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A Scenario-Robust Intuitionistic Fuzzy AHP–TOPSIS Model for Sustainable Healthcare Waste Treatment Selection: Evidence from Türkiye

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Abstract

Selecting a sustainable healthcare waste treatment method is a complex multi-criteria problem influenced by environmental, economic, social and technological factors. This study addresses key gaps in the literature by proposing an intuitionistic fuzzy AHP–TOPSIS framework that explicitly models cognitive uncertainty and expert hesitation, while demonstrating its application through a real-world case study in Adana, Türkiye. In contrast to prior studies utilizing fewer criteria, our framework evaluates four treatment alternatives—incineration, steam sterilization, microwave, and landfill—across 17 comprehensive criteria that directly integrate circular economy principles such as resource recovery and energy efficiency. The results indicate that steam sterilization is the most sustainable option, demonstrating superior performance across environmental, economic, social, and technological dimensions. A 15-scenario sensitivity analysis ensures ranking resilience across varying decision contexts. Furthermore, a systematic comparative analysis highlights the methodological advantages of the proposed framework in terms of analytical granularity and robustness compared to existing models. The study also offers step-by-step operational guidance, creating a transparent and policy-responsive decision-support tool for healthcare waste management authorities to advance sustainable practices.

Keywords: healthcare waste treatment; sustainable waste management; multi-criteria decision-making (MCDM); intuitionistic fuzzy sets; AHP-TOPSIS; uncertainty modeling; scenario analysis; circular economy

1. Introduction

Healthcare services, essential for societal well-being, generate significant volumes of waste that, if mismanaged, can threaten both environmental quality and public health. The rapid growth of populations, particularly in developing economies, has amplified the volume of healthcare waste, intensifying pressures on waste management systems [1,2].

Globally, healthcare waste is defined as any solid or liquid material produced during medical treatment, clinical diagnosis, pathological testing, and related medical research in hospitals or clinics [3]. In Türkiye, healthcare waste management is further regulated by the Medical Waste Control Regulation (Official Gazette No. 29959, 25 January 2017), which establishes requirements for collection, temporary storage, transportation, and disposal within healthcare institutions [4]. This waste often contain infectious pathogens, toxic chemicals, and heavy metals, which pose serious risks to ecosystems and human health [5].

Sustainable management of healthcare waste is therefore a critical challenge, requiring strategies that minimize environmental burdens, optimize resource use, and align with

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circular economy principles. Improper disposal of such waste not only contributes to greenhouse gas emissions, soil and water contamination, and energy inefficiency, but also undermines efforts to establish closed-loop, circular waste systems [6,7].

The World Health Organization emphasizes the importance of selecting treatment technologies suited to local conditions, monitoring practices, and effective governance to prevent pollution and disease transmission [3]. Despite regulatory frameworks, challenges persist, particularly in developing regions where co-disposal with municipal waste and insufficient infrastructure hinder sustainable management. Rising volumes of healthcare waste highlight the urgent need for integrated strategies that ensure environmental sustainability, operational efficiency, and public health protection. As summarized in Table 1 and illustrated in Figure 1, healthcare waste generation in Türkiye demonstrated an overall upward trend from 2017 to 2023, notwithstanding marginal fluctuations during the 2022–2023 period, underscoring the growing pressure on waste management systems and the need for efficient and sustainable treatment technologies.

Table 1. Population and healthcare waste generation in Türkiye (2017–2023). Compiled by the authors based on TURKSTAT Waste Statistics 2023 [8].

Year	Population	Healthcare Waste Generation (Thousand Tons)
2017	80,810.53	98.729
2018	82,003.88	107.400
2019	83,155.00	109.478
2020	83,614.36	125.566
2021	84,680.27	135.869
2022	85,279.55	130.401
2023	85,372.37	130.882

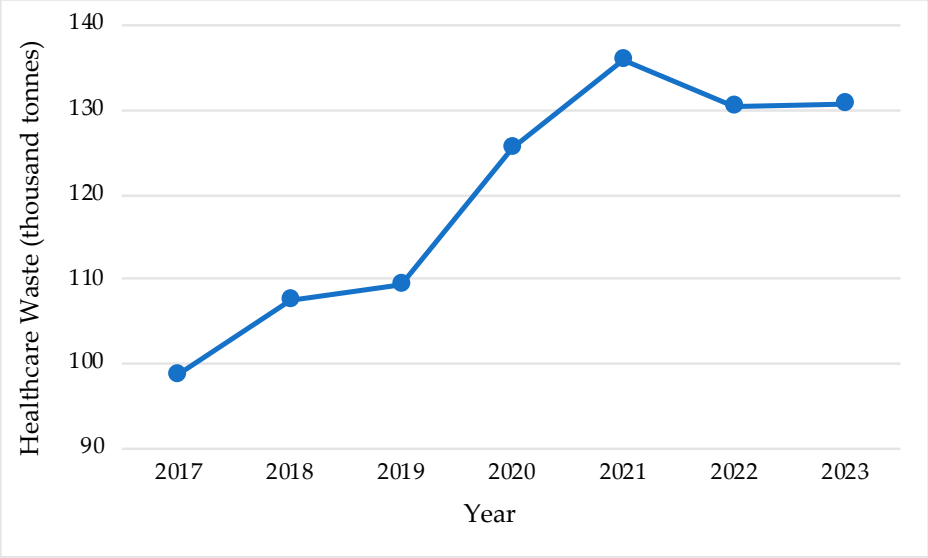


Figure 1. Trend of healthcare waste generation in Türkiye (2017–2023) [8].

Multi-criteria decision-making (MCDM) methods have emerged as essential tools for evaluating healthcare waste treatment alternatives, as they enable systematic consideration of environmental, economic, and technical criteria [9]. Conventional approaches, including the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and Complex Proportional Assessment (COPRAS), offer valuable decision support but

often struggle to incorporate expert uncertainty and hesitation inherent in real-world contexts [9–17]. The integration of intuitionistic fuzzy sets (IFSs) with MCDM techniques addresses these limitations by modeling both membership and non-membership degrees, providing more reliable assessments under uncertainty.

However, existing studies rarely integrate intuitionistic fuzzy (IF) extensions of both AHP and TOPSIS in a unified sustainability-oriented framework, nor do they examine the robustness of rankings under varying scenarios. Moreover, the explicit incorporation of circular economy considerations and uncertainty modeling remains limited in healthcare waste treatment selection. Thus, there is a clear need for comprehensive decision-making approaches that simultaneously account for uncertainty, sustainability, and robustness.

In this regard, this study develops a scenario-robust intuitionistic fuzzy AHP–TOPSIS framework for healthcare waste treatment selection, explicitly accounting for uncertainty, expert divergence, and variations in sustainability-oriented criteria weighting. A real-world case study in Adana, Türkiye, evaluates four treatment alternatives across 17 criteria, complemented by a 15-scenario sensitivity analysis. By linking methodological robustness to circular economy principles and sustainability goals, the proposed framework not only enhances decision reliability but also provides actionable guidance for policymakers and healthcare managers seeking environmentally and economically sustainable waste management solutions.

The objective of this study is twofold: (i) to propose an uncertainty-aware and sustainability-oriented decision-making framework that integrates IF-AHP and IF-TOPSIS with scenario-based sensitivity analysis, and (ii) to demonstrate its practical applicability to sustainable healthcare waste management.

The structure of this article is as follows: Section 2 presents existing studies on healthcare waste management and their evaluation methods; Section 3 details the integrated framework; Section 4 demonstrates the framework's application, including sensitivity analyses and a comparative analysis highlighting the methodological advantages of the proposed approach; Section 5 interprets the findings and situates them within the broader literature; and Section 6 summarizes the study's contributions, practical implications, limitations, and directions for future research.

