A New Pythagorean Fuzzy-based Decision Framework for Assessing Healthcare Waste Treatment

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Abstract

Suitable management and Treatment of Healthcare Waste (HCW) has become a key issue due to its potential risk to human health and the environment, predominantly in emerging nations. The selection of an optimal HCW treatment (HCWT) option is a complicated Multi-Criteria Decision-Making (MCDM) problem that includes several incompatible qualitative and quantitative attributes. This study presents an extended MCDM methodology for assessing and choosing the HCWT options using Pythagorean fuzzy Stepwise Weight Assessment Ratio Analysis (PF-SWARA), and Additive Ratio Assessment (PF-ARAS) approaches. To do this, attribute weights are estimated by the SWARA model and the ARAS framework decides the preference order of the options on Pythagorean Fuzzy Sets (PFSs). Furthermore, a selection problem of HCW treatment options in India is presented within PFSs to illustrate the efficiency and practicality of the introduced framework. Comparative discussions and sensitivity analysis are presented to demonstrate the rationality and stability of the developed approach for prioritizing HCW treatment options.

Keywords: Additive ratio assessment; Decision-making; Healthcare waste treatment; Pythagorean fuzzy sets; SWARA method.

1. Introduction

Healthcare facilities generate a large amount of Healthcare Waste (HCW), which may cause infections of hospital patients, health employees, and society, and also may contaminate the environment. Recently, a massive increase in HCW was reported [1]-[2]. Consequently, proper HCW management (HCWM) has become a global environmental and public health issue, specifically in emerging nations where HCW is frequently diversified with municipal solid waste [3]-[4]. The World Health Organization (WHO) describes HCW as *"wastes generated by the healthcare activities includes a broad range of materials, used needles and syringes to be soiled dressings, body parts, diagnostic samples, blood, chemicals, pharmaceuticals, medical devices, and radioactive materials"* [5]. As per the WHO, approximately 85% of HCW is non-hazardous, while the other 15% is hazardous that may be contagious, toxic, or radioactive. If not properly handled or disposed of this, 15% of HCW pose different types of environmental and health risks. Consequently, it is important that the biomedical waste materials are segregated at the source of generation, preserved properly, and disposed of systematically. Improper treatment of HCW has harmful impacts on the atmosphere and public health [6]. Based on these causes, HCW management has received immense attention from environmentalists, scholars, practitioners, and governments [7]-[9].

HCW management systems provide services for an assortment of waste generated by the healthcare facilities, evaluate transit modes and routes for transport waste to treatment plants, and help to select the treatment option and the disposal site. Due to the economic and environmental impact of HCW, assessing an optimal HCW treatment option has been an increasing global concern. To select the best HCW treatment option, Decision Experts (DEs) need to consider several incompatible tangible or intangible criteria. Each HCW treatment alternative has a distinct performance score based on different assessment criteria. However, no single HCW treatment option is better than the other options for all criteria. The assessment of HCW treatment options is considered a complex MCDM problem due to the involvement of several options and criteria. Thus, an efficient and accurate procedure is required to solve the HCW treatment assessment problem.

1.1 Motivations and Contributions of the Study

Recently, PFSs were demonstrated to be the most effective and useful tools for handling the uncertainty and fuzziness associated with real-life MCDM problems. Thus, the present work focuses based on the PFSs. Consequently, a new MCDM framework is developed that utilizes PFS as the preference information. Recently, increasing concerns have been expressed concerning the management of HCW; thus, in this study, the problem of selecting desirable HCW treatment options is discussed from the perspective of sustainability. However, several MCDM methods have been introduced under the PFSs environment, but no study has been reported for assessing and selecting of desirable HCWT option with the use of the extended framework with using SWARA, and ARAS approaches on PFSs. To deal with this issue, an integrated framework is proposed in this work that can be used to address the inherent uncertainty and the vagueness associated with the opinions of DEs. This study makes the following contributions:

- Extended a new approach called PF-SWARA-ARAS using SWARA and ARAS methods under the PF environment.
- Introduced a new formula for evaluating the DEs weights in a PF environment.
- To evaluate the attribute weights, a PFSs-based SWARA method is utilized.
- Presented an empirical case study for selecting an HCWT option within the context of PFSs to express the applicability of the introduced PF-SWARA-ARAS methodology.
- Next, a comparative analysis is performed along with sensitivity analysis to validate the outcome obtained by the introduced approach.

The overall manuscript is as Section 2 shows the elementary concepts of PFSs. Section 3 discusses the algorithm of the SWARA-ARAS method under the PFSs context. Section 4 utilizes the developed methodology in a case study of selecting desirable HCWT option that demonstrates the applicability and strength of the introduced methodology. Also, discusses the comparative discussions and sensitivity analysis that display the steadiness and robustness of the introduced approach. Section 5 deliberates the implications and discussions related to HCW management and treatment method assessment. Section 6 deliberates the conclusions and future scope.

2. **Literature Review**

In the modern years, several groups have been reviewed studies on the significance of assessing suitable HCW treatment options [7], [10]-[12]. However, due to uncertainties in the available information, it is difficult for DEs to provide crisp judgments/numbers as a preference for the alternatives over the set of criteria. Moreover, these crisp numbers can be inexact and imprecise in certain circumstances. Fuzzy Sets (FSs) pioneered by Zadeh [13], have been successfully implemented to tackle uncertainty and imprecision associated with real-life decision-making situations.

Recently, FSs were used in the detection of dendritic spines [14], fault detection filtering [15], and design of the energy management systems [16]. Various studies regarding the evaluation of HCW treatment options in different uncertain environments have been performed. To assess waste treatment technologies within the context of FSs, Dursun et al. [17] and Dursun et al. [18] used the integrated approaches for evaluating waste disposal methods with a hierarchy procedure on FSs. Liu et al. [19] extended the VIKOR (VlseKriterijumska Optimizcija I Kaompromisno Resenje in Serbian) approach to appraise HCW treatment technologies in Shanghai, China. Lee et al. [7] applied Analytic Hierarchy Process (AHP) tool to evaluate HCW treatment techniques in England. Voudrias [8] discussed the number of different HCW treatment options and assessed them using the AHP procedure. Shi et al. [9] used a combined MCDM model for evaluating optimal HCWT options using Multi-Attributive Border Approximation Area Comparison (MABAC) approach and a cloud model. Xiao [20] reported a novel framework for selecting the best HCW treatment option that is based on D numbers. Li et al. [21] suggested an approach for assessing HCW treatment options from the perspective of sustainability with IVFSs. Hinduja and Pandey [22] proposed a combined framework for assessing HCW treatment options in intuitionistic fuzzy sets (IFSs) with Decision Making Trial and Evaluation Laboratory Method (DEMATEL), Analytic Network Process (ANP), and AHP procedures. Liu et al. [23] evaluated a model for addressing the problem of evaluating HCW treatment options based on the intuitionistic uncertain linguistic term sets.

The theory of FSs has been described as being a constructive and applicable tool for managing the uncertainty associated with practical problems. However, FSs have some limitations regarding the handling of uncertain information. Atanassov [24] originated the conception of the IFSs, defined by Belongingness Degree (BD) and non-Belongingness Degree (NBD) and holds a constraint that the sum of its BD and NBD is less than or equal to unity. Owing to its capability to solve the realistic applications, IFSs have extensively been applied for various purposes in the literature [25]-[27]. Nonetheless, in several applications, the DEs may offer the BD to an option F_i over the attribute B_j with a value of 0.8 and the NBD to an option F_i over the criteria B_j with a value of 0.5. As a result, $0.8 + 0.5 > 1$ and thus, the IFS failed to address this circumstance. Further, Yager [28], [29] pioneered the concept of PFS, categorized by BD and NBD, and fulfills a constraint that the square addition of BD and NBD is restricted to unity. Thus, the aforementioned example can be successfully solved by the PFS theory. Owing to the wide-spread changes and increasing complexity of today's environment, the theory of PFS has received huge consideration from the researchers in the area of decision-making.

