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A Systematic Approach for Evaluating and Selecting Healthcare Waste Treatment Devices using OWCM-CODAS and Triangular Neutrosophic Sets

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Abstract: Healthcare is a fundamental aspect of human life, impacting individuals, communities, and societies. Investing in healthcare infrastructure, services, and education is essential for fostering a healthy, thriving population. Healthcare waste management is a critical aspect of public health, and it requires a concerted effort from healthcare facilities, governments, and communities to ensure that waste is managed in a way that minimizes risks to human health and the environment. This paper proposes a hybrid methodology combining the Opinion Weight Criteria Method (OWCM) and the Combinative Distance-Based Assessment (CODAS) within the framework of Triangular Neutrosophic Sets (TNS) to evaluate and select the optimal healthcare waste treatment devices. The proposed methodology balances various conflicting criteria and incorporates uncertainty in expert assessments to ensure a robust decision-making process. The paper also provides a comprehensive review of healthcare waste management devices and highlights the need for a comprehensive approach to healthcare waste management. The proposed methodology is applied to a case study involving evaluating healthcare waste treatment devices based on different factors such as economic, environmental, technological, and social aspects. The results show that the OWCM-CODAS methodology, integrated with TNS, effectively evaluates and ranks healthcare waste treatment devices based on multiple criteria. The sensitivity analysis demonstrates the robustness of the proposed model, and the results indicate that the model's performance and the relative ranking of the alternatives are not sensitive to changes in the threshold parameter τ within the tested range.

Keywords: Healthcare, OWCM, CODAS, TNS, Waste.

1. Introduction

The healthcare sector plays a vital role in our lives. Its role is to prevent diseases and improve the quality of life. Healthcare management is the backbone of the healthcare industry, playing an essential role in ensuring that healthcare services are delivered efficiently, effectively, and safely [1]. Effective healthcare management is the key to properly handling healthcare waste [2]. Healthcare activities generate healthcare waste, categorized into hazardous and non-hazardous waste [3]. Hazardous waste includes infectious waste, pathological waste, sharps waste, chemical waste, pharmaceutical waste, cytotoxic waste, and radioactive waste [4]. The non-hazardous waste includes general waste that poses no biological, chemical, radioactive, or physical hazard [5].

The significant sources of healthcare waste are hospitals, laboratories, mortuary and autopsy centers, animal research and testing laboratories, blood banks and collection services, and nursing homes for the elderly [6]. Healthcare waste can pose health risks to hospital patients, health workers, and the public. These risks include sharps-inflicted injuries, toxic exposure to pharmaceutical products, chemical burns, air pollution, thermal injuries, and radiation burns [7]. Health waste is a significant concern globally, particularly in countries with poor hygiene and high population density.

Medical centers, including hospitals and clinics, generate hazardous biomedical waste that risks human health and the environment if not managed properly [8]. The World Health Organization (WHO) emphasizes the importance of proper waste management in healthcare facilities to prevent spreading infections and diseases. This includes segregation, collection, storage, transportation, and healthcare waste treatment [9].

Healthcare waste management is critical to ensuring the safe and environmentally sound disposal of waste generated by healthcare activities, especially during and post-COVID-19 pandemic era [10]. Healthcare waste treatment devices are medical waste disposal equipment designed to treat and dispose of hazardous medical waste safely and efficiently [11]. According to the WHO, healthcare waste management involves segregation, collection, storage, transportation, and treatment of healthcare waste [12]. To properly dispose of healthcare waste, especially during a pandemic such as COVID-19, the following steps should be taken [13, 14]:

i). Segregation: Proper segregation of waste at the source is crucial. This involves separating hazardous healthcare waste from non-hazardous waste, which can reduce the overall volume of hazardous waste and associated disposal costs.

ii). Storage: Store waste in designated areas, such as waste storage rooms or containers, to prevent mixing different types of waste.

iii). Transportation: Transport waste to treatment and disposal facilities using designated vehicles and containers to prevent leakage or spillage.

iv). Treatment: Treat waste using appropriate methods, such as autoclaving, incineration, or chemical treatment, to render it non-infectious and non-hazardous.

v). Disposal: Dispose of treated waste in designated landfills or other environmentally sound methods.

The selection of appropriate healthcare waste treatment devices is a complex decision-making process that involves multiple criteria and stakeholders. Using MCDM methods like OWCM and CODAS, healthcare managers can systematically evaluate and select the best healthcare waste treatment devices based on multiple criteria. The systematic decision-making process can guarantee that the chosen solution is effective, cost-efficient, environmentally friendly, and compliant with regulations, ultimately contributing to a healthier society. The OWCM method is used to calculate weight for criteria [15], and CODAS is used to evaluate and rank alternatives based on multiple criteria. Healthcare facilities and waste management authorities can use these methods to evaluate and compare different healthcare waste treatment devices, considering multiple criteria and stakeholder perspectives. This can help ensure that the selected device is the most appropriate and effective for managing healthcare waste safely and environmentally soundly.