2. Literature Review

The term decision-making refers to the process of selecting the most suitable course of action from a set of alternatives, guided by specific criteria. It plays a pivotal role across a wide range of domains—from everyday decisions to complex industrial and environmental challenges. Particularly in problems involving multiple and often conflicting criteria, the decision-making process becomes significantly more intricate. These problems can be classified into single-criteria and multi-criteria decision-making (MCDM) types, where conventional MCDM techniques such as AHP and TOPSIS have laid the foundation for evaluating alternatives under multiple criteria [18,19]. While the former focuses on optimizing one specific objective, MCDM addresses scenarios where alternatives must be evaluated against several potentially conflicting criteria [20]. Such complexity is especially pronounced when cost, performance, environmental impact, and sustainability considerations must be balanced concurrently. MCDM is particularly critical in domains such as environmental management, circular healthcare systems, urban planning, and healthcare waste management. In such cases, prioritizing and evaluating decision criteria becomes vital to identifying the most suitable alternative. MCDM methods offer a structured framework to tackle these complex problems and play a crucial role in guiding sustainable decision-making. Accordingly, MCDM has become a well-established analytical frame-

work for addressing complex sustainability-oriented decision problems across various domains such as energy, environmental planning, logistics, and waste management [21,22].

2.1. Application of MCDM in Healthcare Waste Management

Healthcare waste management (HCWM) constitutes a multidimensional decision-making problem, particularly in developing economies where population growth, expansion of healthcare services, and aging populations drive rapid increases in waste generation [5]. Proper management of healthcare waste is crucial for preventing environmental pollution, safeguarding public health, and minimizing risks from pathogens, toxic chemicals, and heavy metals [3,10,23]. The inherent trade-offs among environmental, economic, technical, and operational factors make systematic and objective evaluation essential, motivating the adoption of MCDM approaches [24].

To address these complexities, previous studies have applied a variety of methods, including Life Cycle Assessment (LCA) [25–28], descriptive cross-sectional surveys [29], pre–post comparison [30], checklist methods [31], observation and laboratory tests [32], statistical analyses [33], cost–benefit analyses [34,35], and risk assessment methods [36–38]. While these approaches provide valuable insights, they often fail to capture the intrinsic uncertainty, expert hesitation, and sustainability requirements of HCWM decision-making.

Current healthcare waste treatment technologies exhibit substantial variation in environmental performance, operational requirements, and economic feasibility. Sustainability considerations—such as resource efficiency, circular waste practices, and compliance with environmental regulations—have therefore become central elements in assessing HCWM systems [6,7]. These multidimensional factors reinforce the need for analytical approaches capable of integrating environmental, technical, and economic trade-offs under uncertainty.

2.2. Intuitionistic Fuzzy Sets (IFSs) and Integrated MCDM Approaches

Given its multi-criteria nature, addressing HCWM as a decision-making problem necessitates the use of systematic and objective methods. Intuitionistic fuzzy sets (IFSs) extend classical fuzzy logic by incorporating not only membership and non-membership degrees but also a degree of hesitation, enabling a more nuanced representation of uncertainty. This capability allows decision-makers to model expert hesitation and uncertainty in criteria weighting and alternative evaluation, resulting in more reliable outcomes [24].

To leverage these advantages, this study employs an integrated methodology combining IF-AHP and IF-TOPSIS. IF-AHP is used for criteria weighting, capturing the relative importance of environmental, economic, social, and technology-related factors under uncertainty. IF-TOPSIS evaluates the alternatives against positive and negative ideal solutions, providing a robust ranking that accounts for both uncertainty and sustainability objectives.

2.3. Applications of IF-AHP and IF-TOPSIS in the Literature

Conventional MCDM methods—such as AHP [10,11,23], TOPSIS [12,13], VIKOR [14,15], and COPRAS [16,17]—have been extensively applied in HCWM for evaluating treatment technologies, environmental risks, and operational performance. Nonetheless, these methods generally assume stable preferences and deterministic evaluations, which are increasingly incompatible with modern sustainability-oriented decision contexts. Healthcare waste treatment decisions are shaped by multi-dimensional sustainability pressures, including environmental emissions, energy efficiency, regulatory compliance, life cycle impacts, circular resource flows, and operational resilience. In such settings, classical MCDM approaches struggle to adequately capture expert hesitation, scenario-driven uncertainty, and the trade-offs among environmental, economic, and technological sustainability criteria. This has driven growing interest in more expressive decision-making frameworks capable of handling uncertainty.

Building on these developments, intuitionistic fuzzy extensions of other classical MCDM methods—such as VIKOR [39], COPRAS [40], and MULTIMOORA [41]—have been increasingly used in sustainability-oriented decision problems. These methods are often integrated with group decision-making frameworks that incorporate hesitant or intuitionistic fuzzy preference relations and scenario-based sustainability analyses. Approaches based on best–worst methods and fuzzy preference relations under hesitant or intuitionistic environments have also been explored, reflecting a broader methodological diversification in uncertainty-aware MCDM. Examples include the hesitant multiplicative Best-Worst Method (BWM) [42] and intuitionistic fuzzy BWM [43], demonstrating how expert hesitation, multi-dimensional sustainability criteria, and robustness testing are systematically accommodated across various MCDM frameworks. These methods also hold significant potential for application in HCWM and other sustainability-oriented decision contexts, where uncertainty, multi-dimensional criteria, and scenario-based analyses are critical.

Within this context, intuitionistic fuzzy extensions of AHP and TOPSIS have emerged as prominent tools for sustainability-oriented evaluations. IF-AHP has been successfully applied to hazardous waste transporter selection [9], drilling fluid evaluation [44], reverse logistics outsourcing [45], and sustainability management in digitalized food supply chains [46], demonstrating its strength in criteria weighting under uncertainty. IF-TOPSIS has been utilized in project portfolio evaluation [47], wind farm siting automotive benchmarking [48], and sustainable supplier selection [49], revealing its suitability for ranking alternatives when sustainability criteria interact in complex ways. Notwithstanding these advances, the application of integrated IF-AHP and IF-TOPSIS in healthcare waste management remains comparatively sparse, particularly in studies that integrate both methods and incorporate scenario-based sustainability analyses. This gap highlights the need for robust frameworks that explicitly address uncertainty while aligning decision-making with environmental sustainability, circular economy principles, and operational feasibility.

2.4. Summary of MCDM Studies on HCWM

Table 2 provides a consolidated overview of existing MCDM applications in HCWM, including evaluation criteria, treatment alternatives, methodological frameworks, and the extent to which uncertainty is addressed. Prior studies have employed a wide range of techniques—such as the Decision-Making Trial and Evaluation Laboratory (DEMATEL), Step-Wise Weight Assessment Ratio Analysis (SWARA), BWM, and fuzzy set extensions, including intuitionistic, Pythagorean, and Fermatean fuzzy approaches—reflecting the growing methodological diversification in the field. Despite this progress, most studies still rely on single-stage models and fail to integrate robust uncertainty modeling with sustainability-oriented evaluation criteria.

Very few studies combine IF-AHP for criteria weighting with IF-TOPSIS for alternative ranking, and even fewer do so within a framework that explicitly incorporates sustainability considerations, circular economy objectives, and scenario-based uncertainty analysis. This reveals a persistent gap in the literature, where existing models either inadequately represent expert hesitation or lack a systematic approach to testing the stability of treatment rankings under varying sustainability priorities. Addressing this gap requires a more comprehensive, uncertainty-aware MCDM framework—precisely the contribution offered in this study.

Table 2. Overview of MCDM applications in healthcare waste management.

Author(s)	Year	Evaluation Criteria/Criteria Set	Alternatives	Uncertainty	Types of Uncertainty	MCDM Method(s)
[50]	2010	9	7	No	-	AHP
[51]	2011	4	4	Yes	Fuzzy Set Theory	Aggregation Operator
[14]	2013	6	4	Yes	Fuzzy Set Theory	VIKOR
[52]	2014	4	4	Yes	Interval 2-Tuple Linguistic Variables	MULTIMOORA
[53]	2016	4	4	No	-	AHP
[54]	2016	4	5	Yes	Intuitionistic Fuzzy Set	Intuitionistic fuzzy values
[55]	2018	6	4	Yes	Fuzzy Set Theory	TOPSIS
[56]	2018	4	4	Yes	D numbers	D numbers
[57]	2019	5	4	Yes	Hesitant Fuzzy Linguistic Term Set	MABAC, MAIRCA
[16]	2020	6	4	Yes	Intuitionistic Fuzzy Set	EDAS
[58]	2020	5	4	Yes	DEMATEL, Interval Valued Fuzzy Set	TOPSIS
[59]	2020	8	8	Yes	Fuzzy Set Theory	ARAS
[60]	2020	8	5	Yes	Pythagorean Fuzzy Set	SWARA, ARAS
[61]	2021	4	9	Yes	Fuzzy Set Theory	VIKOR
[62]	2021	4	6	Yes	D Numbers	MABAC, BWM
[12]	2021	4	4	Yes	Intuitionistic Fuzzy Set	TOPSIS
[63]	2023	4	11	Yes	Fuzzy Set Theory	AHP, VIKOR
[64]	2023	4	4	Yes	Integrated Weighting Procedure, DEMATEL, Fuzzy Set Theory	TOPSIS, GRA
[65]	2024	7	4	No	-	AHP, MARCOS
[66]	2024	7	4	Yes	Intuitionistic Fuzzy Set, DEMATEL	TOPSIS, COPRAS
[67]	2024	8	4	Yes	BWM, Fuzzy Set Theory	MULTIMOORA
[68]	2024	4	9	Yes	Fuzzy Set Theory	PSI, CRADIS