Recently, numerous studies have been utilized in the theory of PFSs for handling diverse MCDM problems [30-34]. Rani et al. [35] studied an extended TOPSIS model for selecting sustainable recycling partners within the context of PFSs. Khan et al. [36] studied new Dombi aggregation operators and employed them in the development of a new MCDM approach within the context of PFSs. However, no studies have been published regarding the assessment and evaluation of HCW treatment with PFSs preference structure. Next, several MCDM models have been developed by numerous authors for different purposes. Some noteworthy models are presented by Maurovich-Horvat et al. [37], Bai et al. [38], Lima et al. [39], Raghunathan et al. [40] and Dowd et al. [41]. In the procedure of MCDM, the criteria weights are significant concerns for DEs. Previously, attribute weights are defined as *objective and subjective* weights [42]. The objective ones are determined from the decision-matrices and are derived according to the knowledge presented by experts [43]. Basically, the subjective ones are enlightened the thoughts of experts concerning the relative importance of attributes [44]. To compute the subjective weights, Kersuliene et al. [45] introduced the SWARA approach. The computational work of the SWARA method is simple as compared to different tools such as AHP.

Many authors have combined the SWARA technique with other MCDM methods. Dehnavi et al. [46] presented an integrated technique for the evaluation of landslide susceptible areas in Iran. Karabasevic et al. [47] suggested an integrated MCDM framework by using ARAS and SWARA models. Rani et al. [48] used combined SWARA and COPRAS models to assess the sustainable supplier for HFSs. Mishra et al. [49] suggested an integrated framework with SWARA and COmplex PRoportional ASsessment (COPRAS) approaches for evaluating bioenergy production technologies with IFSs. Rani and Mishra [50] studied an integrated method that combines SWARA and VIKOR methods and applied to assess the eco-industrial thermal power plants on single-valued neutrosophic sets and also select ideal solar panel selection on PFSs [51]. In the literature, no one has utilized the SWARA approach in the computation of criteria weights for the HCWT selection problem.

Over the last few decades, MCDM was considered as one of the significant procedures of our daily life. In real-life applications, there is a challenging issue to obtain the solution of MCDM concerns [52]. Due to ever-increasing intricacy and extensive changes in today's environment, the classical MCDM methods were not appropriate for handling the MCDM problems. As FSs and its extensions were extensively applied to handle the uncertain information, therefore, several MCDM approaches such as VIKOR [32], [34], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [35], [52], Weighted Aggregates Sum Product Assessment (WASPAS) [31], [53], COPRAS [54], [55], TODIM (an acronym in Portuguese for Interactive and MCDM) [56], [57], Measurement Alternative and Ranking based on COmpromise Solution (MARCOS) [58], [59] and many others [60-62] were introduced in the literature under different uncertain environments. However, the researchers and practitioners usually pick the procedure which depends upon the nature and complication of the problem.

The ARAS method, proposed by Zavadskas and Turskis [63], is associated with the theory that the events of the complex world may be implicit utilizing easy relative comparisons. This method employs the idea of an optimality degree to obtain the preference order. The key outcomes of ARAS procedure are as (i) direct and proportional association with the criteria weights [64], [65]; (ii) potential to solve highly complex problems [66]; (iii) straightforward, direct, and easy steps to evaluate several options or choices on the basis of their performance relative to selected evaluation criteria that yield sensible, suitable and relatively accurate outcomes [63]. The majority of recent implementations of the classical ARAS approach addressed personnel evaluation [67], the ranking of companies based on indicators of corporate social accountability [68], assessment of the chief accountant [69], and the assessment of sustainable building [65]. Recently, many elaborations of this approach were established in different uncertain fields. One example is the ARAS Grey (ARAS-G) approach [70] and its extension under interval-valued triangular fuzzy numbers [71]. Mishra et al. [72] suggested ARAS method to assess and choose desirable Information technology (IT) personnel for a company on IFSs. However, no one has used the ARAS method in the evaluation of HCW treatment alternatives.

3. Research method

Here, firstly, we deliberate the definitions about the PFSs. Next, an extended PF-SWARA-ARAS framework is introduced.

3.1. Preliminaries

Definition 1 [28]: A PFS N on a discourse set $X = \{x_1, x_2, x_3, \ldots, x_n\}$ is given by

$$N = \left\{ \langle x_i, \mu_N(x_i), \nu_N(x_i) \rangle \middle| x_i \in X \right\}, \tag{1}$$

where $\mu_N: X \to [0,1]$ and $\nu_N: X \to [0,1]$ describe the BD and NBD, respectively, of an object $x_i \in X$ with the condition $0 \le (\mu_N(x_i))^2 + (\nu_N(x_i))^2 \le 1$. For each $x_i \in X$, the degree of hesitancy is expressed as $\pi_N(x_i) = \sqrt{1 - \mu_N^2(x_i) - \nu_N^2(x_i)}$. Next, the Pythagorean fuzzy number(PFN) [73], is specified as $\eta = (\mu_\eta, \nu_\eta)$ which satisfies $\mu_\eta, \nu_\eta \in [0,1]$ and $0 \le \mu_\eta^2 + \nu_\eta^2 \le 1$.

Definition 2 [73]: Let $\eta = (\mu_\eta, \nu_\eta)$ be a PFN. Then, the score and accuracy functions are given by

$$S(\eta) = (\mu_\eta)^2 - (\nu_\eta)^2,\ h(\eta) = (\mu_\eta)^2 + (\nu_\eta)^2, \text{ where } S(\eta) \in [-1,1] \text{ and } h(\eta) \in [0,1]. \tag{2}$$

Since $S(\eta) = [-1,1]$, the modified normalized version are defined by [54]

$$S^*(\eta) = \frac{2\mu_\eta^2 + (1 - \nu_\eta^2) + (\mu_\eta^2)^2}{4},\ h^\circ(\eta) = 1 - h(\eta), \text{ where } S^*(\eta),\ h^\circ(\eta) \in [0,1]. \tag{3}$$

Definition 3 [28-29]: Let $\eta = (\mu_\eta, \nu_\eta)$, $\eta_1 = (\mu_{\eta_1}, \nu_{\eta_1})$ and $\eta_2 = (\mu_{\eta_2}, \nu_{\eta_2})$ be the PFNs. Then, the following operations are satisfied with PFSs:

(i) $\eta^c = (\nu_\eta, \mu_\eta)$;

(ii) $\eta_1 \oplus \eta_2 = \left(\sqrt{\mu_{\eta_1}^2 + \mu_{\eta_2}^2 - \mu_{\eta_1}^2 \mu_{\eta_2}^2}, \nu_{\eta_1} \nu_{\eta_2} \right)$;

(iii) $\eta_1 \otimes \eta_2 = \left(\mu_{\eta_1} \mu_{\eta_2}, \sqrt{\nu_{\eta_1}^2 + \nu_{\eta_2}^2 - \nu_{\eta_1}^2 \nu_{\eta_2}^2} \right)$;

(iv) $\lambda \eta = \left(\sqrt{1 - (1 - \mu_\eta^2)^\lambda}, (\nu_\eta)^\lambda \right)$, $\lambda > 0$;

(v) $\eta^\lambda = \left((\mu_\eta)^\lambda, \sqrt{1 - (1 - \nu_\eta^2)^\lambda} \right)$, $\lambda > 0$.

