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A CONSENSUS-BASED FERMATEAN FUZZY WASPAS METHODOLOGY FOR SELECTION OF HEALTHCARE WASTE TREATMENT TECHNOLOGY SELECTION

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***Abstract**: Healthcare waste (HCW) management is a complex issue influenced by many factors, including technological, economic, environmental, and social factors. It is possible to regard the evaluation of the best treatment technique for HCW management as a challenging case of MCDM (multi-criteria decision-making), where various alternatives and evaluation criteria must be considered. The presentation and handling of the shaky data are crucial to choosing the HCW treatment technology. In order to address the issue of MCDM issues with Fermatean fuzzy (FF) data, we first build a consensus-based WASPAS approach in this study. In the suggested integrated methodology, the rank of the alternatives is determined using the WASPAS method in an FF environment, and the attribute weights are estimated using the entropy measure technique. In the preceding, an HCW treatment technology assessment issue is considered to make the proposed structure's applicability more transparent. In this study, four HCW treatment methods—chemical disinfection, microwave disinfection, cremation, and autoclaving—are considered options. According to the study's findings, autoclaving is the most effective HCW treatment method. Additionally, we demonstrate a sensitivity assessment using several criteria weight sets to test the stability of our intriguing proposed approach. We also call attention to a contrast between our suggested approach to decision-making and the practices now in use.*

***Keywords:** Fermatean fuzzy numbers, consensus reaching, WASPAS, healthcare waste treatment technology selection.*

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1. Introduction

Healthcare procedures are designed to save and extend human lives, but the clinical waste they generate contains many bacteria that could naturally contaminate water, soil, and air, spread disease, and jeopardize people's health (Chen et al., 2018; Gusca et al., 2017; Liu et al., 2015). According to the World Health Organization (WHO), "medical waste" includes all garbage created by hospitals, laboratories, and medical research facilities—some of which are among the most toxic and potentially dangerous waste categories that emerge in communities (Aung et al., 2019; Baghapour et al., 2018). Several industrialized and developing countries have passed particular legislation to segregate hazardous and non-hazardous rubbish efficiently. Unlike non-hazardous wastes, which may readily be handled alongside municipal solid waste, hazardous medical waste must be disposed of with special care. Inefficient waste management can cause environmental deterioration and several life-threatening illnesses in humans. Therefore, it is essential to comprehend how to choose safe and effective therapies and properly dispose of medical waste if you care about the welfare of people and the general public health (Badi et al., 2019; Voudrias, 2016).

The process of managing medical waste includes the removal of waste from medical and healthcare facilities, the selection of modes of transportation and routes to the treatment facilities, the technology of treatment, and the location of disposal. Choosing the right technology to treat medical waste has attracted much attention in research because of its substantial effect on the economy, ecology, and society (Hinduja & Pandey, 2018). When choosing the finest medical waste treatment technology, DEs must consider various qualitative and quantitative factors or features. However, no treatment method performs better than the alternatives across the board. In light of this, evaluating medical waste treatment technology is a difficult MCDM problem that can be assessed using a range of qualitative and quantitative metrics. Choosing a reliable technique for comparing different medical waste treatment systems is critical in light of the many conflicting factors.

The concept of Fermatean fuzzy sets (FFSs) was established by Senapati & Yager (2020) as an extension of the fuzzy set (FS) (Zadeh, 1965) and Pythagorean fuzzy set (PFS) (Yager, 2014). The addition of "cube of membership degree" and "cube of non-membership degree" is ≤ 1 for any element of a FFS. Consequently, FFSs act as a significant tool in tackling uncertain data. Recently, works on the FF AOs have been rapidly progressing. To integrate the information with FFSs, the FF weighted algebraic and geometric AOs (Senapati & Yager, 2019), FF Dombi weighted algebraic and geometric AOs (Aydemir & Gunduz, 2020), FF Hamacher weighted algebraic and geometric AOs (Hadi et al., 2021), and FF Einstein weighted algebraic and geometric AOs (Rani & Mishra, 2020, 2021) have been used up until this point. On the other hand, the FF decision support models have been utilized in green construction supplier assessment (Keshavarz-Ghorabaee et al., 2020), electric vehicle charging station selection (Rani & Mishra, 2021), healthcare waste disposal location selection (Mishra & Rani, 2021), occupational risk assessment (Gul et al., 2021), examination of sophisticated programming languages in air transportation (Ucal Sari et al., 2022), taxation of public transit investments (Simic et al., 2021), the blockchain technology selection in the logistics industry (Görçün et al., 2023a), evaluation of the pharmaceutical distribution and warehousing companies (Aytekin et al., 2022) and renewable energy source selection (Mishra et al., 2022), warehouse site selection (Saha et al., 2023) and food waste treatment technology assessment (Rani et al., 2022), and others (Mishra et al., 2022).

A. Research motivation

The selection and prioritization of appropriate medical waste treatment technology is a critical and uncertain MCDM problem encountered by hospitals and medical facilities due to inaccurate knowledge, ambiguous human mind, time constraints, and lack of information, as evidenced by the fact that Fermatean fuzzy (FF) sets have a greater capacity to manage uncertainty and imprecision that happened in various real-life MCDM challenges than IFSs and PFSs. This inspiration led to the current study's concentration on evaluating HCW treatment technologies in a FF sets setting. The available FF decision support models are FF-TOPSIS (Senapati & Yager, 2020), FF-MULTIMOORA (Rani & Mishra, 2021); FF- VIKOR (Gül, 2021), FF-COPRAS (Saraji et al., 2021), and FF-MARCOS (Ucal Sari & Sargin, 2022). In group decision-making, a consensus determination procedure is essential for experts to enhance a consensus level (Liu & Huang, 2020). Unfortunately, none of the previous FF decision support models can deal with the "consensus-reaching process" for experts.