Note: Some studies report only main criteria, while others include sub-criteria. ARAS: Additive Ratio Assessment; CRADIS: Compromise Ranking of Alternatives from Distance to Ideal Solution; EDAS: Evaluation Based on Distance from Average; GRA: Gray Relational Analysis; MABAC: Multi-Attributive Border Approximation Area Comparison; MABAC-D: Multi-Attributive Border Approximation Area Comparison Based on D numbers; MAIRCA: Multi-Attributive Ideal–Real Comparative Analysis; MULTIMOORA: Multi-Objective Optimization on the basis of a Ratio Analysis plus the full MULTIplicative Form; PSI: Preference Selection Index.

2.5. Identified Research Gaps and Study Contributions

Despite the widespread use of MCDM methods in HCWM, several critical gaps remain:

- Application of IF-AHP for criteria weighting is still scarce. While DEMATEL and BWM have been applied extensively, their integration within intuitionistic fuzzy environments remains limited.
- TOPSIS and VIKOR are widely used for alternative evaluation, yet few studies provide comparative assessments using IF-TOPSIS.
- Previous research rarely considers sustainability and circular economy principles explicitly, nor does it systematically evaluate the robustness of rankings under multiple scenarios.

Building upon these gaps, the present study contributes as follows:

- Proposes an integrated IF-AHP and IF-TOPSIS framework for robust, uncertainty-aware evaluation of HCWM strategies;
- Introduces a sustainability-oriented perspective, incorporating environmental, economic, social, and technology dimensions;
- Evaluates alternatives in a real-world case study with 17 criteria and 4 treatment options;
- Conducts sensitivity analyses to assess the stability of rankings under varying scenarios, ensuring reliability of recommendations;
- Provides a methodological framework that is both scalable and adaptable for future research on sustainable HCWM under uncertainty.

3. Proposed Methodology Based on IF-AHP and IF-TOPSIS

3.1. Problem Definition: Selection of Sustainable Healthcare Waste Treatment Alternative

Sustainable healthcare waste treatment is a complex multi-criteria decision problem affected by environmental, social, economic, and technological factors. This study models the problem as a multi-criteria group decision-making (MCGDM) problem, synthesizing the judgments of three domain experts: a Municipal Waste Management Officer, an Environmental Engineer, and a Full Professor specializing in healthcare management and environmental engineering.

To address the uncertainty and hesitation inherent in expert evaluations, the study employs intuitionistic fuzzy sets (IFSs), which capture membership (μ), non-membership (ν), and hesitation (π) degrees to realistically represent uncertainty in expert sustainability assessments.

As illustrated in Figure 2, the proposed methodological framework for sustainable HCWM under uncertainty illustrates a two-stage workflow. In Stage 1, IF-AHP derives criteria weights embedding sustainability and circular economy considerations, such as energy efficiency, resource recovery, and public acceptance, ensuring that weights reflect both short- and long-term sustainability objectives under uncertainty. Stage 2 integrates these weights into IF-TOPSIS to evaluate and rank alternative HCWM strategies based on their proximity to the intuitionistic fuzzy positive ideal solution (IF-PIS) and distance from the negative ideal solution (IF-NIS).

To facilitate practical implementation, we outline how the integrated IF-AHP-IF-TOPSIS framework can be applied by HCWM authorities without requiring methodological simplification. Decision-makers first apply IF-AHP to derive criteria weights using linguistic scales and perform consistency checks. Once weights are obtained, IF-TOPSIS is used to rank alternative treatment strategies systematically. Key computational steps—such as group aggregation via intuitionistic fuzzy weighted averaging (IFWA) and closeness coefficient calculation—remain operationally interpretable for both local and national-level authorities.

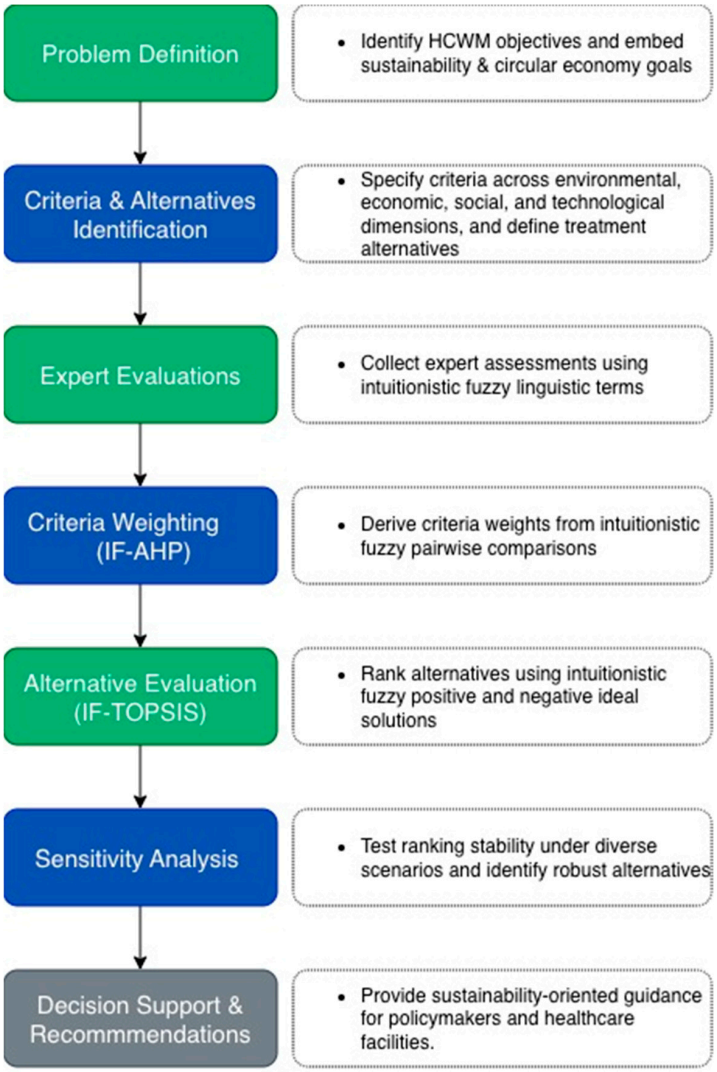


Figure 2. Proposed methodological framework for sustainable HCWM under uncertainty.

Crucially, applying conventional AHP-derived weights directly to conventional TOPSIS can result in semantic inconsistencies. In contrast, the current study adopts IF-AHP to determine criteria weights expressed as intuitionistic fuzzy numbers, which are inherently compatible with IF-TOPSIS, thereby eliminating semantic inconsistencies and maintaining coherent criteria weighting and alternative ranking under the same fuzzy logic principles [9,24].

Consequently, the methodology enables reliable and sustainability-aligned decision making under uncertainty.

3.2. Intuitionistic Fuzzy Sets (IFSs)

In sustainability-oriented decision problems, criteria often depend on linguistic assessments rather than precise numerical information, and expert judgments contain substantial ambiguity and hesitation [69]. Classical fuzzy sets partially capture this uncertainty, yet they do not explicitly model the hesitation that arises in sustainability evaluations involving long-term ecosystem effects, social acceptance, or circularity-driven material recovery.

