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Enhancing Medical Waste Management Using T-Spherical Fuzzy CRITIC-MAUT Methodology

Jafar Anafi[1*], Ali Aslam Khan[2], Keles Dong[3]

[1] Helpman Development Institute, 900211 Abuja, Nigeria
[2] Department of Mathematics and Statistics, The University of Lahore, 54000 Lahore, Pakistan
[3] Center for Research, Rosenheim Technical University of Applied Sciences, 83024 Rosenheim, Germany

[*] Correspondence: Jafar Anafi (janafi@helpmaninstitute.org)

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Abstract: In addressing the pivotal challenge of mitigating environmental and health concerns in medical waste management (MWM), this study introduces a novel, integrated multi-criteria decision-making (MCDM) framework employing T-spherical fuzzy sets (T-SFS) within the ambit of the Criteria Importance Through Inter-criteria Correlation-Multi-Attribute Utility Theory (CRITIC-MAUT) technique. Central to this approach is the deployment of T-SFS for expert evaluation of various treatment technologies, thereby refining the decision-making matrix with enhanced precision. The CRITIC method is adeptly utilized for the determination of weights for each criterion, thereby augmenting the accuracy of the decision-making process. An empirical case study conducted in China serves to validate the approach, evaluating five healthcare waste (HCW) treatment methods against a set of eight criteria. The culmination of this process is achieved through the application of the MAUT approach, facilitating the selection of the most suitable technology. Comparative analysis with extant MCDM methodologies underscores the robustness and reliability of the proposed approach, highlighting its distinct advantage in yielding conclusive results for optimal HCW treatment technology selection. This research not only contributes a novel methodology to the MWM domain but also establishes a comprehensive framework adept at navigating the intricacies inherent in the decision-making process for HCW treatment technologies.

Keywords: T-spherical fuzzy; Medical waste management (MWM); Criteria Importance Through Inter-criteria Correlation-Multi-Attribute Utility Theory (CRITIC-MAUT); Multi-criteria decision-making (MCDM); Health-care waste (HCW)

1 Introduction

In recent years, the escalating challenge of effectively treating and disposing of HCW, compounded by the potential presence of contaminated and infectious materials, has become increasingly apparent, particularly in hospital and healthcare facility contexts [1]. The surge in HCW, attributed to the significant growth and expansion of medical facilities, particularly in developing countries, has been observed over the past few decades [2]. This increase poses not only significant environmental concerns but also potential public health hazards [3]. HCW encompasses a diverse range of hazardous materials, including toxic chemicals, infectious agents, heavy metals, and radioactive substances. The inappropriate management and disposal of these substances pose severe risks to human health and the ecological equilibrium, leading to potential health threats and environmental contamination. Consequently, the MWM has garnered significant attention, especially in developing countries where the need for effective HCW management is imperative [4, 5].

This situation underscores the essentiality of developing and implementing comprehensive MWM strategies to safeguard public health and ensure environmental sustainability amidst these escalating challenges. The cornerstone of MWM lies in the meticulous selection of treatment technologies that aptly treat and degrade HCW. Hospitals and medical institutions typically engage specialized vendors for HCW treatment and disposal, offering a range of options. Managers in this sector face the challenge of analyzing and selecting the most suitable treatment solution, a process that involves considering various critical aspects of treatment technology such as loading capacity, waste type, environmental emissions, technological reliability, health and safety concerns, and the reduction of waste mass and volume [6]. This decision-making process for HCW treatment emerges as a multifaceted MCDM challenge, necessitating the application of MCDM methodologies to identify the optimal treatment technology for MWM [7–9].

In the application of MCDM approaches for selecting treatment technologies, decisions often hinge on expert assessments, introducing an inherent uncertainty due to incomplete information and the subjective nature of expert opinions. Decision-makers often articulate their assessments in linguistic terms, which poses a challenge in accurately modeling this information with precise statistical values. Consequently, approaches like fuzzy sets and evidence theory have become increasingly prevalent for addressing uncertainties in decision-making processes [10–12]. This acknowledgement of uncertainty underscores the need for innovative methodologies that effectively integrate imprecise information and linguistic expressions into the decision-making framework for HCW treatment technology selection.

1.1 Literature Review

The concept of "fuzzy sets" (FS), introduced by Zadeh [13], represents a significant advancement in addressing imprecision in decision-making environments. Zadeh's mathematical framework has been recognized for providing a means to articulate uncertain and ambiguous information, adeptly navigating the complexities in decision-making processes. This seminal concept laid the groundwork for subsequent developments in fuzzy set theory. Atanassov's introduction of "intuitionistic fuzzy sets" (IFS) [14] marked a further evolution, encompassing both membership and non-membership dimensions, thereby enhancing the capability of fuzzy sets in complex decision-making scenarios.

Advancing towards more comprehensive models, Cuong's [15, 16] introduction of "picture fuzzy sets" (PFS) addressed limitations inherent in classical FS and IFS models. PFS incorporated visual representations to more accurately reflect human perspectives in decision-making processes. Subsequent expansions by Cuong and Hai [17] on PFS core concepts, including the establishment of critical operators and properties [18], have been noteworthy. Significant strides were made by Wei et al. [19] through the development of projection models, generalized dice similarity measurements [20], and specialized similarity measures for PFSs [21]. Singh's exploration of "correlation coefficients for picture fuzzy sets" [22] contributed valuable measures for quantifying relationships within PFS frameworks. Notably, Son's [23] development of "DPFCM" presented an innovative clustering technique specifically tailored for PFSs, addressing visual representation challenges. Furthermore, Phong et al.'s [24] investigation into "compositions of PF relations" provided essential insights into the dynamics of fuzzy relations within PFSs.

Li et al. [25] and Ashraf et al. [26, 27] made significant advancements in the domain of fuzzy set theory, introducing innovative concepts such as the generalized simplified neutrosophic Einstein aggregation operators and a distinct distance metric tailored for fuzzy collections of cubic PFSs. These developments, however, highlighted limitations in PFS, especially when addressing scenarios involving combined values exceeding one. This challenge led to the conceptualization and development of SFS [28, 29]. In a pivotal contribution to the field, Mahmood et al. [30] introduced T-SFSs, which demonstrated superior performance over traditional fuzzy structures in managing uncertainty. A key attribute of T-SFSs is their ability to approach a unit interval in the summation of the t-th power of membership grades, thereby offering enhanced precision in uncertainty quantification.

The field of T-SFSs has witnessed diverse contributions, underscoring their adaptability and utility across various applications. Munir et al. [31] developed T-spherical fuzzy Einstein hybrid aggregation operators, illustrating their application in multi-attribute decision-making challenges. Zeng et al.'s [32] exploration of T-spherical fuzzy Einstein interactive aggregation operators for photovoltaic cell selection, Liu et al.'s [33] investigation of T-spherical fuzzy power Muirhead mean operators, and Ullah et al.'s [34] application of T-spherical fuzzy Hamacher aggregation operators for evaluating search and rescue robots exemplify the breadth of T-SFS applications. Özdemirci et al.'s [35] and Sarkar et al.'s [36] utilization of a T-Spherical fuzzy TOP-DEMATEL technique for assessing social banking systems and Gurmani et al.'s [37] development of a linguistic interval-valued T-spherical fuzzy TOPSIS model for construction business selection further illustrate the versatility of T-SFSs in complex decision-making scenarios.