B. Our Contribution

With the help of Fermatean fuzzy information, we have expanded the traditional WASPAS method to choose the best suitable medical waste treatment technology alternative. A consensus-based FF-WASPAS method is the main topic of this study. The novel contributions are:

- A brand-new consensus-based FF-WASPAS approach is created to assess MCDM issues.
- The entropy technique is used to assess the weights of the criteria.
- To demonstrate the viability and applicability of the consensus-based FF-WASPAS technique, a real-world case study of the choice of medical waste treatment technology is explored in the context of the FF system.
- In order to verify the conclusions reached by the suggested framework, a sensitivity investigation is presented.
- In order to prove the superiority of the developed approach, comparative research is presented.

C. Arrangement of the paper

Following is a summary of the remaining paper. We provide a brief review of the literature in Section 2. We introduce a few essential concepts related to FF sets in Section 3. In this section, we design a consensus-based FF-WASPAS strategy where FFNs represent the criteria values. To clarify the created method, we use a case study of the technology selection for HCW treatment in Section 4. Sensitivity investigation of the weights of criteria and Comparative analysis are covered in Section 5. We draw some conclusions from the entire study and summarise the prospects for the future in section 6.

2. Literature review

2.1. Works on healthcare waste management

The literature has, however, published many studies on the techniques used to manage medical waste. For instance, Brent et al. (2007) used the LCA and AHP to assess the healthcare waste management framework. In order to select hospitals and evaluate their contributions to overall solid waste pollution, Karamouz et al. (2007) employed AHP. Alagöz & Kocasoy (2008; 2007) considered Istanbul's medical waste management mechanism the most effective in their study of medical waste in Metropolitan cities. Birpinar et al. (2009) also investigated the production, collection, storage, recycling, transportation, and safe disposal of medical waste. The AHP model was used by Karagiannidis et al. (2010) to compare various methods for disposing of medical waste.

Additionally, Ho (2011) and Dursun et al. (2011b, 2011a) chose the best method for handling and discarding medical waste using a fuzzy-based framework Özkan (2013) examined the situation of waste management in Turkey's healthcare sector at the time and chose the optimum treatment method from a variety of available options. Qian et al. (2016) proposed an original decision-making process to evaluate various medical waste treatment systems. Voudrias (2016) compared the effectiveness of five infectious medical waste treatment systems based on several characteristics using the AHP model. Aung et al. (2019) offered an evaluation method to rank Myanmar's medical waste management system. Yazdani et al. (2020) recently evaluated the locations for disposing of medical waste using an integrated best-worst model and interval rough estimates. The optimal strategy for disposing of medical waste was evaluated using an expanded EDAS methodology with intuitionistic fuzzy sets by (Mishra, Rani, et al., 2019). An evaluation method was developed by Ghram & Frikha (2020) to evaluate healthcare waste technologies under the ARAS-H fuzzy condition. The MCDM method developed by Pamučar et al. (2021) was based on the BWM-MABAC approach with a D-number.

Additionally, this method was applied to assess HCW management. Torkayesh et al. (2021) developed the stratified best-worst multi-criteria decision-making method to choose a sustainable waste disposal solution. An information fusion FMEA method was developed by Ouyang et al. (2021) to assess healthcare risk management. Interval probability and 2-tuple linguistic values were used in this strategy. In order to assess the choice of treatment technology in the field of medical waste, Liu et al. (2021) used a Pythagorean fuzzy approach with a compromise solution method. Salimian & Mousavi (2022) worked on selecting healthcare waste treatment technologies using the Intuitionistic fuzzy sets-based MCDM method. Görçün et al. (2023) evaluated logistics service providers for medical waste disposal treatment in the healthcare industry with the help of a novel integrated approach involving the extended form of the Delphi - SWARA - COPRAS approaches based on Interval Valued Fermatean fuzzy sets. Kundu et al. (2021) assessed medical device selection in private hospitals using fuzzy MCGDM methods consisting of the fuzzy PSI and MARCOS combination.

2.2. WASPAS method

Zavadskas et al. (2012) combined the WSM and WPM to create a unique utility degree-based MCDM method called WASPAS. This methodology was designed to deal with a variety of realistic decision-making concerns. The benefits of WASPAS are as follows: (a) it employs a straightforward method of calculation, (b) it can select the most preferred alternative by making use of AOs, (c) being a mixture of WSM and WPM, it has more accuracy, and (d) it allows us to estimate with the maximum amount of accuracy conceivable. Since the inception of the WASPAS method, numerous works have been done. Deveci et al. (2018) developed interval type-two sets based model with WASPAS and TOPSIS tools. Stanujkić & Karabašević (2018) proposed the Intuitionistic fuzzy (IF) WASPAS technique to survey the websites. Mishra & Rani (2018) assessed reservoir flood control management using the interval-valued IF-WASPAS technique with information measures. Pamučar et al. (2021) identified safety advisors for hazardous material transportation using the linguistic neutrosophic WASPAS tool. Mishra, Singh, et al. (2019) assessed the mobile phone service providers using IF- WASPAS tool. Mishra, Rani, et al. (2019) developed a hesitant fuzzy-WASPAS method for green supplier selections. Kahraman et al. (2019) introduced the Pythagorean fuzzy WASPAS model to select the most reasonable administrators. Keshavarz-Ghorabaee et al. (2019) worked on assessing sustainable developed strategies using Type-2 fuzzy-based WASPAS technique. Bid & Siddique (2019) assessed human hazards resultant combination of WASPAS and TOPSIS techniques. Kutlu Gundogdu & Kahraman (2019) investigated the robot selection problem for the industry using the WASPAS approach with spherical fuzzy data. Krishankumar et al. (2019) worked on selecting construction project risk technique statistical variance and WASPAS technique under dual hesitant fuzzy linguistic term sets. (Schitea et al., 2019) selected the best hydrogen mobility roll-up site utilizing integrated WASPAS, COPRAS, and EDAS under intuitionistic fuzzy sets. Dorfeshan & Mousavi (2020) assessed critical paths of aircraft maintenance planning using a coordinated MABAC and WASPAS under the interval type-two setting. Sharma & Pradhan (2020) examined the machinability criteria for SUS-304L steel using the WASPAS model for fuzzy sets to address the doctor recruitment issue. Mohagheghi & Mousavi (2020) resolved a sustainable project portfolio problem using the WASPAS model with interval-valued Pythagorean fuzzy sets. Davoudabadi et al. (2020) addressed a supplier evaluation issue using a combined approach under an interval-valued IF setting. Rani & Mishra (2020) used the WASPAS approach with q-rung orthopair fuzzy data to assess desirable alternative-fuel technology. Badalpur & Nurbakhsh (2021) investigated the negative impacts of risks on the project using the WASPAS tool. Rudnik et al. (2021) worked on selecting improvement projects with the ordered fuzzy WASPAS method. Simić et al. (2021) solved the issue of selection of last-mile delivery mode using the Picture fuzzy WASPAS method. The selection of eco-friendly vendors was made by Liu et al. (2022) under a Bipolar complex fuzzy environment with the CRITIC-WASPAS tool.