3.2. An Extended PF-SWARA-ARAS Method

This section presents an integrated methodology by combining SWARA and ARAS procedures on PFSs. The SWARA technique is an efficient tool for computing the subjective criteria weights [45]. The key benefit of SWARA method is to determine the precision of the outlooks of the experts about the weights allotted by SWARA process. Additionally, ARAS approach utilizes the philosophy of optimality degree to evaluate the preference order of each alternative/option over a set of criteria. Thus, this work introduces an integrated PF-SWARA-ARAS framework that is based on the concepts of PFSs, criteria weights determination by SWARA procedure, and evaluation of the ranking of the options with the ARAS method. The structure of the proposed PF-SWARA-ARAS methodology is presented in **Fig. (1)** and described as follows:

Step 1: Select the option and criteria

To select the most desirable option among a set of p options $F = \{F_1,\ F_2, \dots, F_p\}$ under the criterion set $B = \{B_1,\ B_2, \dots, B_q\}$. It is assumed that a committee of l experts $D = \{D_1, D_2, \dots, D_l\}$ is created to obtain the ideal option(s). Suppose $Z = \left(z_{ij}^{(k)}\right), i = 1(1)p,\ j = 1(1)q$ be a linguistic decision-matrix obtained by experts, where $z_{ij}^{(k)}$ signifies the evaluation of an option F_i over defined criteria B_j in forms of linguistic values (LVs) for k^{th} experts.

Step 2: Compute the DEs' weights

Let $\lambda = (\lambda_1,\ \lambda_2, \dots, \lambda_l)^T$ be the weights of l experts such that $\sum_{k=1}^{l} \lambda_k = 1$. Let the DEs' weights are measured as LVs that are articulated in PFNs. Let $D_k = (\mu_k, \nu_k)$ be a PFN for the evaluation of the k^{th} DE. Based on [74], the weight of k^{th} expert is specified by

$$\lambda_k = \frac{\left(\mu_k^2 + \pi_k^2\left(\frac{\mu_k^2}{\mu_k^2 + \nu_k^2}\right)\right)}{\sum_{k=1}^{\ell}\left(\mu_k^2 + \pi_k^2\left(\frac{\mu_k^2}{\mu_k^2 + \nu_k^2}\right)\right)}, \quad \forall k. \tag{4}$$

Step 3: Generate the Aggregated PF-Decision Matrix (APF-DM)

To determine the APF-DM, combining each individual matrix into a group decision matrix by utilizing the DEs opinions is required. To accomplish this, PF-Weighted Averaging Operator (PFWAO) [28] is employed and then $R = \left(\varepsilon_{ij}\right)_{m\times n}$ where

$$\varepsilon_{ij} = \left(\mu_{ij}, \nu_{ij}\right) = PFWA_\lambda\left(z_{ij}^{(1)}, z_{ij}^{(2)}, \dots, z_{ij}^{(\ell)}\right) = \left(\sqrt{1 - \prod_{k=1}^{\ell}\left(1 - \mu_{ijk}^2\right)^{\lambda_k}}, \prod_{k=1}^{\ell}\left(\nu_{ijk}\right)^{\lambda_k}\right). \tag{5}$$

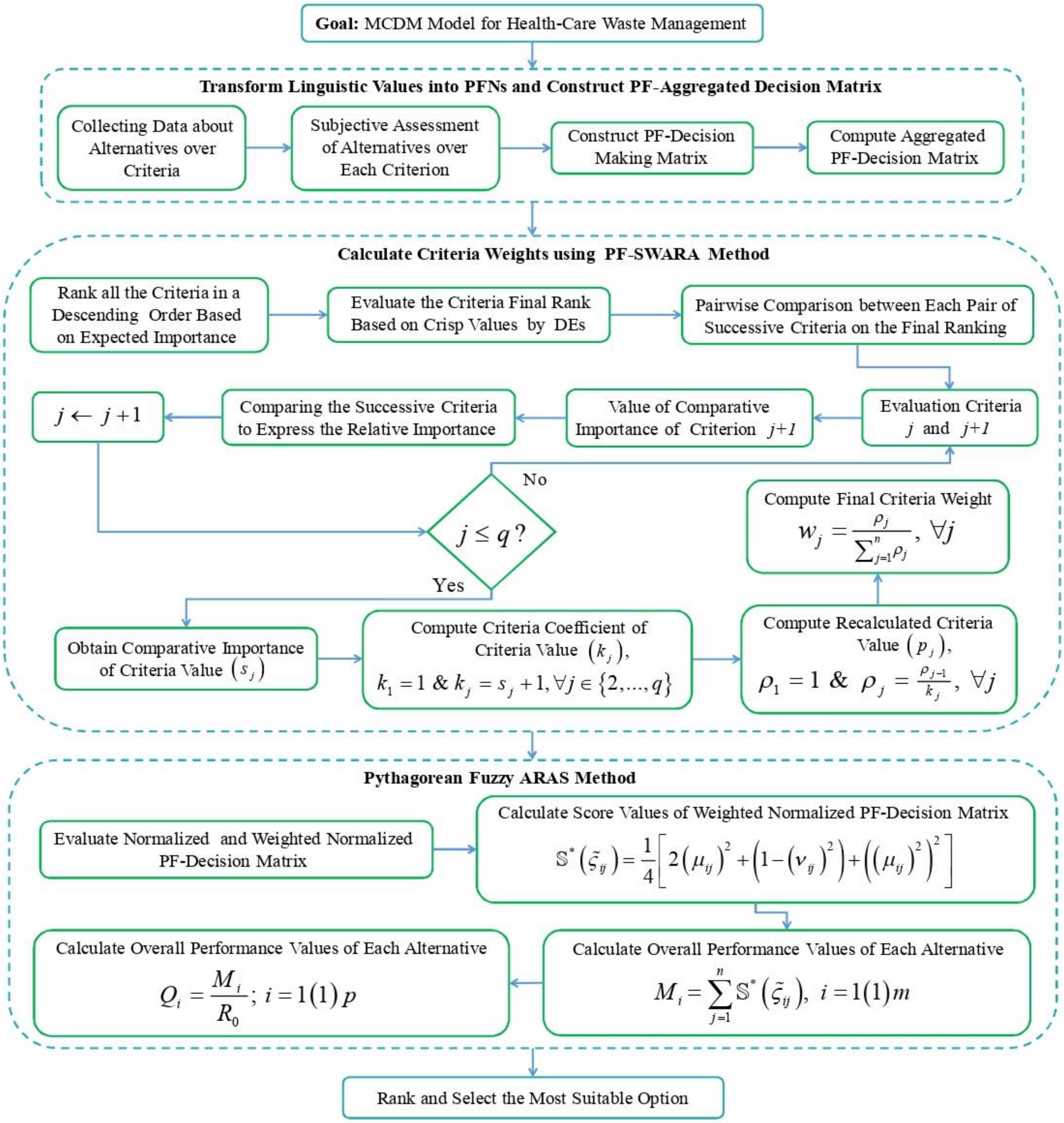

Fig. 1: Implementation procedure of the PF-SWARA-ARAS approach

Step 4: Compute the criteria weights using SWARA method

The process for evaluating the attribute weights by utilizing SWARA model is given by

Step 4.1: Compute the crisp degrees. First, Score values $S^*(\varepsilon_{kj})$ of PFNs using Eq. (3) are computed.

Step 4.2: Rank the attributes. The considered attributes are ordered in accordance with the preference of the DEs, ranging from the highest significance to the lowest significant attribute.

Step 4.3: Estimate the comparative importance. The comparative importance is estimated by comparing criterion B_j and criterion B_{j-1}.

Step 4.4: Calculate the comparative coefficient. The formula for the computation of comparative coefficient is given as

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1, \end{cases} \tag{6}$$

where s_j denotes the comparative importance [45].

