlap. This overlap may cause the selection process to become convoluted and ineffective. Thus, clustering analysis can be used to help in the methodical division of suppliers into discrete groups according to a range of criteria, enabling a more effective and impartial decision-making procedure (e.g., Gardas, Raut, and Narkhede [22], Euchi [20]). In 2021, [41] developed a unique weighted density-based hierarchical clustering approach that integrates AHP, aimed at assisting the medical industry in choosing suitable logistics service providers.

In the above comprehensive literature review, choosing a sustainable 3PL for medical waste companies is still an unresolved issue. To the best of our knowledge, the sustainable 3PL service provider selection problem for medical waste disposal, using a hybrid strategy based on fuzzy TOPSIS and clustering approaches, has not been studied in the literature.

3. Methodology

In our study, we propose FTOPSIS to choice and evaluate the appropriate 3PL for medical waste management in the Saudi healthcare system as described in Fig. 1.

TOPSIS is a technique used in multicriteria decision-making (MCDM) to solve various MCDM problems because of its effectiveness and utility (Aouadni and Aouadni, [3]).

Hwang and Yoon [26] introduced a method designed to select the alternative that is nearest to an optimal solution achieving minimal values for each unfavorable criterion while being furthest from the worst-case scenario, characterized by maximum undesirable values. The chosen option is the one with the greatest similarity to this ideal reference point.

In this section, we study the extension TOPSIS method in a fuzzy set. In literature several applications of this extension version in fuzzy group decision-making problems such as Boran et al. [8]; Kannan, Jabbour, and Jabbour [29]; Javad, Darvishi, and Javad [27]; Baharin, Rashidi, and Mahad [6]; Mehri, Sadeghi, and Shahdany [32].

First, a decision-making trial has been used to comprehend the relationships between several criteria by seeking expert opinion. Thus, considering the above, the social, environmental, and economic criteria for choosing a sustainable healthcare waste company have been determined through the evaluation of earlier research and field surveys. Table 2 provides an explanation and appendix for these criteria.

Table 2

Sustainable criteria to evaluate outsourcing company for MWM.

Criteria	Sub-criteria	Definition
Economic	Contract cost (Cc)	The service price of the 3PL service
	Technology capacity to disposal and recycling waste (Tc)	Technology is available with outsourcing that the company can use to recycle and dispose of MWH.
	Experience of firm in Medical waste healthcare. (Emwh)	The duration of an outsourcing company's operation is in years.
Environment	Emission and pollution minimization (EPM) (Epm)	The features and attributes of transportation systems that minimize emissions and pollution to lessen adverse environmental effects.
	Hygiene and safety (Hs)	The safety guidelines that the workers who handle waste use.
	ISO 14001 certification (Iso)	The application of ISO 14001 standards across the organization's business divisions
	Protection rules (Pr)	Observance of the 1998 HCW Handling & Management Rules and preservation of all documentation.
Social	Rights of employees (Re)	Respect all rights of the employees by the company.
	Work health and safety (Whs)	Implement policies related to preserving the life and health of employees.
	Respect for the policies (Rp)	Adherence to legal and adoption of organizational policies and other regulations to fulfill the company's obligations.

The main steps of this suggested methodology will be described in the following:

Step 1. Gather and standardize data related to the criteria and alternatives by performing scaling procedures.

Step 2. Calculate the combined fuzzy weights () for each criterion, aggregated from evaluations provided by multiple decision-makers.

Step 3. Develop a fuzzy decision-making matrix (FDMM) to organize the evaluated alternatives and criteria.

Step 4. Normalize the FDMM to ensure uniform scaling across all criteria.

Step 5. Apply weighting adjustments to the normalized matrix to reflect the priority level of each criterion.

Step 6. Determine the fuzzy positive ideal solution (FPIS, A+) and fuzzy negative ideal solution (FNIS, A−) as reference benchmarks.

Step 7. Measure the Euclidean distance of each alternative from A+ (ideal solution) and A− (non-ideal solution).

Step 8. Compute the closeness coefficient for each alternative based on these distances, enabling a comparative ranking of all options.

Step 9. Group the suppliers according to their final Fuzzy TOPSIS analysis scores by using fuzzy C-Means clustering and hierarchical clustering.

Step 10. Find the silhouette index for each of the two clustering techniques.

Step 11. For additional examination, keep the clustering strategy with the greatest silhouette index.

Step 12. Analyze the generated clusters to find any trends or patterns among the alternatives that were identified.

Step 13. For every group that has been identified, we offer particular tactics based on the patterns and trends that have been noticed.

3.1 *Fuzzy set theory*

Zadeh [45] introduced *fuzzy set theory* (alternatively termed *uncertain sets theory*) as a mathematical framework to manage uncertainties arising from incomplete or vague data inputs. A central feature of this approach is its capacity to systematically quantify and represent imprecise information through structured mathematical principles. At its foundation lies the concept of a *membership function*, which assigns objects a graded value between 0 and 1 to indicate their degree of affiliation with a defined set (Aouadni and Aouadni, [5]). For instance, the TFN, a common

representation of uncertainty, uses a three-point membership function to model data ambiguity, as illustrated in Figure 1. The methodology for applying fuzzy logic to Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) integrates definitions and principles from established theoretical works, which are summarized in the subsequent discussion.

Definition 1: In the context of a defined universe X, a fuzzy set $\tilde{A}$ is characterized by its membership function $\mu_{\tilde{A}}(x)$. This function maps each element x ∈ X to a numerical value within the range [0,1], representing the extent to which x is affiliated with $\tilde{A}$, where values closer to 1 indicate stronger membership. The value $\mu_{\tilde{A}}(x)$ serves as a measure of the element's membership strength in the fuzzy set.

Definition 2: A TFN is parametrically denoted as $\tilde{A} = (n_1, n_2, n_3)$ where n1 ≤n2≤n3. Its membership function $\mu_{\tilde{A}}(x)$ defines a piecewise-linear, triangular relationship: membership increases linearly from n1 to n2, peaks at n2, and decreases linearly from n2 to n3.