To better represent such ambiguity, this study employs intuitionistic fuzzy set (IFS) theory, introduced by Atanassov [70], which enhances classical fuzzy sets by defining three parameters: membership (μ), non-membership (ν), and hesitation (π). Let X denote the universe of discourse, and let $\tilde{A}$ be an intuitionistic fuzzy set defined as

$$\widetilde{A} = \{(x, \mu_A(x),\ \nu_A(x)) | x \in X\}$$

subject to

$$0 \leq \mu_A + \nu_A \leq 1,\ \ \forall x \in X$$

The hesitation degree is given by

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$$

representing the level of uncertainty about the membership of x [71]. In the following definitions and equations, μ, ν, and π denote the membership, non-membership, and hesitation degrees, respectively, for each element x.

IFSs are particularly suitable for sustainability and circular economy assessments, where experts often hesitate due to incomplete data, technological variability, and long-term uncertainties. By capturing this hesitation explicitly, IFSs provide a more realistic representation of expert uncertainty, strengthening the robustness and validity of both the IF-AHP and IF-TOPSIS stages.

3.3. IF-AHP

The intuitionistic fuzzy analytic hierarchy process (IF-AHP) extends the classical AHP by enabling decision-makers to express judgments with intuitionistic fuzzy evaluations rather than precise pairwise ratios. Whereas conventional AHP relies on deterministic numerical comparisons, IF-AHP utilizes membership (μ), non-membership (ν), and hesitation (π) degrees, allowing uncertainty, hesitation, and cognitive ambiguity to be modeled explicitly. This leads to more robust and realistic prioritization of criteria in complex decision environments. In the IF-AHP procedure, μ, ν, and π values are used to capture the degree of confidence and uncertainty in experts' pairwise comparisons.

This study uses IF-AHP to derive the weights of the criteria. The procedure follows the steps summarized below [72]:

Step 1: Hierarchical Structuring

The decision hierarchy is established by defining the alternatives $A = \{A_1,\ A_2,\ \ldots,\ A_m\}$ and the criteria $X = \{X_1,\ X_2,\ \ldots,\ X_n\}$.

Step 2: Construction of Intuitionistic Fuzzy Pairwise Comparison Matrices

Decision-makers provide pairwise comparisons of criteria using intuitionistic fuzzy linguistic terms. These linguistic terms are mapped to intuitionistic fuzzy numbers (μ, ν, π) as defined in Table 3 below. μ and ν values are directly assigned by experts based on Saaty's 0.1–0.9 importance scale [72], while $\pi = 1 - \mu - \nu$.

Table 3. Intuitionistic fuzzy linguistic scale and corresponding descriptions.

Scale Value	Importance Description
0.1	Extremely low importance
0.2	Very low importance
0.3	Low importance
0.4	Moderately low importance
0.5	Equal importance
0.6	Moderately high importance
0.7	High importance
0.8	Very high importance
0.9	Extremely high importance

For each decision-maker $k = 1, 2, \ldots, l$, an intuitionistic fuzzy pairwise comparison matrix is constructed.

Step 3. Consistency Adjustment of Intuitionistic Preference Matrices

Each intuitionistic fuzzy pairwise comparison matrix is checked for multiplicative consistency. Using Algorithm 1, the perfectly consistent intuitionistic preference matrix $\overline{R} = (\overline{r}_{ik})nxn$ is generated. Here, $\overline{r}_{ik}$ corresponds to adjusted consistent intuitionistic fuzzy value.

Algorithm 1. Computation of intuitionistic fuzzy aggregated values $\overline{r}_{ik}$ in IF-AHP [72]

For $k > i + 1$, let $\overline{r}_{ik} = (\overline{\mu}_{ik}, \overline{\nu}_{ik})$, where

$$\overline{\mu}_{ik} = \frac{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \mu_{it} * \mu_{tk}}}{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \mu_{it} * \mu_{tk}} + \sqrt[k-i-1]{\prod_{t=i+1}^{k-1} (1-\mu_{it}) * (1-\mu_{tk})}}$$

$$\overline{\nu}_{ik} = \frac{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \nu_{it} * \nu_{tk}}}{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \nu_{it} * \nu_{tk}} + \sqrt[k-i-1]{\prod_{t=i+1}^{k-1} (1-\nu_{it}) * (1-\nu_{tk})}}$$

For $k = i + 1$, let $\overline{r}_{ik} = r_{ik}$.

For $k < i + 1$, let $\overline{r}_{ik} = (\overline{\nu}_{ki}, \overline{\mu}_{ki})$. $i, k = 1, 2, \ldots, n$.

Step 4: Consistency Verification

The consistency degree between the original and adjusted matrices is computed using Equation (1).

$$d(R, \overline{R}) = \frac{1}{2(n-1)(n-2)} \sum_{i=1}^{n} \sum_{k=1}^{n} \left(|\overline{\mu}_{ik} - \mu_{ik}| + |\overline{\nu}_{ik} - \nu_{ik}| + |\overline{\pi}_{ik} - \pi_{ik}| \right) \quad (1)$$

If the distance measure for consistency verification $d(R, \overline{R}) < \tau$ (consistency threshold, where $\tau = 0.1$), the matrix is considered consistent. If consistency is not achieved, the matrix is modified using Equations (2) and (3), where σ is a decision maker-defined control parameter:

$$\widetilde{\mu}_{ik} = \frac{\left(\mu_{ik}^{(p)}\right)^{1-\sigma} \left(\overline{\mu}_{ik}{}^{\sigma}\right)}{\left(\mu_{ik}^{(p)}\right)^{1-\sigma} (\overline{\mu}_{ik})^{\sigma} + \left(1 - \mu_{ik}^{(p)}\right)^{1-\sigma} (1 - \overline{\mu}_{ik})^{\sigma}} \quad (2)$$

$$\widetilde{\nu}_{ik} = \frac{\left(\nu_{ik}^{(p)}\right)^{1-\sigma} \left(\overline{\nu}_{ik}{}^{\sigma}\right)}{\left(\nu_{ik}^{(p)}\right)^{1-\sigma} (\overline{\nu}_{ik})^{\sigma} + \left(1 - \nu_{ik}^{(p)}\right)^{1-\sigma} (1 - \overline{\nu}_{ik})^{\sigma}} \quad (3)$$

Step 5: Derivation of Local Criteria Weights

Once consistency is ensured, intuitionistic fuzzy weights for each criterion are computed using Equation (4):

$$w_i = \left(\frac{\sum_{k=1}^{n} \mu_{ik}}{\sum_{i=1}^{n} \sum_{k=1}^{n} (1 - \nu_{ik})}, 1 - \frac{\sum_{k=1}^{n} (1 - \nu_{ik})}{\sum_{i=1}^{n} \sum_{k=1}^{n} \mu_{ik}} \right), \quad i = 1, 2, \ldots, n \quad (4)$$

Step 6: Aggregation of Group Weights via IFWA

To obtain a single set of group weights, the intuitionistic fuzzy weighted averaging (IFWA) operator proposed by Xu (2007) is applied [73]:

$$w_j = IFWA_{\lambda}\left(w_j^{(1)}, w_j^{(2)}, \ldots, w_j^{(l)}\right)$$

$$= \left[1 - \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda_k} - \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda_k}\right] \quad (5)$$

Here, $w_j^{(1)}$, $w_j^{(2)}$, …, $w_j^{(l)}$ represent the individual intuitionistic fuzzy weights assigned to the j-th criterion by l individual decision-makers ($k = 1, 2, \ldots, l$), respectively, and λ_k denotes the weight of the k-th decision maker, with $\sum_{k=1}^{l} \lambda_k = 1$. The resulting weight vector W is then used as input for the IF-TOPSIS procedure. The IFWA operator aggregates individual intuitionistic fuzzy weights from multiple decision-makers into a single group weight, accounting for both consensus and hesitation.

3.4. IF-TOPSIS

The intuitionistic fuzzy TOPSIS (IF-TOPSIS) method, extended in intuitionistic fuzzy environments by Xu [73], provides a ranking mechanism based on the relative proximity of each alternative to the ideal and anti-ideal solutions. IF-TOPSIS evaluates alternatives based on their proximity to IF-PIS and distance from IF-NIS, with all ratings expressed as intuitionistic fuzzy numbers capturing μ, ν, and π. Unlike IF-AHP, which focuses on deriving criteria weights from pairwise judgments, IF-TOPSIS operates directly on the performance ratings of alternatives and evaluates them within the intuitionistic fuzzy domain by integrating decision- makers' assessments through aggregation operators. This complementary role allows IF-TOPSIS to exploit the intuitionistic structure not to model the importance of criteria, but rather to refine the measurement of alternative performance under uncertainty [49,70]. Thus, the procedural implementation of the IF-TOPSIS framework in this study follows the sequential steps outlined below:

Step 1: Determination of Decision-Maker Weights.