This paper aims to develop a systematic and reliable methodology for evaluating and selecting the optimal healthcare waste treatment devices. This methodology balances various conflicting criteria and incorporates uncertainty in expert assessments to ensure a robust decision-making process. This paper also addresses the growing concern about improper healthcare waste management and its impact on human health and the environment. To this end, a framework for healthcare facilities and waste management authorities is provided to evaluate and select effective healthcare waste treatment devices that meet their specific needs and constraints. The paper also contributes to the existing body of knowledge on healthcare waste management by:

i). Providing a comprehensive literature review on healthcare waste management devices.

ii). Highlight the need for a comprehensive approach to healthcare waste management that considers the entire waste management cycle, from segregation to disposal.

iii). Contribute to developing sustainable and environmentally sound healthcare waste management practices prioritizing human health and environmental protection.

iv). Proposing a novel approach to evaluating and selecting healthcare waste management devices using MCDM methods.

v). Applying the proposed approach to a real-world problem, demonstrating its effectiveness in evaluating and selecting the most suitable healthcare waste management device.
vi). Conducting a sensitivity analysis to test the robustness of the proposed approach and provide insights for future research.

The paper is structured as follows. Section 2 presents a literature survey for healthcare waste management devices. Section 3 discusses the methodology by introducing MCDM methods that can be used for healthcare waste management. Section 4 presents the case study to choose the most suitable healthcare waste management device. Section 5 presents the experimental results and sensitivity analysis, followed by a conclusion in Section 6.

2. Literature Review

Healthcare waste management is a critical concern globally, particularly in developing countries where improper disposal can lead to severe public health and environmental issues. Effective management involves selecting appropriate treatment devices to handle various types of healthcare waste. Selecting the best healthcare waste treatment device is a critical decision-making problem involving evaluating multiple criteria. The MCDM methods have been widely used to address this problem. Several studies have proposed different MCDM methods to evaluate and select the best healthcare waste treatment devices. For example, a FUCOM-CRADIS method for selecting the best healthcare waste incinerator technique is proposed in [17]. The study identified four main factors for evaluating six healthcare waste incinerator alternatives. Another study uses the interval-valued intuitionistic fuzzy (IVIFS) methodology to assess healthcare waste treatment methods [18]. A hybrid approach is proposed in [19] that combines Pythagorean fuzzy sets with compromise solution methods to evaluate and select the best medical waste treatment technology. Arunodaya Raj Mishra et al. have used IVIFSs with the COPRAS method for healthcare evaluation. Considering the uncertainty and imprecision inherent in the decision-making process, the proposed approach can provide a more comprehensive and nuanced evaluation of healthcare facilities' performance in hazardous waste recycling [20]. Healthcare waste disposal firms also play a crucial role in ensuring the safe and environmentally responsible disposal of hazardous waste generated by healthcare facilities. Therefore, Ankur Chauhan et al. proposed a multi-method approach for selecting healthcare waste disposal firms [21]. Ahmad Abdelhafeez et al. have used a neutrosophic MCDM model to evaluate and rank different solutions for healthcare waste management [22]. Tuba Adar et al. discuss a new approach to selecting the best healthcare waste treatment technology (HCWTT) using a multi-criteria hesitant fuzzy linguistic term set (MC-HFLTS) [23]. Khalil al-Sulbi et al. present a fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) approach for comprehensive evaluation of bio-medical waste management (BMWM) systems [24]. The proposed method aims to advance sustainability and decision-making in BMWM by developing a multi-criteria decision analysis (MCDA) framework that incorporates fuzzy logic and TOPSIS. Mohammad Ali Beheshtinia et al. present a hybrid MCDM method to evaluate and prioritize healthcare waste disposal center locations [25]. Prioritizing healthcare waste disposal methods that consider environmental health using an enhanced multi-criteria decision-making method involves evaluating and ranking different disposal methods based on their environmental health impacts [26].

The OWCM is a decision-making approach that can be applied to the optimal selection of healthcare waste treatment devices. Using OWCM, decision-makers can evaluate and prioritize treatment options based on various criteria, such as cost-effectiveness, sustainability, and environmental health. The OWCM method is particularly useful in MCDA to ensure zero inconsistency in the weight assignment process. As a result, the weights assigned to each criterion are consistent and reliable, which is necessary in evaluating and prioritizing different factors systematically [15]. The CODAS method is an MCDM technique used to evaluate and select the best option among alternatives [16]. For example, an integrated SWARA-CODAS using spherical fuzzy sets is proposed in [27]. The TNS is a mathematical framework used to represent uncertain and imprecise information. It's an extension of fuzzy sets, where each element is characterized by three membership functions: truth (T), indeterminacy (I), and falsity (F). TNS represents these membership functions as triangular numbers [28].

3. Material and Methods

This section presents the methodology for the assessment of healthcare waste treatment devices. The methodology integrates the OWCM and the CODAS within the TNS theory framework to comprehensively evaluate key aspects and their sub-indicators, determine their weights, and rank the selected alternatives.

3.1 Concepts and Preliminaries related to TNS [28, 29]

Triangular Neutrosophic Sets (TNS): A TNS is a mathematical framework representing uncertain and imprecise information. It's an extension of fuzzy sets, where each element is characterized by three membership functions: truth (T), indeterminacy (I), and falsity (F).
A single-valued triangular neutrosophic set is given by: $\breve{A} = (A_1, A_2, A_3); \alpha_{\breve{A}}, \theta_{\breve{A}}, \beta_{\breve{A}}$,

where A_1, A_2, A_3 are the lower, middle, and upper parts of the neutrosophic numbers. A single-valued triangular neutrosophic number is represented as a triplet (T, I, F), where T is the membership degree, I is the indeterminacy degree, and F is the non-membership degree.