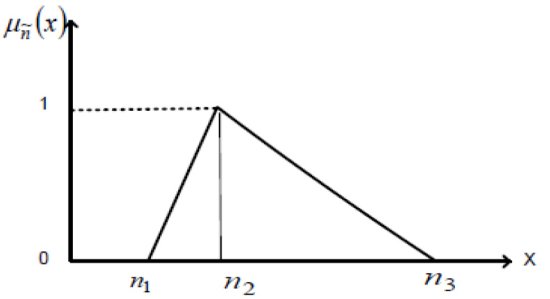


Figure 2

A triangular-shaped fuzzy number

The membership function is $\mu_{\tilde{n}}(x)$ defined as [11]:

$$\mu_{\tilde{n}}(x) = \begin{cases} \frac{x-n_1}{n_2-n_1}, & \text{if } n_1 \le x \le n_2, \\ \frac{x-n_2}{n_3-n_2}, & \text{if } n_2 \le x \le n_3, \\ 0, & \text{otherwise.} \end{cases}$$

Definition 3: Let ā = (a1, a2, a3) and b = (b1, b2, b3) be two Fuzzy triangular numbers. The vertex method is used to determine their distance from one another by:

$$d(\tilde{a},\tilde{b}) = \sqrt{\frac{1}{3}[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]}$$

3.2 *Fuzzy TOPSIS technique*

The fuzzy TOPSIS technique extends the standard TOPSIS approach that is utilized to compare a set of alternatives to predetermined criteria. The fuzzy TOPSIS approach determines the optimal solution by choosing a possibility that is nearest to the FPIS and most distant to the FNIS.

The optimal performance values for each alternative are included in the FPIS, whereas the worst performance values are included in the FNIS. The Fuzzy TOPSIS method offers many advantages when it comes to solving MCDM issues. The purpose of the Fuzzy TOPSIS method is to reconcile uncertainties in data that come from human judgment. TFN modeling has been found to yield better results in solving MCDM problems for various uncertain situations. Moreover, the FTOPSIS method is a straightforward and uncomplicated way to solve MCDM problems with imprecise data.

The following steps outline the Fuzzy TOPSIS methodology used to assess the importance of criteria weights and to rank the available alternatives:

Step 1: Develop a hierarchical framework to systematically organize the decision problem into distinct levels, such as overarching objectives, sub-criteria, and potential alternatives.

Step 2: Standardize the evaluation data for all criteria and alternatives by applying normalization procedures based on the linguistic scales (Tables 3 and 4) assigned to criteria and alternatives, respectively. the decision maker(s) ranked the alternatives and assigned weight to the criteria.

Step 3: Compute for each criterion the aggregated fuzzy weight, $\tilde{w}_j$ of the kth decision maker described as:

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

Where

Table 3
Qualitative variables and TFNs for criteria.

Importance	
Linguistic variable	TFNs
Definitely low (DL)	(0, 0, 0.1)
Extremely low (EL)	(0, 0.1, 0.2)
Very low (VL)	(0.1, 0.2, 0.3)
Low (L)	(0.2, 0.3, 0.4)
Medium low (ML)	(0.3, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.6)
Medium high (MH)	(0.5, 0.6, 0.7)
High (H)	(0.6, 0.7, 0.8)
Very high (VH)	(0.7, 0.8, 0.9)
Extremely high (EH)	(0.8, 0.9, 1)
Definitely high (DH)	(0.9, 1, 1)

$$w_{j1} = \min_k \{w_{j1}^k\}, w_{j2} = \frac{1}{k}\sum_{k=1}^{K} w_{j2}^k, w_{j3} = \max_k \{w_{j3}^k\},\ j = 1,2,\ldots,n \text{ criteria} \quad (0)$$

Step 4: Create the fuzzy decision matrix (FDM).

We suppose that we have m alternative Ai (i=1, 2,…, m) evaluated on n criteria Cj (j=1,2,…n).

$$\tilde{X} = [\tilde{x}_{ij}]_{m\times n} \quad (1)$$

Step 5: Development of the fuzzy-decision-making matrix (FDMM).

$$\tilde{V} = [\tilde{v}_{ij}]_{m\times n} \quad i = 1,\ldots,m \text{ and } j = 1,\ldots,n \quad (2)$$

$$\text{Where:} \qquad \tilde{v}_{ij} = \tilde{x}_{ij} \times \tilde{w}_j \qquad j = 1,\ldots,n \quad (3)$$

$\tilde{w}_j$: A fuzzy weight vector representing the aggregated importance values assigned to each criterion in the decision-making framework.

This vector captures the relative significance of the criteria, derived from normalized inputs or expert evaluations.

Step 6: Normalize the fuzzy decision-making matrix (FDMM)**.** The TFN are scaled to the range [0,1] to ensure comparability. The fuzzy decision matrix after normalization, indicated as

$$\tilde{R} = [r_{ij}]_{m\times n}; \quad (4)$$

(For i=1,…,m ; j=1,…,n,) is constructed by transforming each fuzzy element $\tilde{x}_{ij} = (\tilde{a}_{ij}, \tilde{b}_{ij}, \tilde{c}_{ij})$).

For benefit-type criteria, normalization is performed using the following approach:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right) \text{ that } c_j^+ = max_i c_{ij} \tag{5}$$

For cost criteria:

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{b_j^-}{c_{ij}}, \frac{c_j^-}{c_{ij}} \right) \text{ that } a_j^- = min_i a_{ij} \tag{6}$$

Step 7: Establish the normalized DMM weighted.