3. Methodology

3.1. Basic concepts

Definition 1 (Senapati & Yager, 2020): An FFS ζ on Γ is described by $\zeta = \{\langle y_i, \mu(y_i), \nu(y_i)\rangle | y_i \in \Gamma\}$, where $\mu,\ \nu: \Gamma \to [0,\ 1]$ are the membership and non-membership degrees of $y_i \in \Gamma$ to ζ, , respectively, satisfying $0 \le (\mu(y_i))^3 + (\nu(y_i))^3 \le 1$. Also, we use $\pi_\zeta(y_i) = \sqrt[3]{1 - (\mu_\zeta(y_i))^3 - (\nu_\zeta(y_i))^3}$. An FFS ζ transforms to a FF number (FFN) if Γ contains only one element, and we write $\zeta =< \mu, \nu >$, for $\mu,\ \nu \in [0,\ 1]$ and $0 \le \mu^3 + \nu^3 \le 1$.

Definition 2 (Mishra & Rani, 2021): Consider an FFN $\zeta =< \mu,\ \nu >$. Then:

$$\mathbb{S}_\zeta = \frac{1}{2}(1 + \mu^3 - \nu^3),$$
$$\mathbb{A}_\zeta = \mu^3 + \nu^3, \quad (1)$$

are known as the accuracy and score values of ζ, where $\mathbb{A}_\zeta \in [0,\ 1]$and $\mathbb{S}_\zeta \in [0,\ 1]$. For the FFNs $\zeta_1 =< \mu_1,\ \nu_1 >$ and $\zeta_2 =< \mu_2,\ \nu_2 >$, a ranking rule is:

$$(i)\ \zeta_1 \succ \zeta_2 \ \left|\ \begin{array}{l} \mathbb{S}_{\zeta_1} > \mathbb{S}_{\zeta_2}, \\ \mathbb{S}_{\zeta_1} = \mathbb{S}_{\zeta_2},\ \mathbb{A}_{\zeta_1} > \mathbb{A}_{\zeta_2} \end{array}\right.$$
$$(ii)\ \zeta_1 = \zeta_2 \ |\ \mathbb{S}_{\zeta_1} = \mathbb{S}_{\zeta_2},\ \mathbb{A}_{\zeta_1} = \mathbb{A}_{\zeta_2}.$$

Definition 3 (Mishra & Rani, 2021): For the FFNs $\zeta_1 =< \mu_1,\ \nu_1 >$ and $\zeta_2 =< \mu_2,\ \nu_2 >$, the basic operations are:

$(i)\ \zeta_1^c =< \nu_1,\ \mu_1 >$,

$(ii)\ \zeta_1 \oplus \zeta_2 = \left\langle \sqrt[3]{\mu_1^3 + \mu_2^3 - \mu_1^3\mu_2^3}, \nu_1\nu_2 \right\rangle$,

$(iii)\ \zeta_1 \otimes \zeta_2 = \left\langle \mu_1\mu_2, \sqrt[3]{\nu_1^3 + \nu_2^3 - \nu_1^3\nu_2^3} \right\rangle$,

$(iv)\ \lambda\zeta_1 = \left\langle \sqrt[3]{1 - (1 - \mu_1^3)^\lambda},\ \nu_1^\lambda \right\rangle (\lambda > 0)$,

$(v)\ \zeta_1^\lambda = \left\langle \mu_1^\lambda,\ \sqrt[3]{1 - (1 - \nu_1^3)^\lambda} \right\rangle (\lambda > 0)$.

Definition 4 (Mishra & Rani, 2021): Let $\zeta_1 =< \mu_1,\ \nu_1 >$ and $\zeta_2 =< \mu_2,\ \nu_2 >$ be two FFNs. Then the distance between these FFNs is defined as:

$$Dist(\zeta_1,\ \zeta_2) = \sqrt{0.5 \times ((\mu_1^3 - \mu_2^3)^2 + (\nu_1^3 - \nu_2^3)^2 + (\pi_1^3 - \pi_2^3)^2)}. \quad (2)$$

Definition 5 (Mishra & Rani, 2021): Assume $\zeta_j = (\mu_j, \nu_j), j = 1,2,\ldots,n$ be FFNs. Then FFWA and FFWG operators are given respectively by

$$FFWA(\zeta_1, \zeta_2, \ldots, \zeta_n) = \overset{n}{\underset{j=1}{\oplus}} w_j\zeta_j = \left\langle \sqrt[3]{1 - \prod_{j=1}^n (1 - \mu_j{}^3)^{w_j}}, \prod_{j=1}^n \nu_j{}^{w_j} \right\rangle, \quad (3)$$

$$FFWG(\zeta_1, \zeta_2, \ldots, \zeta_n) = \overset{n}{\underset{j=1}{\otimes}} w_j\zeta_j = \left\langle \prod_{j=1}^n \mu_j{}^{w_j}, \sqrt[3]{1 - \prod_{j=1}^n (1 - \nu_j{}^3)^{w_j}} \right\rangle, \quad (4)$$

where w_j is the weight of $\zeta_j, j = 1(1)n$, with $\sum_{j=1}^{n} w_j = 1, w_j \in [0,1]$.

