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Healthcare Waste Management through Multi-Stage Decision-Making for Sustainability Enhancement

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Abstract: The possible threats that healthcare waste management (HWM) poses to the environment and public health are making it more and more crucial for medical facility administrators to be worried about it. This is in line with the global trend towards firms giving sustainability more of a priority. Many organizations, including the World Health Organization (WHO) and other organizations, as well as national and state laws, have mandated the proper disposal of infectious and hazardous healthcare waste. To effectively address the complex problem of selecting the best treatment option for HWM, a multi-criteria decision-making (MCDM) procedure must be used. The alternative ranking order method accounting for two-step normalization (AROMAN) methodology is provided in the context of q-rung orthopair fuzzy environment. This method comprises two steps of normalization and is based on the criteria importance through intercriteria correlation (CRITIC) paradigm. Whereas the AROMAN methodology uses vector and linear normalization techniques to improve the accuracy of the data for further computations, the CRITIC method assesses the intercriteria correlations and scores the significance of each criterion. The ranking from the proposed method is $Al_5 > Al_4 > Al_3 > Al_1 > Al_2$. The study's conclusions indicate that recycling (Al_5) is the best option since it lessens trash production, aids in resource recovery, and protects the environment. Using this method helps decision makers deal with subjectivity and ambiguity more skillfully, promotes consistency and transparency in decision making, and streamlines the process of choosing the best waste management system. Sustainable waste management practices have been implemented in the biomedical industry with some success. The proposed technique is a helpful tool for legislators and practitioners seeking to improve waste management systems.

Keywords: healthcare waste management; CRITIC-AROMAN methodology; decision making; sustainability; technology selection

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1. Introduction

Within the domain of human interaction, waste materializes as an unavoidable consequence, consisting of depleted resources. The necessity to appropriately handle this type of refuse stems from the potential risks it poses, which necessitate careful disposal methods [1]. Sewage, industrial effluents, and agricultural residues are significant contributors to air, water, and soil contamination, which endanger ecosystems and human health. Similarly, medical establishments, including hospitals, produce substantial volumes of refuse that harbor potential health hazards, including HIV, Hepatitis B and C, and Tetanus. Biomedical waste, which is generated during the course of diagnosing and treating illnesses in both humans and animals, requires the cooperation of all parties involved in its production, storage, collection, transportation, and treatment. Biomedical waste comprises an extensive variety of substances, which span from innocuous and readily controllable to exceptionally dangerous and contagious [2]. The latter classification presents not only imminent hazards but also enduring perils in the form of intergenerational disease transmission. Furthermore, the inadequate disposal of biomedical waste presents a significant ecological hazard by introducing contaminants into soil, water, and the atmosphere. The dearth of awareness among healthcare personnel regarding the proper disposal of biomedical waste is a matter of great concern, as evidenced by research [3]. This underscores the critical nature of the situation and the need for improved education and training in waste management protocols. As a result, it is critical to increase public consciousness regarding the proper handling and disposal of biomedical waste in order to alleviate the detrimental effects it has on the environment and human health [4].

The collection of waste materials from healthcare organizations is the initial step in the complex process of handling healthcare waste (HCW). Following collection, the trash is sent to approved disposal locations and treated with the relevant technology. Making the most of the available financial and environmental resources is a major focus of this stage of the treatment procedure [5]. The importance of choosing the right technology has been highlighted by recent studies. These studies have shown that a project's financial viability and environmental sustainability are significantly impacted by the technology chosen. In order to choose the best technological solutions for healthcare treatment, decision makers (DMs) now rely heavily on MCDM methodologies. In response to the identified demand, this is being done [6]. However, DMs typically encounter difficulties when attempting to assess decisions using precise and clear values because of the inherent fuzziness of human cognition. The choice of HCW treatment technique is inherently complicated, which is a substantial problem in and of itself. This is just one more obstacle. Throughout the review process, it is also critical to evaluate the subjective inputs provided by DMs. Frequently, these inputs are expressed in linguistic words. Given the complexity of the problems involved in the choice of HCW treatment methods, the significance of this language characteristic cannot be emphasized enough. Traditional quantitative measures may misinterpret the complex nature of selection criteria [7].

The use of HCW treatment technology that incorporates MCDM methodologies not only empowers patients to make more educated decisions, but also recognizes the industry's complexity and unpredictability. By integrating linguistic assessments and accounting for the quirks of human cognitive processes, the MCDM frameworks provide an effective way to manage human knowledge workers involved in (HCW) activities, boost productivity, and reduce environmental impact. The very nature of real-world apps is unpredictable, which presents a big challenge for DMs trying to make the optimal decision. Since its original introduction by Zadeh [8], the notion of fuzzy sets (FSs) has proven useful in a number of contexts. During this period, Atanassov [9] created intuitionistic fuzzy sets (IFSs). These sets were thought to have several benefits in terms of managing uncertainty. "Pythagorean fuzzy set" (PFS) was initiated by Yager and Abbasov [10] as amplification of IFS that emerged to extend the valuation space for MG and N-MG values. Yager also [11] defined the notion of q-ROFSs to address vague information, in which the sum of the qth powers of the MG and N-MG is less than or equal to 1. In aggregating, the q-ROF weighted averaging (q-ROFWA) and weighted geometric (q-ROFWG) operators were introduced for efficient synthesis of information from diverse sources [12]. Using edge cloud computing and deep learning for risk assessment in China's international trade and investment [13], and a multi-criteria decision-making model for evaluating road section safety [14], and the use of interval-valued picture fuzzy uncertain linguistic Dombi operators in industrial fund selection [15] are just a few examples of the varied approaches to risk management and decision making that are presented in this literature review.

In contemporary decision-making contexts, the application of MCDM methods is pivotal for addressing complex and multifaceted challenges. The CRITIC technique is especially remarkable when compared to other approaches for objectively establishing the weights of criteria [16]. Mishra et al. [17] introduced a new technique that leverages the CRITIC approach together with the GLDS methodology and Fermatean fuzzy numbers to enhance decision-making processes. When Monte Carlo simulation is used in conjunction with the CRITIC technique—which was first presented by Cui et al. [18]—decision making becomes more reliable and consistent. The CRITIC approach is found to be helpful in the manufacturing of vehicles [19], in addition to its application in software reliability modelling [20] and smartphone addiction assessment [21]. It is important to include MCDM methodology in blockchain assessments, as Zafar et al. [22] provide an efficient blockchain evaluation system based on the entropy-CRITIC weight method and MCDM procedures. Bączkiewicz et al. [23] explore methodical aspects of MCDM in the context of an E-commerce recommender system, focusing on the design and implementation of MCDM-based recommender systems and their impact on E-commerce platforms.