Let the importance evaluation of decision-maker k be represented by the intuitionistic fuzzy number $D_k = (\mu_k, \nu_k, \pi_k)$. The qualitative descriptors and their corresponding intuitionistic fuzzy numbers used for these assessments follow the structure proposed in Ref. [74] but are reconstructed by the authors, as summarized in Table 4.

Table 4. Weighting scale for evaluating the relative importance of decision-makers, constructed based on Ref. [74].

Qualitative Descriptor	Abbreviation	Intuitionistic Fuzzy Number Triplet (μ, ν, π)
Very Low Importance	VLI	(0.10, 0.90, 0.00)
Low Importance	LI	(0.35, 0.60, 0.05)
Moderate Importance	MI	(0.50, 0.45, 0.05)
High Importance	HI	(0.75, 0.20, 0.05)
Very High Importance	VHI	(0.90, 0.10, 0.00)

Following Xu (2007), the weight of each decision maker is computed as follows [73]:

$$\lambda_k = \frac{\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k+\nu_k}\right)\right)}{\sum_{k=1}^{l}\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k+\nu_k}\right)\right)}, \quad \sum_{k=1}^{l} \lambda_k = 1 \quad (6)$$

This weighting scheme accounts for both membership strength and hesitation, thus preventing underestimation of partially confident evaluations.

Step 2. Aggregation of Individual Intuitionistic Fuzzy Decision Matrices.

Each decision maker k provides an individual intuitionistic fuzzy decision matrix, $R^{(k)} = \left(r_{ij}^{(k)}\right)_{mxn}$, $r_{ij}^{(k)} = (\mu_{ij}^{(k)}, \nu_{ij}^{(k)}, \pi_{ij}^{(k)})$, constructed using the linguistic terms defined

in Table 5, which presents the intuitionistic fuzzy scale adopted for rating the performance of the alternatives.

Table 5. Linguistic evaluation scale for alternative performance, constructed based on Ref. [49].

Qualitative Descriptor	Abbreviation	Intuitionistic Fuzzy Number Triplet (μ, ν, π)
Very Highly Weak	VHW	(0.10, 0.90, 0.00)
Highly Weak	HW	(0.10, 0.75, 0.15)
Weak	W	(0.25, 0.60, 0.15)
Moderately Weak	MW	(0.40, 0.50, 0.10)
Moderate	M	(0.50, 0.40, 0.10)
Moderately Strong	MS	(0.60, 0.30, 0.10)
Strong	S	(0.70, 0.20, 0.10)
Highly Strong	HS	(0.80, 0.15, 0.05)
Very Highly Strong	VHS	(0.85, 0.10, 0.05)
Exceptionally Strong	ES	(1.00, 0.00, 0.00)

To obtain the group decision matrix, the IFWA operator is applied [73]:

$$r_{ij} = IFWA_{\lambda}(r_{ij}^{(1)}, r_{ij}^{(2)}, \ldots, r_{ij}^{(l)})$$

$$= \left[1 - \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda_k} - \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda_k}\right] \quad (7)$$

The resulting aggregated intuitionistic fuzzy decision matrix is $R = \left(r_{ij}\right)_{m*xn}$.

Step 3. Adoption of Criteria Weights from IF-AHP.

The criteria weights required for the IF-TOPSIS procedure are directly adopted from the aggregated intuitionistic fuzzy weights w_j derived through the IF-AHP method (Section 3.3). Formally, the aggregated weight vector is represented as

$$W = (w_1, w_2, \ldots, w_n), \quad w_j = \mu_j, \nu_j, \pi_j, \ j = 1, 2, \ldots, n.$$

These weights already reflect the consistency-adjusted intuitionistic preference matrices, aggregation across decision makers via the IFWA operator, and normalization respecting intuitionistic constraints.

By directly using IF-AHP-derived weights, no additional computation of criteria weights is performed within IF-TOPSIS. This approach ensures methodological consistency and eliminates redundancy between the two frameworks.

Step 4. Construction of the Weighted Intuitionistic Fuzzy Decision Matrix.

The aggregated intuitionistic fuzzy decision matrix $R = \left(r_{ij}\right)_{mxn}$ is weighted using the intuitionistic fuzzy multiplication operator defined by Atanassov (1986) [70]. For each criterion j with weight $w_j = (\mu_j, \nu_j, \pi_j)$ and each aggregated intuitionistic fuzzy evaluation $r_{ij} = (\mu_{ij}, \nu_{ij}, \pi_{ij})$, the weighted intuitionistic fuzzy value r'_{ij} is obtained as

$$\mu'_{ij} = \mu_{ij}.\mu_j \quad (8)$$

$$\nu'_{ij} = \nu_{ij} + \nu_j - \nu_{ij}.\nu_j \quad (9)$$

$$\pi'_{ij} = 1 - \mu'_{ij} - \nu'_{ij} \quad (10)$$

Thus, the weighted intuitionistic fuzzy decision matrix is given by $R' = \left(r'_{ij}\right)_{mxn}$, $r'_{ij} = (\mu'_{ij}, \nu'_{ij}, \pi'_{ij})$.

Step 5. Determination of the Intuitionistic Fuzzy Positive Ideal Solution (IF-PIS) and Intuitionistic Fuzzy Negative Ideal Solution (IF-NIS).

Let J_1 and J_2 denote the sets of benefit and cost criteria, respectively. The intuitionistic fuzzy positive ideal solution (IF-PIS) is denoted by $A^* = (r_1'^*, r_2'^*, \ldots, r_n'^*)$, $r_j'^* = (\mu_j'^*, \nu_j'^*, \pi_j'^*)$. Similarly, the intuitionistic fuzzy negative ideal solution (IF-NIS) is expressed as $A^- = (r_1'^-, r_2'^-, \ldots, r_n'^-)$, $r_j'^- = (\mu_j'^-, \nu_j'^-, \pi_j'^-)$.

The IF-PIS and IF-NIS are computed as follows:

$$\mu_j'^* = \begin{cases} \max\limits_i \left(\mu_{ij}'\right) & j \in J_1, \\ \min\limits_i \left(\mu_{ij}'\right) & j \in J_2, \end{cases} \tag{11}$$

$$\nu_j'^* = \begin{cases} \min\limits_i \left(\nu_{ij}'\right) & j \in J_1, \\ \max\limits_i \left(\nu_{ij}'\right) & j \in J_2, \end{cases} \tag{12}$$

$$\mu_j'^- = \begin{cases} \min\limits_i \left(\mu_{ij}'\right) & j \in J_1, \\ \max\limits_i \left(\mu_{ij}'\right) & j \in J_2, \end{cases} \tag{13}$$

$$\nu_j'^* = \begin{cases} \max\limits_i \left(\nu_{ij}'\right) & j \in J_1, \\ \min\limits_i \left(\nu_{ij}'\right) & j \in J_2, \end{cases} \tag{14}$$

Step 6. Computation of Separation Measures.

To evaluate the distance between alternatives in the context of intuitionistic fuzzy sets, several distance metrics can be employed, including the generalized Hamming and Euclidean distances and their normalized forms [75–77]. Once a distance metric is selected, separation measures from the ideal solutions S_i^* and S_i^-, representing the distance of each alternative from the intuitionistic fuzzy positive ideal solution and negative ideal solution, respectively, are computed.

This study adopts the normalized Euclidean distance proposed by [76]. The separation measures are calculated as follows:

$$S^* = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left[\left(\mu_{ij}' - \mu_j'^*\right)^2 + \left(\nu_{ij}' - \nu_j'^*\right)^2 + \left(\pi_{ij}' - \pi_j'^*\right)^2\right]} \tag{15}$$

$$S^- = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left[\left(\mu_{ij}' - \mu_j'^-\right)^2 + \left(\nu_{ij}' - \nu_j'^-\right)^2 + \left(\pi_{ij}' - \pi_j'^-\right)^2\right]} \tag{16}$$

Step 7: Determination of the Relative Closeness Coefficient to the Intuitionistic Ideal Solution.