This research trajectory underscores the ongoing enhancement of fuzzy set theories, addressing complex challenges in decision-making processes and advancing methodologies for effectively managing uncertainty.

In recent decades, there has been significant focus on the study and evaluation of HCW treatment technologies. Voudrias [6] comprehensively analyzed five primary methods for managing infectious medical waste, utilizing the analytic hierarchy process (AHP) to identify the most suitable option, considering environmental, economic, technological, and social factors. Ho [38] employed fuzzy AHP to derive objective weights for key assessment criteria in evaluating various infectious medical waste disposal services. Xiao [39] introduced an innovative MCDM technique for HCW treatment systems assessment, leveraging D numbers to replicate expert judgments. Ghoushchi et al. [40] proposed a new MCDM approach for the optimal selection of landfill sites for medical waste, integrating spherical fuzzy step-wise weight assessment ratio analysis. Liu et al. [3] developed the Pythagorean fuzzy combination compromise solution (PF-CoCoSo) method, a novel approach for evaluating and ranking different treatment technology options, which includes a unique mechanism for calculating criterion weights. Narayanamoorthy et al. [41] presented a novel MCDM methodology for MWM, combining the hesitant fuzzy subjective and objective weight integrated approach

(HF-SOWIA) with hesitant fuzzy multi-objective optimization based on simple ratio analysis (HF-MOOSRA). Furthermore, Mishra et al. [42] adopted the distance from average solution (EDAS) framework, utilizing parametric divergence metrics within an intuitionistic fuzzy environment, for selecting MWM treatments.

Manupati et al. [43] conducted a comprehensive investigation into nine HCW disposal options, devising a distinctive assessment and selection framework that incorporates socio-technical and triple bottom line perspectives. Their approach utilized the fuzzy VIKOR method for the evaluation and ranking of these options. Rani et al. [44] suggested an integrated MCDM technique for assessing and choosing appropriate HCW treatment technology, integrating Pythagorean fuzzy stepwise weight assessment ratio analy-sis (PF-SWARA) and additive ratio assessment (PF-ARAS) methodologies. Chen et al. [45] introduced a novel decision-making method for analyzing and selecting appropriate medical waste treatment technologies, based on Z numbers and the TODIM method. It is noteworthy that, despite the comprehensiveness of these studies, they predominantly focus on intuitionistic fuzzy sets and Pythagorean fuzzy sets, lacking the capacity to generate reliable results using Fermatean fuzzy information. This gap indicates a potential avenue for future research in this area.

The CRITIC-MAUT methodologies have increasingly been recognized as potent tools for decision-making across various sectors. Karakis [46] applied these methodologies to the complex task of machine selection within the textile industry, making a significant contribution to this field. This study not only validated the practical applicability of CRITIC-MAUT but also shed light on their effectiveness in addressing real-world decision-making challenges. Adal and Işık [47] explored the intricacies of contract manufacturer selection within supply chain management.

Their work provided crucial insights into optimizing the selection process through CRITIC-MAUT techniques, taking into account a multitude of features and criteria. In the aviation sector, Sarigül et al. [48] conducted an exhaustive financial performance analysis of European carriers, employing CRITIC-based MAUT and MARCOS methodologies. This application underscored the versatility of these decision-making tools in assessing and comparing the performance of entities in a dynamic and complex industry. Similarly, Özdağoğlu et al. [49] focused on performance evaluation in aviation, utilizing CRITIC and MEREC-based MAUT, along with PSI techniques. Their study enriched the existing knowledge base by enhancing decision-making processes in this specific industry context using various methodologies. Adalı and Işık [50] investigated the contract manufacturer selection dilemma, affirming the effectiveness of CRITIC-MAUT techniques. Their research deepened the understanding of decision-making processes in supplier selection, addressing the issue from multiple perspectives. Collectively, these studies underscore the adaptability and efficacy of CRITIC-MAUT approaches in diverse decision-making scenarios, offering valuable insights.

1.2 Motivation and Contribution

The MWM is increasingly critical within global healthcare systems, necessitating comprehensive solutions that ensure both environmental sustainability and public health protection. The complexity of HCW and the array of treatment technologies available underscore the need for a sophisticated decision-making framework. This study is motivated by the recognition that the selection of HCW treatment technologies requires a nuanced approach, which must consider a variety of criteria including environmental impact, cost-effectiveness, and regulatory compliance, as well as the uncertainties inherent in expert evaluations. The recent surge in the development and implementation of diverse treatment technologies in healthcare, ranging from traditional methods like incineration and autoclaving to innovative techniques such as microwave treatment and chemical disinfection, has amplified the challenge of navigating through numerous criteria to make informed choices. This study is driven by the imperative to address existing gaps in decision-making procedures for MWM, particularly in the context of global urgency for sustainable practices across various industries, including healthcare. The environmental implications of medical waste, particularly concerning greenhouse gas emissions, hazardous material disposal, and energy consumption, demand an exhaustive evaluation of treatment technologies. This research aims to contribute to the broader discourse on sustainable hospital waste management by introducing a novel decision-making methodology.

This study makes a significant contribution to the field of MWM by developing an integrated MCDM method within a T-SFS framework. The proposed method innovatively combines the CRITIC criterion weighting technique with the subsequent application of the MAUT for technology appraisal. The integration of CRITIC enables a precise and flexible weighting system for various parameters, effectively addressing the dynamic challenges in HCW treatment. The application of MAUT offers a structured and comprehensive approach to evaluating different technologies based on weighted criteria, providing decision-makers with a quantitative basis for comparison. The T-SFS framework, by incorporating uncertainties in expert judgments, allows for a more realistic representation of imprecise criteria assessments. This combination yields a robust decision-making framework that is intelligent, practical, and adaptable, equipping decision-makers in HCW management with a reliable tool for the accurate and dependable selection of optimal treatment technologies.

1.3 Structure of the Paper

Section 2 establishes the foundational elements by exploring the fundamental concepts and operations of T-SFSs. Section 3 delineates the methodology, introducing the CRITIC approach for criterion weighting and its integration with the MAUT within the T-SFS framework. Section 4 demonstrates the practical application of the proposed CRITIC-MAUT methodology in a real-world context, focusing on a case study in China where HCW treatment methods are evaluated against specific criteria. Section 5 presents a comparative analysis of the CRITIC-MAUT approach with existing MCDM methodologies. This final section also provides a summary of the study's findings, outlines the contributions made, and suggests future research directions in the realm of HCW treatment technology selection.

2 Preliminaries

Definition 2.1 Given a universal set W, a fuzzy set E within W is defined as [13]:

$$E = \{x, \epsilon(x) : x \in W\}$$

where, $\epsilon(x)$ represents the degree of membership (DoM) of the element x in the universal set W.

Definition 2.2 Within the framework of the universe set W, a PFS, denoted as E, is represented as [15, 16]:

$$A = \{\langle x, \epsilon(x), \chi(x), \zeta(x) \mid x \in W \rangle\}$$

where, $\epsilon(x) \in [0, 1]$ represents the degree of positive membership (PMD) of W in E, $\chi(x) \in [0, 1]$ represents the degree of neutral membership (NuMD) of W in E, and $\zeta(x) \in [0, 1]$ represents the degree of negative membership of W in E, subject to the condition $0 \leq \epsilon(x) + \chi(x) + \zeta(x) \leq 1$ for all $x \in W$.