Bošković et al. give an AROMAN approach together with a case study on the choosing of electric vehicles. By offering a systematic technique for assessing and ranking options, this approach improves decision-making processes [24]. Nikolić et al. [25] employed an interval type-2 fuzzy AROMAN decision-making technique to improve the postal network's sustainability in rural regions. This work improves decision-making processes in complicated systems with uncertain inputs by implementing fuzzy logic principles. Čubranić-Dobrodolac et al. [26] provide a decision-making model that combines fuzzy logic with AROMAN and Fuller for the goal of professional driver selection. This study shows how the AROMAN strategy may be readily combined with other decision-making techniques to address specific problems that are unique to a certain region. Xiang et al. [27] offer the Fuzzy AROMAN technique, which is based on linear programming. This method is intended to provide a thorough assessment of the expansion of the digital economy in rural areas. Advanced decision-making methods, including Fermatean fuzzy aggregation operators [28] and Pythagorean fuzzy Hamacher aggregation operators [29], are highlighted along with their applications and contributions to various fields, including the FMEA-QFD for risk assessment in distribution processes [30]. Riaz and Farid [31] gave the idea of soft-max aggregation operators in the context of linear Diophantine fuzzy enviroment.

The aim of this manuscript is to address the critical issue of HWM by presenting a novel MCDM approach. Specifically, it introduces the CRITIC- AROMAN within a q-rung orthopair fuzzy environment to enhance decision-making accuracy. The study evaluates the effectiveness of this methodology in selecting optimal waste treatment options, ultimately highlighting recycling as the preferred solution. The findings aim to aid decision makers in implementing more sustainable and efficient waste management practices in the healthcare sector.

Here are some main contributions of the paper:

1. The study introduces a novel approach by combining the CRITIC method with the AROMAN method. This integration gives decision makers a strong foundation for choosing the best treatment technology for HWM by enabling a thorough examination of criteria and alternative rankings.
2. By leveraging vector and linear normalization techniques within the AROMAN method, the proposed approach improves the accuracy and reliability of data used in decision-making processes.
3. The research findings advocate for recycling as the optimal treatment technology for HWM. This recommendation is supported by its ability to reduce waste, recover valuable resources, and mitigate environmental impact, aligning with sustainability goals and regulations.

The subsequent sections of this manuscript are organized as follows: The initial definitions are provided in Section 2, and the q-rung orthopair fuzzy CRITIC-AROMAN approach is elaborated upon in Section 3. The fourth section provides specifics regarding the case study, potential alternatives, and criteria. In Section 5, the outcomes of a case study are discussed. Furthermore, relevant recommendations are presented in the concluding section of this paper, which also includes a concise summary of the research findings.

2. Some Basic Concepts

In this part, we introduce the score and accuracy functions, as well as a few key components of the q-ROFS and its operating rules.

Definition 1 ([11]). *Let $q \geq 1$. A q-rung orthopair fuzzy set $\mathbb{A}$ in $\mathcal{S}$ is defined as*

$$\mathbb{A} = \{\langle \varkappa, \tau_{\mathbb{A}}(\varkappa), \eta_{\mathbb{A}}(\varkappa)\rangle : \varkappa \in \mathcal{S}\},$$

where $\tau_{\mathbb{A}}, \eta_{\mathbb{A}} : \mathcal{S} \to [0,1]$ defines the membership and non-membership of the alternative $\varkappa \in \mathcal{S}$, and for every $\varkappa$, we have

$$0 \leq \tau^q_{\mathbb{A}}(\varkappa) + \eta^q_{\mathbb{A}}(\varkappa) \leq 1.$$

$\pi_{\mathbb{A}}(\varkappa) = (1 - \tau^q_{\mathbb{A}}(\varkappa) - \eta^q_{\mathbb{A}}(\varkappa))^{1/q}$ *is called the indeterminacy degree of $\varkappa$ to $\mathbb{A}$.*

Following are the operating rules that Liu and Wang proposed to combine with the q-ROFN data.

Definition 2 ([12]). *Let $\mathcal{H}_1 = \langle \tau_1, \eta_1 \rangle$ and $\mathcal{H}_2 = \langle \tau_2, \eta_2 \rangle$ be q-ROFN. Then,*
(1) $\bar{\mathcal{H}}_1 = \langle \eta_1, \tau_1 \rangle$;
(2) $\mathcal{H}_1 \vee \mathcal{H}_2 = \langle max\{\tau_1, \eta_1\}, min\{\tau_2, \eta_2\}\rangle$;
(3) $\mathcal{H}_1 \wedge \mathcal{H}_2 = \langle min\{\tau_1, \eta_1\}, max\{\tau_2, \eta_2\}\rangle$;
(4) $\mathcal{H}_1 \oplus \mathcal{H}_2 = \langle (\tau_1^q + \tau_2^q - \tau_1^q \tau_2^q)^{1/q}, \eta_1 \eta_2 \rangle$;
(5) $\mathcal{H}_1 \otimes \mathcal{H}_2 = \langle \tau_1 \tau_2, (\eta_1^q + \eta_2^q - \eta_1^q \eta_2^q)^{1/q} \rangle$;
(6) $\sigma \mathcal{H}_1 = \langle (1 - (1 - \tau_1^q)^\sigma)^{1/q}, \eta_1^\sigma \rangle$;
(7) $\mathcal{H}_1^\sigma = \langle \tau_1^\sigma, (1 - (1 - \eta_1^q)^\sigma)^{1/q} \rangle$.

Definition 3 ([12]). *Consider $\hat{\mathfrak{R}} = \langle \tau, \eta \rangle$ as a q-ROFN; then, the score function M of $\hat{\mathfrak{R}}$ will be given as*

$$M(\hat{\mathfrak{R}}) = \tau^q - \eta^q,$$

$M(\hat{\mathfrak{R}}) \in [-1, 1]$. *A q-ROFN's rating determines its ranking; that is, a high score indicates a solid q-ROFN selection. Nevertheless, there are a few situations in which the score characteristic is useless. As such, it is crucial to not always depend on the score function while examining q-ROFNs. To tackle this difficulty, we provide an additional technique: the accuracy characteristic.*

Definition 4 ([12]). *The accuracy function $\mathcal{G}$ of $\hat{\mathfrak{R}}$ is defined as follows:*

$$\mathcal{G}(\hat{\mathfrak{R}}) = \tau^q + \eta^q,$$

where $\mathcal{G}(\hat{\mathfrak{R}}) \in [0,1]$. This assumes that $\hat{\mathfrak{R}} = \langle \tau, \eta \rangle$ is a q-ROFN. The strong preference of $\hat{\mathfrak{R}}$ is defined by the high value of the accuracy degree $\mathcal{G}(\hat{\mathfrak{R}})$.