The relative closeness of an alternative A_i to the intuitionistic fuzzy positive ideal solution A^* is computed using the separation measures obtained in Step 6. The relative closeness coefficient C_i^* is defined as

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-}, \quad 0 \le C_i^* \le 1, \ i = 1, 2, \ldots, m \tag{17}$$

Step 8. Ranking the Alternatives.

Once the relative closeness coefficients C_i^* are computed for all alternatives, the alternatives are ranked in descending order. Alternatives with larger C_i^* values are con-

sidered more desirable, representing closer proximity to the intuitionistic fuzzy positive ideal solution.

4. Case Study: Application of the IF-AHP–IF-TOPSIS Framework and Results

To demonstrate the applicability and practical value of the proposed multi-criteria decision-making framework, a case study was conducted in Adana, Türkiye. The results illustrate how local authorities can interpret the ranking of healthcare waste treatment alternatives to inform decision-making, including prioritization of technologies, allocation of resources, and alignment with environmental, social, and economic sustainability objectives. Step-by-step calculations, as detailed later in this section, provide actionable insights that can be directly applied in real-world contexts.

Adana, the fifth most populous province in Türkiye, has experienced persistent demographic growth over the last decade. This growth has directly increased the demand for healthcare services and, consequently, the quantity of healthcare waste generated across the province.

Table 6 presents the annual population figures and healthcare waste volumes in Adana between 2016 and 2022. During this period, the population increased by 72,436 individuals, corresponding to an average annual growth of approximately 12,072 people. More critically, the amount of healthcare waste generated in the province rose from 3145.24 tons in 2016 to 4125.71 tons in 2022, representing an overall increase of 980.47 tons—or an average annual increase of 163.41 tons. This upward trend highlights the escalating pressure on the regional healthcare waste management infrastructure.

Table 6. Population and healthcare waste volumes in Adana (2016–2022). Compiled by the authors based on TURKSTAT Waste Statistics 2022 [8].

	2016	2017	2018	2019	2020	2021	2022
Population (person)	2,201,670	2,216,475	2,220,125	2,237,940	2,258,718	2,263,373	2,274,106
Healthcare waste (tons)	3145.240	3190.990	3296.083	3084.679	3730.256	3759.115	4125.708

According to the 2024 Adana Province Zero Waste Management Plan, a total of 283 healthcare institutions operate within the province, generating an average of 305 tons of medical waste per month (approximately 3660 tons annually). This waste is collected and transported to the province's Medical Waste Sterilization Facility. The sterilization process is carried out using pressurized steam, after which the treated waste is transferred to the Adana Solid Waste Landfill Site.

However, the sterilization facility has a daily operational capacity of approximately 6–8 tons. Assuming an average throughput of 6.5 tons per day, the facility's maximum annual capacity is limited to around 2373 tons. When compared with the 3660 tons of waste generated annually, a substantial annual capacity deficit of approximately 1288 tons per year becomes evident [78]. This capacity gap underscores the insufficiency of existing infrastructure to manage the province's increasing healthcare waste.

Adana thus provides a critical context for evaluating alternative healthcare waste treatment options. The rising healthcare waste load, coupled with infrastructure constraints, emphasizes the necessity of an evidence-based, multi-criteria decision-making framework to guide municipal authorities toward more sustainable and resilient waste management solutions.

4.1. Determining Criteria Weights via IF-AHP for Healthcare Waste Strategies

Step 1: A panel of three decision-makers (DMs) with expertise in healthcare management, environmental engineering, and sustainable waste processing was convened for the evaluation process. Their professional experience ranged from 10 to 23 years, ensuring informed assessments of both the criteria and alternatives. Interviews with these experts constituted the primary data source for determining criteria weights and evaluating healthcare waste treatment alternatives (see Table 7).

Table 7. Decision-makers participating in this study.

DM No	Field of Expertise	Experience (Years)	Title	Education	Role Summary
1	Waste management, local governance	10	Municipal Waste Management Officer	Bachelor	Oversees waste collection and disposal
2	Environmental engineering, medical waste management, sustainable waste processing methods	16	Environmental Engineer	Master	Designs and implements sustainable waste processing methods
3	Healthcare management, environmental engineering, MCDM	23	Full Professor	PhD	Conducts research and analysis on medical waste strategies

To clarify their contributions, the decision-makers were explicitly involved in

- Criteria Weighting: Each expert assessed the importance of all 17 criteria using the linguistic scale, and their evaluations were aggregated via the IFWA operator to produce the final criteria weights.
- Alternative Evaluation: Each expert scored all alternatives against every criterion, reflecting their professional knowledge and practical experience.
- Ensuring Reliability: Aggregation and consistency checks were applied to minimize bias and maintain coherent results.

These steps render the decision-makers' roles transparent and demonstrate that their inputs were systematically integrated, supporting the credibility and robustness of the evaluation process.

Based on expert input and the literature, seventeen evaluation criteria were identified, grouped under four dimensions: environmental (nine criteria), economic (three criteria), social (two criteria), and technological (three criteria). Environmental criteria assess the potential hazards, resource consumption, and residual impacts of each waste management strategy. Economic criteria evaluate costs and resource efficiency, while social criteria consider operator skills and public acceptance. Technological criteria address system reliability, treatment capacity, and effectiveness. Detailed definitions and literature sources are provided in Supplementary Materials (SM) Table S1. The study also evaluated four healthcare waste treatment alternatives, derived from expert opinions and prior studies (Table 8).

These criteria and alternatives provided the basis for the IF-AHP evaluation, ensuring that expert knowledge, literary evidence, and methodological rigor guided the weighting and ranking of alternatives.

Step 2: After identifying the criteria and alternatives, each decision-maker conducted pairwise comparisons, translating linguistic evaluations into numeric values using the

0.1–0.9 importance scale (Table 3). The complete intuitionistic preference matrices for decision-makers 1, 2, and 3 are presented in Supplementary Materials Tables S2–S4.

Table 8. Healthcare waste treatment alternatives used in this study.

Alternative No	Alternative Name	Description
A_1	Incineration	High-temperature burning of waste to reduce volume and neutralize pathogens
A_2	Steam Sterilization	Autoclaving process using saturated steam
A_3	Microwave	Disinfection using microwave energy
A_4	Landfill	Final disposal of treated or untreated waste in designated land areas

Sources: [14,16,51,52,56–58,64]. Studies that provide a detailed analysis of these four alternatives are listed here. Studies that reference these alternatives without a detailed discussion are not included in this section but are cited in the literature review.

Step 3: The consistency of each decision-maker's intuitionistic preference matrix is evaluated. Using Algorithm 1, the multiplicatively consistent intuitionistic preference matrices were derived (Supplementary Materials Tables S5–S7).

Step 4: Consistency was assessed using Equation (1), where a matrix is considered consistent if $d(R, \overline{R}) < 0.1$. As shown in Supplementary Materials Table S8, all decision-makers' matrices fall below this threshold, confirming their consistency.

Step 5: After confirming the consistency of each decision-maker's intuitionistic preference matrix, the criteria weights were calculated using Equation (4). The weights, expressed as intuitionistic fuzzy numbers (μ, ν, and π), are presented in Supplementary Materials Table S9. This procedure ensures that the relative importance of each criterion is quantified rigorously while preserving the uncertainty inherent in expert judgments.

Step 6: The IFWA operator (Equation (5)) was applied to aggregate the individual decision-maker weights, producing the final set of criteria weights used in the evaluation. Table 9 presents the aggregated weights for each criterion. These aggregated weights serve as the basis for the subsequent IF-TOPSIS analysis, ensuring that expert judgments and methodological rigor are incorporated into the ranking of healthcare waste treatment alternatives.

Table 9. Aggregated criteria weights for each criterion.