Definition 2.3 A T-SFS in W is defined as [30]:

$$\psi = \{\langle \Upsilon, \epsilon_{\psi}(\Upsilon), \zeta_{\psi}(\Upsilon), \chi_{\psi}(\Upsilon) \mid \Upsilon \in W \rangle\} \tag{1}$$

where, $\epsilon_{\psi}(\Upsilon), \zeta_{\psi}(\Upsilon), \chi_{\psi}(\Upsilon) \in [0, 1]$, such that $0 \leq \epsilon^t_{\psi}(\Upsilon)+\zeta^t_{\psi}(\Upsilon)+\chi^t_{\psi}(\Upsilon) \leq 1$ for all $\Upsilon \in W$. $\epsilon_{\psi}(\Upsilon), \zeta_{\psi}(\Upsilon), \chi_{\psi}(\Upsilon)$ denote membership degree (MD), abstinence degree (AD) and non-membership degree (N-MD) respectively for some $\Upsilon \in W$.

In this article, the tripl $\daleth = (\epsilon_{\daleth}, \zeta_{\daleth}, \chi_{\daleth})$ is referred to as a T-SFN, with the stipulatio $\epsilon_{\daleth}, \zeta_{\daleth}, \chi_{\daleth} \in [0, 1]$ and $\epsilon^t_{\daleth} + \zeta^t_{\daleth} + \chi^t_{\daleth} \leq 1$.

Definition 2.4 In the practical application of T-SFNs, categorization is essential. For this purpose, a "score function" (SF) is associated with a T-SFN $\daleth = (\epsilon_{\daleth}, \zeta_{\daleth}, \chi_{\daleth})$ and is defined as [30]:

$$S(\daleth) = \epsilon^t_{\daleth} - \chi^t_{\daleth} \tag{2}$$

However, in many cases, the score function alone may not be sufficient for effectively categorizing T-SFNs across varied scenarios, as it might not adequately distinguish which is preferable. To address this, an "accuracy function H" of $\daleth$ is defined as:

$$\hbar^{\wp}(\daleth) = \epsilon^t_{\daleth} + \zeta^t_{\daleth} + \chi^t_{\daleth} \tag{3}$$

Operational principles for aggregating T-SFNs will be provided to further facilitate their application in practical scenarios.

Definition 2.5 Let $\daleth_1 = \langle \epsilon_1, \zeta_1, \chi_1 \rangle$ and $\daleth_2 = \langle \epsilon_2, \zeta_2, \chi_2 \rangle$ be two T-SFNs, then [33]:

$$\daleth_1^{Cr} = \langle \chi_1, \zeta_1, \epsilon_1 \rangle \tag{4}$$

$$\daleth_1 \vee \daleth_2 = \left\langle max\{\epsilon_1, \epsilon_2\}, min\{\zeta_1, \zeta_2\}, min\{\chi_1, \chi_2\} \right\rangle \tag{5}$$

$$\daleth_1 \wedge \daleth_2 = \left\langle min\{\epsilon_1, \epsilon_2\}, max\{\zeta_1, \zeta_2\}, max\{\chi_1, \chi_2\} \right\rangle \tag{6}$$

$$\daleth_1 \oplus \daleth_2 = \left\langle \sqrt[t]{\epsilon_1^t + \epsilon_2^t - \epsilon_1^t \epsilon_2^t}, \zeta_1 \zeta_2, \chi_1 \chi_2 \right\rangle \tag{7}$$

$$\daleth_1 \otimes \daleth_2 = \left\langle \epsilon_1 \epsilon_2, \sqrt[t]{\zeta_1^t + \zeta_2^t - \zeta_1^t \zeta_2^t}, \sqrt[t]{\chi_1^t + \chi_2^t - \chi_1^t \chi_2^t} \right\rangle \tag{8}$$

$$\sigma \daleth_1 = \left\langle \sqrt[t]{1 - (1 - \epsilon_1^t)^\sigma}, \zeta_1^\sigma, \chi_1^\sigma \right\rangle \tag{9}$$

$$\daleth_1^\sigma = \left\langle \epsilon_1^\sigma, \sqrt[t]{1 - (1 - \zeta_1^t)^\sigma}, \sqrt[t]{1 - (1 - \chi_1^t)^\sigma} \right\rangle \tag{10}$$

Definition 2.6 Let $\daleth_1 = \langle \epsilon_1, \zeta_1, \chi_1 \rangle$ and $\daleth_2 = \langle \epsilon_2, \zeta_2, \chi_2 \rangle$ be two T-SFNs and $H, H_1, H_2 > 0$ be the real numbers, then we have,

1. $\daleth_1 \oplus \daleth_2 = \daleth_2 \oplus \daleth_1$
2. $\daleth_1 \otimes \daleth_2 = \daleth_2 \otimes \daleth_1$
3. $H\left(\daleth_1 \oplus \daleth_2\right) = \left(\mathbb{H}\daleth_1\right) \oplus \left(H\daleth_2\right)$
4. $\left(\daleth_1 \otimes \daleth_2\right)^H = \daleth_1^H \otimes \daleth_2^H$
5. $\left(H_1 + H_2\right)\daleth_1 = \left(H_1\daleth_1\right) \oplus \left(H_2\daleth_2\right)$
6. $\daleth_1^{H_1+H_2} = \daleth_1^{H_1} \otimes \daleth_2^{H_2}$

If $\epsilon_{\daleth_1} = \zeta_{\daleth_1}$ and $\epsilon_{\daleth_2} = \zeta_{\daleth_2}$ then from Definition 2.5, it can be inferred that, $\epsilon_{\daleth_1 \oplus \daleth_2} \neq \zeta_{\daleth_1 \oplus \daleth_2}, \epsilon_{\daleth_1 \otimes \daleth_2} \neq \zeta_{\daleth_1 \otimes \daleth_2}, \epsilon_{\mathbb{H}\daleth_1} \neq \zeta_{\mathbb{H}\daleth_1}, \epsilon_{\daleth_1^{\mathbb{H}}} \neq \zeta_{\daleth_1^{\mathbb{H}}}$. Thus none of the operations $\daleth_1 \oplus \daleth_2, \daleth_1 \otimes \daleth_2, \mathbb{H}\daleth_1, \daleth_1^{\mathbb{H}}$ found to be neutral or fair indeed. Consequently, our focus must first be on developing fair operations amongst T-SFNs.

Definition 2.7 For T-SFNs $T_j = (j = 1, 2, 3, \ldots, m)$, the T-spherical fuzzy weighted geometric (T-SFWG) operator is defined as

$$\text{T-SFWG}\left(T_1, T_2, \ldots, T_m\right) = \prod_{j=1}^{m} T_j^{w_j}$$

where, $w = \left(w_1, w_2, \ldots, w_m\right)^T$ is the weighted vector of $G_j = (j = 1, 2, 3, \ldots, k), w_j > 0$, and $\sum_{j=1}^{m} w_j = 1$. Based on Definition 2.7 , the outcome described in Theorem 2.8 can be derived as a result.