Theorem 1 ([12]). *Let $\mathcal{N} = \langle \tau_{\mathcal{N}}, \eta_{\mathcal{N}} \rangle$ and $\mathfrak{J} = \langle \tau_{\mathfrak{J}}, \eta_{\mathfrak{J}} \rangle$ be any two q-ROFN, $M(\mathcal{N}), M(\mathfrak{J})$ be the score function of $\mathcal{N}$ and $\mathfrak{J}$, and $\mathcal{G}(\mathcal{N}), \mathcal{G}(\mathfrak{J})$ be the accuracy function of $\mathcal{N}$ and $\mathfrak{J}$, respectively; then,*
(1) If $M(\mathcal{N}) > M(\mathfrak{J})$, then $\mathcal{N} > \mathfrak{J}$;
(2) If $\mathcal{G}(\mathcal{N}) > \mathcal{G}(\mathfrak{J})$ then $\mathcal{N} > \mathfrak{J}$.

The score feature has a value in the range of -1 to 1. We include all additional score features, $H(\mathfrak{R}) = \frac{1+\tau^q_{\mathfrak{R}} - \eta^q_{\mathfrak{R}}}{2}$, in order to facilitate further research. Obviously, $0 \leq H(\mathfrak{R}) \leq 1$. This new score function satisfies all the properties of a score function.

3. The q-Rung Orthopair Fuzzy CRITIC-AROMAN Method

Suppose we have a collection of n alternatives, $Al = \{Al_1, \ldots, Al_i, \ldots, Al_n\}$, where n is larger than or equal to 2. A finite set of criteria is represented by R, which is written as follows: $R = \{R_1, \ldots, R_j, \ldots, R_m\}(m \geq 2)$. Assume that the collection of invited DMs is represented by the following $D = \{D_1, \ldots, D_e, \ldots, D_z\}(z \geq 2)$. Through the following steps, the q-rung orthopair fuzzy CRITIC-AROMAN technique may be explained.

Step 1:
Utilizing linguistic values (LVs), determine the weights of DMs expressed as q-ROFNs. Table 1 contains the LVs. Take $\widetilde{\Pi}_k$ as the q-ROFN for the kth DM, represented by $\left\langle \tau_k, \eta_k \right\rangle$. Thus, the following formula may be used to determine the potential value of the kth DM, ζ_k:

$$\zeta_k = \frac{\left(\tau_k^q + \pi_k^q \times \left(\frac{\tau_k^q}{\tau_k^q + v_k^q}\right)\right)}{\sum_{k=1}^{\ell}\left(\tau_k^q + \pi_k^q \times \left(\frac{\tau_k^q}{\tau_k^q + v_k^q}\right)\right)}, k = 1, 2, 3, \ldots, l \quad (1)$$

Table 1. Linguistic values for DMs.

Linguistic Values	q-ROFNs
Very significant (VSi)	(0.950, 0.150)
Significant (Si)	(0.850, 0.250)
Average (Av)	(0.700, 0.450)
Very insignificant (VIn)	(0.400, 0.550)
Extremely insignificant (EIn)	(0.150, 0.750)

Step 2:
With the linguistic variables (LVs) obtained from the DMs and given in Table 2, create the linguistic decision matrix (LDM).

Table 2. LV for the LDM.

Linguistic Values	q-ROFNs
Absolutely high (AHg)	(0.900, 0.150)
Very high (VHg)	(0.800, 0.250)
High (Hg)	(0.750, 0.350)
Moderate high (MHg)	(0.650, 0.450)
Moderate (Mo)	(0.550, 0.550)
Low (Lo)	(0.350, 0.750)
Very low (VLo)	(0.250, 0.850)

Step 3:
Create the evaluation matrix $E^{\mathcal{G}}{}_{(p)}$ by organizing the LVs' q-ROFNs in a similar way. The matrix $(\mathfrak{Y}_{ji}^{(p)})_{n \times m}$ should be represented with dimensions of $n \times m$.

$$
\begin{array}{cc}
 & \begin{array}{cccc} R_1 & R_2 & & R_m \end{array} \\
\begin{array}{c}
D_1 \quad Al_1 \\ Al_2 \\ \vdots \\ Al_n \\ D_2 \quad Al_1 \\ Al_2 \\ \vdots \\ Al_n \\ D_p \quad Al_1 \\ Al_2 \\ \vdots \\ Al_n
\end{array}
&
\begin{bmatrix}
(\tau_{11}^{1}, \eta_{11}^{1}) & (\tau_{12}^{1}, \eta_{12}^{1}) & \cdots\cdots & (\langle \tau_{1m}^{1}, \eta_{1m}^{1})[t] \\
(\tau_{21}^{1}, \eta_{21}^{1}) & (\tau_{22}^{1}, \eta_{22}^{1}) & \cdots\cdots & (\tau_{2m}^{1}, \eta_{2m}^{1}) \\
\vdots & \vdots & \ddots\ddots & \vdots \\
(\tau_{n1}^{1}, \eta_{n1}^{1}) & (\tau_{n2}^{1}, \eta_{n2}^{1}) & \cdots\cdots & (\tau_{nm}^{1}, \eta_{nm}^{1})[b] \\
(\tau_{11}^{2}, \eta_{11}^{2}) & (\tau_{12}^{2}, \eta_{12}^{2}) & \cdots\cdots & (\tau_{1m}^{2}, \eta_{1m}^{2})[t] \\
(\tau_{21}^{2}, \eta_{21}^{2}) & (\tau_{22}^{2}, \eta_{22}^{2}) & \cdots\cdots & (\tau_{2m}^{2}, \eta_{2m}^{2}) \\
\vdots & \vdots & \ddots\ddots & \vdots \\
(\tau_{n1}^{2}, \eta_{n1}^{2}) & (\tau_{n2}^{2}, \eta_{n2}^{2}) & \cdots\cdots & (\tau_{nm}^{2}, \eta_{nm}^{2})[b] \\
(\tau_{11}^{p}, \eta_{11}^{p}) & (\tau_{12}^{p}, \eta_{12}^{p}) & \cdots\cdots & (\tau_{1m}^{p}, \eta_{1m}^{p})[t] \\
(\tau_{21}^{p}, \eta_{21}^{p}) & (\tau_{22}^{p}, \eta_{22}^{p}) & \cdots\cdots & (\tau_{2m}^{p}, \eta_{2m}^{p}) \\
\vdots & \vdots & \ddots\ddots & \vdots \\
(\tau_{n1}^{p}, \eta_{n1}^{p}) & (\tau_{n2}^{p}, \eta_{n2}^{p}) & \cdots\cdots & (\tau_{nm}^{p}, \eta_{nm}^{p})[b]
\end{bmatrix}
\end{array}
$$