The following formula can be used to calculate the normalized decision matrix with assigned weights, consider the various values attributed for every criterion within the fuzzy decision matrix after normalization

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, \tag{7}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_{ij} \qquad j = 1, \ldots, m$$

Where $\tilde{w}_{ij}$ corresponds to the weight of the criterion c_j

Step 8: Determine the Fuzzy Positive Ideal Solution (A^+) and the Fuzzy Negative Ideal Solution (A^-)

As follows, we can express the possibilities FPIS and FNIS.

$$A^+ = \{\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\} = \{(\max_j v_{ij})\} \tag{8}$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\} = \{(\min_j v_{ij})\} \tag{9}$$

Indices i and j range from 1 to n and 1 to m, respectively

- $\tilde{v}_j^+ = (1,1,1)$ indicating full membership or ideal performance),
- $\tilde{v}_j^- = (0,0,0)$ (indicating no membership or non-ideal performance),

Step 9: Calculate the separation of each alternative frome the fuzzy positive ideal solution A^* and from the fuzzy negative ideal solution A^-

The following formulas determine the distance between each alternative, FPIS, and FNIS.

$$S_i^+ = \Sigma_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^+)\ i = 1,\ 2, \ldots, n,\ j = 1, \ldots, m \tag{10}$$

$$S_i^- = \Sigma_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-)\ i = 1,\ 2, \ldots, n,\ j = 1, \ldots, m \tag{11}$$

If two TFNs (a_1, b_1, c_1) and (a_2, b_2, c_2) are given, then d is the distance between them. The following formula can be used to get the two's distance:

$$d_v(\tilde{M}_1, \tilde{M}_2) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]}$$

Note that $d(\tilde{v}_{ij}, \tilde{v}_j^+)$ and $d(\tilde{v}_{ij}, \tilde{v}_j^-)$ are crisp numbers.

Step 10: Calculate the closeness coefficient and rank the alternatives. Each alternative's closeness coefficient can be computed using the following formula, which will then be used to establish the ranking order.

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{13}$$

The optimal choice is located most distant from the FNIS and nearest to the (FPIS).

3.3 *Examination of Cluster Grouping*

During the process of sorting data by likenesses and contrasts, a technique called cluster analysis is employed. The k-mean, Ward, mean, Euclidean distance, and median are a few methods for executing these groups (de Oliveira et al., 2023). According to Dalmaijer et al. [13], cluster analysis is a statistical method that uses a categorization algorithm to divide a collection of datasets into clusters for easy modifications.

Rather to selecting a single supplier, certain researchers recommended forming supplier groups and considering the different traits or business methods of suppliers. According to Diabat and Lu [29] [30], this approach has the following advantages: (i) eliminating suppliers who don't suit the requirements; (ii) forming smaller, easier-to-manage supplier groups; and (iii) developing customized supplier growth strategies for different supplier clusters.

In this study, Fuzzy TOPSIS scores and others sustainable criteria will be used to compare and validate the robustness of supplier groupings through the use of Fuzzy C-Means (FCM) clustering and hierarchical clustering techniques.

Refers to, [37], to cluster objects according to their similarity, hierarchical clustering technique is the most often used kind of hierarchical clustering. By treating each individual data point as a single cluster at the beginning of the clustering process, the method takes a bottom-up approach. It then constantly merges these clusters based on similarities until a single, large cluster made up of all the objects is formed. A fuzzy membership is used in the FCM technique to assign a membership degree to each class. Objects are moved between clusters by the FCM clustering method until the objective function can no longer be decreased. The idea behind it is to minimize an objective function that describes the space between every given data point and a cluster center, with the weights assigned based on the membership valuation of that data point [17].

4. Sustainable 3PL Provider Selection: A Case Study in the Saudi Healthcare System

The focus of the current study is on evaluating the 3PL service provider logistics for medical waste disposal in healthcare institutions in the Kingdom of Saudi Arabia.

The chief managers (three decision-makers) of this institution determined the environmental, social, and economic criteria for selecting the third-party provider of logistics services for medical waste. Based on the importance of this topic, the responses were quick and comprehensive from all decision-makers. The sustainable criteria for 3PL providers for medical waste are identified in Table 2.

Step 1: Carry out the criteria and alternative data scaling procedure.

In this research, three specialists were engaged to delineate the critical criteria influencing (3PL) provider selection within the decision-making framework. Through collaborative consensus, these criteria were systematically prioritized in alignment with fuzzy TOPSIS method. In this study, these experts defined ten 3PL providers for medical waste and 10 sustainable criteria that should be considered when evaluating and selecting 3PL providers. As Table 4 illustrates, the average value method is used in our study to combine the fuzzy judgment values of various evaluators based on the same assessment dimensions.

Through collaborative consensus, these criteria were systematically prioritized in alignment with [...].

Table 4

Linguistic terms applied to assess each option

Linguistic variable	Corresponding TFN
very weak	(0, 1, 3)
weak	(1; 3, 5)
moderate	(3, 5, 7)
strong	(5, 7, 9)
very strong	(7, 9, 10)

Step 2: Compute the aggregated fuzzy criterion weight, $\tilde{w}_j$ of the kth decision maker described as:

The importance and the aggregation fuzzy criteria weights determined by each decision-maker in the hospital are presented in Tables 5 and 6.

Table 5

Assignation of criteria significance by the decision-makers

	Cc	Tc	Emwh	Epm	Hs	Iso	Pr	Re	Whs	Rp
DM1	VH	EH	MH	M	M	MH	H	MH	EH	H
DM2	H	VH	M	M	M	M	H	VH	H	H
DM3	VH	EH	H	M	H	M	MH	EH	H	H

Table 6

The aggregated fuzzy criterion weight.

Criteria	**Cc**	**Tc**	**Emwh**	**Epm**	**Hs**
DM1	(0.7, 0.8, 0.9)	(0.8, 0.9, 1)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)
DM2	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.6)
DM3	(0.7, 0.8, 0.9)	(0.8, 0.9, 1)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)
$\tilde{w}_j$	**(0.6, 0.7667, 0.9)**	**(0.7, 0.8667, 1)**	**(0.4, 0.6, 0.8)**	**(0.4, 0.5, 0.6)**	**(0.4, 0.5667, 0.8)**
Criteria	Iso	Pr	Re	Whs	Rp
DM1	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)	(0.8, 0.9, 1)	(0.6, 0.7, 0.8)
DM2	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)
DM3	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(0.8, 0.9, 1)	(0.6, 0.7, 0.8)	(0.6, 0.7, 0.8)
$\tilde{w}_j$	**(0.4, 0.533, 0.7)**	(0.5, 0.667, 0.8)	(0.5, 0.7667, 1)	(0.6, 0.7667, 1)	(0.6, 0.7, 0.8)

Step 3: Build the FDM.