Criteria	μ	ν	π	Criteria	μ	ν	π
C_{En1}	0.095	0.854	0.050	C_{Ec1}	0.096	0.850	0.054
C_{En2}	0.090	0.855	0.055	C_{Ec2}	0.094	0.848	0.058
C_{En3}	0.084	0.858	0.058	C_{Ec3}	0.082	0.861	0.057
C_{En4}	0.086	0.855	0.059	C_{S1}	0.086	0.859	0.055
C_{En5}	0.097	0.851	0.052	C_{S2}	0.092	0.853	0.054
C_{En6}	0.098	0.844	0.059	C_{T1}	0.095	0.858	0.047
C_{En7}	0.087	0.853	0.061	C_{T2}	0.096	0.853	0.052
C_{En8}	0.103	0.840	0.057	C_{T3}	0.100	0.850	0.050
C_{En9}	0.098	0.842	0.060				

4.2. Evaluating Healthcare Waste Treatment Alternatives Using IF-TOPSIS

Step 1: The weights (importance) of the three DMs were determined using linguistic terms and subsequently converted into intuitionistic fuzzy numbers according to Equation (6). The calculated weights (λ), reflecting each DM's influence on the group decision, are presented in Table 10. Incorporating these weights ensures that the subsequent aggregation of evaluations appropriately accounts for the expertise and judgment of each participant.

Table 10. Weights of the decision-makers based on linguistic assessments.

	DM 1	DM 2	DM 3
Linguistic Term	MI	HI	VHI
Weight (λ)	0.238	0.356	0.406

Step 2: Each decision-maker evaluated all alternatives against each criterion, producing an intuitionistic fuzzy decision matrix. This matrix is provided in Supplementary Materials Table S10. Subsequently, using Equation (7), the individual matrices were aggregated into a single group-level intuitionistic fuzzy decision matrix, presented in Supplementary Materials Table S11.

Step 3: Rather than recalculating criterion weights within IF-TOPSIS, the aggregated criteria weights obtained from the IF-AHP approach were administered. These weights, derived by combining individual decision-maker weights via the IFWA operator, ensure consistency between the weighting and ranking stages. The aggregated criteria weights were presented in Table 9.

Step 4: The aggregated weighted intuitionistic fuzzy decision matrix was constructed using Equations (8)–(10), and the results are provided in Supplementary Materials Table S12.

Step 5: The IF-PIS and the IF-NIS were determined according to Equations (11)–(14) in the methodology section. Among the 17 criteria, C_{Ec2}, C_{S2}, C_{T1}, C_{T2}, and C_{T3} were defined as benefit (maximization) criteria, while the remaining criteria were cost (minimization) criteria. The corresponding sets are $J_1 = \{C_{Ec2}, C_{S2}, C_{T1}, C_{T2}, C_{T3}\}$ and $J_2 = \{C_{En1}, C_{En2}, C_{En3}, C_{En4}, C_{En5}, C_{En6}, C_{En7}, C_{En8}, C_{En9}, C_{Ec1}, C_{Ec3}, C_{S1}\}$. The computed IF-PIS and IF-NIS are provided in Supplementary Materials Table S13.

Step 6–8: Using Equations (15) and (16), the separation measures S_i^* and S_i^- were calculated for each alternative, representing the distances from the IF-PIS and IF-NIS, respectively. Subsequently, the relative closeness coefficients C_i^* were computed according to Equation (17). Finally, alternatives were ranked based on their C_i^* values, with higher values indicating better performance. The results are summarized in Table 11.

Table 11. Separation measures, relative closeness coefficients, and ranking of alternatives.

Alternatives	S_i^*	S_i^-	C_i^*	Ranking
A_1	0.058	0.010	0.143	4
A_2	0.009	0.058	0.860	1
A_3	0.027	0.037	0.583	2
A_4	0.036	0.029	0.446	3

As illustrated in Table 11, A_2 steam sterilization is the best-performing healthcare waste treatment technology among the alternatives evaluated.

4.3. Sensitivity Analysis

To evaluate the robustness of the proposed IF-AHP–TOPSIS framework, a sensitivity analysis was conducted by systematically varying the weights of the criteria across multiple scenarios. Scenarios S1–S10 explored gradual shifts in overall weight distribution among all criteria, ranging from a single dominant criterion (e.g., S1: (1.00, 0.00, 0.00)) to more balanced configurations (e.g., S10: (0.10, 0.90, 0.00)), representing varying levels of decision-maker certainty. Scenarios S11–S15 focused on theme-based weight variations, highlighting environmental, economic, social, and technological clusters individually or in combination.

The numerical results of all scenarios are presented in Supplementary Materials Table S14, while Figure 3 below visualizes the IF-TOPSIS scores for each alternative. In all scenarios, A_2 (steam sterilization) consistently attained the highest scores, validating its methodological robustness and minimal sensitivity to criteria weight fluctuations. A_1 exhibited substantial variation under certain scenarios, particularly when environmental criteria were deprioritized, indicating higher sensitivity. Meanwhile, A_3 and A_4 remained relatively stable, with minor fluctuations, and A_3 showed notable improvement under scenarios emphasizing minimal criteria weights (S10), suggesting conditional advantages.

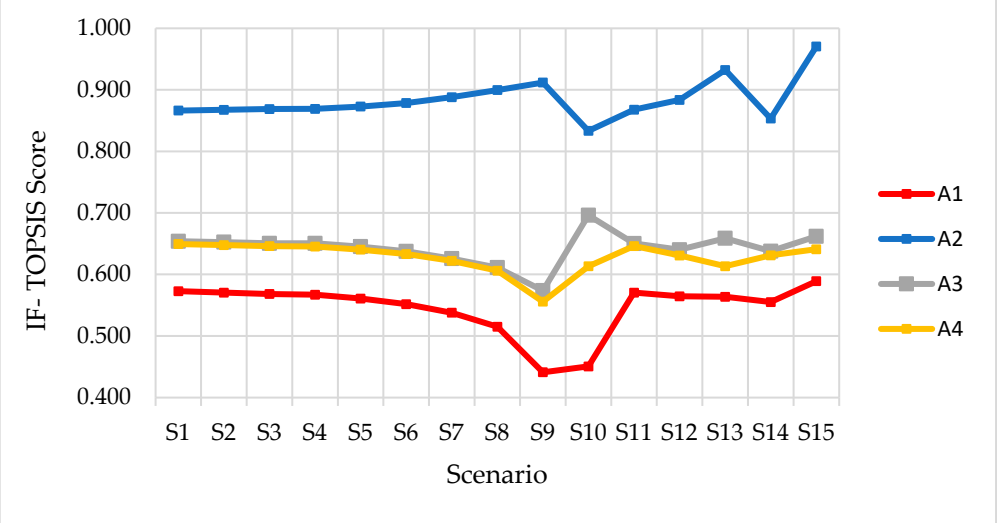


Figure 3. Sensitivity analysis results: ranking stability of alternatives across scenarios S1–S15.

These observations demonstrate that the proposed decision-making framework is robust, with A_2 emerging as the most resilient option under varying decision contexts. The sensitivity analysis underscores the critical influence of environmental and technological criteria clusters on alternative rankings, emphasizing the importance of adaptable decision-support tools capable of accommodating shifting stakeholder priorities.

4.4. Comparative Analysis and Methodological Advantages

To delineate the specific advantages of the proposed framework, this section conducts a comparative analysis between the current study and existing MCDM approaches in the literature. To contextualize the methodological contributions of this study, Table 12 contrasts the proposed IF-AHP–IF-TOPSIS framework with representative HCWM-related MCDM studies with respect to methodological structure, uncertainty modeling capability, sustainability scope, and analytical robustness.

Table 12. Comparative analysis of the proposed framework with the selected HCWM literature.

Comparison Dimension	Liu et al. [52]	Ghram et al. [59]	Manupati et al. [61]	Etim et al. [11]	Current Study (This Work)
Methodology	Modified MULTIMOORA	Fuzzy ARAS-H	Fuzzy VIKOR	AHP/Fuzzy AHP	Integrated IF-AHP and IF-TOPSIS
Uncertainty Modeling	Interval 2-Tuple Linguistic	Limited	Limited	Limited	Integrated Intuitionistic Fuzzy Sets (IFSs)
Number of Criteria	8	8	10	9	17 (Comprehensive)

Table 12. *Cont.*

Comparison Dimension	Liu et al. [52]	Ghram et al. [59]	Manupati et al. [61]	Etim et al. [11]	Current Study (This Work)
Circular Economy Consideration	Low	Low	Low	Low	High (Direct Integration)
Methodological Integration	Single Stage	Single Stage	Single Stage	Single Stage	Unified Weighting and Ranking
Sensitivity/ Robustness Analysis	None	None	Limited	7 Scenarios	15 Robust Scenarios

As shown in Table 12, existing studies typically exhibit one or more of the following limitations:

(i) Insufficient treatment of expert uncertainty;
(ii) Fragmented methodological structures (e.g., single-stage or inconsistent integration);
(iii) Limited sustainability or circular economy considerations;
(iv) Lack of robustness verification through sensitivity or scenario analysis.