3.2. A consensus-based FF-WASPAS methodology

Assume that m is the number of alternatives A_i ($i = 1,\ 2,\ \ldots,\ m$) and n is the number of criteria C_j ($j = 1,\ 2,\ \ldots,\ n$) connected with a group decision-making issue in which each alternative is evaluated by the decision-makers E_r ($r = 1,\ 2,\ \ldots,\ l$) under the FF environment. Consider that the initial findings examined by the decision-makers are depicted as the FF decision matrices $M_r = [\zeta_r^{(ij)}]_{m\times n} = [< \mu_r^{(ij)}, \nu_r^{(ij)} >]_{m\times n}$.

Step 1: Obtain the aggregated FF decision matrix using the FFWA (or FFWG) operator.

The aggregated FF decision matrix is $[\zeta^{(ij)}]_{m\times n} = [< \mu^{(ij)},\ \nu^{(ij)} >]_{m\times n}$, where:

$\zeta^{(ij)} = FFWA(\zeta_1^{(ij)},\ \zeta_2^{(ij)},\ \ldots,\ \zeta_l^{(ij)}) = \overset{l}{\underset{r=1}{\oplus}} (\varpi_r\zeta_r^{(ij)}) (i = 1,\ 2,\ \ldots,\ m;\ j = 1,\ 2,\ \ldots,\ n)$, (5)

where ϖ_r is the weight of the decision-maker E_r ($r = 1,\ 2,\ \ldots,\ l$).

Step 2: Find the consensus degree of each decision-maker.

Utilizing the fact that the correlation measure is capable of describing the similarity degree between various opinions, we define the correlation measure $\Xi_j^{(r)}$ of the decision-maker E_r under the criterion C_j in this way:

$$\Xi_j^{(r)} = \frac{\sum_{i=1}^{m}\left[\left(\frac{Dist_{ij}^{(r)}}{Dist_j^{(r)}} - \frac{1}{m}\sum_{i=1}^{m}\frac{Dist_{ij}^{(r)}}{Dist_j^{(r)}}\right)\times\left(\frac{Dist_{ij}}{Dist_j} - \frac{1}{m}\sum_{i=1}^{m}\frac{Dist_{ij}}{Dist_j}\right)\right]}{\sqrt{\sum_{i=1}^{m}\left(\frac{Dist_{ij}^{(r)}}{Dist_j^{(r)}} - \frac{1}{m}\sum_{i=1}^{m}\frac{Dist_{ij}^{(r)}}{Dist_j^{(r)}}\right)^2} \times \sqrt{\sum_{i=1}^{m}\left(\frac{Dist_{ij}}{Dist_j} - \frac{1}{m}\sum_{i=1}^{m}\frac{Dist_{ij}}{Dist_j}\right)^2}}$$

$$(j = 1,\ 2,\ \ldots,\ n;\ r = 1,\ 2,\ \ldots,\ l), \quad (6)$$

where

$$\zeta_r^{(ij)(+)} = \left\langle \max_i \mu_r^{(ij)},\ \min_i \nu_r^{(ij)} \right\rangle, \zeta_r^{(ij)(-)} = \left\langle \min_i \mu_r^{(ij)},\ \max_i \nu_r^{(ij)} \right\rangle,$$

$$\zeta^{(ij)(+)} = \left\langle \max_i \mu^{(ij)},\ \min_i \nu^{(ij)} \right\rangle, \zeta^{(ij)(-)} = \left\langle \min_i \mu^{(ij)},\ \max_i \nu^{(ij)} \right\rangle,$$

$$Dist_{ij}^{(r)} = Dist(\zeta_r^{(ij)},\ \zeta_r^{(ij)(+)}), Dist_j^{(r)} = Dist(\zeta_r^{(ij)(+)}, \zeta_r^{(ij)(-)}),$$

$$Dist_{ij} = Dist(\zeta^{(ij)(+)},\ \zeta^{(ij)}), \text{and } Dist_j = Dist(\zeta^{(ij)(+)},\ \zeta^{(ij)(-)}).$$

Next, the consensus degree $\rho^{(r)}$ of the decision-maker E_r can be defined as:

$$\rho^{(r)} = \frac{1}{n}\sum_{j=1}^{n}\Xi_j^{(r)} (r = 1,\ 2,\ \ldots,\ l). \quad (7)$$

It can be verified that $-1 \leq \rho^{(r)} \leq 1$. The greater value $\rho^{(r)}$ means the stronger consensus degree of the decision-maker E_r in the group. If ρ denotes the minimum consensus degree, then $\rho^{(r)} \geq \rho$ needs to be attained. When $\rho^{(r)} < \rho$, the FF decision matrices from Step 1 should be modified until $\rho^{(r)} \geq \rho$ is obtained for all decision-makers.

Step 3: Normalize the aggregated FF decision matrix.

Suppose that the normalized aggregated FF decision matrix is $\left[\tilde{\zeta}^{(ij)}\right]_{m\times n} = \left[< \tilde{\mu}^{(ij)}, \tilde{\nu}^{(ij)} >\right]_{m\times n}$, where:

$$\tilde{\zeta}^{(ij)} = \begin{cases} < \mu^{(ij)},\ \nu^{(ij)} > \text{,if} C_j \text{is beneficial criteria} \\ < \nu^{(ij)},\ \mu^{(ij)} > \text{,if} C_j \text{is non-beneficial criteria} \end{cases} (i = 1,\ 2,\ \ldots,\ m;\ j = 1,\ 2,\ \ldots,\ n). \quad (8)$$

Step 4: Estimation of the criteria weights.

The notion of entropy has been widely employed in the theory of uncertainty as it measures the degree of informational uncertainty. Motivated by this, we use the entropy measure to determine weights of the criteria.

Step 4.1: Obtain the normalized score matrix.