Step 4:
Take a close look at the q-ROF assessment matrix. All individual perspectives must be combined and added to create a group view when building the cumulative q-ROF decision matrix. This is necessary to support group decision making. For this purpose, we applied the weighted average operator q-ROF. Consider the aggregated q-ROF decision matrix $P = \left(\beth_{ij}\right)_{n \times m}$.
Step 5:
Determine which criteria are more important than others using the CRITIC approach.
Step 5.1:
Using the SF of q-ROFNs, the score matrix should be evaluated as $\Psi = \left(S\left(\beth_{ij}\right)\right)_{n \times m}$.

$$
\begin{array}{cc}
 & \begin{array}{cccccc} R_1 & R_2 & R_3 & \ldots & R_m \end{array} \\
\begin{array}{c} Al_1 \\ Al_2 \\ Al_3 \\ \vdots \\ Al_m \end{array}
&
\begin{bmatrix}
S(\beth_{11}) & S(\beth_{12}) & S(\beth_{13}) & \ldots & S(\beth_{1m})[t] \\
S(\beth_{21}) & S(\beth_{22}) & S(\beth_{23}) & \ldots & S(\beth_{2m}) \\
S(\beth_{31}) & S(\beth_{32}) & S(\beth_{33}) & \ldots & S(\beth_{3m}) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
S(\beth_{n1}) & S(\beth_{n2}) & S(\beth_{n3}) & \ldots & S(\beth_{nm})[b]
\end{bmatrix}
\end{array}
$$

Step 5.2:
Using the provided Equation (2), the correlation coefficient between characteristics may be calculated.

$$\rho_{jk} = \frac{\sum_{i=1}^{m} (\beth_{ij} - \bar{x}_j)(\beth_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{m} (\beth_{ij} - \bar{x}_j)^2 \sum_{i=1}^{m} (\beth_{ik} - \bar{x}_k)^2}} \tag{2}$$

The means of the jth and kth qualities are shown by $\bar{x}_j$ and $\bar{x}_k$. Using Equation (3), $\bar{x}_j$ is calculated. Likewise, $\bar{x}_k$ yields the same result. Furthermore, ρ_{jk} represents the correlation coefficient between the j and kth qualities.

$$\bar{x}_j = \frac{1}{n}\sum_{j=1}^{n} \beth_{ij}; \quad i = 1, \ldots, m \tag{3}$$

Step 5.3:
The following Equation (4) is used to estimate the standard deviation for each attribute first.

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n} \left(\beth_{ij} - \bar{x}_j\right)^2}; \quad i = 1, \ldots, m \tag{4}$$

Then, the index (C) is calculated using Equation (5).

$$R_j = \sigma_j \sum_{k=1}^{n} \left(1 - \rho_{jk}\right); \quad j = 1, \ldots, n \tag{5}$$

Step 5.4:
Equation (6) is utilized in the process of determining attribute weights.

$$w_j = \frac{R_j}{\sum\limits_{j=1}^{n} R_j}; \quad j = 1, \ldots, n \tag{6}$$

Step 6:
Standardizing the input data is the next step after determining the criterion weights. Equations (7) and (8) are the two normalization methods that are used to standardize the decision matrix. The linear form of normalization is given by Equation (7), whereas the vector form is given by Equation (8). Step 6's normalization techniques are used to the benefit and cost categories of criterion.

$$\mathfrak{z}_{ij} = \frac{\beth_{ij} - \min(\beth_{ij})}{\max(\beth_{ij}) - \min(\beth_{ij})}; \quad i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m; \tag{7}$$

$$\mathfrak{z}^{*}_{ij} = \frac{\beth_{ij}}{\sqrt{\sum\limits_{i=1}^{n} \beth_{ij}^{2}}}; \quad i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m; \tag{8}$$

Step 7:
Equation (9) is used to carry out the aggregated averaged normalization process.

$$\mathfrak{z}^{\aleph}_{ij} = \frac{\xi\, \mathfrak{z}_{ij} + (1-\xi)\mathfrak{z}^{*}_{ij}}{2}; \quad i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m; \tag{9}$$

We assigned a value of ξ of 0.50 in this specific case. As a weighting factor, the variable ξ has a range from 0 to 1. There are several methods for managing the information aggregation process within the discipline of MCDM. Using the centroid mean or the geometric mean is one of these choices. Because the arithmetic mean is widely accepted as the most often used measure of central tendency, that is why we choose to employ it.

Step 8:
Utilizing Equation (10) and the weights assigned to the criterion, compute the weighted decision matrix by multiplying the aggregated, averaged, and normalized decision-making matrix.

$$\mathfrak{W}_{ij} = \mathfrak{N}_i^{\beta} \times \mathfrak{Z}_{ij}^{\aleph}; \quad i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m; \tag{10}$$

Step 9:
Analyze the benefit type criterion B_i and the cost type criterion C_i using their normalized weighted values. Equations (11) and 12 may be used to determine these, respectively.

$$C_i = \sum_{j=1}^{m} \mathfrak{W}_{ij}^{\min}; \quad i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m; \tag{11}$$

$$B_i = \sum_{j=1}^{m} \mathfrak{W}_{ij}^{\max}; \quad i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m; \tag{12}$$

Step 10:
Using the following Equation (13), get the final ranking values Y_i.

$$Y_i = C_i^{\lambda} + B_i^{(1-\lambda)}; \quad i = 1, 2, \ldots, n; \tag{13}$$

The coefficient degree of the criteria type is indicated by λ. Including both types of criteria allowed us to conclude that the value of parameter λ was 0.5.