Accordingly, the proposed framework addresses these gaps through four key methodological advantages, which constitute the core distinctions of this study and are elaborated as follows:

- Handling Cognitive Uncertainty and Expert Hesitation: Conventional MCDM methods—such as AHP, TOPSIS, and VIKOR—often rely on deterministic evaluations and struggle to adequately capture the expert uncertainty and hesitation inherent in real-world contexts [2,6,23]. To overcome these limitations, this study utilizes intuitionistic fuzzy sets (IFSs), which extend conventional fuzzy logic by explicitly modeling membership, non-membership, and hesitation degrees [70,73]. This approach allows for a more realistic representation of the ambiguity in sustainability evaluations compared to conventional single-layer fuzzy sets [22].
- Methodological Coherence and Semantic Consistency: A significant gap in the existing HCWM literature is the reliance on single-stage models that focus only on ranking without integrated weighting [61]. This study addresses these gaps by integrating IF-AHP and IF-TOPSIS within a unified framework, as suggested by the need for coherent decision support systems [24]. This integration eliminates semantic inconsistency issues, often caused by mixing classical weights with fuzzy rankings, ensuring that the entire process remains within a consistent intuitionistic fuzzy environment [47,49].
- Comprehensive Sustainability and Circular Economy Focus: Many previous studies evaluate treatment technologies based on limited operational or technical criteria without explicitly embedding long-term environmental goals [59]. This study addresses this limitation by evaluating alternatives across 17 comprehensive criteria, a set specifically developed in this study to incorporate circular economy principles, such as resource recovery and energy efficiency. While studies like Etim et al. (2021) have emphasized the need for sustainability-oriented assessment in healthcare waste management [11], this study operationalizes these goals through a more extensive and integrated criteria set directly linked to circularity objectives.
- Evidence of Ranking Stability via Scenario Analysis: While existing studies rarely examine the stability of treatment rankings under varying priorities [52,59], a core advantage of this study is the inclusion of a 15-scenario sensitivity analysis. By testing the model's robustness across extreme weight distributions from single-criterion dominance to balanced weighting, the study confirms that steam sterilization remains

a resilient and stable option. This provides decision-makers with a higher degree of reliability and transparency compared to the limited assessment models discussed in prior research [11,61].

5. Discussion

The results indicate that steam sterilization consistently ranks as the most sustainable healthcare waste treatment technology under uncertainty when evaluated using the integrated IF-AHP–IF-TOPSIS framework. Its performance across environmental, economic, social, and technologic dimensions suggests a generally balanced sustainability profile, which remains stable across multiple weighting scenarios and diverse stakeholder priorities.

These findings correspond to prior empirical and technical research reporting lower emissions, effective pathogen neutralization, and reduced long-term risks for steam-based systems compared to incineration, microwave, and landfill disposal [14,16,51,52,56–58,64]. The consistency between our results and the existing literature reinforces the robustness of steam sterilization as a practical and sustainable option, particularly in regions with comparable infrastructure and regulatory contexts.

Methodologically, this study demonstrates how intuitionistic fuzzy logic enhances sustainability assessments by capturing hesitation and ambiguity in expert judgment. Conventional MCDM approaches using deterministic or single-layer fuzzy evaluations provide limited representation of cognitive uncertainty. Incorporating intuitionistic fuzzy sets into both criteria weighting and alternative ranking stages allows for a more nuanced reflection of complex, real-world decision environments where data may be incomplete or qualitative.

Although this study validates its outcomes against the prior empirical and technical literature, it is acknowledged that direct validation using site-specific operational data from existing healthcare waste management systems was not feasible. Access to detailed performance data at the facility or municipal level was limited, preventing a direct empirical comparison. Nevertheless, the observed alignment with previous studies provides indirect support for the framework's potential applicability. Future work could extend this study by incorporating real-world operational datasets to strengthen empirical validation.

From a practical standpoint, the framework offers a transparent, adaptable decision-support tool for healthcare authorities and municipal waste managers. The robustness of steam sterilization supports its prioritization, especially where incineration presents environmental concerns or landfill practices pose long-term public health risks. Stakeholders can systematically evaluate alternatives and reconcile competing priorities, aligning decisions with regional sustainability goals.

6. Conclusions

This study represents a hybrid IF-AHP–IF-TOPSIS framework that integrates intuitionistic fuzzy logic in both criteria weighting and alternative ranking to support sustainable healthcare waste management decisions under uncertainty. By effectively capturing hesitation, imprecision, and conflicting stakeholder preferences, the model provides a realistic representation of complex decision environments.

The results consistently identify steam sterilization as the preferred treatment option, demonstrating strong performance across environmental, economic, social, and technological dimensions. Its stability across varying weighting scenarios underscores its resilience to shifts in stakeholder priorities. In the example of Adana, this technology aligns with existing infrastructure and regulatory conditions, offering a practical and low-impact solution for healthcare waste treatment.

This framework offers actionable guidance for local and national authorities, thereby facilitating a systematic evaluation of treatment technologies, investment prioritization, and alignment with broader sustainability objectives. By following the methodology and interpretation steps outlined in Sections 3 and 4, healthcare waste management authorities can operationalize the IF-AHP–IF-TOPSIS framework to support evidence-based decision-making under uncertainty, ensuring that both scientific rigor and practical applicability are maintained.

Limitations include the reliance on a single regional case (Adana) and a limited expert pool, as well as the exclusion of spatial logistics and facility location considerations. Focusing on a single metropolitan context may influence the relative importance of certain criteria such as treatment capacity, energy consumption, operating costs, or public acceptance and may therefore affect the transferability of the ranking results to regions with different healthcare capacities, geographic characteristics, or waste generation profiles. Similarly, a limited number of experts may affect the dispersion of judgments and constrain the representation of institutional heterogeneity, although the use of intuitionistic fuzzy sets partially mitigates individual bias by explicitly modeling hesitation and uncertainty. These limitations can be mitigated by applying the proposed IF-AHP–IF-TOPSIS framework or other suitable methods across multiple regions and institutional contexts. Expanding expert participation to include a broader range of stakeholders and integrating spatial decision-support tools such as GIS can further capture transportation distances and facility location effects.

Furthermore, incorporating dynamic or real-time operational data and complementary sustainability assessment methods can enhance the robustness, adaptability, and policy relevance of the framework, enabling more context-sensitive and implementation-oriented decision support.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su18031167/s1, Table S1. Comprehensive Evaluation Criteria: Definitions, Circular Economy Focus, and Supporting Literature. Table S2. Intuitionistic Preference Relation Matrix for Decision Maker 1. Table S3. Intuitionistic Preference Relation Matrix for Decision Maker 2. Table S4. Intuitionistic Preference Relation Matrix for Decision Maker 3. Table S5. Perfect Multiplicative Intuitionistic Preference Relation Matrix for Decision Maker 1. Table S6. Perfect Multiplicative Intuitionistic Preference Relation Matrix for Decision Maker 2. Table S7. Perfect Multiplicative Intuitionistic Preference Relation Matrix for Decision Maker 3. Table S8. Consistency Values $\mathrm{d}(R, \overline{R})$ Across All Criteria and Decision Makers. Table S9. Individual Criteria Weights for Each Decision Maker. Table S10. Intuitionistic Fuzzy Decision Matrix Based on Expert Evaluations. Table S11. Aggregated Intuitionistic Fuzzy Decision Matrix. Table S12. Aggregated Weighted Intuitionistic Fuzzy Decision Matrix. Table S13. Intuitionistic Fuzzy Positive (A^*) and Negative (A^-) Ideal Solutions. Table S14. (a) Sensitivity Analysis Results: IFS-TOPSIS Scores under General Criterion Weight Scenarios (S1–S10). (b) Sensitivity Analysis Results: IFS-TOPSIS Scores under Theme-Based Criterion Cluster Weight Scenarios (S11–S15). References [14,16,41–44,47,48,50–52,55,57,59] are cited in Supplementary Materials.

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