The normalized score matrix $\left[\mathbb{S}(\tilde{\zeta}^{(ij)})\right]_{m\times n}$ is derived using the following equation:

$$\mathbb{S}(\tilde{\zeta}^{(ij)}) = \frac{1+(\tilde{\mu}^{(ij)})^3-(\tilde{\nu}^{(ij)})^3}{2} (i = 1,\ 2,\ \ldots,\ m;\ j = 1,\ 2,\ \ldots,\ n). \quad (9)$$

Step 4.2: The entropy value Δ_j corresponding to the criterion C_j is clarified by:

$$\Delta_j = -\frac{1}{ln(m)}\sum_{i=1}^{m}\mathbb{S}(\tilde{\zeta}^{(ij)}) \times ln(\mathbb{S}(\tilde{\zeta}^{(ij)}))\ (j = 1,\ 2,\ \ldots,\ n). \quad (10)$$

Step 4.3: The objective weight of the criteria is ascertained as:

$$w_j = \frac{|1-\Delta_j|}{\sum_{k=1}^{n}|1-\Delta_k|} (j = 1,\ 2,\ \ldots,\ n). \quad (11)$$

where $w_j \in [0,\ 1] \forall j$, and $\sum_{j=1}^{n} w_j = 1$.

Step 5: Estimate the FF "relative significance degree" (RSD) for every option.

Step 5.1: The FF-RSD of A_i using WSM is calculated as:

$$\overline{RSD}(A_i) = \bigoplus_{j=1}^{n} (w_j \tilde{\zeta}^{(ij)}) \tag{12}$$

The FF-RSD of A_i using WPM is calculated as:

$$\overline{RSD}(A_q) = \bigotimes_{j=1}^{n} (\tilde{\zeta}^{(ij)})^{w_j} \tag{13}$$

Step 5.2: The overall FF significance degree of A_i is calculated by:

$$\eta_i = \left(p\overline{RSD}(A_i)\right) \tilde{\oplus} \left((1-p)\overline{RSD}(A_i)\right)(i = 1,2,\ldots,m) \tag{14}$$

or

$$\eta_i = \left(\overline{RSD}(A_i)\right)^p \tilde{\otimes} \left(\overline{RSD}(A_q)\right)^{(1-p)} (i = 1,2,\ldots,m) \tag{15}$$

Here, $p \in [0,1]$. For$p = 1$, and $p = 0$, WASPAS reduces to WSM and WPM respectively.

Step 5.3: Compute the scores of the FFNs$\eta_i (i = 1,2,\ldots,m)$.

Step 5.4: Generate the ranking order of alternatives and chose the best option.

Figure 1 describes the proposed methodology.