Step 4.5: Assess the weights. The formula for computing the weights is

$$\rho_j = \begin{cases} 1, & j = 1 \\ \dfrac{\rho_{j-1}}{\kappa_j}, & j > 1. \end{cases} \tag{7}$$

Step 4.6: Compute the normalized weight. In general, the attribute weights are deliberated by the expression:

$$w_j = \frac{\rho_j}{\sum_{j=1}^{q} \rho_j}. \tag{8}$$

Step 5: Estimate the optimal performance rating

$$R_0 = \begin{cases} \max \varepsilon_{ij}, & j \in B_b \\ \min \varepsilon_{ij}, & j \in B_n, \end{cases} \tag{9}$$

where B_b and B_n are benefit-type and cost-type criteria , respectively.

Step 6: Generate the normalized APF-DM

The formula for determination of normalized APF-DM $U = \left(\varsigma_{ij}\right)_{p\times q}$, as follows

$$\varsigma_{ij} = \begin{cases} \varepsilon_{ij} = \left(\mu_{ij}, \nu_{ij}\right), & j \in B_b \\ \left(\varepsilon_{ij}\right)^c = \left(\nu_{ij}, \mu_{ij}\right), & j \in B_n \end{cases}; \forall i,\ j. \tag{10}$$

Step 7: Generate a weighted normalized APF-DM

Consider $w = \left(w_1, w_2, ..., w_n\right)^T$ be the weights of attributes B_j: $j = 1(1)q$, then the weighted normalized APF-DM $U_w = \left(\tilde{\varsigma}_{ij}\right)_{p\times q}$ is assembled as

$$\tilde{\varsigma}_{ij} = \left\langle \tilde{\mu}_{ij}, \tilde{\nu}_{ij} \right\rangle = \bigoplus_{j=1}^{q} w_j\, \varsigma_{ij} = \left\langle \sqrt{1 - \prod_{j=1}^{q} \left(1 - \mu_{ij}\right)^{w_j}}, \prod_{j=1}^{q} \left(\nu_{ij}\right)^{w_j} \right\rangle, \tag{11}$$

Step 8: Evaluation of score values

Using Eq. (3), the score values of the weighted normalized APF-D matrix $U_w = \left(\tilde{\varsigma}_{ij}\right)_{p\times q}$ are computed as follows [54]:

$$S^*\left(\tilde{\varsigma}_{ij}\right) = \left[\frac{2\left(\tilde{\mu}_{ij}\right)^2 + \left(1-\left(\tilde{\nu}_{ij}\right)^2\right) + \left(\left(\tilde{\mu}_{ij}\right)^2\right)^2}{4}\right]; \ \forall i, j. \tag{12}$$

Step 9: Determine the overall performance degree and utility degree

The overall performance values are computed by

$$M_i = \sum_{j=1}^{q} S^*\left(\tilde{\varsigma}_{ij}\right), \ \ \forall i. \tag{13}$$

The optimal option has the maximum degree of M_i, while the worst option has the minimum degree of M_i. In the evaluation procedure, the optimality function M_i has the straight and proportional relation with $\tilde{\varsigma}_{ij}$ and w_j of the explored criteria weights. As a result, the maximal degree of the function M_i represents the more efficient alternative. The preferences of the alternatives can be evaluated based on M_i.

In the process of MCDM, it is not only essential to compute the optimal option, but it is also significant to find the virtual impact of the obtained options with respect to the most favorable alternative. The variant utility degree is calculated by assessing the examined variant with the optimal alternative R_0. The degree of utility Q_i of option $F_i: i = 1(1)p$ is defined by

$$Q_i = \frac{M_i}{R_0}; \ i = 1(1)\, p. \tag{14}$$

In Eq. (14), $Q_i \in [0,1]$. The value of Q_i can be prescribed in an ascending degrees to obtain the preference order. The relative efficiency of an optimal option is computed according to utility degree.

Step 10: Choose the most desirable alternative

The determined options are ranked as per the ascending order of Q_i, that is, the option with the maximum degree M^* is more suitable for the process and so on. Therefore, the optimal alternative can be computed by

$$M^* = \left\{M_i \mid \max_i Q_i; \ i = 1(1)\, p\right\}, \tag{15}$$

4. An Empirical Case Study of Healthcare Waste Treatment Selection

Here, the PF-SWARA-ARAS method is utilized to evaluate alternative HCW treatment methods in India. During the past decade, medical services in India, including super specialty healthcare services, have constantly been increasing. The increasing number of healthcare services has resulted in an increasing amount of biomedical waste produced by these facilities. However, existing HCW treatment options cannot adequately handle such large amounts of medical waste; therefore, a large amount of waste is disposed of into landfills. Additionally, a large portion of HCW is disposed of as ordinary waste because there is a lack of treatment options and a shortage of suitable authorizations for dumping biomedical wastes [75].

Hence, introducing new HCW disposal treatment options is essential. Since treatment options have a substantial impact on the financial system, the environment, and the public, therefore, it is necessary to establish an optimal HCW treatment option. For this, we analyzed and reviewed existing HCW treatment options. Additionally, we discussed the current status of HCW management in India based on our investigations of major hospitals and existing HCW treatment options and conducted interviews with ecological experts, authorities, and waste management professors [76].

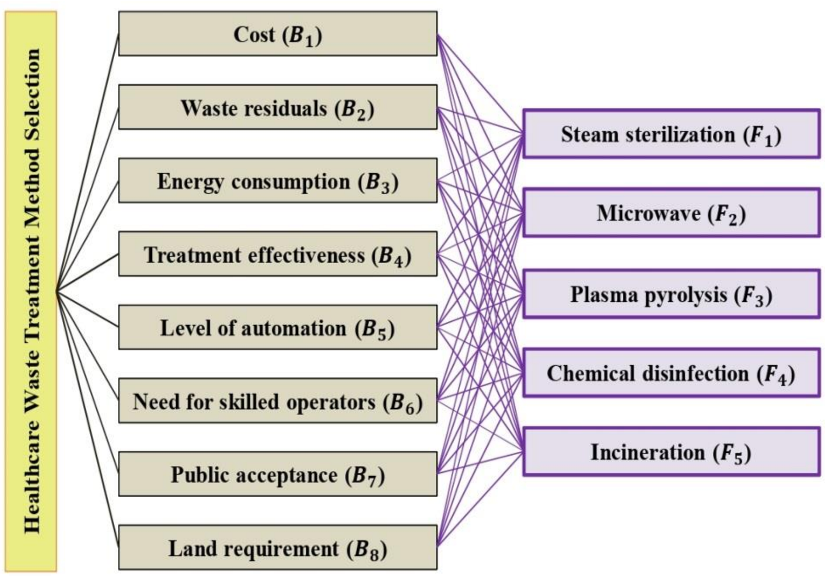

Fig. 2: A framework to choose HCW method selection

After the pre-evaluation, five treatment options were considered for HCW treatment. These HCW treatment options are: F_1: steam sterilization, F_2: microwave, F_3: plasma pyrolysis, F_4: chemical disinfection and F_5: incineration. These methods were evaluated with respect to four main parameters: economic, environmental, technical, and social, each of which have eight criteria, including cost (B_1), waste residuals (B_2), energy consumption (B_3), treatment effectiveness (B_4), level of automation (B_5), need for skilled operators (B_6), public acceptance (B_7) and land requirement (B_8). To select the optimal HCW treatment alternative, a team of four DEs (D_1, D_2, D_3, D_4) was created. These experts are from various areas or organizations including environmental engineer, an expert from a waste treatment enterprise, HCWM expert, and an industrial engineer. Here, we provide the hierarchical framework of HCW option selection procedure in **Fig. (2)**.

The procedure for execution of the PF-SWARA-ARAS approach on the present application is described as below:

Table 1 shows the LVs utilized to estimate the relative significance of DEs, expressed as PFNs. The weights of the DEs shown in Table 2 were evaluated based on Table 1 and Eq. (4). According to PFNs, Table 3 shows the LVs for the selected criteria and the performance of HCW treatment options. Table 4 shows the individual decision matrices of each alternative F_i over the assessment criteria. Tables 2-4 are used to form Table 5 by applying Eq. (5).