Definition 2.8 The aggregated value of a collection of T-SFNs $G_j (j = 1, 2, 3, \ldots, k)$ using the T-SFWG operator is also a T-SFN, and

$$\text{T-SFWG}\left(T_1, T_2, \ldots, T_k\right) = \left(\prod_{j=1}^{k} \left(\epsilon_j + \chi_j\right)^{w_j} - \prod_{j=1}^{k} \chi_j^{w_j}, \prod_{j=1}^{k} \chi_j^{w_j}, \sqrt[n]{1 - \prod_{j=1}^{k} \left(1 - \zeta_j^k\right)^{w_j}} \right)$$

3 Algorithm

Step 1: Enter the T-SFNs dataset, which represents $Al_k; (k = 1, 2, ..., p)$ alternatives against various criteria $\mathtt{Cr}_\mathtt{k}; (k = 1, 2, ..., q)$

Decision-makers enter the decision matrices $Cr = \left[Cr_{ij}\right]_{q \times p}$

$$\begin{array}{c} \\ \mathtt{Al}_1 \\ \mathtt{Al}_2 \\ \vdots \\ \mathtt{Al}_\mathtt{n} \end{array}
\begin{array}{c}
\begin{array}{cccc} \mathtt{Cr}_1 & \mathtt{Cr}_2 & & \mathtt{Cr}_\mathtt{q} \end{array} \\
\begin{bmatrix}
(\mathtt{H}_{11}, \mathtt{H}_{11}, \mathtt{H}_{11}) & (\mathtt{H}_{12}, \mathtt{H}_{12}, \mathtt{H}_{12},) & \ldots & (\mathtt{H}_{1m}, \mathtt{H}_{1m}, \mathtt{H}_{1q}) \\
(\mathtt{H}_{21}, \mathtt{H}_{21}, \mathtt{H}_{21}) & (\mathtt{H}_{22}, \mathtt{H}_{22}, \mathtt{H}_{22}) & \ldots & (\mathtt{H}_{2q}, \mathtt{H}_{2q}, \mathtt{H}_{2q}) \\
\vdots & \vdots & \ddots & \vdots \\
(\mathtt{H}_{p1}, \mathtt{H}_{p1}, \mathtt{H}_{p1},) & (\mathtt{H}_{p2}, \mathtt{H}_{p2}, \mathtt{H}_{p2}) & \ldots & (\mathtt{H}_{pq}, \mathtt{H}_{pq}, \mathtt{H}_{pq})
\end{bmatrix}
\end{array}$$

where, $Cr_{ij} = \left(H_{ij}, H_{ij}, H_{ij}\right)$, $\quad$ (i = $1, 2, \ldots,$ p) and (j = $1, 2, \ldots,$ q) represents the T-SFNs information. This information corresponds to the various alternatives under the decision-maker's criteria. The evaluation criteria for each alternative are encapsulated by eight linguistic terms, as elaborated in Table 1. Additionally, linguistic expressions related to expertise, detailed in Table 2, supplement these terms. This extensive compilation of linguistic terms facilitates a thorough and comprehensive evaluation process, enabling nuanced assessments based on a wide range of qualitative factors.

Table 1. Linguistic terms for evaluation in medical waste treatment technologies

Evaluation Term	Description	(T-SFNs)
1. Cost-Efficient (CE)	Achieves exceptional cost-efficiency, low investment, and operational costs.	$\langle 0.85, 0.05, 0.10\rangle$
2. Highly Reliable (HR)	Demonstrates outstanding reliability, flexibility, and supply security.	$\langle 0.83, 0.10, 0.15\rangle$
3. Positive Impact (PI)	Provides a strong positive impact on economic development, low carbon emissions, and waste disposal.	$\langle 0.80, 0.17, 0.18\rangle$
4. Moderately Effective (ME)	Exhibits decent cost-efficiency and operational effectiveness.	$\langle 0.75, 0.22, 0.23\rangle$
5. Acceptable (A)	basic requirements without significant advantages or disadvantages.	$\langle 0.63, 0.27, 0.40\rangle$
6. Marginally Satisfactory (MS)	Displays some positive aspects but also significant drawbacks or uncertainties.	$\langle 0.52, 0.33, 0.55\rangle$
7. Inappropriate (I)	Demonstrates a moderate level of cost-effectiveness and operational efficiency.	$\langle 0.32, 0.45, 0.60\rangle$
8. Highly Inappropriate (HI)	Involves high costs, unreliability, and adverse effects on economic and environmental factors.	$\langle 0.21, 0.50, 0.85\rangle$

Table 2. Decision-makers in medical waste treatment technologies 1

Decision-Maker	Role	Key Decisions/Responsibilities
Government Health Authorities	Policymakers initiating and implementing HCW management reforms.	Decisions on regulations, technology standards, and overall HCW policy.
(CE)	(HR)	(PI)
Environmental Regulatory Agencies	Oversee environmental compliance and bridge between government health authorities and the waste treatment industry.	Decide on environmental standards, and emissions control, and ensure sustainable waste management practices.
(ME)	(A)	(PI)
HCW Treatment Facilities	Implement reforms, and adapt to new technologies for medical waste treatment.	Decide on investments, technology adoption, and operational efficiency in treating HCW.
(ME)	(PI)	(A)

Step 2: Determine the weights of decision-makers using a scoring function provided in Eq. (2). Subsequently, apply the obtained scores in the specified Eq. (11).

$$\mathfrak{S}_{ij} = \frac{\sum_i^3 \left(\epsilon^t_{\daleth_i} - \chi^t_{\daleth_i}\right)}{\sum_j^3 \left(\sum_i^3 \left(\epsilon^t_{\daleth_i} - \chi^t_{\daleth_i}\right)\right)} \tag{11}$$

Step 3: Find the aggregated decision matrix $M = [M_{ij}]_{q\times p}$ by using the Eq. (12).

$$\mathrm{T-SFWG}(T_1, T_2, \ldots, T_k) = \left(\prod_{j=1}^{k}(\epsilon_j + \chi_j)^{w_j} - \prod_{j=1}^{k}\chi_j^{w_j}, \prod_{j=1}^{k}\chi_j^{w_j}, \sqrt[n]{1 - \prod_{j=1}^{k}\left(1-\zeta_j^k\right)^{w_j}}\right) \tag{12}$$

Step 4: CRITIC Method

In the context of MCDM, the CRITIC technique is employed to assess the relative significance of various criteria. The forthcoming sections will elucidate the detailed procedure for performing these calculations.

Step 4.1: Compute the score value for the aggregated decision matrix using the given Eq. (13).

$$\mathfrak{S}_{ij} = \epsilon^{t}_{\daleth} - \chi^{t}_{\daleth} \tag{13}$$

Step 4.2: Transform the matrix $\mathfrak{S}$ into standard T-SFNs matrix by using Eq. (14).

$$\widetilde{\mathfrak{S}}_{ij} = \begin{cases} \frac{\mathfrak{S}_{ij} - \mathfrak{S}_j^-}{\mathfrak{S}_j^+ - \mathfrak{S}_j^-}, & j \in Cr_b \\ \frac{\mathfrak{S}_j^+ - \mathfrak{S}_{ij}}{\mathfrak{S}_j^+ - \mathfrak{S}_j^-}, & j \in Cr_c \end{cases} \tag{14}$$

where, $\mathfrak{S}_j^+ = \max_i \mathfrak{S}_{ij}, \mathfrak{S}_j^- = \min_i \mathfrak{S}_{ij}, Cr_b$ and Cr_c represent the benefit-type and cost-type criteria, respectively.

Step 4.3: Using the provided Eq. (15), calculate an estimate of the standard deviations for the criteria.

$$\beth_j = \sqrt{\frac{\sum_{i=1}^{n} \left(\mathfrak{S}_{ij} - \overline{\mathfrak{S}}_j\right)^2}{n}} \tag{15}$$

where, $\overline{\mathfrak{S}}_j = \sum_{i=1}^{n} \widetilde{\mathfrak{S}}_{ij}/n$.