However, by taking the particular requirement into consideration, several variations of the parameter λ may be produced. In the event where the decision-making issue comprises one benefit-type criterion and two cost-type criteria, $\frac{2}{3}$ should be assigned to the coefficient λ. This logic may be applied to determine which of the investigated solutions is preferred.

4. Case Study

In order to assess the efficacy of the suggested method, this section provides a practical example that involves choosing a technology for managing infectious healthcare waste. In a rapidly expanding urban region, the proliferation of hospitals and healthcare facilities has led to an increase in the production of medical waste. Unfortunately, a substantial amount of this trash is not being adequately handled or disposed of. The widespread increase of medical waste has presented significant risks to both human health and the environment. In order to accomplish this objective, the recommended method is employed to assess and select appropriate technology for the treatment of medical waste. In order to properly tackle the intricate issue of picking the optimal treatment option for HWM, a decision-making approach must be employed. The CRITIC-AROMAN approach is presented within the framework of a q-rung orthopair fuzzy environment. This method consists of two steps: normalization and finding the significance of criteria through the intercriteria correlation paradigm. The AROMAN methodology employs vector and linear normalization techniques to enhance the correctness of the data for subsequent computations. In contrast, the CRITIC method evaluates the intercriteria correlations and assigns scores to determine the relevance of each criterion.

4.1. Identification of Different Alternatives

The evaluation of biomedical waste management methods requires the identification of a range of choices in order to enable a detailed investigation of the techniques, instruments, and procedures that are used in actual healthcare environments. The capacity to examine the viability and efficacy of different waste management systems is advantageous to decision makers, as it guarantees a thorough assessment covering a broad range of options. This approach remains paramount given the dynamic nature of waste management practices, necessitating continual adaptation to evolving regulations, technological advancements, and emerging best practices. By delineating multiple options, DMs are empowered to conduct a nuanced analysis, weighing the merits and drawbacks of each strategy against their unique requirements, resource availability, and environmental considerations. Furthermore, offering a variety of choices stimulates imagination and the search for novel ideas, which promotes continuous improvement of biomedical waste management procedures. Therefore, the identification of several options forms the basis of the assessment procedure, allowing decision makers the flexibility to choose the most appropriate and long-lasting waste management solutions [32].

(1) Incineration (Al_1)— One common method used to deal with biological waste is "incineration", which is the controlled burning of waste materials at temperatures typically between 800 and 1200 degrees Celsius. Incineration reduces the quantity of garbage generated while also getting rid of potentially dangerous microorganisms thanks to the process of heat breakdown. Sharps, pharmaceutical residues, infectious contaminants, and other biological waste categories are just a few of the categories that this method is utilized to handle. There are several advantages to burning waste. First off, healthcare facilities that generate a lot of biological waste might benefit greatly from its ability to handle large amounts of trash. A large number of germs are successfully eliminated during the burning process, lowering the risk of disease transmission to nearby people and the environment. Another advantage of the process might be the creation of renewable energy resources through the use of waste-to-energy technology [33]. In addition to the many benefits of incineration, there are a number of issues and worries associated with it. Incineration may release pollutants such furans, dioxins, and greenhouse gases that are harmful to the environment and public health if proper management is not implemented. To deal with these toxins, scrubbers and filters—along with other state-of-the-art technologies for air pollution control—are very essential. Furthermore, it is important to do regular maintenance, have specialized infrastructure, and make significant financial expenditures to guarantee the efficacy and safety of incineration operations.

(2) Microwaving (Al_2)—An emerging trend in biomedical waste management involves the utilization of "microwaving" as an alternative method. This approach entails the sterilization and disinfection of waste through microwave technology, making it particularly suitable for items such as sharps, laboratory waste, liquid residues, and small quantities of biomedical waste. Microwaving offers several advantages as a waste management solution. Notably, its swift and efficient treatment process relies on the generation of heat within the waste itself, ensuring rapid disinfection [34]. Moreover, microwaving contributes to waste volume reduction, streamlining storage, transportation, and eventual disposal processes. However, employing microwaves for waste management presents certain challenges. Ensuring optimal operation necessitates a reliable power supply and appropriate setup infrastructure. Furthermore, careful waste processing and packing procedures are needed to provide consistent heating and disinfection. Moreover, some biomedical waste kinds—like specific chemicals, pharmaceuticals, or radioactive materials—may not be microwave-safe and might require other disposal techniques.

(3) Autoclaving (Al_3)—Biological waste is being disposed of using "autoclaving", a technique that involves sanitizing and sterilizing trash by immersing it in high-pressure saturated steam within an autoclave. Solid waste, laboratory trash, and medical device waste are just a few of the waste types that can be treated using this technology in healthcare settings. When considering waste management options, autoclaving has several benefits. The first benefit is that it efficiently destroys pathogens including bacteria, viruses, and spores, reducing the chance of infection transmission and making the waste safe for handling and disposal later on. Processes for storage and transportation become more efficient when waste volume is reduced by autoclaving. The environmental emissions from autoclaving are usually lower than those from other processes, such as incineration, and it requires less infrastructure to operate [35]. Nonetheless, during autoclaving, a few things need to be kept in mind. To generate the necessary steam for the operation, a constant supply of electricity and water is needed. Furthermore, not all waste kinds are acceptable

for autoclaving, despite the fact that it may cure some hazardous or chemically polluted waste streams.

(4) Landfilling (Al_4)—The conventional approach of "landfilling", which is dumping garbage at approved landfill sites created to securely store and manage waste materials, is a well-established substitute for handling biomedical waste. Landfills may be used to dispose of a variety of biomedical waste materials, such as non-infectious, non-hazardous trash, and some kinds of sharps. Landfilling is a standard waste management method; however, it has a number of advantages. First of all, it is a commonly used and useful trash disposal technique that guarantees accessibility and simplicity of use. The functions of landfills include trash containment, waste movement reduction, and environmental contamination risk mitigation. Furthermore, landfilling offers long-term storage options—often at a cheaper cost than alternative waste treatment methods—for garbage that does not immediately endanger public health or the environment. Biomedical waste disposal raises issues and difficulties [36]. When biomedical waste is handled improperly, potentially dangerous substances may seep into the environment, endangering ecosystems as well as human health. Tight laws and efficient waste segregation techniques are needed to guarantee the safe disposal of medical waste in landfills.