Table 1. Linguistic terms for the significance of DEs

LVs	PFNs
Extremely significant (ES)	(0.95, 0.10)
Very significant (VS)	(0.80, 0.25)
Significant (S)	(0.65, 0.40)
Moderate (M)	(0.55, 0.50)
Insignificant (I)	(0.45, 0.55)
Very insignificant (VI)	(0.30, 0.75)
Extremely insignificant (EI)	(0.15, 0.90)

Table 2. Computation of expert weight

DEs	D_1	D_2	D_3	D_4
LTs\Ratings	Significant (S)	Moderate (M)	Very significant (VS)	Insignificant (I)
PFNs	(0.6500, 0.4000)	(0.5500, 0.5000)	(0.8000, 0.2500)	(0.4500, 0.5500)
Weights (λ_k)	0.2806	0.2118	0.3524	0.1551

Table 3. Performance ratings of the criteria and the alternatives

LVs	PFNs
Extremely Low (EL)	(0.15, 0.95)
Very Low (VL)	(0.25, 0.90)
Low (L)	(0.30, 0.85)

Medium Low (ML)	(0.35, 0.75)
Medium (M)	(0.45, 0.65)
Medium-High (MH)	(0.60, 0.40)
High (H)	(0.70, 0.35)
Very High (VH)	(0.80, 0.30)
Very High (VVH)	(0.85, 0.25)
Extremely High (EH)	(0.95, 0.20)

Table 4. The LVs evaluation of options given by experts

Alternatives	DEs	Attributes							
		B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8
F_1	D_1	H	L	VH	M	VH	H	VH	L
	D_2	M	M	H	L	L	VL	H	MH
	D_3	ML	L	L	L	M	MH	VH	H
	D_4	M	L	L	VH	M	H	MH	M
F_2	D_1	VH	M	H	ML	H	H	VH	VL
	D_2	L	M	H	L	M	ML	MH	H
	D_3	M	L	ML	MH	MH	M	H	MH
	D_4	M	VL	L	H	M	VH	L	LH
F_3	D_1	H	L	H	ML	H	H	MH	VL
	D_2	L	H	H	M	M	L	VH	H
	D_3	M	L	L	ML	M	M	H	H
	D_4	L	M	VL	H	H	MH	ML	VL
F_4	D_1	VH	MH	H	MH	VH	MH	M	ML
	D_2	L	M	MH	H	H	L	MH	MH
	D_3	M	L	L	ML	H	M	MH	M
	D_4	M	VL	L	H	VH	M	ML	L
F_5	D_1	VH	M	VH	MH	VH	MH	H	H
	D_2	VH	MH	M	H	MH	H	H	VH
	D_3	L	H	L	ML	H	L	ML	L
	D_4	L	MH	MH	M	H	M	L	L

Table 5. Aggregated PF-decision matrix for HCWT selection

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8
F_1	(0.522, 0.575, 0.630)	(0.339, 0.803, 0.490)	(0.616, 0.526, 0.587)	(0.491, 0.671, 0.490)	(0.586, 0.554, 0.591)	(0.609, 0.448, 0.654)	(0.759, 0.324, 0.565)	(0.570, 0.508, 0.645)
F_2	(0.586, 0.554,	(0.379, 0.751,	(0.570, 0.525,	(0.522, 0.548,	(0.591, 0.460,	(0.605, 0.499,	(0.685, 0.396,	(0.587, 0.526,

	0.591)	0.540)	0.632)	0.540)	0.663)	0.620)	0.612)	0.615)
F_3	(0.511, 0.603, 0.612)	(0.460, 0.676, 0.576)	(0.559, 0.554, 0.617)	(0.458, 0.646, 0.576)	(0.586, 0.496, 0.640)	(0.549, 0.536, 0.641)	(0.671, 0.396, 0.627)	(0.579, 0.528, 0.621)
F_4	(0.586, 0.554, 0.591)	(0.441, 0.656, 0.613)	(0.531, 0.565, 0.632)	(0.585, 0.475, 0.613)	(0.750, 0.327, 0.575)	(0.479, 0.600, 0.641)	(0.534, 0.505, 0.678)	(0.449, 0.653, 0.610)
F_5	(0.651, 0.509, 0.563)	(0.610, 0.437, 0.661)	(0.595, 0.533, 0.601)	(0.543, 0.523, 0.661)	(0.717, 0.345, 0.605)	(0.534, 0.547, 0.645)	(0.570, 0.525, 0.632)	(0.604, 0.531, 0.594)

Table 6. Assessment of criteria weights

Criteria	D_1	D_2	D_3	D_4	**Aggregated PFNs**	**Crisp values** $S^*\left(\tilde{\varepsilon}_{kj}\right)$
B_1	ML	M	L	ML	(0.359, 0.760, 0.541)	0.174
B_2	L	L	M	VL	(0.357, 0.780, 0.514)	0.166
B_3	VH	MH	VH	H	(0.755, 0.327, 0.568)	0.590
B_4	M	H	H	ML	(0.609, 0.469, 0.514)	0.415
B_5	H	H	MH	VH	(0.690, 0.358, 0.629)	0.513
B_6	L	ML	L	VL	(0.305, 0.835, 0.458)	0.124
B_7	VL	L	VL	ML	(0.279, 0.864, 0.418)	0.104
B_8	L	VL	M	VL	(0.349, 0.790, 0.505)	0.159

Table 7. Criteria weights assessed by the SWARA method

Criteria	**Crisp values**	**Comparative significance** (s_j)	**Coefficient** (k_j)	**Recalculated weight** (ρ_j)	**Final weight** (w_j)
B_3	0.590	-	1	1	0.1644
B_5	0.513	0.077	1.077	0.928	0.1525
B_4	0.415	0.098	1.098	0.845	0.1389
B_1	0.174	0.241	1.241	0.681	0.1119
B_2	0.166	0.008	1.008	0.676	0.1111
B_8	0.159	0.007	1.007	0.671	0.1103
B_6	0.124	0.035	1.035	0.648	0.1065
B_7	0.104	0.020	1.020	0.635	0.1044

The role of DEs is very significant to evaluate and calculate the attribute weights by applying the SWARA procedure and is shown in Table 6. Subsequently, the criteria are arranged by the DEs, from higher to lower score values. Each DE employs individual implicit knowledge and skills. In the SWARA approach, the most important attribute is preferred first, while the least important criterion is ranked last. Final attributes weights are computed corresponding to the mediocre value of ranks. The calculated criteria weights are presented in Table 7. Thus, the weight values of the attribute set is given by

$$w_j = (0.1644, 0.1525, 0.1389, 0.1119, 0.1111, 0.1103, 0.1065, 0.1044)^{T.} \tag{16}$$

Next, Eq. (9) is used to find the optimal performance ratings of HCW treatment options. The optimal HCW treatment performance ratings are specified in Table 8.

Table 8. Optimal Pythagorean fuzzy performance values for HCW treatment selection

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8
R_0	(0.511, 0.603, 0.612)	(0.339, 0.803, 0.490)	(0.616, 0.526, 0.587)	(0.585, 0.475, 0.613)	(0.750, 0.327, 0.575)	(0.609, 0.448, 0.654)	(0.759, 0.324, 0.565)	(0.604, 0.531, 0.594)

Table 9 is the normalized APF-D matrix, which is obtained by applying Eq. (10) to Table 5. It is done to transform all the preference values into a single type viz., cost, or benefits criteria type. Next, the weighted APF-DM for HCW treatment alternatives was constructed based on Table 9, Eq. (11), and Eq. (16), and it is depicted in Table 10.