Three decision-makers (DM), ten criteria, and four alternatives that are classed using the fuzzy TOPSIS procedure are included in the current study.

The attributes of the criterion and the weights allotted to them are detailed in Table 7.

Table 7

The weight is assigned to sustainable criteria.

	Criteria	Type	Weights
1	Cost of contract (Cc)	Minimum	(0.6, 0.7667, 0.9)
2	Technology capacity to waste elimination and recycling processes (Tc)	Maximum	(0.7, 0.8667, 1)
3	Experience of firm in Medical waste healthcare. (Emwh)	Maximum	(0. 4, 0.6, 0.8)
4	Emission and pollution minimization (Epm)	Minimum	(0.4, 0.5, 0.6)
5	Hygiene and safety (Hs)	Maximum	(0.4, 0.5667, 0.8)
6	certification compliant with ISO 14001(Iso)	Maximum	(0.4, 0.533, 0.7)
7	Protection rules (Pr)	Maximum	(0. 5, 0.667, 0.8)
8	Rights of employees (Re)	Maximum	(0.5, 0.7667, 1)
9	Work health and safety (Whs)	Maximum	(0.6, 0.7667, 1)
10	Respect for the policies (Rp)	Maximum	(0.6, 0.7, 0.8)

The decision-makers placed importance on the assessment criteria and prioritized the options using five-point fuzzy scale linguistic variables, which are: very weak, weak, moderate, strong, and very strong, as presented in Table 4, to express their views on the assessment of 10 possibilities (the 3PL provider for hospital waste) regarding the 10 sustainable criteria presented in Table 8.

Table 8

Evaluators' subjective perceptions regarding the five levels of qualitative variables

	Cc	Tc	Emwh	Epm	Hs	Iso	Pr	Re	Whs	Rp
A_1	(47, 68.6, 88)	(39.6, 57.3, 72.6)	(44.3, 63.3, 80)	(44, 63.6, 81.3)	(37, 51.3, 62.6)	(46.3, 66, 82.6)	(41.3, 61, 78.6)	(40, 57, 72)	(416, 60, 75.3)	*(43, 61, 75.6)*

Contd...

A_2	(42.6, 61.6, 78)	(42, 59.3, 73.6)	(39.3, 54.3, 66.6)	(29.3, 43, 54.6)	(44, 63.6, 81.3)	(43, 61, 75.6)	(41.6, 57, 69)	(38, 55.3, 70.3)	(28.6, 41.6, 55.3)	*(32.6, 48.3, 62.6)*
A_3	(39, 54.6, 67.3)	(34, 48.6, 60.3)	(43, 61, 75.6)	(34, 49, 62)	(44.3, 62.3, 77)	(44.3, 62.3, 77)	(37.6, 53.3, 66)	(36.6, 51.6, 64)	(45.6, 64, 79.3)	*(32.6, 47.6, 60.6)*
A_4	(41.6, 58, 72)	(40, 57, 72)	(30, 43, 54.6)	(36.3, 52, 64.6)	(29.3, 43.6, 56.6)	(28, 39.6, 50)	(36.6, 51.6, 64)	(42.3, 59, 72.3)	(39.3, 56.6, 71)	*(36, 52, 65)*
A_5	(32.6, 47.6, 60.6)	(27.3, 39.6, 50.6)	(42, 59.3, 73.6)	(31.3, 43.6, 54)	(29.3, 43, 54.6)	(32.6, 47.6, 60.6)	(37.3, 53.3, 67)	(37.6, 53.3, 66)	(36.6, 51.6, 64)	*(28.6, 41.6, 53.3)*
A_6	(37.6, 53, 65)	(41.6, 58, 72)	(37.3, 53.3, 66.3)	(42, 60.3, 76.6)	(34, 49, 62)	(29.3, 43, 54.6)	(32.6, 45, 54.6)	(28, 39, 48)	(42.3, 59, 72.3)	*(45.6, 64, 79.3)*
A_7	(36, 52.3, 66.6)	(35.3, 52.6, 68.3)	(31.3, 43.6, 54)	(43, 61, 75.6)	(34, 48.6, 60.3)	(34, 49, 62)	(33.3, 50.3, 66)	(44.3, 62.3, 77)	(37.6, 53.3, 66)	*(39.3, 56.6, 71)*
A_8	(30.6, 44.3, 56)	(32.6, 44.6, 53.6)	(23.3, 32.6, 40.3)	(28, 38.6, 47)	(28, 38.6, 47)	(28, 38.6, 47)	(28, 38.6, 47)	(32, 45.6, 57.3)	(28.6, 40.6, 50.3)	*(30.6, 44.3, 56)*
A_9	(39.3, 56.67, 71)	(32, 46.3, 59.3)	(23.3, 33, 41.3)	(42, 60.3, 76.6)	(35.3, 51, 64.6)	(31.3, 43.6, 54)	(38.6, 55, 68.6)	(36.3, 52.6, 66.6)	(44.3, 62.3, 77)	*(42.3, 59, 72.3)*
A_{10}	(35.3, 50.3, 63.3)	(34.6, 50.6, 64.3)	(34, 49, 62)	(35.3, 50, 61.6)	(33.3, 47, 58)	(36.6, 51.6, 64)	(30.6, 44.3, 56)	(44, 63, 79.3)	(34, 49, 61.3)	*(34, 49, 62)*

Step 4: Find the normalization FDMM.

A FDMM can be determined by the equations (4), (5) and (6) see Table 9.

Table 9

Normalized FDMM.