Step 4.4: To determine the correlation coefficient for the criterion, use Eq. (16).

$$k_{jt} = \frac{\sum_{i=1}^{n} \left(\mathfrak{S}_{ij} - \overline{\mathfrak{S}}_j\right)\left(\mathfrak{S}_{ij} - \overline{\mathfrak{S}}_t\right)}{\sqrt{\sum_{i=1}^{n} \left(\mathfrak{S}_{ij} - \overline{\mathfrak{S}}_j\right)^2 \left(\mathfrak{S}_{ij} - \overline{\mathfrak{S}}c_t\right)^2}} \tag{16}$$

Step 4.5: Using Eq. (17), examine the information for each criterion.

$$\mathfrak{c}_{\mathfrak{j}} = \beth \sum_{t=1}^{m} (1 - k_{jt}) \tag{17}$$

As the value of c_j increases, it indicates that a specific criterion carries more information compared to others. Consequently, the weight attributed to that criterion is proportionally increased relative to other factors.

Step 4.6: Find the objective weight that each criterion should have using Eq. (18).

$$w_j = \frac{c_j}{\sum\limits_{j=1}^{p} c_j} \tag{18}$$

3.1 MAUT

Step 5: The normalization process of values in the choice matrix depends on the nature of the qualities, whether positive or negative. Positive attribute values undergo normalization using the expression given in Eq. (19), and negative attribute values undergo normalization using the expression in Eq. (20).

$$\mathfrak{S}_{ij}^{*} = \frac{\mathfrak{S}_{ij} - \min\left(\mathfrak{S}_{ij}\right)}{\max\left(\mathfrak{S}_{ij}\right) - \min\left(\mathfrak{S}_{ij}\right)} \tag{19}$$

$$\overline{\mathfrak{S}}_{ij}^{*} = 1 + \frac{\min\left(\mathfrak{S}_{ij}\right) - \mathfrak{S}_{ij}}{\max\left(\mathfrak{S}_{ij}\right) - \min\left(\mathfrak{S}_{ij}\right)} \tag{20}$$

Step 6: Calculate the marginal utility score using Eq. (21):

$$M_{ij} = \frac{e^{(\mathfrak{S}^*)^2} - 1}{1.71} \tag{21}$$

Step 7: The final utility score for each alternative is calculated using Eq. (22). Subsequently, the alternatives are ranked according to their respective utility score values.

$$J_i = \sum_{j=1}^{m} M_{ij} \cdot w_{\mathrm{j}} \tag{22}$$

The flowchart given in Figure 1 serves to visually delineate the methodology, providing a clear, step-by-step graphical representation of the logic and decision-making process involved.

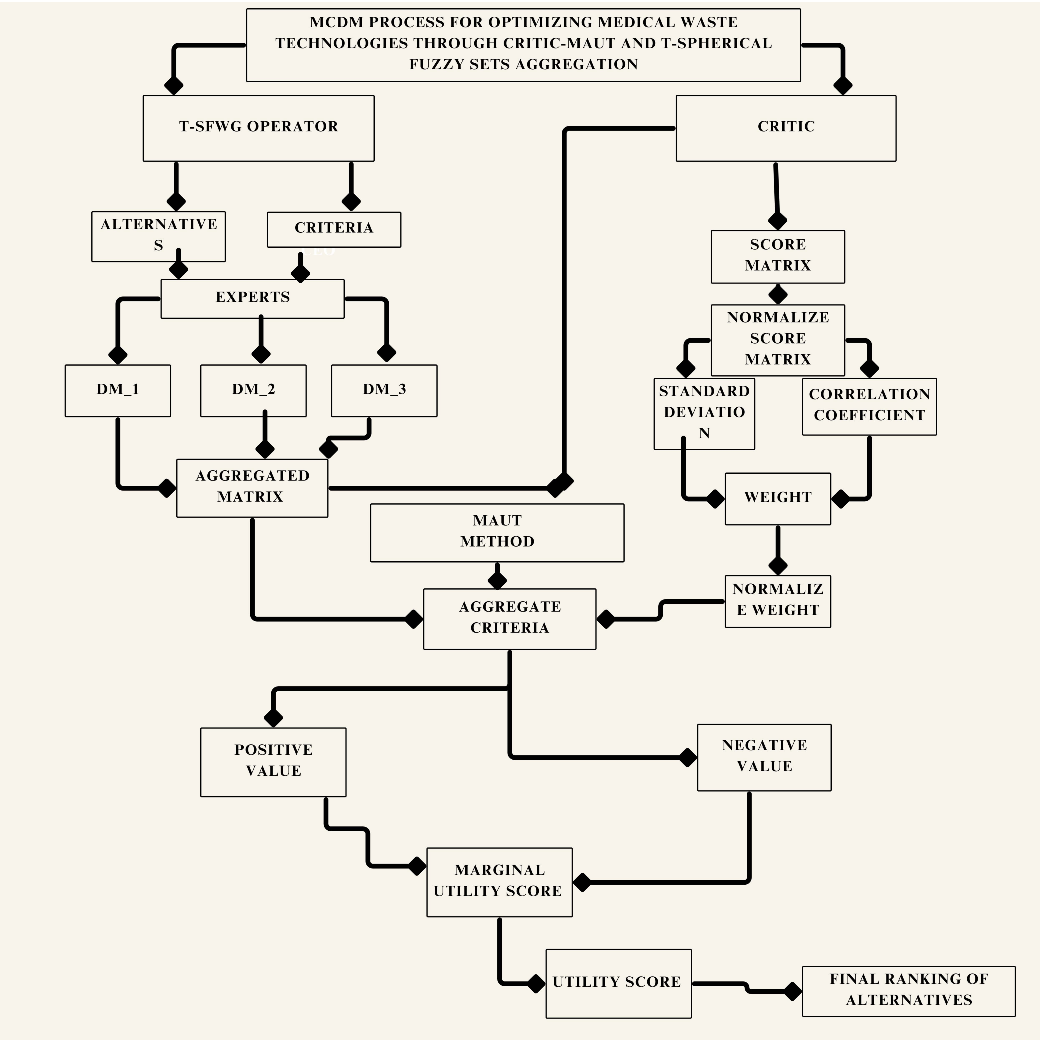

Figure 1. The algorithm's operational procedure

4 Case Study

MWM is a critical issue for mitigating environmental and health risks associated with improper disposal. In China, the rapid expansion of hospitals and healthcare facilities has led to a significant increase in medical waste production. Unfortunately, a considerable portion of this waste remains untreated, presenting substantial threats to public health and the environment. Addressing this challenge necessitates the careful selection of appropriate medical waste treatment technologies. Various technologies are available for consideration, each with its unique advantages and limitations. Steam sterilization (Al_1), incineration (Al_2), chemical disinfection (Al_3), microwaves (Al_4), and landfill disposal (Al_5) are among them. Each technology possesses distinct characteristics; for instance, steam sterilization is renowned for its simplicity and reliability, while incineration offers rapid disposal but raises concerns regarding emissions. Chemical disinfection, employing agents such as chlorine, is effective for both liquid and solid waste. Microwave disinfection utilizes electromagnetic waves, offering reduced volume and energy consumption compared to incineration. Conversely, landfill disposal, while a more general approach, can be potentially hazardous. Eight criteria (Cr_1) to (Cr_8) are evaluated when evaluating these medical waste treatment methods.