(5) Recycling (Al_5)— "Recycling" is becoming a prominent and ecologically friendly biomedical waste management option. By recovering and reusing materials from waste streams, this strategy seeks to minimize waste production and lower the demand for raw resources. Although recycling is often connected with non-biomedical waste, certain biomedical waste components—such as plastics, metals, and glass—have unique recycling prospects. Recycling has several advantages over traditional trash management techniques. Recycling encourages resource conservation by removing useful components from garbage and reintegrating them into the manufacturing cycle. This lessens the need for additional raw materials, saves energy, and lessens the negative effects that mining and manufacturing operations have on the environment. Recycling also lessens the total environmental impact of waste management initiatives and helps to reduce trash [37].

4.2. Identification of Different Criteria

Developing a multitude of criteria is crucial when assessing biological waste management systems to guarantee a thorough evaluation. If a variety of factors are taken into consideration, we are able to provide decision makers with a thorough grasp of the options that are accessible to them as well as a full awareness of the complexity of waste management. Each criterion describes a certain aspect of waste management and focuses on crucial elements that are required to make wise selections [38]. The methodical selection and elaboration of criteria provide the basis for carrying out a comprehensive and enlightening examination of the different approaches to biological waste treatment. These evaluations, which ensure that the best waste management practices are followed, safeguard both the environment's purity and public health [39].

(i) Cost: [MIN]
The financial elements of biological waste management are thoroughly assessed through the use of cost criteria, which consider both the overall expenses of the process and the distribution of resources. This organization's main goal is to find solutions that are both inexpensive and successful in terms of how resources are used and how well things function overall. Among the many approaches that might be researched to find a middle ground between practically viable waste management options and effective waste management techniques are waste segregation, recycling, and treatment enhancement. This might be achieved by looking at how cost-effective certain specific tactics are.

(ii) Environmental Impact: [MAX]
By evaluating a number of aspects, such as preventing contamination, preserving resources, and reducing emissions, the Environmental Impact criterion assesses the ecological footprint of waste management systems. By evaluating the system's re-

source efficiency, pollutant reduction, and eco-friendliness, it should be possible to ascertain how much the system contributes to environmental preservation and gain insight into possible changes that could lessen the likelihood of unintended effects.

(iii) Technological Feasibility: [MAX]
The equipment's applicability, accessibility, and compatibility with waste quality are all examined using the Technological Feasibility criteria. The purpose of this review is to assess the technological elements of managing biomedical waste. This organization's goal is to identify inefficiencies and recommend technology advancements that will make waste collection, treatment facilities, and disposal methods more efficient, effective, and environmentally benign. Our goal is to guarantee that waste management equipment is effective, trustworthy, and equipped to tackle the difficulties associated with managing biomedical waste.

(iv) Compliance with Regulations: [MAX]
Biological waste management methods are assessed using Regulatory Compliance criteria to see if they adhere to local, state, and federal rules and regulations. This is done to ensure that environmental preservation, worker safety, and public health goals are all met. This identifies any loopholes or instances of noncompliance with the rules governing the collection, handling, processing, disposal, and treatment of waste. This evaluation's goals are to boost overall regulatory compliance and pinpoint areas that might be improved in order to support the law's requirements for the safe and responsible treatment of biomedical waste.

(v) Safety and Health: [MAX]
The Health and Safety standards examine the procedures that have been implemented to safeguard employees, patients, and members of the public when it comes to handling biological waste. The use of personal protective equipment (PPE), training employees on handling hazardous waste, safety procedures, and lowering workplace hazards are all covered in this study. Evaluation focuses on risk management efficacy to mitigate health risks, including pathogen exposure, chemical hazards, and sharps injuries. Identifying gaps in waste management practices, this criterion aims to enhance safety standards and protect individuals involved in waste handling through necessary modifications.

5. Decision Making and Experimental Results

There are four alternatives, given as $A = \{Al_1, Al_2, Al_3, Al_4, Al_5\}$, that are explained above, and $C = \{R_1, R_2, R_3, \ldots, R_5\}$ are the criteria, which are also explained above. Three DMs $D = \{D_1, D_2, D_3\}$ are invited.

Step 1:
Determine the weights of DMs by using the LVs given in Table 1. In Table 3, importance of each DMs is given, which is determined using Equation (1).

Table 3. Weights of DMs.

	LVs	q-ROFNs	Weights
D_1	VSi	(0.950, 0.150)	0.4744
D_2	Av	(0.700, 0.450)	0.2180
D_3	Si	(0.850, 0.250)	0.3075

Step 2:
Construct the LDM using the LVs given in Table 2 from the DMs. LDM is given in Table 4.

Table 4. DM evaluations for the alternatives in linguistic terms.

Experts	Alternatives	Criterion				
		R_1	R_2	R_3	R_4	R_5
D_1	Al_1	AHg	VHg	AHg	VHg	AHg
	Al_2	VHg	Hg	AHg	MHg	VHg
	Al_3	Lo	Hg	VHg	VLo	AHg
	Al_4	AHg	MHg	Hg	Hg	Lo
	Al_5	AHg	MHg	Hg	Hg	Lo
D_2	Al_1	Hg	AHg	Hg	MHg	Lo
	Al_2	MHg	Lo	Hg	AHg	Hg
	Al_3	Mo	MHg	Hg	Lo	AHg
	Al_4	AHg	MHg	Hg	Hg	Lo
	Al_5	Hg	MHg	Hg	Mo	Lo
D_3	Al_1	AHg	Hg	Hg	AHg	Hg
	Al_2	Hg	MHg	MHg	MHg	Hg
	Al_3	VLo	VHg	Hg	Lo	AHg
	Al_4	AHg	MHg	Hg	Hg	Lo
	Al_5	Hg	Mo	Hg	Hg	VLo

Step 3:

Construct the assessment matrix $E^{\mathcal{G}}{}_{(p)} = (\mathfrak{Y}_{ji}^{(p)})_{n \times m}$ using corresponding q-ROFNs of LVs, given in Table 5.

Table 5. Assessment matrix using corresponding q-ROFNs.