	Cc	**Tc**	**Emwh**	**Epm**	**Hs**	**Iso**	**Pr**	**Re**	**Whs**	**Rp**
A1	(0.534, 0.78, 1)	(0.538, 0.778, 0.986)	(0.554, 0.792, 1)	(0.541, 0.783, 1)	(0.455, 0.631, 0.77)	(0.56, 0.798, 1)	(0.525, 0.775, 1)	(0.504, 0.718, 0.908)	(0.525, 0.756, 0.95)	(0.542, 0.769, 0.954)
A_2	(0.485, 0.701, 0.886)	(0.57, 0.805, 1)	(0.492, 0.679, 0.833)	(0.361, 0.529, 0.672)	(0.541, 0.783, 1)	(0.52, 0.738, 0.915)	(0.53, 0.725, 0.877)	(0.479, 0.697, 0.887)	(0.361, 0.525, 0.672)	(0.412, 0.609, 0.79)

Contd...

A_3	(0.443, 0.621, 0.765)	(0.462, 0.661, 0.819)	(0538, 0.763, 0.946)	(0.418, 0.602, 0.762)	(0.545, 0.766, 0.947)	(0.536, 0.754, 0.931)	(0.479, 0.678, 0.839)	(0.462, 0.651, 0.807)	(0.576, 0.807, 1)	(0.412, 0.601, 0.765)
A_4	(0.473, 0.659, 0.818)	(0.543, 0.774, 0.977)	(0.375, 0.538, 0.683)	(0.447, 0.639, 0.795)	(0.361, 0.537, 0.697)	(0.339, 0.48, 0.605)	(0.466, 0.657, 0.814)	(0.534, 0.744, 0.912)	(0.496, 0.714, 0.895)	(0.454, 0.655, 0.819)
A_5	(0.371, 0.542, 0.689)	(0.371, 0.538, 0.688)	(0.525, 0.742, 0.921)	(0.385, 0.537, 0.664)	(0.361, 0.529, 0.972)	(0.395, 0.577, 0.734)	(0.475, 0.678, 0.852)	(0.475, 0.672, 0.832)	(0.462, 0.651, 0.807)	(0.361, 0.525, 0.672)
A_6	(0.428, 0.602, 0.739)	(0.566, 0.787, 0.977)	(0.467, 0.667, 0.829)	(0.516, 0.742, 0.943)	(0.418, 0.602, 0.762)	(0.355, 0.52., 0.661)	(0.415, 0.572, 0.695)	(0.353, 0.492, 0.605)	(0.534, 0.744, 0.912)	(0.576. 0.807, 1)
A_7	(0.409, 0.595, 0.758)	(0.48, 0.715, 0.928)	(0.392, 0.546, 0.675)	(0.529, 0.75, 0.93)	(0.418, 0.598, 0.742)	(0.411, 0.593, 0.75)	(0.424, 0.64, 0.839)	(0.559, 0.786, 0.971)	(0.475, 0.672, 0.832)	(0.496, 0.714, 0.895)
A_8	(0.348, 0.504, 0.636)	(0.443, 0.606, 0.729)	(0.292, 0.408, 0.504)	(0.344, 0.475, 0.578)	(0.344, 0.475, 0.578)	(0.339, 0.468, 0.569)	(0.356, 0.492, 0.597)	(0.403, 0.576, 0.723)	(0.361, 0.513, 0.634)	(0.387, 0.559, 0.706)
A_9	(0.447, 0.644, 0.807)	(0.434, 0.629, 0.805)	(0.292, 0.413, 0.517)	(0.516, 0.742, 0.943)	(0.434, 0.627, 0.795)	(0.379, 0.528, 0.653)	(0.492, 0.669, 0.873)	(0.458, 0.664, 0.84)	(0.559, 0.786, 0.971)	(0.534, 0.744, 0.912)
A_{10}	(0.402, 0.572, 0.72)	(0.471, 0.688, 0.873)	(0.425, 0.613, 0.775)	(0.434, 0.615, 0.758)	(0.41, 0.578, 0.713)	(0.444, 0.625, 0.774)	(0.39, 0.564, 0.712)	(0.555, 0.794, 1)	(0.429, 0.618, 0.773)	(0.429, 0.618, 0.782)

Step 5: Compute the weighted normalized DMM.

In this step, the weighted normalized FDMM is calculated using Equation (7). The outcomes of the weighted FDMM are shown in Table 10.

Table 10

Normalized FDMM weighted.

	Cc	**Tc**	**Emwh**	**Epm**	**Hs**	**Iso**	**Pr**	**Re**	**Whs**	**Rp**
A1	(0.32, 0.598, 0.9)	(0.377, 0.675, 0.986)	(0.222, 0.475, 0.8)	(0.216, 0.391, 0.6)	(0.182, 0.358, 0.616)	(0.224, 0.426, 0.7)	(0.263, 0.517, 0.8)	(0.252, 0.551, 0.908)	(0.315, 0.58, 0.95)	(0.325, 0.538, 0.763)
A_2	(0.291, 0.537, 0.798)	(0.399, 0.698, 1)	(0.197, 0.408, 0.667)	(0.144, 0.264, 0.403	(0.216, 0.444, 0.8)	(0.208, 0.394, 0.641)	(0.265, 0.483, 0.702)	(0.239, 0.535, 0.887)	(0.217, 0.403, 0.672)	(0.247, 0.426, 0.632)
A_3	(0.266, 0.476, 0.689)	(0.323, 0.573, 0.819)	(0.215, 0.458, 0.757)	(0.167, 0.301, 0.457)	(0.218, 0.434, 0.757)	(0.215, 0.402, 0.652)	(0.239, 0.452, 0.671)	(0.231, 0.499, 0.807)	(0.345, 0.619, 1)	(0.247, 0.421, 0.612)

Contd...