The definitions for single-valued triangular neutrosophic numbers are as follows:
Definition 1. Single-valued triangular neutrosophic a = $((a_1, a_2, a_3) : \alpha_a, \theta_a, \beta_a)$ is a neutrosophic set on the real line set R. The set a is classified as a truth-membership function (T_a), indeterminacy membership function (I_a) and falsity membership function (F_a) and the equation formed by these memberships is as follows:

- T(x) represents the degree of truth that the element x belongs to the neutrosophic set.

$$T_a(x) = \begin{cases} \alpha_a \left(\frac{x-a_1}{a_2-a_1}\right) & (a_1 \le x \le a_2) \\ \alpha_a & (x = \alpha_2) \\ \alpha_a \left(\frac{a_3-x}{a_3-a_2}\right) & (a_2 \le x \le a_3) \\ 0 & otherwise \end{cases}$$

- I(x) represents the degree of uncertainty or ambiguity that the element x belongs to the neutrosophic set.

$$I_a(x) = \begin{cases} \theta_a \left(\frac{a_2-x}{a_2-a_1}\right) & (a_1 \le x \le a_2) \\ \theta_a & (x = \alpha_2) \\ \theta_a \left(\frac{x-a_3}{a_3-a_2}\right) & (a_2 \le x \le a_3) \\ 1 & otherwise \end{cases}$$

- F(x) represents the degree of falsity that the element x belongs to the neutrosophic set.

$$F_a(x) = \begin{cases} \beta_a \left(\frac{a_2-x}{a_2-a_1}\right) & (a_1 \le x \le a_2) \\ \beta_a & (x = \alpha_2) \\ \beta_a \left(\frac{(x-a_3)}{a_3-a_2}\right) & (a_1 \le x \le a_3) \\ 1 & otherwise \end{cases}$$

where $\alpha_a, \theta_a, \beta_a \in [0,1]$ and $a_1, a_2, a_3 \in$ R, $a_1 \le a_2 \le a_3$)
Defintion2: let X = $((a_1, a_2, a_3) : \alpha_a, \theta_a, \beta_a)$ and Y = $((b_1, b_2, b_3) : \alpha_b, \theta_b, \beta_b)$ be two single-valued triangular neutrosophic numbers and $\gamma \neq 0$ be any real numbers. Then,

i). Addition of two triangular neutrosophic numbers
X + Y = $\langle (a_1 + b_1, a_2 + b_2, a_3 + b_3); \alpha_a \wedge \alpha_b, \theta_a \wedge \theta_b, \beta_a \wedge \beta_b \rangle$

ii). Subtraction of two triangular neutrosophic numbers

$X - Y = \langle (a_1 - b_3, a_2 - b_2, a_3 - b_1); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b \rangle$

iii). The inverse of triangular neutrosophic number

$a^{-1} = ((\frac{1}{a_3}, \frac{1}{a_2}, \frac{1}{a_1}) : \alpha_a, \theta_a, \beta_a), \text{ where } (a \neq 0)$

iv). Multiplication of two triangular neutrosophic numbers X* Y

$$XY = \begin{cases} ((a_1 b_1, a_2 b_2, a_3 b_3); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b) if\ (a_3 > 0,\ b_3 > 0) \\ ((a_1 b_3, a_2 b_2, a_3 b_1); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b) if\ (a_3 > 0,\ b_3 > 0) \\ ((a_3 b_3, a_2 b_2, a_1 b_1); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b) if\ (a_3 > 0,\ b_3 > 0) \end{cases}$$

v). Division of two triangular neutrosophic numbers X/ Y

$$\frac{X}{Y} = \begin{cases} \left(\left(\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}\right); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b\right) if\ (a_3 > 0,\ \ b_3 > 0) \\ \left(\left(\frac{a_3}{b_3}, \frac{a_2}{b_2}, \frac{a_1}{b_1}\right); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b\right) if\ (a_3 > 0,\ \ b_3 > 0) \\ \left(\left(\frac{a_3}{b_3}, \frac{a_2}{b_2}, \frac{a_1}{b_1}\right); \alpha_a \wedge \alpha_b, \theta_a \vee \theta_b, \beta_a \vee \beta_b\right) if\ (a_3 > 0,\ \ b_3 > 0) \end{cases}$$

vi). Score Function to convert to crisp numbers

$$S(r_{ij}) = \frac{(L_{ij} + m_{ij} + u_{ij})}{9} * (2 + T - I - F) \quad (1)$$

A linguistic variable is a variable that is expressed in linguistic terms, which are then displayed by triangular neutrosophic numbers. This study uses a linguistic scale from Table 1 to obtain the relative weights of the criteria. The triangular neutrosophic scale is given by [29]:

Table 1. TFN scale.

Linguistic Scale	**Triangular neutrosophic Number**
1	((1,1,1);0.50,0.50,0.50)
3	((2,3,4);0.30,0.75,0.70)
5	((4,5,6);0.80,0.15,0.20)
7	((6,7,8);00.90,0.10,0.10)
9	((9,9,0);1.00,00.0,0.00)

In the context of healthcare waste treatment device evaluation, TNS can effectively handle the uncertainty and vagueness inherent in expert assessments.

3.2 Proposed Hybrid Methodology OWCM-CODAS

The following are the steps to follow the OWCM-CODAS methodology:

- **Phase 1: Criteria and sub-indicators identification**
  Step 1. Determine the main criteria for assessing healthcare waste treatment devices, such as economic, environmental, technological impact, and social.
  Step 2. Break down each key aspect into measurable sub-indicators. For example, environmental impacts may include waste reduction, energy consumption, and air emissions.
- **Phase 2: Expert input and data collection**
  Step 3. Collect assessments from experts on the importance of each criterion and sub-indicator. Use TNS to capture the uncertainty in their judgments. Evaluate each alternative healthcare waste treatment device against each sub-indicator using TNS, resulting in a triangular neutrosophic decision matrix. The evaluation can be done using a linguistic scale, such as 1, 3, 5, 7, and 9, given in Table 1, which are then converted to TNNs. Then, the score function in Eq. (1) is used to convert TNS numbers into crisp numbers to get a crisp matrix.