Experts	Alternatives	Criterion				
		R_1	R_2	R_3	R_4	R_5
D_1	Al_1	(0.750, 0.350)	(0.650, 0.450)	(0.900, 0.150)	(0.800, 0.250)	(0.900, 0.150)
	Al_2	(0.800, 0.250)	(0.900, 0.150)	(0.900, 0.150)	(0.650, 0.450)	(0.800, 0.250)
	Al_3	(0.350, 0.750)	(0.750, 0.350)	(0.800, 0.250)	(0.250, 0.850)	(0.900, 0.150)
	Al_4	(0.900, 0.150)	(0.650, 0.450)	(0.750, 0.350)	(0.750, 0.350)	(0.350, 0.750)
	Al_5	(0.650, 0.450)	(0.350, 0.750)	(0.650, 0.450)	(0.900, 0.150)	(0.350, 0.750)
D_2	Al_1	(0.750, 0.350)	(0.900, 0.150)	(0.750, 0.350)	(0.650, 0.450)	(0.350, 0.750)
	Al_2	(0.650, 0.450)	(0.350, 0.750)	(0.650, 0.450)	(0.800, 0.250)	(0.750, 0.350)
	Al_3	(0.550, 0.550)	(0.750, 0.350)	(0.750, 0.350)	(0.350, 0.750)	(0.900, 0.150)
	Al_4	(0.900, 0.150)	(0.650, 0.450)	(0.750, 0.350)	(0.750, 0.350)	(0.350, 0.750)
	Al_5	(0.750, 0.350)	(0.650, 0.450)	(0.750, 0.350)	(0.550, 0.550)	(0.350, 0.750)
D_3	Al_1	(0.750, 0.350)	(0.750, 0.350)	(0.650, 0.450)	(0.900, 0.150)	(0.750, 0.350)
	Al_2	(0.650, 0.450)	(0.750, 0.350)	(0.650, 0.450)	(0.650, 0.450)	(0.750, 0.350)
	Al_3	(0.350, 0.750)	(0.750, 0.350)	(0.800, 0.250)	(0.350, 0.750)	(0.750, 0.350)
	Al_4	(0.900, 0.150)	(0.750, 0.350)	(0.750, 0.350)	(0.800, 0.250)	(0.350, 0.750)
	Al_5	(0.750, 0.350)	(0.550, 0.550)	(0.800, 0.250)	(0.750, 0.350)	(0.250, 0.850)

Step 4:

Evaluate the collective decision matrix using q-ROFEIWG operator, given in Table 6.

Table 6. Aggregated matrix using operator.

Alternatives	Criterion				
	R_1	R_2	R_3	R_4	R_5
Al_1	(0.6843, 0.4549)	(0.5438, 0.8290)	(0.6465, 0.3236)	(0.5434, 0.5632)	(0.7158, 0.5212)
Al_2	(0.4010, 0.8304)	(0.6352, 0.6362)	(0.8244, 0.2516)	(0.7914, 0.4034)	(0.7670, 0.3283)
Al_3	(0.4464, 0.5298)	(0.4148, 0.2902)	(0.7530, 0.3633)	(0.3534, 0.7631)	(0.9543, 0.1565)
Al_4	(0.6364, 0.3566)	(0.6716, 0.4972)	(0.7424, 0.2341)	(0.2346, 0.7313)	(0.8356, 0.5267)
Al_5	(0.8432, 0.1236)	(0.1634, 0.3245)	(0.4421, 0.3530)	(0.2456, 0.2451)	(0.3538, 0.4545)

Step 5:
Use the CRITIC method for the estimation of criteria weights.
Step 5.1:
Evaluate the score matrix using the SF of q-ROFNs as $\Psi = \left(S\left(\beth_{ij}\right)\right)_{n\times m}$, given in Table 7.

Table 7. Score function of aggregated DMs.

Alternatives	Criterion				
	R_1	R_2	R_3	R_4	R_5
Al_1	0.588226	0.307575	0.581863	0.49329	0.594365
Al_2	0.275179	0.499486	0.728949	0.682894	0.667234
Al_3	0.480462	0.511256	0.511256	0.33825	0.914377
Al_4	0.573929	0.571166	0.650386	0.358509	0.705282
Al_5	0.752634	0.494812	0.511337	0.500015	0.486499

Step 5.2:
The correlation coefficient between the attributes is given in Table 8.

Table 8. Correlation coefficient between the attributes.

1	−0.1321	−0.7165	−0.4622	−0.4984
−0.1321	1	0.1634	−0.2479	0.3362
−0.7165	0.1634	1	0.5885	−0.0432
−0.4622	−0.2479	0.5885	1	−0.5033
−0.4984	0.3362	−0.0432	−0.5033	1

Step 5.3:
The standard deviation of each attribute is calculated as given in Table 9. The index C is given in Table 10.

Table 9. Standard deviation of each attribute.

Criterion				
σ_1	σ_2	σ_3	σ_4	σ_5
0.1748	0.0995	0.0938	0.1382	0.1584

Table 10. The index C.

Criterion				
R_1	R_2	R_3	R_4	R_5
1.0153	0.3859	0.3759	0.6394	0.7456

Step 5.4:
The determination of attribute weights is accomplished through the use of Equation (6), given in Table 11.

Table 11. Weights of the attributes.

Criterion				
w_1	w_2	w_3	w_4	w_5
0.3211	0.1220	0.1189	0.2022	0.2358

Step 6:
Equations (7) and (8) are employed to normalize the fuzzy decision matrix. Equation (7) gave the linear form normalization and Equation (8) gave the vector form normalization, given in Table 12 and Table 13, respectively.

Table 12. Linear normalization of fuzzy decision matrix.

R_1	R_2	R_3	R_4	R_5
0.6557	0	0.3243	0.4499	0.2521
0	0.7281	1	1	0.4224
0.4300	0.7727	0	0	1
0.6257	1	0.6391	0.0588	0.5113
1	0.7103	0.0004	0.4694	0

Table 13. Vector normalization of fuzzy decision matrix.

R_1	R_2	R_3	R_4	R_5
0.4727	0.2836	0.4318	0.4498	0.3862
0.2211	0.4605	0.5410	0.6227	0.4335
0.3861	0.4713	0.3794	0.3084	0.5941
0.4612	0.5266	0.4827	0.3269	0.4583
0.6048	0.4562	0.3795	0.4559	0.3161

Step 7:
Find aggregated averaged normalization values using Equation (9), taking the value of ξ as 0.50, given in Table 14.

Table 14. Aggregated averaged normalization values.

R_1	R_2	R_3	R_4	R_5
0.2821	0.0709	0.1890	0.2249	0.1596
0.0553	0.2971	0.3852	0.4057	0.2140
0.2040	0.3110	0.0949	0.0771	0.3985
0.2717	0.3816	0.2804	0.0964	0.2424
0.4012	0.2916	0.0950	0.2313	0.0790

Step 8:
Compute the weighted decision matrix using Equation (10), given in Table 15.