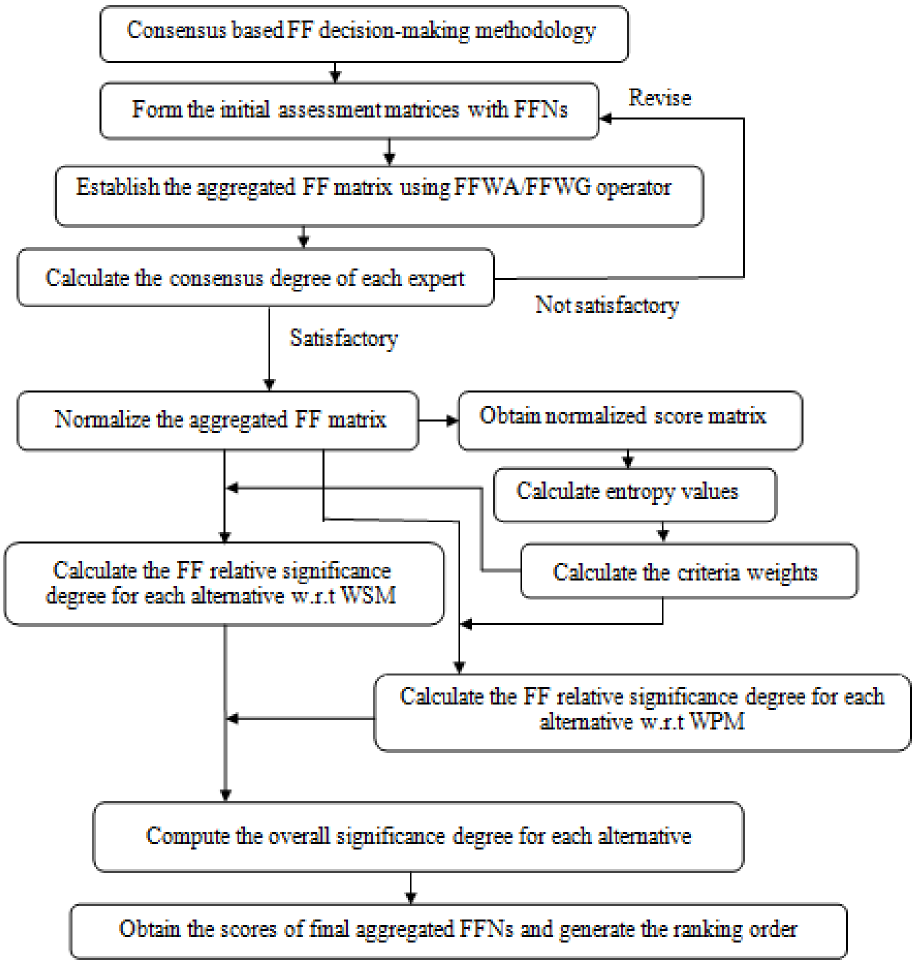

Figure 1. Flow chart of the proposed methodology

4. Case study and it's solution

Improper hospital waste disposal can pose serious dangers to the environment and public health (ASSOCHAM, 2022). There are several accessible and developing methods to deal with regulated medical waste (RMW) and reduce it to a less hazardous state in these places, each with specific advantages and responsibilities. Four medical waste treatment technology alternatives are chosen over the 15 criteria after initial screening. These are "chemical disinfection" (A1), "autoclaving" (A2), "microwave disinfection" (A3), and "incineration" (A4). The criteria are: "cost acceptance" (C_1) (Karagiannidis et al., 2010; Lu et al., 2016; Özkan, 2013; Tudor et al., 2009; Voudrias, 2016), "technology acceptance" (C_2) (Lu et al., 2016; Özkan, 2013; Voudrias, 2016), "need for skilled operators" (C_3) (Dursun et al., 2011b; Voudrias, 2016), "automation" (C_4) (Dursun et al., 2011b; Voudrias, 2016), "treatment effectiveness (C_5) (Dursun et al., 2011a; Lu et al., 2016), "microbial inactivation" (C_6) (Dursun et al., 2011a; Voudrias, 2016), "volume reduction" (C_7) (Dursun et al., 2011b; Özkan, 2013; Voudrias, 2016), "environmental impact of solid residues" (C_8) (Dursun et al., 2011b; Voudrias, 2016), "environmental impact of liquid residues" (C_9) (Voudrias, 2016; Zhao et al., 2009), "disposal cost" (C_{10}) (Voudrias, 2016; Zhao et al., 2009), "operation and maintenance costs (C_{11}) (Karagiannidis et al., 2010; Lu et al., 2016; Özkan, 2013; Tudor et al., 2009; Voudrias, 2016), "capital cost" (C_{12}) (Karagiannidis et al., 2010; Lu et al., 2016; Özkan, 2013; Tudor et al., 2009; Voudrias, 2016), "water consumption" (C_{13}) (Dursun et al., 2011b; Voudrias, 2016; Zhao et al., 2009), "energy consumption" (C_{14}) (Voudrias, 2016; Zhao et al., 2009), and "greenhouse gas emissions" (C_{15}) (Voudrias, 2016; Zhao et al., 2009). A team of three decision-making specialists was constituted to select the best option among these five medical waste treatment methods. One of them specializes in HCW management, while the other two are industrial and environmental engineers, respectively. LVs and their accompanying FFNs were defined by experts in Table 1. In this step, four DMEs are used to evaluate each choice in light of the criteria considered. The FF linguistic decision matrix is therefore shown in Table 1.

Table 1. Linguistic ratings

LVs	FFNs
Very very unimportant (VVU)	(0.20,0.95)
Very unimportant (VU)	(0.30,0.90)
Slightly unimportant (SU)	(0.40,0.85)
Unimportant (U)	(0.50,0.80)
Fair (F)	(0.60,0.70)
Important (I)	(0.75,0.60)
Slightly important (SI)	(0.80,0.50)
Very important (VI)	(0.85,0.40)
Very very important (VVI)	(0.90,0.30)
Absolutely important (AI)	(0.95,0.20)

To obtain a reasonable result, we implement the proposed consensus-based FF decision support model to prioritize the considered options under those predefined conflicting evaluation criteria. Assume that DEs' weights are respectively 0.2693, 0.2965, 0.1982, and 0.2360. Then, the aggregated FF decision matrix (Table 2) is obtained by using the FFWA operator. Assume that the minimum consensus degree is $\rho = 0.35$. The consensus degree of each expert is calculated based on Eqs. (6) and

(7) as: $\rho^{(1)} = 0.617$, $\rho^{(2)} = 0.488$, $\rho^{(3)} = 0.195$, and $\rho^{(4)} = 0.586$. Since $\rho^{(3)} < 0.35$, the initial assessments for 3rd expert should be modified. In the revised assessment matrix, for the 3rd expert, the new entries are: (7,2): **AI**, (9,2): **AI**, (9,3): **U**, (13, 3): **VVU**, (9, 4): **F**. We represent the revised aggregated matrix in Table 3. The consensus degrees are recalculated with the help of Eqs. (6) and (7) as: $\rho^{(1)} = 0.624$, $\rho^{(2)} = 0.488$, 0.363and $\rho^{(4)} = 0.574$. Since $\rho^{(r)} > 0.35$ $(r = 1,\ 2,\ 3{,}4)$, desired consensus reaching process has been done.

Table 2. Aggregated matrix

Crit.	A1	A2	A3	A4
C1	<.7771, .5472>	<.5553, .7489>	<.7584, .5642>	<.6336, .6931>
C2	<.6236, .7007>	<.6266, .7118>	<.7867, 0.5278>	<.7785, .5445>
C3	<.7111, .6177>	<.778, .5313>	<.6773, 0.6693>	<.792, .4977>
C4	<.7033, .6256>	<.7517, .5707>	<.6934, 0.64>	<.7067, .6304>
C5	<.6526, .6702>	<.6143, .7121>	<.5162, 0.7793>	<.7176, .6108>
C6	<.7435, .5897>	<.5836, .7455>	<.7449, 0.589>	<.7493, .5792>
C7	<.6916, .6456>	<.7755, .5537>	<.6916, 0.6456>	<.7268, .6109>
C8	<.6877, .6483>	<.7195, .601>	<.7321, 0.6121>	<.7273, .5972>
C9	<.6997, .6282>	<.7933, .5133>	<.6014, .729>	<.7179, .6075>
C10	<.7584, .5642>	<.7153, .6041>	<.5038, .7895>	<.6998, .6394>
C11	<.6982, .6403>	<.7014, .6262>	<.6696, .6754>	<.7973, .5096>
C12	<.7017, .6342>	<.6422, .6788>	<.7175, .6064>	<.661, .6867>
C13	<.7075, .6203>	<.7659, .5546>	<.7033, .6256>	<.6898, .6566>
C14	<.6014, .729>	<.5836, .7538>	<.7794, .5253>	<.6777, .6658>
C15	<.6671, .679>	<.6048, .7343>	<.6777, .6658>	<.7027, .6262>