Step 4. Then aggregate these matrices to get the decision matrix, using Eq. (2).

$$\mathcal{D}_{ij} = \frac{\sum_{j=1}^{n} S(\mathcal{Y})}{N}, \quad (2)$$

where N refers to the number of decision-makers. The decision matrix form is given by Eq. (3):

$$x = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \quad (3)$$

where x_{ij} indicates that i = 1,2…..,m ; j= 1,2,…..,n.

- **Phase 3: Weight determination using OWCM**

Use the OWCM to process expert opinions and calculate the weights for each criterion and sub-indicator. This involves the following steps:

Step 5. Normalizing the decision matrix, given by Eq. (4):

$$\mathcal{R}_{ij} = \frac{x_{ij}}{x_j^{max}} \quad (4)$$

where $\mathcal{X}_j^{max}$ is the max value for each criterion.

Step 6. Calculating the average score, given by Eq. (5):

$$\mathcal{K} = \frac{1}{N} \sum_{i=1}^{m} \mathcal{R}_{ij} \quad (5)$$

where N is the number of alternatives.

Step 7. Calculating the degree of preference variation, given by:

$$\mathcal{Q}_j = \sum_{i=1}^{m} [\mathcal{R}_{ij} - \mathcal{K}]^2 \quad (6)$$

Step 8. Determine the difference in preference level, given by:

$$\varphi_j = 1 - \mathcal{Q}_j \quad (7)$$

Step 9. In the final step, the weight for each criterion can be found, given by:

$$\boldsymbol{w}_j = \frac{\varphi_j}{\sum_{j=1}^{n} \varphi_j} \quad (8)$$

- **Phase 4: Distance calculation using CODAS**

Step 10. The decision matrix in Eq. (3), using Eq. (2), can be normalized and is given by:

$$x_{ij} = \begin{cases} \frac{x_{ij}}{max_i \, x_{ij}}, & j \in B \\ \frac{min_i \, x_{ij}}{x_{ij}}, & j \in C \end{cases} \quad (9)$$

Step 11. The weighted normalized decision matrix can be obtained using the weights obtained in Eq. (8), and is given by:

$$R = [r_{ij}]_{nxm} = \mathcal{W}_j \,.\, x_{ij} \quad (10)$$

Step 12. The Negative-Ideal Solution (NS matrix) formed the worst-case scenario for each criterion and is given by:

$$NS = [ns_{ij}]_{nxm} = min_i \; r_{ij} \quad (11)$$

Step 13. Given the Negative-Ideal Solution in Eq. (11), the Euclidean and Taxicab distances of each alternative can be computed and are given by:

a) The Euclidean distance to measure the overall deviation is as follows:

$$E_i = \sqrt{\sum_{j=1}^{n} (r_{ij} - NS_j)^2} \quad (12)$$

b) The Taxicab distance is as follows:

$$T_i = \sum_{j=1}^{n} \left| r_{ij} - NS_j \right| \quad (13)$$

Step 14. Build the relative assessment matrix $[h_{is}]_{nxm}$ based on the following:

$$h_{is} = (E_i - E_k) + (\gamma \, ((E_i - E_k).(T_i - T_k) \quad (14)$$

where s ∈ {1,2,….m} and γ denotes a threshold function to recognize the equality of the Euclidean distances of two alternatives and is given as follows:

$$\gamma(x) = \begin{cases} 1, & |x| \geq \tau \\ 0, & |x| < \tau \end{cases} \quad (15)$$

Note that the τ in Eq. (15) is the threshold parameter that the decision-maker can set. Setting this parameter at a value between 0.01 and 0.05 is suggested. If the difference between Euclidean distances of two alternatives is less than τ, these two alternatives are also compared by the Taxicab distance. In this paper, we use τ = 0.02 for the calculations.

Step 15. Combine Distance Scores using the following Eq. (16):

$$H_i = \sum_{k=1}^{n} h_{ik} \tag{16}$$

Step 16. Rank the alternatives based on their relative closeness values. The alternative with the highest relative closeness value is considered the best option.

4. Case Study

Healthcare facilities generate significant amounts of waste that require effective and safe treatment. The selection of appropriate healthcare waste treatment devices is critical to ensure environmental safety, operational efficiency, cost-effectiveness, and overall public health. However, the decision-making process is complex due to the multiple criteria involved and the inherent uncertainties in expert judgments. The optimal selection of healthcare waste treatment devices is a crucial decision-making problem that involves evaluating multiple criteria and considering the uncertainty and imprecision of the data. The TNN approach is a suitable method for addressing this problem. The approach handles the uncertainty and imprecision in decision-making problems. This paper presents a hybrid methodology combining the OWCM and the CODAS within the Trapezoidal Neutrosophic Sets (TNS) framework. The methodology is designed to provide a comprehensive, consistent, and uncertainty-aware evaluation of healthcare waste treatment devices. The proposed methodology aims to enhance the decision-making process for selecting healthcare waste treatment devices, ensuring that the chosen solution is optimal in terms of efficiency, cost, environmental impact, and safety. This approach improves operational outcomes and environmental and public health management in healthcare settings.