A_4	(0.284, 0.505, 0.736)	(0.38, 0.671, 0.977)	(0.15, 0.323, 0.547)	(0.179, 0.32, 0.477)	(0.144, 0.304, 0.557)	(0.135, 0.256, 0.423)	(0.233, 0.438, 0.651)	(0.267, 0.57, 0.912)	(0.297, 0.548, 0.895)	(0.272, 0.459, 0.655)
A_5	(0.223, 0.415, 0.620)	(0.260, 0.467, 0.688)	(0.21, 0.445, 0.737)	(0.154, 0.268, 0.398)	(0.144, 0.3, 0.538)	(0.158, 0.308, 0.514)	(0.237, 0.452, 0.681)	(0.237, 0.515, 0.832)	(0.277, 0.499, 0.807)	(0.217, 0.368, 0.538)
A_6	(0.257, 0.462, 0.665)	(0.396, 0.682, 0.977)	(0.187, 0.4, 0.663)	(0.207, 0.371, 0.566)	(0.167, 0.341, 0.61)	(0.142, 0.277., 0.463)	(0.208, 0381., 0.556)	(0.176, 0.377, 0.605)	(0.320, 0.57, 0.912)	(0.345. 0.565, 0.8)
A_7	(0.245, 0.456, 0.682)	(0.336, 0.62, 0.928)	(0.157, 0.328, 0.54)	(0.211, 0.375, 0.558)	(0.167, 0.339, 0.593)	(0.165, 0.316, 0.525)	(0.212, 0.427, 0.671)	(0.279, 0.602, 0.971)	(0.285, 0.515, 0.832)	(0.297, 0.5, 0.716)
A_8	(0.209, 0.386, 0.573)	(0.310, 0.526, 0.729)	(0.117, 0.245, 0.403)	(0.138, 0.238, 0.347)	(0.138, 0.269, 0.462)	(0.135, 0.249., 0.398)	(0.178, 0328., 0.478)	(0.202, 0.441, 0.723)	(0.217, 0.393, 0.634)	(0.232, 0.391, 0.565)
A_9	(0.268, 0.494 0.726)	(0.304, 0.545, 0.805)	(0.117, 0.248, 0.413)	(0.207, 0.371, 0.566)	(0.174, 0.355, 0.636)	(0.152, 0.282, 0.457)	(0.246, 0.466, 0.698)	(0.229, 0.509, 0.84)	(0.335, 0.602, 0.971)	(0.320, 0.521, 0.729)
A_{10}	(0.241, 0.439, 0.648)	(0.329, 0.596, 0.873)	(0.17, 0.368, 0.62)	(0.174, 0.307, 0.455)	(0.164, 0.327, 0.57)	(0.177, 0.333, 0.542)	(0.195, 0.376, 0.569)	(0.277, 0.474, 0.773)	(0.257, 0.474, 0.773)	(0.257, 0.432, 0.625)

Step 6: Determine the reference benchmarks for the (FPIS) and (FNIS).

Then, we can define the FPIS and the FNIS as A+ and A- by using formulas (8) and (9). The FPIS and the FNIS are presented in Table 11.

Table 11

The FPIS and the FNIS

Criteria	Positive ideal	Negative ideal
Cc	0.6, 0.767, 0.9	0
Tc	0.7, 0.867, 1	0
Emwh	0.4, 0.6, 0.8	0
Epm	0.4, 0.5, 0.6	0
Hs	0.4, 0.567, 0.8	0
Iso	0.4, 0.533, 0.7	0
Pr	0.5, 0.667, 0.8	0
Re	0.5, 0.767, 1	0
Whs	0.6, 0.767, 1	0
Rp	0.6, 0.7, 0.8	0

Step 7: Find out the length between each alternate (3PL), FPIS, and FNIS

The length between each 3PL is calculated by applying the equations (10), (11), and (12).

$$S_1^+ = 1.721$$

$$S_1^- = 5.454$$

Step 8: Calculate the closeness coefficient and rank the alternatives accordingly.

Step 8: Compute the closeness coefficient and assign rankings to the alternatives based on the results

The proximity coefficient of each 3PL is calculated by formula (13). The final rank is presented in the following table 12:

$$\widetilde{CC}_1^- = \frac{5.454}{5.454 + 1.721} = 0.760$$

$$\widetilde{CC}_1^+ = \frac{1.721}{5.454 + 1.721} = 0.239$$

Table 12

Closeness coefficients of each 3PL and final rank.

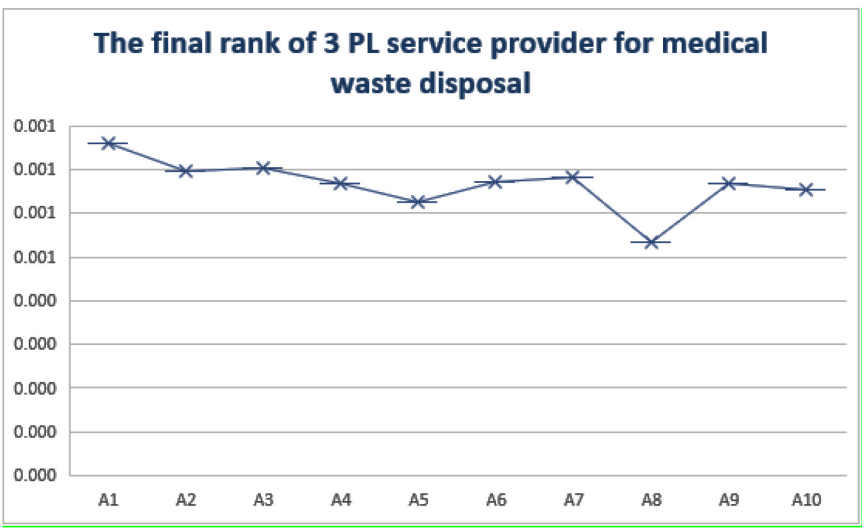
	Distance from (S^+)	**Distance from (S^-)**	**Level of discrepancy in $\widetilde{CC}^+$**	**Level of satisfaction for $\widetilde{CC}^-$**	**Final rank**
$\mathbf{A_1}$	1.721	5.454	0.239	**0.760**	1
$\mathbf{A_2}$	2.135	4.903	0.303	**0.697**	3
$\mathbf{A_3}$	2.083	4.966	0.295	**0.705**	2
$\mathbf{A_4}$	2.316	4.679	0.331	**0.669**	6
$\mathbf{A_5}$	2.616	4.340	0.376	**0.624**	9
$\mathbf{A_6}$	2.309	4.714	0.328	**0.671**	5
$\mathbf{A_7}$	2.238	4.802	0.317	**0.682**	4
$\mathbf{A_8}$	3.209	3.659	0.467	**0.533**	10
$\mathbf{A_9}$	2.320	4.686	0.331	**0.669**	7
$\mathbf{A_{10}}$	2.425	4.573	0.346	**0.653**	8