Table 9. Normalized APF-D matrix for HCW treatment selection

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8
R_0	(0.603, 0.511, 0.612)	(0.803, 0.339, 0.490)	(0.616, 0.526, 0.587)	(0.585, 0.475, 0.613)	(0.750, 0.327, 0.575)	(0.609, 0.448, 0.654)	(0.759, 0.324, 0.565)	(0.604, 0.531, 0.594)
F_1	(0.575, 0.522, 0.630)	(0.803, 0.339, 0.490)	(0.616, 0.526, 0.587)	(0.491, 0.671, 0.490)	(0.586, 0.554, 0.591)	(0.609, 0.448, 0.654)	(0.759, 0.324, 0.565)	(0.570, 0.508, 0.645)
F_2	(0.554, 0.586, 0.591)	(0.751, 0.379, 0.540)	(0.570, 0.525, 0.632)	(0.522, 0.548, 0.540)	(0.591, 0.460, 0.663)	(0.605, 0.499, 0.620)	(0.685, 0.396, 0.612)	(0.587, 0.526, 0.615)
F_3	(0.603, 0.511, 0.612)	(0.676, 0.460, 0.576)	(0.559, 0.554, 0.617)	(0.458, 0.646, 0.576)	(0.586, 0.496, 0.640)	(0.549, 0.536, 0.641)	(0.671, 0.396, 0.627)	(0.579, 0.528, 0.621)
F_4	(0.554, 0.586, 0.591)	(0.656, 0.441, 0.613)	(0.531, 0.565, 0.632)	(0.585, 0.475, 0.613)	(0.750, 0.327, 0.575)	(0.479, 0.600, 0.641)	(0.534, 0.505, 0.678)	(0.449, 0.653, 0.610)
F_5	(0.509, 0.651, 0.563)	(0.437, 0.610, 0.661)	(0.595, 0.533, 0.601)	(0.543, 0.523, 0.661)	(0.717, 0.345, 0.605)	(0.534, 0.547, 0.645)	(0.570, 0.525, 0.632)	(0.604, 0.531, 0.594)

Table 10. Weighted normalized APF-D matrix for HCW treatment

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8
R_0	(0.268, 0.895, 0.356)	(0.382, 0.848, 0.367)	(0.253, 0.915, 0.315)	(0.214, 0.920, 0.328)	(0.296, 0.883, 0.364)	(0.223, 0.915, 0.335)	(0.296, 0.887, 0.355)	(0.215, 0.936, 0.278)
F_1	(0.253,	(0.382,	(0.253,	(0.174,	(0.214,	(0.223,	(0.296,	(0.200,

	0.899, 0.359)	0.848, 0.367)	0.915, 0.315)	0.956, 0.235)	0.936, 0.278)	0.915, 0.335)	0.887, 0.355)	0.932, 0.303)
F_2	(0.242, 0.916, 0.320)	(0.345, 0.862, 0.370)	(0.230, 0.914, 0.333)	(0.187, 0.935, 0.302)	(0.216, 0.917, 0.334)	(0.221, 0.926, 0.305)	(0.255, 0.906, 0.337)	(0.208, 0.935, 0.287)
F_3	(0.268, 0.895, 0.356)	(0.298, 0.888, 0.349)	(0.225, 0.921, 0.317)	(0.161, 0.952, 0.259)	(0.214, 0.925, 0.314)	(0.197, 0.934, 0.300)	(0.248, 0.906, 0.343)	(0.204, 0.935, 0.288)
F_4	(0.242, 0.916, 0.320)	(0.287, 0.883, 0.372)	(0.212, 0.924, 0.319)	(0.214, 0.920, 0.328)	(0.296, 0.883, 0.364)	(0.168, 0.945, 0.280)	(0.187, 0.930, 0.317)	(0.152, 0.956, 0.249)
F_5	(0.219, 0.932, 0.289)	(0.178, 0.927, 0.329)	(0.243, 0.916, 0.319)	(0.196, 0.930, 0.311)	(0.278, 0.888, 0.365)	(0.191, 0.936, 0.297)	(0.202, 0.934, 0.295)	(0.215, 0.936, 0.278)

Table 11. Computational outcomes of the PF-SWARA-ARAS method for HCW treatment

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	Overall performance rating
R_0	0.087	0.149	0.074	0.062	0.101	0.066	0.099	0.055	0.691
F_1	0.081	0.149	0.074	0.037	0.054	0.066	0.099	0.053	0.613
F_2	0.070	0.127	0.068	0.049	0.063	0.061	0.078	0.053	0.571
F_3	0.087	0.099	0.064	0.036	0.059	0.052	0.077	0.053	0.526
F_4	0.070	0.098	0.060	0.062	0.101	0.041	0.052	0.033	0.516
F_5	0.058	0.051	0.070	0.053	0.093	0.050	0.053	0.055	0.482

The score values $S^*(\tilde{\varsigma}_{ij})$ of PFNs shown in Table 11 were determined using the values presented in Table 10 and Eq. (12). The overall performance rating (M_i) of each HCW treatment shown in Table 11 was computed using Eq. (13). The degree of utility or relative quality (Q_i) was computed using Eq. (14), given as: $Q_1 = 0.887, Q_2 = 0.826, Q_3 = 0.761, Q_4 = 0.747, Q_5 = 0.698$. Then, the rank order of the HCW treatment options was determined as $Q_1 \succ Q_2 \succ Q_3 \succ Q_4 \succ Q_5$. Hence, the desirable HCW treatment alternative is Q_1, i.e.,F_1 (steam sterilization) is the best HCW treatment option.

4.1. Comparative Discussion

This section presents comparison and sensitivity analysis to the introduced methodology.

4.1.1 PF-TOPSIS technique

In this section, the outcomes obtained from PF-SWARA-ARAS method and the results generated by the PF-TOPSIS method [73] is compared. Firstly, the calculation steps of PF-TOPSIS procedure are given by

Steps 1-4: As per previous procedure given in Section 3.

Step 5: Assess PF- Ideal Solution (PF-IS) and PF-Anti-Ideal Solution (PF-AIS).

Assume that $\varphi^+$and φ^- are the PF-IS and PF-AIS, respectively, that are computed as follows:

$$\varphi^+ = \begin{cases} \max\limits_i \mu_{ij}, \text{ for benefit-type attribute } B_j \\ \min\limits_i \nu_{ij}, \text{ for cost-type attribute } B_j \end{cases} \tag{17}$$

$$\varphi^- = \begin{cases} \min\limits_i \mu_{ij}, \text{ for benefit-type attribute } B_j \\ \max\limits_i \nu_{ij}, \text{ for cost-type attribute } B_j \end{cases} \text{ for } \forall\, j. \tag{18}$$

Step 6: Evaluate the degree of distances from PF-IS and PF-AIS.

Here, the value of weighted distance $D(F_i,\varphi^+)$ over the options F_i and PF-IS φ^+ are calculated.

$$D(F_i,\varphi^+) = \frac{1}{2}\sum_{j=1}^{q}\left[w_j\left(\left|\mu_{ij}^2 - \mu_{\varphi^+}^2\right| + \left|\nu_{ij}^2 - \nu_{\varphi^+}^2\right| + \left|\pi_{ij}^2 - \pi_{\varphi^+}^2\right|\right)\right]. \tag{19}$$

Generally, the alternative F_i with minimum $D(F_i,\varphi^+)$ value is highly preferred, and so on. Let

$$D_{\min}(F_i,\varphi^+) = \min_{1\le i\le p} D(F_i,\varphi^+), \tag{20}$$

and the distance $D(F_i,\varphi^-)$ between the related options F_i and the PF-AIS φ^- is calculated as

$$D(F_i,\varphi^-) = \frac{1}{2}\sum_{j=1}^{q}\left[w_j\left(\left|\mu_{ij}^2 - \mu_{\varphi^-}^2\right| + \left|\nu_{ij}^2 - \nu_{\varphi^-}^2\right| + \left|\pi_{ij}^2 - \pi_{\varphi^-}^2\right|\right)\right]. \tag{21}$$

Generally, the alternative F_i with maximum $D(F_i,\varphi^-)$ value is highly preferred, and so on. Let

$$D_{\max}(F_i,\varphi^-) = \max_{1\le i\le p} D(F_i,\varphi^-). \tag{22}$$

Step 7: Assess the relative Closeness Index (CI).