Table 3. Revised aggregated matrix

Crit.	A1	A2	A3	A4
C_1	<.7771, .5472>	<.5553, .7489>	<.7584, .5642>	<.6336, .6931>
C_2	<.6236, .7007>	<.6266, .7118>	<.7867, .5278>	<.7785, .5445>
C_3	<.7111, .6177>	<.778, .5313>	<.6773, .6693>	<.792, .4977>
C_4	<.7033, .6256>	<.7517, .5707>	<.6934, .64>	<.7067, .6304>
C_5	<.6526, .6702>	<.6143, .7121>	<.5162, .7793>	<.7176, .6108>
C_6	<.7435, .5897>	<.5836, .7455>	<.7449, .589>	<.7493, .5792>
C_7	<.6916, .6456>	<.8252, .4826>	<.6916, .6456>	<.7268, .6109>
C_8	<.6877, .6483>	<.7195, .601>	<.7321, .6121>	<.7273, .5972>
C_9	<.6997, .6282>	<.863, .4004>	<.5319, .729>	<.6916, .6264>
C_{10}	<.7584, .5642>	<.7153, .6041>	<.5038, .7895>	<.6998, .6394>
C_{11}	<.6982, .6403>	<.7014, .6262>	<.6696, .6754>	<.7973, .5096>
C_{12}	<.7017, .6342>	<.6422, .6788>	<.7175, .6064>	<.661, .6867>
C_{13}	<.7075, .6203>	<.7659, .5546>	<.6295, .7105>	<.6898, .6566>
C_{14}	<.6014, .729>	<.5836, .7538>	<.7794, .5253>	<.6777, .6658>
C_{15}	<.6671, .679>	<.6048, .7343>	<.6777, .6658>	<.7027, .6262>

Next, we calculate the score matrix (extended form) (Table 4). Since C_{10}-C_{15} all are cost-type criteria is present, normalization is done. Then, the entropy values are determined by using Eq. (10). Finally, the weights of the criteria are calculated based on Eq. (11) as: w_1=0.073, w_2=0.0968, w_3=0.1487, w_4=0.0792, w_5=0.0095, w_6=0.0882, w_7=0.1313, w_8=0.0826, w_9=0.1365, w_{10}=0.0295, w_{11}=0.0311, w_{12}=0.012, w_{13}=0.0179, w_{14}=0.0466, and w_{15}=0.0171. The FF-RSD of all alternatives using WSM and WPM are calculated using Eqs. (12) and (13) respectively and are presented in Tables 4 and 5. The overall FF significance degree of alternatives are calculated by Eq. (14) (taking p=0.5) and are given as:

$$\eta_1=<0.8691, 0.4156>, \eta_2=<0.8874, 0.38365>, \eta_3=<0.8614, 0.4237>,$$
$$\eta_4=<0.8816, 0.3914>.$$

The scores of these FFNs are respectively 0.7924, 0.8213, 0.7815, 0.8126 according to which $A_2 \succ A_4 \succ A_1 \succ A_3$ ("" means "superior to") as preference order with A_2as the most suitable option.

Table 4. FF-RSD of alternatives using WSM

Crit.	A1	A2	A3	A4
C1	<.3562, .9569>	<.2388, .9791>	<.3448, .9591>	<.2768, .9736>
C2	<.2982, .9662>	<.2998, .9676>	<.3969, .94>	<.3912, .9429>
C3	<.4002, .9309>	<.4487, .9102>	<.3776, .942>	<.4596, .9014>
C4	<.3217, .9635>	<.3499, .9566>	<.3161, .9653>	<.3236, .9641>
C5	<.1456, .9962>	<.1358, .9968>	<.112, .9976>	<.1635, .9953>
C6	<.3573, .9545>	<.2685, .9744>	<.3582, .9544>	<.361, .953>
C7	<.3718, .9442>	<.4683, .9088>	<.3718, .9442>	<.395, .9373>
C8	<.3174, .9648>	<.3354, .9588>	<.3429, .9603>	<.34, .9583>
C9	<.3818, .9385>	<.508, .8826>	<.2803, .9578>	<.3765, .9381>
C10	<.1799, .9919>	<.1942, .9902>	<.2705, .98>	<.2072, .9895>
C11	<.2113, .9889>	<.2059, .989>	<.225, .9876>	<.164, .993>
C12	<.1523, .9958>	<.1651, .9947>	<.1447, .996>	<.1674, .995>
C13	<.1694, .9938>	<.1494, .9952>	<.1992, .9918>	<.181, .9934>
C14	<.2827, .9766>	<.2952, .9752>	<.1938, .9885>	<.2529, .982>
C15	<.1856, .9931>	<.2047, .9915>	<.1813, .9934>	<.1687, .994>

Table 5. FF-RSD of alternatives using WPM

Crit.	A1	A2	A3	A4
C1	<.9818, .235>	<.958, .3391>	<.98, .243>	<.9672, .3077>
C2	<.9553, .3419>	<.9558, .3486>	<.9771, .2481>	<.9761, .2566>
C3	<.9505, .3396>	<.9633, .2879>	<.9437, .3723>	<.9659, .2686>
C4	<.9725, .2801>	<.9777, .2528>	<.9714, .2876>	<.9729, .2826>
C5	<.996, .1503>	<.9954, .1619>	<.9937, .1825>	<.9969, .1349>
C6	<.9742, .2716>	<.9536, .3586>	<.9744, .2713>	<.9749, .2663>
C7	<.9527, .3429>	<.9751, .2495>	<.9527, .3429>	<.959, .3221>
C8	<.9696, .296>	<.9732, .2715>	<.9746, .2771>	<.974, .2695>
C9	<.9524, .3366>	<.9801, .2081>	<.9174, .4015>	<.9509, .3355>
C10	<.9833, .256>	<.9852, .2373>	<.993, .1591>	<.9869, .2308>
C11	<.9862, .2343>	<.9855, .2356>	<.9879, .2227>	<.9792, .2792>
C12	<.9945, .1719>	<.9954, .1545>	<.994, .1768>	<.9955, .1599>
C13	<.9915, .1982>	<.9895, .2197>	<.9939, .1723>	<.9925, .192>
C14	<.9854, .2248>	<.9869, .2174>	<.9704, .3089>	<.9812, .2583>
C15	<.9934, .1817>	<.9947, .1621>	<.9931, .1851>	<.992, .1935>

5. Discussions

5.1. Sensitivity analysis of the parameter

This part aims to analyze the sensitivity of the introduced consensus-based FF WASPAS model to changes in values of the trade-off parameter' p'. Different values of the parameter p, ranging from 0 to 0.95, are employed. The scores of the overall significance degrees of the alternatives are shown in Figure 2. From Figure 2, it folles that scores of alternatives are increasing with the increasing values of the parameter 'p'. Since in each scenario, ranking order remains unchanged, the parameter' p' is not sensitive.