The following criteria and sub-indicators identified for evaluation are given by [30]:

- **Economic Criteria**

  C1: Investment Costs (Cost): The capital expenditure required to acquire and install the treatment device.

  C2: Annual Usage Costs (Cost): The ongoing costs of operating and maintaining the device annually.

- **Environmental Criteria**

  C3: Waste Reduction (Benefit): The device's efficiency in reducing waste volume and harmfulness.

  C4: Energy Consumption (Cost): The energy required to operate the device.

  C5: Air Emissions (Cost): The level of pollutants released to the atmosphere from using the device.

- **Technological Criteria**

  C6: Treatment Effectiveness (Benefit): The device's capability to effectively treat various types of healthcare waste.

  C7: Treatment Flexibility (Benefit): The ability of the device to handle different waste streams and adapt to changing requirements.C8: Automation Level (Benefit): The extent to which the device can operate with minimal human intervention.

- **Social Criteria**

  C9: Health Impact (Cost): The potential health benefits or risks to workers and the public due to the use of the device.

  C10: Public Acceptance (Benefit): The level of acceptance and support from the community and stakeholders for using the device.

5. Decision-making and Experimental Results

The section describes the experimental results from the case study. The section is organized into three parts: the methodology application steps, a discussion of the obtained results, and a sensitivity analysis of the model.

5.1 Application of TNS-OWCM-CODAS Methodology

- **Phase 1. Criteria and Sub-Indicators Identification**
  Step 1. Identified key criteria: Economic, Environmental, Technological, and Social.
  Step 2. Sub-indicators for each criterion were defined in Section 4.
- **Phase 2. Expert Input and Data Collection**
  Step 3. Experts provided assessments for each criterion using TNS to capture uncertainty in their judgments to get an evaluation matrix, given in Table 2.

Table 2. Decision maker opinion.

DMs		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DM1	A1	1	3	5	9	3	9	3	7	5	3
	A2	5	5	3	7	1	5	7	3	5	7
	A3	7	3	7	5	9	1	5	9	7	5
	A4	9	7	3	5	1	3	7	1	1	1
DM2	A1	3	3	3	5	7	5	7	3	9	1
	A2	7	5	1	5	9	1	3	7	5	5
	A3	3	7	9	7	3	9	9	7	1	7
	A4	1	9	5	1	5	3	5	1	3	9
DM3	A1	5	3	5	1	3	1	3	5	3	5
	A2	5	7	7	7	5	3	7	9	7	9
	A3	9	5	5	9	7	5	5	7	5	7
	A4	7	1	7	3	1	7	3	3	1	3

Step 4. Convert TNS numbers into crisp numbers using the score function in Eq. (1) to obtain the crisp matrix. Then, the matrix will be aggregated using Eq. (2) to get the decision matrix using Table 3.

Table 3. Decision matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	1.81	0.85	3.01	3.53	2.67	3.53	2.67	3.74	3.64	1.81
A2	4.82	4.82	2.55	5.56	3.53	1.81	4.48	4.38	4.82	5.46
A3	4.38	3.74	5.46	5.46	4.38	3.53	4.72	6.2	3.63	5.56
A4	4.27	4.27	3.74	1.81	1.69	2.67	3.74	0.62	0.62	2.45

- **Phase 3. Weight Determination Using OWCM**
  Step 5. Normalize the decision matrix in Table 3 using Eq. (4) to get the normalized OWCM matrix in Table 4.

Table 4. Normalized matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.376	0.176	0.550	0.634	0.608	1.000	0.565	0.604	0.756	0.326
A2	1.000	1.000	0.467	1.000	0.805	0.513	0.949	0.707	1.000	0.982
A3	0.909	0.776	1.000	0.982	1.000	1.000	1.000	1.000	0.752	1.000
A4	0.885	0.885	0.686	0.326	0.387	0.756	0.793	0.099	0.128	0.441

Step 6. Calculate the average score using Eq. (5).
Step 7. Calculate the degree of preference variation using Eq. (6).
Step 8. Determine the difference in preference level using Eq. (7).
Step 9. Calculate the final weight using Eq. (8), which is given in Table 5 below.

Table 5. Final weight.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.173691	0.284219	0.01572052	0.010231	0.008385	0.033371	0.068675	0.000001807	0.009365	0.130602
A2	0.043123	0.084455	0.04359727	0.069953	0.011	0.092378	0.015042	0.010897414	0.11629	0.086998
A3	0.013607	0.004504	0.10514614	0.060764	0.090038	0.033371	0.03001	0.157927900	0.008708	0.09793
A4	0.008548	0.030766	0.00009838	0.167969	0.098202	0.003772	0.001144	0.253146036	0.282074	0.060764
N	0.792339	0.709389	0.675738	0.735514	0.699937	0.817323	0.826765	0.602599	0.658986	0.687063
Ωj	0.761031	0.596056	0.83543769	0.691083	0.792375	0.837108	0.885128	0.578026843	0.583563	0.623706
Wj	0.105941	0.082976	0.11629927	0.096204	0.110305	0.116532	0.123217	0.080465723	0.081236	0.086825

- **Phase 4. Distance Calculation Using CODAS**
  Step 10. The normalized CODAS matrix is given in Table 6, which can be obtained using the decision matrix in Table 3, normalized by Eq. (9).
  Step 11. The weighted normalized decision matrix is obtained in Table 7, using the weights given in Table 5 and by using Eq. (10).
  Step 12. The Negative-Ideal Solution (NS matrix) formed the worst-case scenario for each criterion and is given in the last row of Table 7.
  Step 13. Compute both Euclidean and Taxicab distances of each alternative from the Negative-Ideal Solution using Eqs. (12) and (13) and are given in Table 8.
  Step 14. Build the relative assessment matrix $[h_{is}]_{nxm}$ using Eq. (14) and by assuming that the τ = 0.02.
  Step 15. Combine distance scores using Eq. (16).
  Step 16. Rank the alternatives based on their relative closeness values.
  The alternative with the highest relative closeness value is considered the best option and is shown in Table 9.