4.1 Details of Treatment Technologies

1. Steam Sterilization (Al_1):
Steam sterilization is recognized as a reliable and established method for treating medical waste. This technique utilizes an autoclave, wherein saturated steam is applied at a specific pressure to attain the required temperature within the chamber. The efficacy of steam sterilization hinges on its ability to accomplish thorough disinfection, while concurrently adhering to regulatory standards. Notably, this method is acclaimed for its straightforward operation, effective monitoring capabilities, and well-established validation procedures.

2. Incineration (Al_2):
Incineration is a method that utilizes high-temperature burning to dispose of medical waste rapidly and effectively. Operating at temperatures between 900 to 1000 degrees Celsius, incineration offers a straightforward and expedient means of disposal. However, concerns regarding emissions associated with this process remain a point of contention. Despite these environmental considerations, certain regions actively advocate for incineration, highlighting its benefits as a preferred treatment method for medical waste.

3. Chemical Disinfection (Al_3):
Chemical disinfection involves the application of various chemical agents, notably chlorine, to disinfect medical waste. This method is particularly effective for liquid waste, although it is also applicable to solid waste. Chemical disinfection is notable for its high efficacy in pathogen inactivation, making it a widely adopted strategy for managing diverse types of medical waste.

4. Microwave (Al_4):
Microwave technology disinfects medical waste through the application of electromagnetic radiation. The high frequency of microwaves induces rapid vibration in waste molecules, effectively neutralizing organic materials. The process commences with shredding the waste, which is then mixed with water and subjected to internal heating. This technique not only ensures the disinfection of the waste but also contributes to a reduction in its volume. Significantly, this method is characterized by lower energy consumption compared to traditional incineration methods.

5. Landfill Disposal (Al_5):
Landfill disposal, favored for its simplicity and low cost, is a commonly used method for disposing of medical waste. In this process, medical waste is deposited in landfills. However, due to the potentially infectious nature of the waste, this method can pose environmental risks. While it is a widely applicable and cost-effective strategy, the suitability of landfill disposal is contingent on effective management and compliance with environmental regulations.

4.2 Evaluation Criteria

1. Cost (Cr_1):
Criterion (Cr_1) assesses the financial implications associated with each medical waste treatment option. This evaluation includes initial investment, operational expenses, and any ancillary costs related to the technology. The economic aspect is pivotal in determining the feasibility and long-term sustainability of the selected medical waste treatment method.

2. Waste Residuals (Cr_2):
Criterion (Cr_2) focuses on the byproducts or residuals generated during the medical waste treatment process. It evaluates both the quantity and nature of the residuals produced by each technology. The minimization of waste residuals is crucial for reducing environmental impacts and for compliance with waste management regulations.

3. Release with Health Effects (Cr_3):
Criterion (Cr_3) assesses the potential impacts of medical waste treatment on public health. This includes considerations of emissions, byproducts, or any other compounds released that could be detrimental to human health. Ensuring that the chosen technology minimizes health risks is a critical aspect of effective MWM.

4. Energy Consumption (Cr_4):
Criterion (Cr_4) evaluates the energy requirements for operating each medical waste treatment alternative. This criterion addresses the sustainability of the technology by considering its energy efficiency. Opting for methods that consume less energy is a step towards environmental conservation.

5. Reliability (Cr_5):

Criterion (Cr_5) measures the dependability and consistency of each medical waste treatment technology. It encompasses factors such as the performance of the technology, its maintenance needs, and overall reliability. A reliable process is crucial to ensure continuous and effective treatment of medical waste.

6. Volume Reduction (Cr_6):

Criterion (Cr_6) evaluates the degree to which a medical waste treatment option reduces the original volume of waste. This criterion measures the effectiveness of the technology in decreasing the space needed for waste disposal. Treatment methods that achieve significant volume reductions are instrumental in enhancing waste management practices.

7. Treatment Effectiveness (Cr_7):

Criterion (Cr_7) assesses the efficiency of each medical waste treatment method in eliminating infections and hazardous elements from the waste. It examines the technology's capability to thoroughly disinfect while adhering to regulatory standards. Treatment effectiveness is paramount for ensuring public safety and safeguarding the environment.

8. Public Acceptance (Cr_8):

Criterion (Cr_8) gauges the community's perceptions and attitudes towards different medical waste treatment technologies. It considers factors such as community concerns, viewpoints, and cultural considerations. Ensuring that the selected technology aligns with public acceptance is essential for the successful implementation of MWM strategies and fostering community cooperation.

This case study aims to systematically evaluate and identify the optimal medical waste treatment technology in China, employing the CRITIC-MAUT approach. The criteria considered include cost, waste residuals, health impact releases, energy consumption, reliability, volume reduction, treatment effectiveness, and public acceptance. To ensure a thorough and dependable decision-making process, Expert Committee 2, consisting of specialists from diverse disciplines, scrutinizes each technology against these established criteria.

The procedure can be broken down into the following steps:

Step 1: Experts utilize the T-SFNs dataset, incorporating linguistic terms from Table 1, for each alternative (Al_p) (where p = 1,2,..., m) under the influence of various criteria Cr_p, as detailed in Table 3.

Table 3. Evaluation table given by DMs

DMs	Alternatives	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
	Al_1	HR	CE	MS	HI	A	I	ME	I
	Al_2	PI	CE	MS	PI	I	A	ME	I
DM_1	Al_3	I	ME	PI	MS	HR	A	MS	HI
	Al_4	A	CE	ME	A	I	PI	MS	I
	Al_5	MS	I	CE	HI	HI	HR	PI	HI
	Al_1	ME	A	I	HR	PI	MS	CE	HI
	Al_2	CE	I	ME	MS	PI	A	HR	MS
DM_2	Al_3	MS	PI	CE	I	ME	HI	A	HI
	Al_4	A	I	MS	PI	HR	ME	CE	HI
	Al_5	I	HR	HI	ME	PI	MS	CE	A
	Al_1	I	ME	MS	A	CE	HR	PI	ME
	Al_2	CE	I	A	ME	PI	MS	ME	HI
DM_3	Al_3	MS	ME	HI	PI	CE	A	I	PI
	Al_4	A	PI	CE	I	MS	HR	ME	MS
	Al_5	ME	CE	A	MS	HI	PI	I	HI

Step 2: Determine the weights of DMs by employing the scoring function outlined in Eq. (2). Subsequently, utilize the computed scores in Eq. (11), and the resulting values are presented in Table 4.

Step 3: Calculate the aggregated decision matrix $M = [M_{ij}]_{q\times p}$ by using the Eq. (12) and the outcomes are displayed in Table 5.