The definitions of the satisfaction degree and Level of discrepancy in the i-th alternative are $\widetilde{CC}_i^-$ and $\widetilde{CC}_i^+$, respectively. Derived from a fuzzy group of acceptable alternatives, we can decide which gaps should be improved and how to close them to reach aspiration levels and obtain a win-win strategy. The FTOPSIS has an aspirational/desired satisfaction degree of 1.00.

Table 12 indicates the satisfaction and gap degrees of 3 PL provider services.

The final rank presented in Table 12 reveals that:

$A_1 > A_3 > A_2 > A_7 > A_6 > A_4 > A_9 > A_{10} > A_5 > A_8$.



Source: Author's findings.

Figure 1

The final rank of 3PL service provider for hospital waste clearance

Step 9: Group the suppliers according to their final Fuzzy TOPSIS analysis scores by using fuzzy C-Means clustering and hierarchical clustering

This study includes the sustainable 3PL service provider selection problem related to medical waste handling issues in Aseer Town hospitals, KSA. This section introduces the application of clustering approaches such as the hierarchical clustering method and fuzzy C-means to help choose the best 3PL provider of medical waste in the hospital. The data in the Table 13 was obtained from the manager of the medical waste department.

- i=A set of medical waste companies (i=1, 2,…m)
- C_i=average a lost waste of 5% in collected waste occurs when it reaches the waste disposal site.
- p_i =Price per kilogram charged for disposing of medical waste by a company i
- m_i =The element of medical waste that can be recycled by a disposal company i
- f_i: Fixed cost of choosing a disposal firm i.

Table 13

The data for the clustering model.

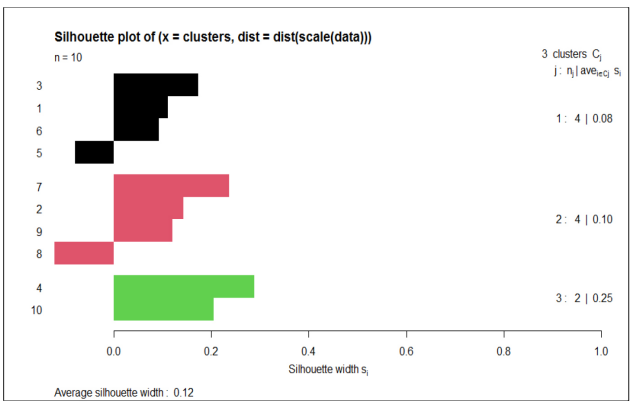
3PL Waste Company	C_i	p_i	m_i	f_i
A1	500	4	11%	6
A2	400	5	10%	8
A3	800	4	16%	5
A4	500	3	16%	9
A5	700	4	14%	5
A6	300	3	11%	4
A7	600	5	10%	7
A8	300	4	14%	7
A9	500	5	11%	6
A10	400	3	10%	8

In this study, sustainable criteria (Table 13) and Fuzzy TOPSIS (Table 12) scores will be used to evaluate and verify the strength of supplier groupings through the use of Fuzzy C-Means (FCM) clustering and hierarchical clustering techniques

The clustering solution shows the top silhouette score will be employed in this investigation. In actuality, providers are organized most logically and distinctly as possible by selecting the clustering approach having the top silhouette score, which produces the best possible cluster separability and tightness (Caliskan et al., [10])

The R software will be used to apply all clustering approaches for this investigation. Large libraries for clustering, a wealth of graphical and statistical approaches, and strong community support for learning and troubleshooting are the reasons R is chosen.

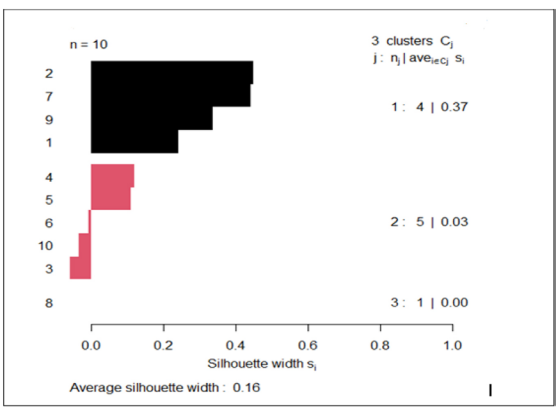
When we refer to Figure 2 and Figure 3 and we compare the FCM method to the hierarchical clustering method, we find that the silhouette index achieved by the FCM method was 0.16 (Figure 3), while our application of the hierarchical method produced a silhouette index of 0.12 (Figure 2). This finding suggests that we will select when comparing the two methods; that the quality of the clusters created by FCM is significantly higher. As a result, we will cluster the providers using the FCM clustering method (Figure 4).



Source: Author's findings.