Table 6. Normalized matrix.

	C1 -	C2 -	C3 +	C4 -	C5 -	C6 +	C7 +	C8 +	C9 -	C10 +
A1	1	1	0.550356	0.513386	0.635417	1	0.564706	0.603943	0.169207	0.325674
A2	0.375576	0.176267	0.466938	0.325674	0.480315	0.513386	0.949412	0.706989	0.12788	0.982018
A3	0.413181	0.227003	1	0.331638	0.386565	1	1	1	0.169985	1
A4	0.424479	0.199219	0.685656	1	1	0.755906	0.792941	0.099462	1	0.440559

Table 7. Weighted normalized matrix.

	C1 -	C2 -	C3 +	C4 -	C5 -	C6 +	C7 +	C8 +	C9 -	C10 +
A1	0.105941	0.082976	0.064006	0.04939	0.070089	0.116532	0.069581	0.048597	0.013746	0.028277
A2	0.039789	0.014626	0.054305	0.031331	0.052981	0.059826	0.116983	0.056888	0.010389	0.085263
A3	0.043773	0.018836	0.116299	0.031905	0.04264	0.116532	0.123217	0.080466	0.013809	0.086825
A4	0.04497	0.01653	0.079741	0.096204	0.110305	0.088087	0.097704	0.008003	0.081236	0.038251
NS	0.039789	0.014626	0.054305	0.031331	0.04264	0.059826	0.069581	0.008003	0.010389	0.028277

Table 8. Euclidean and Taxicab distances

	Ei	Ti
A1	0.122867	0.290368
A2	0.089393	0.163615
A3	0.136602	0.315535
A4	0.127173	0.302266

Table 9. Final rank.

	A1	A2	A3	A4	Hi	RANK
A1	0	0.033558	-0.01373	-0.00431	0.015525	3
A2	-0.03339	0	-0.04706	-0.03768	-0.11813	4
A3	0.013742	0.047352	0	0.009431	0.070525	1
A4	0.004308	0.037885	-0.00943	0	0.032766	2

5.2 Ranking Discussion

Finally, alternatives A1 to A4 were ranked based on their relative closeness values (Hi) derived from the relative assessment matrix. Table 9 shows the final ranking of the alternatives. Alternative A3 emerges as the top-ranked option (Rank 1), indicating it performs best overall compared to A1, A2, and A4. The alternative A3 has the highest relative closeness value (0.070525), indicating it is the best option. Alternative A4 is ranked second, followed by A1 and A2. A3 likely excels in multiple criteria, possibly demonstrating superior economic, environmental, technological, and social in healthcare waste treatment. The methodology provides insights into each alternative's strengths and weaknesses across various dimensions, aiding decision-makers in selecting the most suitable healthcare waste treatment device. The OWCM-CODAS methodology, integrated with TNS, effectively evaluates and ranks healthcare waste treatment devices based on multiple criteria. The results obtained from this structured approach provide a clear hierarchy of alternatives, facilitating informed decision-making to optimize healthcare waste management strategies. This methodology's robustness in handling uncertainty and ensuring evaluation consistency enhances its applicability across diverse decision contexts.

5.3 Sensitivity Analysis

This paper uses sensitivity analysis to assess the robustness of the proposed OWCM-CODAS model and understand how threshold parameter (τ) changes affect the ranking of alternatives. Conducted a sensitivity analysis by varying the value of τ within a defined range. Then, the impact of the change of value τ can be identified on the ranking of the alternatives. We use fourteen values for τ in the range of 0.01 to 1. The ranking results obtained by the CODAS method in different values of *τ* are presented in Table 10. The graphical showing the ranking of alternatives is also depicted in Figure 1. According to Table 10 and Figure 1, the rankings of the alternatives (A1, A2, A3, and A4) remain consistent across all values of τ from 0.01 to 1. Figure 1 also shows the stability of the rankings across different values of τ, demonstrating the robustness of the CODAS method. The results indicate that the model's performance and the relative ranking of the alternatives are not sensitive to changes in the threshold parameter τ within the tested range. Therefore, we can confirm the results of the CODAS method.