Step 4.1: Find the aggregated decision matrix's score value using Eq. (13).

$$\mathfrak{S}\mathfrak{c}_{\mathfrak{ij}} = \begin{bmatrix} -0.0022 & 0.2368 & 0.0316 & 0.0881 & 0.4433 & 0.3895 & 0.3275 & 0.2238 \\ 0.4437 & -0.0082 & 0.0984 & 0.2369 & 0.3229 & 0.0367 & 0.2370 & -0.0159 \\ 0.0309 & 0.2369 & -0.0088 & 0.3233 & 0.4436 & 0.0888 & -0.0028 & 0.3126 \\ 0.0978 & 0.3235 & 0.4434 & -0.0027 & 0.0311 & 0.3937 & 0.2370 & 0.0210 \\ 0.2322 & 0.4398 & 0.0893 & 0.0261 & -0.0206 & 0.3275 & -0.0021 & -0.0210 \end{bmatrix}$$

Table 4. Decision-makers in medical waste treatment technologies 2

Decision-Maker	Role	Key Decisions/Responsibilities	Weights
Government Health Authorities	Policymakers initiating and implementing HCW management reforms.	Decisions on regulations, technology standards, and overall HCW policy.	
(CE)	(HR)	(PI)	0.3779
Environmental Regulatory Agencies	Oversee environmental compliance and bridge between government health authorities and the waste treatment industry.	Decide on environmental standards, and emissions control, and ensure sustainable waste management practices.	
(ME)	(A)	(PI)	0.3340
HCW Treatment Facilities	Implement reforms, and adapt to new technologies for medical waste treatment.	Decide on investments, technology adoption, and operational efficiency in treating HCW.	
(ME)	PI	(A)	0.2881

Table 5. Aggregated decision matrix

$\mathbf{Cr_i}$	$\mathbf{Al_1}$	$\mathbf{Al_2}$	$\mathbf{Al_3}$	$\mathbf{Al_4}$	$\mathbf{Al_5}$
Cr_1	$\langle 0.320, 0.354, 0.471\rangle$	$\langle 0.850, 0.134, 0.146\rangle$	$\langle 0.520, 0.373, 0.569\rangle$	$\langle 0.630, 0.270, 0.400\rangle$	$\langle 0.750, 0.348, 0.513\rangle$
Cr_2	$\langle 0.750, 0.223, 0.315\rangle$	$\langle 0.320, 0.410, 0.547\rangle$	$\langle 0.750, 0.209, 0.219\rangle$	$\langle 0.800, 0.335, 0.448\rangle$	$\langle 0.850, 0.330, 0.442\rangle$
Cr_3	$\langle 0.520, 0.364, 0.567\rangle$	$\langle 0.630, 0.243, 0.463\rangle$	$\langle 0.210, 0.391, 0.689\rangle$	$\langle 0.850, 0.193, 0.399\rangle$	$\langle 0.630, 0.397, 0.696\rangle$
Cr_4	$\langle 0.630, 0.407, 0.711\rangle$	$\langle 0.750, 0.207, 0.425\rangle$	$\langle 0.800, 0.338, 0.510\rangle$	$\langle 0.320, 0.360, 0.487\rangle$	$\langle 0.520, 0.412, 0.727\rangle$
Cr_5	$\langle 0.850, 0.206, 0.301\rangle$	$\langle 0.800, 0.344, 0.461\rangle$	$\langle 0.850, 0.168, 0.180\rangle$	$\langle 0.520, 0.0.370, 0.534\rangle$	$\langle 0.210, 0.462, 0.798\rangle$
Cr_6	$\langle 0.853, 0.259, 0.335\rangle$	$\langle 0.820, 0.254, 0.377\rangle$	$\langle 0.650, 0.304, 0.432\rangle$	$\langle 0.866, 0.313, 0.547\rangle$	$\langle 0.645, 0.290, 0.512\rangle$
Cr_7	$\langle 0.361, 0.418, 0.732\rangle$	$\langle 0.523, 0.414, 0.741\rangle$	$\langle 0.550, 0.294, 0.411\rangle$	$\langle 0.322, 0.354, 0.623\rangle$	$\langle 0.562, 0.356, 0.602\rangle$
Cr_8	$\langle 0.730, 0.321, 0.547\rangle$	$\langle 0.864, 0.271, 0.498\rangle$	$\langle 0.850, 0.361, 0.643\rangle$	$\langle 0.520, 0.364, 0.655\rangle$	$\langle 0.863, 0.315, 0.569\rangle$

Step 4.2: Transform the matrix $\overline{\mathfrak{S}c}$ into standard T-SFSs matrix by using Eq. (14).

$$\mathfrak{Sc}_{\mathrm{ij}}^{-} = \begin{bmatrix} 1 & 0.4533 & 0.9107 & 0.7216 & 0.9995 & 0.9882 & 1 & 0.7338 \\ 0 & 1 & 0.7630 & 0.2650 & 0.7399 & 0 & 0.7259 & 0.0154 \\ 0.9258 & 0.4529 & 1 & 0 & 1 & 0.1458 & 0 & 1 \\ 0.7757 & 0.2597 & 0 & 1 & 0.1113 & 1 & 0.7259 & 0.1260 \\ 0.4742 & 0 & 0.7831 & 0.9116 & 0 & 0.8145 & 0.0021 & 0 \end{bmatrix}$$

Step 4.3: Calculate an estimate of the standard deviations for the criterion by using Eq. (15).

$$\beth_j = \begin{bmatrix} 0.4082 & 0.3674 & 0.3984 & 0.4307 & 0.4831 & 0.4802 & 0.4609 & 0.4613 \end{bmatrix}$$

Step 4.4: Eq. (16) is used to determine the criteria' correlation coefficient.

$$r_{jt} = \begin{bmatrix} 1 & -0.5028 & 0.0190 & 0.1263 & 0.2548 & 0.5259 & 0.0073 & 0.7517 \\ -0.5028 & 1 & 0.2243 & -0.6378 & 0.6197 & -0.7136 & 0.4500 & 0.0315 \\ 0.0190 & 0.2243 & 1 & -0.6272 & 0.6546 & -0.4638 & -0.3136 & 0.5218 \\ 0.1263 & -0.6378 & -0.6272 & 1 & -0.7495 & 0.9023 & 0.2763 & -0.5377 \\ 0.2548 & 0.6197 & 0.6546 & -0.7495 & 1 & -0.4701 & 0.2451 & 0.7737 \\ 0.5259 & -0.7136 & -0.4638 & 0.9023 & -0.4701 & 1 & 0.3036 & -0.1229 \\ 0.0073 & 0.4500 & -0.3136 & 0.2763 & 0.2451 & 0.3036 & 1 & -0.0986 \\ 0.7517 & 0.0315 & 0.5218 & -0.5377 & 0.7737 & -0.1229 & -0.0986 & 1 \end{bmatrix}$$

Step 4.5: Examine the information for each criterion by using Eq. (17).

$$\mathfrak{c}_j = \begin{bmatrix} 2.3751 & 2.7658 & 2.7827 & 3.5523 & 2.7400 & 3.3801 & 2.8251 & 2.6206 \end{bmatrix}$$

Step 4.6: Find the objective weight that each criterion should have using Eq. (18).

$$w_j = \begin{bmatrix} 0.1031 & 0.1200 & 0.1208 & 0.1542 & 0.1189 & 0.1467 & 0.1226 & 0.1137 \end{bmatrix}$$

4.3 MAUT

Step 5: The values of the choice matrix are normalised according to whether they are positive or negative traits. Positive attribute values are normalised using Eq. (19), while negative attribute values are normalised using Eq. (20).

$$\mathfrak{Sc}^*_{\mathrm{ij}} = \begin{bmatrix} 0 & 0.5467 & 0.0893 & 0.2784 & 0.0005 & 0.0118 & 0 & 0.2662 \\ 1 & 0 & 0.2370 & 0.7350 & 0.2601 & 1 & 0.2741 & 0.9846 \\ 0.0742 & 0.5471 & 0 & 1 & 0 & 0.8542 & 1 & 0 \\ 0.2243 & 0.7403 & 1 & 0 & 0.8887 & 0 & 0.2741 & 0.8740 \\ 0.5258 & 1 & 0.2169 & 0.0884 & 1 & 0.1855 & 0.9979 & 1 \end{bmatrix}$$