The relative CI of each alternative is specified as

$$C(F_i) = \frac{D(F_i,\varphi^-)}{D(F_i,\varphi^+) + D(F_i,\varphi^-)}, \ \forall i. \tag{23}$$

As per the increasing values of CI, the desirable HCW treatment option is determined, and hence, the options are ranked. Though, in most of the examples, the relative CI cannot achieve the target of the optimal option concurrently, having minimal discrimination from IS and the maximal discrimination from AIS [77]. Thus, the modified CI of each option is presented as

$$RC(F_i) = \frac{D(F_i, \varphi^-)}{D_{\max}(F_i, \varphi^-)} - \frac{D(F_i, \varphi^+)}{D_{\min}(F_i, \varphi^+)}, \quad \forall i. \tag{24}$$

Step 8: Select the highest degree $RC(F_k)$, among the degrees $RC(F_i)$. Hence, F_k is the desired alternative.

Based on Table 5 and Eqs. (17)-(18), PF-IS, and PF-AIS are calculated. The whole process of the PF-TOPSIS [74] method is presented in Table 12.

$\varphi^+ =$ {(0.511, 0.603, 0.612), (0.339, 0.803, 0.490), (0.616, 0.526, 0.587), (0.585, 0.475, 0.613), (0.750, 0.327, 0.575), (0.609, 0.448, 0.654), (0.759, 0.324, 0.565), (0.604, 0.531, 0.594)}.

$\varphi^- =$ {(0.651, 0.509, 0.563), (0.610, 0.437, 0.661), (0.531, 0.565, 0.632), (0.491, 0.671, 0.490), (0.586, 0.554, 0.591), (0.479, 0.600, 0.641), (0.534, 0.505, 0.678), (0.449, 0.653, 0.610)}.

Table 12. The rank order of PF- TOPSIS for HCWT option selection

Options	$D(F_i, \varphi^+)$	$D(F_i, \varphi^-)$	$C(F_i)$	Ranking	$RC(F_i)$	Ranking
F_1	0.0622	0.1736	0.7361	1	0.000	1
F_2	0.0893	0.1501	0.6269	2	-0.5711	2
F_3	0.1092	0.1279	0.5395	3	-1.0189	3
F_4	0.1253	0.0998	0.4433	4	-1.4396	4
F_5	0.1510	0.0851	0.3604	5	-1.9374	5

Therefore, the ranking of the HCW treatment alternatives is $F_1 \succ F_2 \succ F_3 \succ F_4 \succ F_5$. The alternative F_1 (steam sterilization) has the highest degree of suitability among all healthcare treatment options.

Table 13. Comparison of different parameters with various methodologies

Aspects	Lu et al. [78]	Zhang and Xu [73]	Hinduja and Pandey [22]	Rani et al. [31]	Proposed Framework
Approaches	Interval 2-Tuple Linguistic Variables-based TOPSIS method	Distance measure based PF- TOPSIS method	An integrated approach based on DEMATEL, IF-ANP, and IF-AHP model	Entropy and divergence measures based PF-WASPAS method	Integrated SWARA-ARAS methodology
Alternatives/criteria assessment	I2TLVs	PFNs	IFNs	PFSs	PFSs
Aggregation process	interval 2-tuple induced ordered	Arithmetic	Arithmetic, Geometric	Arithmetic, geometric	Arithmetic, geometric

	weighted distance operator				
Theme of prioritization	Compromise solution	Compromise solution	Scoring model	Utility theory	Utility theory
Criteria weights	Assumed	Assumed	Evaluated by IF-ANP method	Evaluated based on entropy and divergence measures	Evaluated by SWARA method
MCDM process	Group	Single	Single	Group	Group
Hesitation degree in assessments	Excluded	Included	Excluded	Included	Included
Expert weights	Assumed	Assumed	NA	Computed	Computed
Normalization type	Vector	Vector	Linear	Linear	Linear, Vector
Optimal HCWT option	F_1	F_1	F_1	F_1	F_1

Next, we have implemented the same numerical example using the different existing approaches methods for making comparisons with the developed methodology. From Table 13, it is clear that the option F_1 (steam sterilization) has the highest utility degree in all the methods. As compared to existing approaches, the key advantages of the developed PF-SWARA-ARAS methodology are given by

a) The methods PF-TOPSIS [73], PF-WASPAS [31], and proposed PF-SWARA-ARAS are introduced within PFSs context, unlike Hinduja and Pandey [22] method is proposed under IFSs context, a particular case of the PFSs, while Lu et al., [78] are utilized Intuitionistic 2-Tuple Linguistic Variables (I2TLVs).
b) The developed PF-SWARA-ARAS model only assesses the PF-IS, while the PF-TOPSIS [73] and I2TL-TOPSIS [78] procedures require to obtain the PF-IS and PF-AIS, respectively. This specifies that, for MCDM concerns with more attributes or options, the PF-SWARA-ARAS framework can increase the operational efficiency to some amount and has superior operability.
c) For the PF-TOPSIS [73] and I2TL-TOPSIS [78] procedures, it is essential to estimate the distances between each options on considered attributes and that of the PF-IS, which is time-consuming and lessens the precision of the outcomes, while, in the proposed approach, the ratio between each option and the PF-IS can be expressed in the introduced methodology in the terms of “utility degree.” Also, the calculation process of PF-SWARA-ARAS framework

is easy and straightforward, and thus the precision and steadfastness of the outcomes are higher.

d) In [22], the DEMATEL method is applied to estimate the attribute weights, but its main drawback is a lack of consistency degree, to certify the achieved outcomes. Hence, the DEMATEL model is mostly applied to illustrate the interaction between attributes and the relations diagram. In [73] and [78], author(s) are assumed the criteria and experts weights, leaving no room to treat uncertainty, while, in the developed methodology, the SWARA procedure was implemented to compute the subjective weights of attributes due to its easiness and a lesser number of steps, which marks the developed methodology more sensible, flexible and efficient.

4.2. Sensitivity Analysis

Here, we discuss the sensitivity analysis to explore the behavior of introduced method. Eight different attribute weight sets were considered, and performance outcomes are depicted in Table 14 and Fig. (3). As shown in Table 14 and Fig. (3), one attribute in each set has the highest weight, and other attributes have minimum weights. Applying the procedure, an adequate variety of attribute weights was obtained formed to inspect the sensitivity of introduced framework to the variation of attribute weights.

Table 14. Various criteria weight sets for HCW treatment selection

	Set-I	**Set-II**	**Set-III**	**Set-IV**	**Set-V**	**Set-VI**	**Set-VII**	**Set-VIII**
B_1	0.1644	0.1525	0.1389	0.1119	0.1111	0.1103	0.1065	0.1044
B_2	0.1525	0.1389	0.1119	0.1111	0.1103	0.1065	0.1044	0.1644
B_3	0.1389	0.1119	0.1111	0.1103	0.1065	0.1044	0.1644	0.1525
B_4	0.1119	0.1111	0.1103	0.1065	0.1044	0.1644	0.1525	0.1389
B_5	0.1111	0.1103	0.1065	0.1044	0.1644	0.1525	0.1389	0.1119
B_6	0.1103	0.1065	0.1044	0.1644	0.1525	0.1389	0.1119	0.1111
B_7	0.1065	0.1044	0.1644	0.1525	0.1389	0.1119	0.1111	0.1103
B_8	0.1044	0.1644	0.1525	0.1389	0.1119	0.1111	0.1103	0.1065

The outcomes of the SA are shown in Table 15 and Fig. (4), which shows that the utility degree $Q_i \in [0, 1]$ can fluctuate over diverse attribute weight sets, and accordingly, the preferences of HCW treatment options is obtained. For example, the optimal option F_1 (steam sterilization) in each criteria weight set is the same, but when experts consider sets- V, VI, and VII, the HCW treatment alternatives F_3 and F_4 are interchanged. Hence, the HCW treatment evaluation is dependent on and is sensitive to attribute weight sets. Hence, the stability of the introduced approach is adequate as compared to other criteria weight sets.