Figure 2

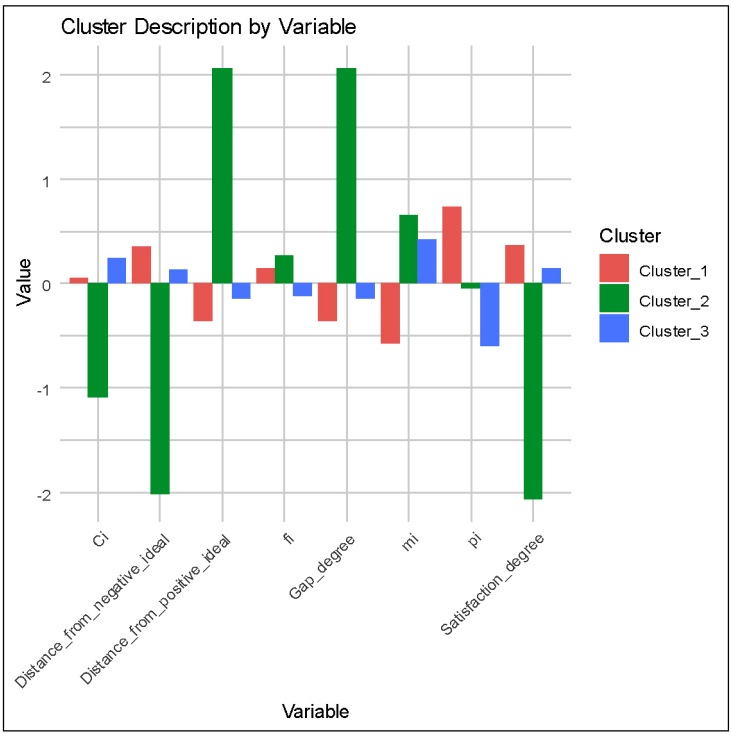
Silhouette plot of hierarchical clustering Method



Source: Author's findings.

Figure 3

Silhouette plot of FCM Method



Source: Author's findings.

Figure 4

Description of the clusters by the variables

Table 14

Description of the clusters by the variables

	Variable	Cluster_1	Cluster_2	Cluster_3
1	Distance_from_positive_ideal	-0.36353085	2.06422437	-0.1462424
2	Distance_from_negative_ideal	0.35953213	-2.01968002	0.1348194
3	Gap_degree	-0.36512838	2.06811094	-0.1452238
4	Satisfaction_degree	0.36539493	-2.06865021	0.1456143
5	Ci	0.05514385	-1.08579324	0.2452697
6	pi	0.73528069	-0.05075635	-0.6004757
7	mi	-0.57794263	0.65787556	0.4221438
8	fi	0.14054376	0.26444504	-0.1259067

As a result of the Fuzzy C-Means approach, Table 14 displays the centroids (centers of gravity) for each cluster or the average values for each variable within each category of firms. The mean value for each firm in a

cluster is represented by a centroid, which is the central point. Centroids are essential for comparing the various clusters and comprehending the general traits of the businesses within each cluster.

Managers can benefit from centroids by:

- Recognize the traits that firms in each cluster typically possess.
- Examine the average performance of firms in each cluster.
- Determine the advantages and disadvantages of every cluster.
- Make well-informed choices about which providers to use by considering factors like price, processing capacity, and recycling policies.

Refers to Table 14, firms in cluster 1 have higher prices, less recyclable components, moderate scores with the principles, and comparatively controllable fixed costs. This implies that although the fixed costs are reasonable, these firms may be only modestly efficient at charging greater rates. Firms with extreme scores, poor processing capacity, moderate pricing, higher recyclable component counts, and a range of fixed costs are found in cluster 2. These firms may have a wider range of specializations and traits, performing better in certain domains but falling short in others. Inside cluster 3 firms have modest recyclable components, cheaper pricing, intermediate ratings, and controllable fixed costs. These firms probably offer a better balance between price and performance because they are more sensible and affordable.

Recommendations

- Practical strategies for decision-makers in the healthcare sector.
- Guidelines for selecting sustainable 3PL providers based on study findings.

Managerial Insights

- **Cluster 1:** Firms with excessive costs and minimal recyclable materials
  - Give providers who make investments in cutting-edge recycling technologies priority and examine the policies and procedures of providers to make sure that trash is managed responsibly.

- Look for ways to maximize fixed or variable costs through operational efficiency, even if prices are higher. While maintaining the caliber and sustainability of the services, bargain for reasonable prices.
- To bolster the commitment to sustainability, form alliances with suppliers who hold comparable environmental principles.

- **Cluster 2**: Firms with high recycling performance but low processing capacity
  - Make sure the facilities can handle the present and future waste management needs. And choose providers who are prepared to invest to increase their medical waste processing capacities.
  - Seek out providers who can help the company save money over the long run by managing fixed costs effectively.
  - Appreciate providers who use cutting-edge technologies to enhance recycling and lessen their total environmental effects.
- **Cluster 3**: Firms with reasonable prices and effective fixed-cost management
  - Verify that providers who provide competitive pricing uphold high levels of service quality and comply with waste management regulations.
  - Select vendors who uphold socially and environmentally conscious standards, as this will improve your brand's reputation and satisfy customers.
  - Choose providers who can adjust to changing regulations and the company's unique waste management requirements.

5. Conclusion

In this study, we addressed the problem of selecting 3PL service providers for medical waste disposal within the Saudi healthcare system. The primary objective was to develop a hybrid methodology combining fuzzy TOPSIS with clustering techniques to evaluate 3PL earners based on ten sustainability-criteria encompassing economic, social, and environmental factors. Expert opinions were used to assign weights to these criteria, and fuzzy logic was employed to account for uncertainty in human decision-making. The framework was deployed in a practical, real-world situation in a Saudi healthcare company, where ranking and

assessment were performed using fuzzy TOPSIS the performance of the 3PL providers.

In the second stage, a clustering analysis was performed, grouping the providers based on performance scores from the fuzzy TOPSIS results, as well as other critical factors such as pricing, processing capacity, recycling potential, and fixed costs. The clusters identified allowed for the development of tailored managerial strategies and recommendations, enhancing the sustainability and effectiveness of 3PL provider selection for medical waste management.

This research presents a comprehensive framework that bridges theoretical and practical challenges in sustainable 3PL selection. The hybrid fuzzy TOPSIS-clustering approach offers healthcare organizations a data-driven tool for making sustainable logistics decisions. Future research could investigate the application of other MCDM techniques, such as fuzzy PROMETHEE or VIKOR, to validate the model in different healthcare contexts and regions, and further enhance its robustness.

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