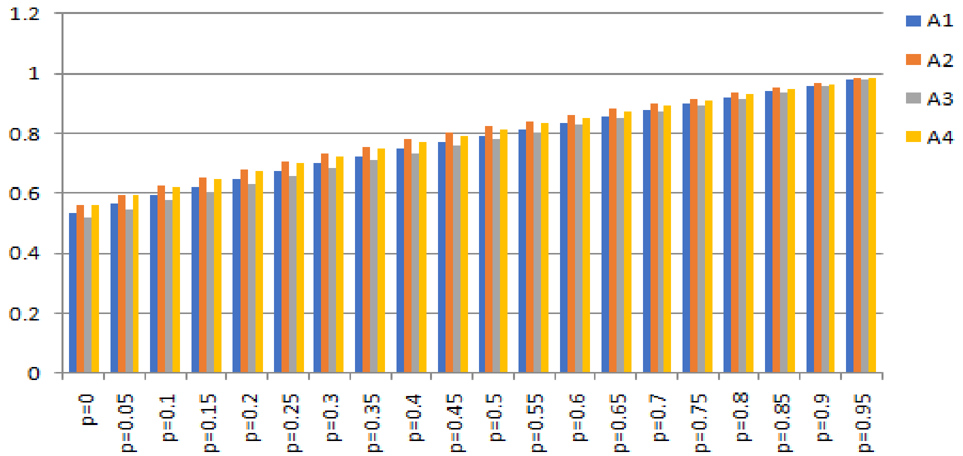

Figure 2. The sensitivity analysis to changes in parameter p.

5.2. Comparative Analysis

This part aims to provide a comparative analysis of the developed consensus-based FF decision support model with the existing FF MCDM methods, namely FF-WASPAS (Keshavarz-Ghorabaee et al., 2020), FF-TOPSIS (Senapati & Yager, 2020), and FF-CoCoSo (Mishra et al., 2022). These methods are applied to solve the addressed selection issue of HWTTs. According to the comparison results that are presented in Figure 2, the ranking order obtained by FF-WASPAS (Keshavarz-Ghorabaee et al., 2020), TOPSIS (Senapati & Yager, 2020), and FF-CoCoSo (Mishra et al., 2022) are respectively, $A_4 \succ A_2 \succ A_1 \succ A_3$, $A_2 \succ A_4 \succ A_3 \succ A_1$, and $A_2 \succ A_4 \succ A_3 \succ A_1$. However, our method generates an order $A_2 \succ A_4 \succ A_1 \succ A_3$ different from those methods due to including the "consensus reaching concept" in our method.

Some advantages of the consensus-based FF-WASPAS tool are:

1. The consensus-reaching process for decision-makers is integrated into the introduced model, while the available FF methods (Keshavarz-Ghorabaee et al., 2020; Mishra et al., 2022; Senapati & Yager, 2020) are unable to rectify the consensus level of experts. As a result, our model lessens decision-making process biases, making the process more significant and logical.
2. In the current method, we employ WASPAS, which has the following advantages: (i)It enables us to estimate things with the highest degree of precision, (ii) It is more accurate than WPM and WSM, (iii) Finally, it can select the optimal choice

using AOs when other methods only allow them to choose the option that is closest to the perfect answer.

3. The proposed methodology framework is useful for assessing and prioritizing HCW treatment technologies under real-life scenarios when quantitative input information is lacking.

6. Conclusions

The significance of medical waste management in an integrated solid waste management regime varies depending on the advanced country. When choosing an efficient method for treating medical waste, decision-makers need to consider several aspects, including economic, environmental, technological, and social factors. The MCDM technique is one of the most significant entry points for decision-makers. In order to analyze and rank the medical waste treatment technology possibilities, we have established an integrated methodology in this study. When developing this decision-making approach, we represented the criteria values regarding FFNs. In the suggested methodology, the final ranks of the alternatives are determined using the WASPAS method, and criteria weights are determined using the entropy measure. Here, a numerical example on the subject of choosing an HCW treatment technique is taken into consideration, and the findings are contrasted with those from several similar approaches, allowing for a more thorough comprehension of the method we previously illustrated. We can clearly state that the proposed approach can be employed in HCW treatment technology challenges under the regime of the FF environment, thanks to the comparison study component. The impact of changing the suggested approach's parameters on the decision results is also investigated in this study. Although we have used FFSs, in the future other sets (Mahmood et al., 2019, 2023; 2022) can also be utilized in our decision-making model.

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Appendix: List of abbreviations

Abbreviation	Full form
FF	Fermatean fuzzy
FFS	Fermatean fuzzy set
FFN	Fermatean fuzzy number
DE	Decision expert
AO	Aggregation operator
FFWA	Fermatean fuzzy weighted averaging

Abbreviation	Full form
FFWG	Fermatean fuzzy weighted geometric
HCW	Health care waste
HCWTT	Health care waste treatment technology
CoCoSo	Combined compromise solution
WSM	Weighted sum model
WPM	Weighted product model
RSD	Relative significance degree
TOPSIS	Technique for order preference by similarity to ideal solution
WASPAS	Weighted sum product assessment
COPRAS	Complex proportional assessment
VIKOR	VIekriterijumsko KOmpromisno Rangiranje
MULTIMOORA	Multi-objective optimization on the basis of ratio analysis plus full multiplicative form
MARCOS	Measurement of alternatives and ranking according to compromise solution
EDAS	Evaluation based on distance from average solution
CRITIC	CRiteria Importance Through Intercriteria Correlation
TODIM	TOmada de Decisao Interativa Multicriterio
MCDM	Multi-criteria decision-making

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