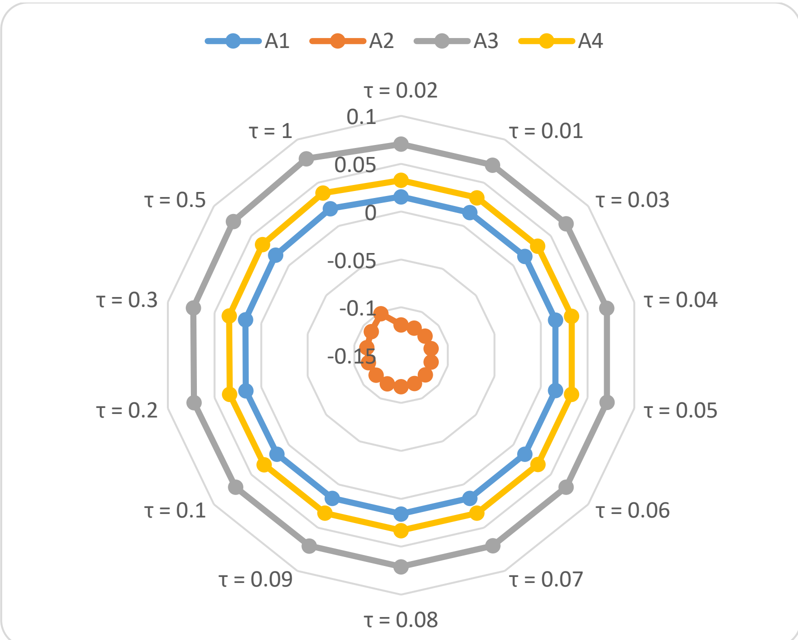

Figure 1. Graphical representation of rankings with different values of τ.

Table 10. Ranking results with different values of τ.

	τ = 0.02	τ = 0.01	τ = 0.03	τ = 0.04	τ = 0.05	τ = 0.06	τ = 0.07	τ = 0.08	τ = 0.09	τ = 0.1	τ = 0.2	τ = 0.3	τ = 0.5	τ = 1
A1	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A2	4	4	4	4	4	4	4	4	4	4	4	4	4	4
A3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A4	2	2	2	2	2	2	2	2	2	2	2	2	2	2

6. Conclusion

Healthcare waste management is vital to ensuring the safe and environmentally sound disposal of waste generated by healthcare activities. The improper management of healthcare waste poses significant risks to human health and the environment. Selecting appropriate healthcare waste treatment technologies is a complex decision-making process involving multiple criteria and stakeholders. Using MCDM methods, healthcare facilities and waste management authorities can evaluate and compare different healthcare waste treatment devices, considering multiple criteria and stakeholder perspectives. This can help ensure that the selected device is the most appropriate and effective for managing healthcare waste safely and environmentally soundly. The study presents a systematic and reliable methodology for evaluating and selecting healthcare waste treatment devices, combining OWCM and CODAS within TNS. The robustness of the methodology is confirmed through sensitivity analysis, ensuring consistent and reliable decision-making for optimal healthcare waste management. This approach enhances operational outcomes, environmental safety, and public health management in healthcare settings. The case study results show that the proposed OWCM-CODAS methodology, integrated with TNS, is a reliable and effective tool for evaluating and selecting healthcare waste treatment devices. The methodology can be applied to various decision-making problems in healthcare waste management, contributing to better environmental and public health management in healthcare settings.

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All authors contributed equally to this research.

Data availability
The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

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Conflict of interest
The authors declare that there is no conflict of interest in the research.

References

1. L.J. Basile, N. Carbonara, U. Panniello, R. Pellegrino, 2024, The role of big data analytics in improving the quality of healthcare services in the Italian context: The mediating role of risk management, https://doi.org/10.1016/j.technovation.2024.103010
2. Theodore H. Tulchinsky, Elena A. Varavikova, 2014,Chapter 12 - Planning and Managing Health Systems, https://doi.org/10.1016/B978-0-12-415766-8.00012-4