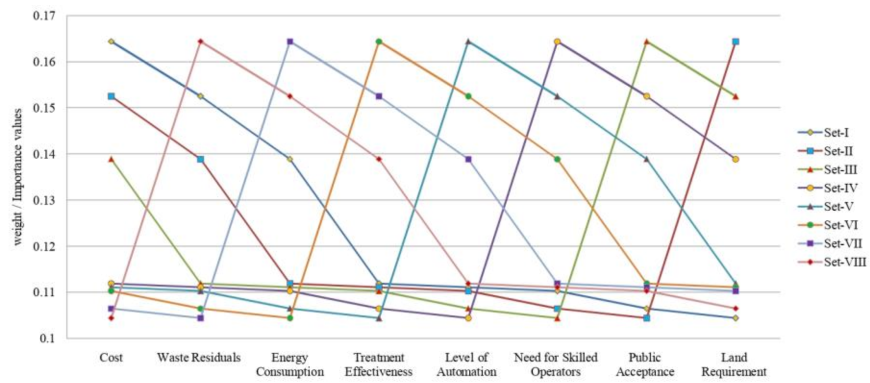

Fig. 3: Preference order of HCW treatment criteria using the SWARA method with different weight sets

Table 15. Utility degree for HCW treatment alternatives for various criteria weight sets

	Set-I	Set-II	Set-III	Set-IV	Set-V	Set-VI	Set-VII	Set-VIII
F_1	0.887	0.885	0.890	0.893	0.866	0.852	0.861	0.882
F_2	0.826	0.830	0.826	0.831	0.814	0.815	0.819	0.827
F_3	0.761	0.767	0.769	0.764	0.749	0.743	0.750	0.748
F_4	0.747	0.741	0.728	0.724	0.749	0.765	0.765	0.747
F_5	0.698	0.712	0.710	0.712	0.722	0.733	0.739	0.699

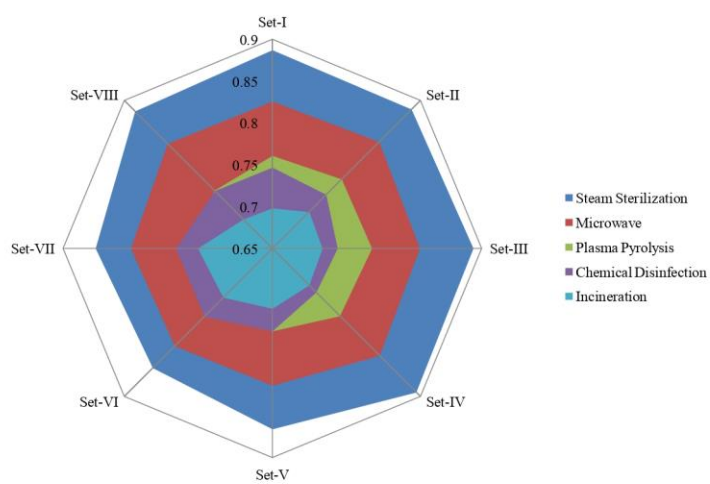

Fig. 4: Variation outcomes for HCW treatment options over different weight set values

5. Implications and Discussions

Based on the PFSs-based SWARA approach presented in this work, the energy consumption (B_3) is the most essential attribute with a weight of 0.1644, level of automation (B_5) is the second most significant attribute with a weight of 0.1575, and public acceptance (B_7) is the minimum significant criterion with a weight of 0.1044. These outcomes suggest that the environmental and technical aspects (that is energy consumption (B_3) and level of automation (B_5)) should be given higher priority during the evaluation of optimal HCW treatment alternatives. Additionally, the SWARA approach can be used to examine the subjective or qualitative behavior of the considered criteria. These results demonstrate that environmental and technical aspects have more considerable influence as compared to other attributes, indicating that they are the most critical attributes in the process of appraising and improving HCW treatment options.

In this work, steam sterilization (F_1) was shown to be the optimal HCWT option, followed by microwave (F_2), plasma pyrolysis (F_3), chemical disinfection (F_4), and incineration (F_5). Out of these five alternatives, steam sterilization (B_1) is most socially acceptable, because it has the desirable preference information for sustainable resources, elevated economics, and environmental & technical considerations from the DEs. The managerial propositions of steam sterilization are listed as (a) this option performed better on environmental, social, and sustainable resources with minimal operating costs. Emerging economies encompass a diverse range of developing countries; therefore, steam sterilization is a superior option for emerging economies. (b) Steam sterilization can help to refurbish the atmosphere and improve air quality since it can systematically dispose of the HCWs and contribute to a pollution-free atmosphere.

6. Conclusion

The selection of a proper and effective HCW treatment technique has been a significant concern in the management of HCW in recent years, predominantly in developing nations. The problem of HCWT selection is a time-consuming and intricate MCDM issue due to the occurrence of multiple conflicting criteria. In recent times, PFSs are a more flexible and efficient tool to handle the uncertainty arisen in realistic MCDM problems, so that the objective of the paper is to introduce a methodology under the PFSs environment. To do this, a combined decision-making framework with SWARA and ARAS approaches within the PFSs was developed. The present method utilizes the concept of PFSs to tackle the uncertainty arises in DEs' opinions and to rank the HCW treatment alternatives properly.

Moreover, the weights of the DEs were computed based on a new formula, and the criteria weights were calculated with the SWARA procedure. Further, a case study of HCW treatment selection problem was implemented under the PFSs environment, which reveals the efficiency and usefulness of introduced methodology. To validate the results, a comparison was discussed.

To certify the stability of introduced methodology, a sensitivity analysis was also presented. The outcomes demonstrated that the developed framework could successfully address the problem of evaluating HCW treatment options in uncertain environments.

Further, we will enhance the work by combining objective and subjective knowledge regarding the weights of criteria. In addition, we will further suggest some methods (like Gained and Lost Dominance Score (GLDS), MARCOS, double normalization-based multiple aggregations (DNMA)) to assess COVID-19 medication, sustainable biomass crop selection, and other MCDM problems.

Some limitations and recommendations related to the HCW domains are given as follows:

- The contribution of the paper was designated as the assessment of attributes from literature and field inspection, and the extension MCDM procedure method for healthcare waste disposal method selection. For authorities namely HCWD practices, these attributes and methodology would assist in the assessment of HCWDM over the economic, social, technical and environmental dimension. The current would create an effective involvement to the expensive cost and thin profit making profession of HCWD. Moreover, the safe, protected and clean atmosphere for entirely living creatures could be accomplished.
- From expert's opinion, the management of HCWD organizations shown that the future arrangement is another concern ahead of them, thus, they termed that there is a requirement of MCDM procedure for capacity planning comprising number of incinerators, vehicles labor, and others. Nevertheless, there is no statistical validation of outcomes assessed from MCDM models and can only be certified with the help of experts domain (as considered in this work).
- The useful improvement of a HCWM strategy needs an effective human resource management. This should comprise training to doctors, hospital staff as well as waste collection employees. Furthermore, patients and their companions should also be educated about benefits of adopting systematic HCWD. Moreover, technological innovation, government regulation and sustainable strategies can also be utilized for healthier HCWM.

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