Table 15. Aggregated averaged normalization values.

R_1	R_2	R_3	R_4	R_5
0.0906	0.0086	0.0225	0.0455	0.0376
0.0178	0.0363	0.0458	0.0820	0.0505
0.0655	0.0379	0.0113	0.0156	0.0940
0.0873	0.0466	0.0333	0.0195	0.0572
0.1288	0.0356	0.0113	0.0468	0.0186

Step 9:
Evaluate the normalized weighted values of the cost type criteria C_i and the benefit type criteria B_i. This can be calculated by applying Equations (11) and (12), given in Table 16.

Table 16. Sum of all benefit criteria and cost criteria values.

C_1	0.1142	B_1	0.0906
C_2	0.2145	B_2	0.0178
C_3	0.1587	B_3	0.0655
C_4	0.1566	B_4	0.0873
C_5	0.1123	B_5	0.1288

Step 10:
Find the final ranking values Y_i using Equation (13), given in Table 17.

Table 17. Final ranking values.

Y_1	0.6389
Y_2	0.5964
Y_3	0.6544
Y_4	0.6911
Y_5	0.6941

As per these values, ranking is $Al_5 > Al_4 > Al_3 > Al_1 > Al_2$.

5.1. Managerial Implications

The CRITIC-AROMAN strategy has several managerial ramifications for managers of healthcare companies that handle waste in relation to waste management. First of all, it provides a systematic way to assess various treatment technology options according to how well they meet the goals of the company, the requirements of regulatory agencies, and sustainability standards. Additionally, by highlighting the most successful treatment alternatives, it helps managers make more effective use of their financial and human resources. The third advantage is that by using the suggested technology, healthcare institutions can lower the likelihood of regulatory violations and the associated penalties. The procedure also helps to lessen the risks associated with improper waste management, which is advantageous for the environment's and the public's health. As a result, it promotes accountability, self-assurance, and teamwork among all stakeholders, ultimately resulting in heightened engagement and cooperation. This is achieved by instituting a clear and equitable decision-making process.

5.2. Theoretical Limitations

One of the main drawbacks of the CRITIC-AROMAN system is its reliance on predefined weights and criteria. The complex and dynamic nature of hospital waste management systems may not be sufficiently reflected by these weights and criteria. Although the technique offers a methodical approach to decision making, it could overlook some contextual factors or changing norms that could influence the technology selection. It is likely that non-linear interactions or feedback loops within the decision-making process are not adequately taken into account by the approach. Its assumption of linear relationships between the criteria is the cause of this. The simplifying of the data representation caused by the AROMAN approach's reliance on vector and linear normalization techniques may lead to information loss or data distortion. Finally, the quality and accessibility of the data inputs may have an effect on the technique's effectiveness; these factors may vary according on the healthcare setting and the legal country. Upon evaluation of these theoretical limitations, it is clear that ongoing validation and enhancement are necessary for the CRITIC-AROMAN approach to make it more appropriate for handling complex healthcare waste scenarios.

5.3. Comparative Analysis

A comprehensive comparative analysis was conducted to assess the efficacy of the suggested methodology in comparison to several alternative approaches. Although there were some small inconsistencies in the arrangement of possibilities, as outlined in Table 18, a clear and consistent pattern formed with the alternatives that received the highest scores. It is crucial to recognize that the suggested approach is remarkable for its notable computing capacity, especially in assessing the level of usefulness for each option.

Table 18. Comparative analysis with other techniques.

Methods	**Ranking**
CRITIC-CODAS method [40]	$Al_5 > Al_3 > Al_4 > Al_2 > Al_1$
CRITIC-EDAS method [41]	$Al_5 > Al_4 > Al_1 > Al_3 > Al_2$
Proposed method	$Al_5 > Al_4 > Al_3 > Al_1 > Al_2$

5.4. Sensitivity Analysis

The sensitivity analysis of choice outcomes in Table 19 demonstrates a consistent ordering of options, denoted as Al_1 to Al_5, as the parameter λ ranges from 0.1 to 0.8. This highlights the durability and reliability of the decision-making model. The recommended order, notably, is $Al_5 > Al_4 > Al_3 > Al_1 > Al_2$. An analysis of various λ values on the joint generalized criterion reveals a noticeable pattern. As the value of λ approaches 1, the relative relevance of the values becomes more additive. Conversely, as λ approaches zero, the relative importance shifts towards being more multiplicative.

Table 19. The influence of the parameter λ on the outcome of the decision.

λ	Ranking
$\lambda = 0.1$	$Al_5 > Al_4 > Al_3 > Al_1 > Al_2$
$\lambda = 0.2$	$Al_5 > Al_4 > Al_3 > Al_1 > Al_2$
$\lambda = 0.3$	$Al_5 > Al_4 > Al_3 > Al_1 > Al_2$
$\lambda = 0.4$	$Al_5 > Al_4 > Al_3 > Al_1 > Al_2$
$\lambda = 0.7$	$Al_5 > Al_4 > Al_3 > Al_1 > Al_2$
$\lambda = 0.8$	$Al_5 > Al_4 > Al_3 > Al_1 > Al_2$

6. Conclusions

Healthcare facility managers may find the CRITIC-AROMAN approach's framework to be very helpful in the selection of waste management solutions. Managers can now prioritize treatment technologies that align with organizational goals, regulatory mandates, and sustainability objectives thanks to the integration of the CRITIC and AROMAN methodologies, which rank options and assess the significance of criteria, respectively. The dependence on preset criteria and weights, linear assumptions, and oversimplifications of data presentation are only a few of the theoretical flaws that must all be addressed. Future research aiming at addressing these drawbacks may concentrate on robust and flexible methods of decision making, including fuzzy logic or machine learning techniques. The method's practicality and usefulness may be better understood if efforts were made to improve it through empirical case studies and validation. Hospital waste management programs may also benefit from interdisciplinary cooperation and stakeholder involvement programs that include a range of viewpoints and specialized knowledge into decision making. These programs could be advantageous. Plans that are more thorough and appropriate for the situation would arise from this. When taken as a whole, the CRITIC-AROMAN methodology has a lot of promise for encouraging environmentally friendly waste management techniques and stimulating innovation in the healthcare industry.

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