3. Janik-Karpinska E, Brancaleoni R, Niemcewicz M, Wojtas W, Foco M, Podogrocki M, Bijak M. Healthcare Waste-A Serious Problem for Global Health. Healthcare (Basel). 2023 Jan 13;11(2):242. doi: 10.3390/healthcare11020242. PMID: 36673610; PMCID: PMC9858835.
4. K.K. Padmanabhan, Debabrata Barik, 2019, Chapter 8 - Health Hazards of Medical Waste and its Disposal, https://doi.org/10.1016/B978-0-08-102528-4.00008-0
5. Kenny C, Priyadarshini A. Review of Current Healthcare Waste Management Methods and Their Effect on Global Health. Healthcare (Basel). 2021 Mar 5;9(3):284. doi: 10.3390/healthcare9030284. PMID: 33807606; PMCID: PMC7999172.
6. Danladi Chiroma Husaini, Vinlee Bernandez, Naim Zetina, David Ditaba Mphuthi, 2023, Healthcare industry waste and public health: a systematic review, DOI:10.1108/AGJSR-01-2023-0026
7. Padmanabhan KK, Barik D. Health Hazards of Medical Waste and its Disposal. Energy from Toxic Organic Waste for Heat and Power Generation. 2019:99–118. doi: 10.1016/B978-0-08-102528-4.00008-0. Epub 2018 Nov 9. PMCID: PMC7152398.
8. Anne Woolridge, Selin Hoboy, 2019, Chapter 27 - Medical Waste, https://doi.org/10.1016/B978-0-12-815060-3.00027-X
9. World Health Organization (WHO) https://www.who.int/news-room/fact-sheets/detail/health-care-waste
10. Vijaya Kumar Manupati, M. Ramkumar, Vinit Baba, Aayush Agarwal, 2021, Selection of the best healthcare waste disposal techniques during and post COVID-19 pandemic era, https://doi.org/10.1016/j.jclepro.2020.125175
11. R. Krishankumar, Arunodaya Raj Mishra, Pratibha Rani, Edmundas Kazimieras Zavadskas, K.S. Ravichandran, Samarjit Kar, 2022, A new decision model with integrated approach for healthcare waste treatment technology selection with generalized orthopair fuzzy information, https://doi.org/10.1016/j.ins.2022.08.022
12. Yadav D, Mann S, Balyan A. Waste management model for COVID-19: recommendations for future threats. Int J Environ Sci Technol (Tehran). 2023;20(6):6117-6130. doi: 10.1007/s13762-022-04357-8. Epub 2022 Jul 12. PMID: 35855821; PMCID: PMC9274959.
13. Hernan G. Mazzei, Stefania Specchia, 2023,Latest insights on technologies for the treatment of solid medical waste: A review, https://doi.org/10.1016/j.jece.2023.109309
14. Samuel Kojo Abanyie, Ebenezer Ebo Yahans Amuah, Nang Biyogue Douti, Casmid Charles Amadu, Manaf Bayorbor, 2021, Healthcare waste management in the Tamale Central Hospital, northern Ghana. An assessment before the emergence of the COVID-19 pandemic in Ghana, https://doi.org/10.1016/j.envc.2021.100320
15. A. D. A. Mandil, M. M. Salih and Y. R. Muhsen, "Opinion Weight Criteria Method (OWCM): A New Method for Weighting Criteria With Zero Inconsistency," in IEEE Access, vol. 12, pp. 5605-5616, 2024, doi: 10.1109/ACCESS.2024.3349472.
16. Supriya Raheja, Mohammad S. Obaidat, Manoj Kumar, Balqies Sadoun, Shashi Bhushan, 2022, A hybrid MCDM framework and simulation analysis for the assessment of worst polluted cities, https://doi.org/10.1016/j.simpat.2022.102540
17. Puška A, Stević Ž, Pamučar D. Evaluation and selection of healthcare waste incinerators using extended sustainability criteria and multi-criteria analysis methods. Environ Dev Sustain. 2022;24(9):11195-11225. doi: 10.1007/s10668-021-01902-2. Epub 2021 Oct 26. PMID: 34720689; PMCID: PMC8546840.
18. Al-Barakati, A., Rani, P. Assessment of healthcare waste treatment methods using an interval-valued intuitionistic fuzzy double normalization-based multiple aggregation approach. Environ Dev Sustain (2023). https://doi.org/10.1007/s10668-023-03154-8
19. Peide Liu, Pratibha Rani, Arunodaya Raj Mishra,2021,A novel Pythagorean fuzzy combined compromise solution framework for the assessment of medical waste treatment technology, https://doi.org/10.1016/j.jclepro.2021.126047
20. Arunodaya Raj Mishra, Pratibha Rani, Abbas Mardani, Kamal Raj Pardasani, Kannan Govindan, Melfi Alrasheedi, 2020, Healthcare evaluation in hazardous waste recycling using novel interval-valued intuitionistic fuzzy information based on complex proportional assessment method, https://doi.org/10.1016/j.cie.2019.106140

21. Ankur Chauhan, Surya Prakash Singh, 2021, Selection of healthcare waste disposal firms using a multi-method approach, https://doi.org/10.1016/j.jenvman.2021.113117
22. Ahmad Abdelhafeez, Hoda K. Mohamed, Nariman A. Khalil, 2023,Rank and Analysis Several Solutions of Healthcare Waste to Achieve Cost Effectiveness and Sustainability Using Neutrosophic MCDM Model, DOI:10.61356/j.nswa.2023.8
23. Tuba Adar and Elif Kılıç Delīce, 2019, New integrated approaches based on MC-HFLTS for healthcare waste treatment technology selection, DOI:10.1108/JEIM-10-2018-0235
24. Khalil al-Sulbi,Pawan Kumar Chaurasia, Abdulaziz Attaallah, Alka Agrawal, Dhirendra Pandey, Vandna Rani Verma, Vipin Kumar and Md Tarique Jamal Ansari, 2023, A Fuzzy TOPSIS-Based Approach for Comprehensive Evaluation of Bio-Medical Waste Management: Advancing Sustainability and Decision-Making, https://doi.org/10.3390/su151612565
25. Beheshtinia MA, Bahrami F, Fathi M, Asadi S. Evaluating and prioritizing the healthcare waste disposal center locations using a hybrid multi-criteria decision-making method. Sci Rep. 2023 Sep 13;13(1):15130. doi: 10.1038/s41598-023-42455-w. PMID: 37704751; PMCID: PMC10499883.
26. Mohammad Ali Beheshtinia, Sanaz Jafari Kahoo, Masood Fathi, 2023, PPrioritizing healthcare waste disposal methods considering environmental health using an enhanced multi-criteria decision-making method, DOI:10.1080/26395940.2023.2218568
27. Saeid Jafarzadeh Ghoushchi, Harish Garg, Shabnam Rahnamay Bonab, Aliyeh Rahimi, 2023, An integrated SWARA-CODAS decision-making algorithm with spherical fuzzy information for clean energy barriers evaluation, https://doi.org/10.1016/j.eswa.2023.119884
28. Khalid A. Eldrandaly, Nissreen El Saber, Mona Mohamed and Mohamed Abdel-Basset, 2022, Sustainable Manufacturing Evaluation Based on Enterprise Industry 4.0 Technologies, https://doi.org/10.3390/su14127376
29. N. A. Nabeeh, M. Abdel-Basset, H. A. El-Ghareeb and A. Aboelfetouh, "Neutrosophic Multi-Criteria Decision Making Approach for IoT-Based Enterprises," in IEEE Access, vol. 7, pp. 59559-59574, 2019, doi: 10.1109/ACCESS.2019.2908919.
30. Puška, A., Štilić, A., Pamucar, D. et al. Optimal selection of healthcare waste treatment devices using fuzzy-rough approach. Environ Sci Pollut Res (2024). https://doi.org/10.1007/s11356-024-32630-5

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