Step 6: Calculate the marginal utility score using the Eq. (21).

$$M_{ij} = \begin{bmatrix} 0 & 0.2038 & 0.0047 & 0.0471 & 0.0016 & 0.0081 & 0 & 0.0429 \\ 1.0048 & 0 & 0.0338 & 0.4190 & 0.0409 & 1.0048 & 0.0456 & 0.9569 \\ 0.0032 & 0.2041 & 0 & 1.0048 & 0 & 0.6283 & 1.0048 & 0 \\ 0.0302 & 0.4268 & 1.0048 & 0 & 0.7036 & 0 & 0.0456 & 0.6706 \\ 0.1862 & 1.0048 & 0.0282 & 0.0046 & 1.0048 & 0.0205 & 0.9981 & 1.0048 \end{bmatrix}$$

Step 7: The ultimate utility score of each alternative is determined by applying Eq. (22) to the data and ranking the alternative by using the utility score values is $A_5 > A_2 > A_3 > A_4 > A_1$.

$$u = \begin{bmatrix} 0.0372 & 0.4390 & 0.3951 & 0.3412 & 0.5031 \end{bmatrix}$$

4.4 Comparative Analysis

The feasibility and effectiveness of decision-making strategies within T-SFNs were systematically explored in our in-depth comparison investigation. By conducting rigorous studies and adding comprehensive validation and robustness checks throughout the inquiry, we ensured the reliability and stability of our results. These considerations raise the significance of our research as a whole, giving a solid foundation for our findings. Table 6 captures a persuasive picture of the significant findings from our investigation. Each scrutinized factor helps to untangle the subtle findings, providing for a detailed comprehension of the advantages and disadvantages of various decision-making processes. In essence, our research provides decision-makers with trustworthy insights for strategically integrating T-SFSs, enhancing our understanding of decision-making within the T-SFS framework.

Table 6. Aggregated decision matrix

Authors	Methodology	Ranking of Alternatives	Optimal Alternative
Chen [51]	VIKORA	$Al_5 > Al_2 > Al_3 > Al_1 > Al_4$	Al_5
Ju et al. [52]	TODIM	$Al_5 > Al_2 > 2Al_4 > Al_3 > Al_1$	Al_5
Fan et al. [53]	COPRAS	$Al_5 > Al_2 > Al_1 > Al_4 > Al_3$	Al_5
Zhang and Wei [54]	CPT-CoCoSo and D-CRITIC	$Al_5 > Al_2 > Al_4 > Al_2 > Al_3$	Al_5
Özdemirci et al. [35]	TOP-DEMATEL	$Al_5 > Al_3 > Al_2 > Al_4 > Al_4$	Al_5
Ali [55]	CRITIC-MARCOS	$Al_5 > Al_4 > Al_2 > Al_1 > Al_3$	Al_5
Proposed	CRITIC-MAUT	$A_5 > A_2 > A_3 > A_4 > A_1$	Al_5

The CRITIC-MAUT methodology introduced in this study demonstrates superior performance over existing aggregation operators for ranking medical waste treatment alternatives. Through a comprehensive comparison with various methodologies, including VIKOR, TODIM, COPRAS, CPT–CoCoSo, D-CRITIC, TOP-DEMATEL, and CRITIC-MARCOS, the effectiveness of the CRITIC-MAUT approach is clearly established. Its consistent identification of Al_5 as the optimal alternative highlights the efficacy of CRITIC-MAUT in making informed decisions within the realm of medical waste treatment technologies.

4.5 Discussion

The CRITIC-MAUT methodology, anchored in the T-SFS framework, provides a comprehensive and systematic approach to the intricate task of selecting suitable medical waste treatment methods. This analysis encompasses eight distinct criteria, spanning a wide spectrum from economic factors to environmental impacts and public perceptions, thereby illustrating the multifaceted nature of MWM. The meticulous assessment of each criterion, including cost (Cr_1), waste residuals (Cr_2), release with health impacts (Cr_3), energy consumption (Cr_4), reliability (Cr_5), volume reduction (Cr_6), treatment efficacy (Cr_7), and public acceptance (Cr_8), is conducted. The evaluation encompasses five distinct medical waste treatment alternatives, representing various methodologies: steam sterilization (A_1), incineration (A_2), chemical disinfection (A_3), microwave technology (A4), and landfill disposal (A_5). T-SFNs assigned to each alternative based on specific criteria create a detailed dataset for subsequent multi-attribute utility analysis. The CRITIC method plays a vital role in determining the relative importance of each criterion while recognizing the intrinsic inter-criteria correlations inherent in MWM. This informed weighting approach ensures a balanced consideration of criteria in the subsequent application of MAUT. The MAUT method, in turn, facilitates a comprehensive assessment of each alternative, integrating both the criteria weights and linguistic evaluations. The resulting utility scores lead to a systematic hierarchy of medical waste treatment technologies: $A_5 > A_2 > A_3 > A_4 > A_1$. This ranking, derived through the CRITIC-MAUT approach, offers practical guidance for decision-makers in HCW management, directing them towards the selection of the most apt technology based on a transparent and thorough evaluation process. The incorporation of T-SFSs enhances the method's ability to accommodate the inherent uncertainties in MWM. In conclusion, within the T-SFS framework, the CRITIC-MAUT methodology stands out as an effective tool for informed and sustainable decision-making in the realm of HCW treatment.

5 Conclusion

The CRITIC-MAUT methodology, integrated into the T-SFS framework, presents itself as a comprehensive and robust solution for the critical task of selecting suitable medical waste treatment technologies. The systematic assessment of eight diverse criteria, encompassing economic, environmental, and social aspects, offers a holistic perspective on MWM. The incorporation of T-SFNs alongside linguistic expressions effectively captures the uncertainties and complexities inherent in decision-making processes. The CRITIC technique streamlines the estimation of criterion weights by acknowledging inter-criteria correlations, thus facilitating a nuanced and informed multi-attribute utility analysis.

Utilizing the weights derived from the CRITIC method, the MAUT facilitates a thorough evaluation of each medical waste treatment option. The linguistic assessments and T-SFNs associated with each alternative contribute to a more detailed understanding of their respective performances. The resulting systematic ranking ($A_5 > A_2 > A_3 > A_4 > A_1$) offers actionable insights for decision-makers, guiding the selection of the most suitable technology based on a balanced consideration of various factors. The integration of T-SFSs augments the methodology's ability to accommodate uncertainties in MWM, rendering it a valuable tool for informed and long-term decision-making. This research not only introduces a new dimension to the field but also establishes a comprehensive framework for navigating the complexities of HCW treatment decision-making.

Despite the efficacy of the CRITIC-MAUT approach within the T-SFS framework, there are avenues for future research. Firstly, introducing new criteria or refining existing ones could enhance the decision-making process. Exploring the integration of emerging technologies or innovative waste treatment methods could expand the scope and applicability of the methodology. Additionally, considering dynamic factors such as technological advancements, changes in legislation, or shifts in public perception over time would create a more dynamic and flexible decision-making framework. Future research might also explore the incorporation of real-time data and advanced analytics to refine the accuracy of predictions and evaluations. In conclusion, the CRITIC-MAUT technique, coupled with T-SFSs, lays a solid foundation for medical waste treatment decision-making, with potential for further enhancement through ongoing research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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