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Fermatean Fuzzy IWP-TOPSIS-GRA Multi-Criteria Group Analysis and Its Application to Healthcare Waste Treatment Technology Evaluation

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Abstract: The growth of healthcare waste (HCW) was driven by the spread of COVID-19. Effective HCW eradication has become a pressing global issue that requires immediate attention. Selecting an effective healthcare waste treatment technology (HCWTT) can aid in preventing waste buildup. HCWTT selection can be seen as a complex multi-criteria group evaluation problem as the process involves multiple types of criteria and decision-makers (DMs) facing uncertain and vague information. The key objective of this study is to create a useful tool for the evaluation of HCWTT that is appropriate for the organization's needs. A novel index system for assessing the HCWTT during the decision-making evaluation process is first presented. Then a new approach based on entropy measure, decision-making trial and evaluation laboratory (DEMATEL), and game theory for the integrated weighting procedure (IWP) is presented under a Fermatean fuzzy environment. A multi-criteria group analysis based on IWP, a technique for order of preference by similarity to ideal solution (TOPSIS) and grey relational analysis (GRA), named IWP-TOPSIS-GRA framework suited to Fermatean fuzzy evaluation information, is developed. In a real-world case of HCWTT selection, through comparative analysis and sensitivity analysis, it is verified that the presented method is feasible and robust.

Keywords: healthcare waste treatment; Fermatean fuzzy set; game theory; TOPSIS; grey relational analysis

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1. Introduction

In the past few decades, rapid economic development has also brought about serious waste pollution. The increasing amount of waste not only disrupts daily life but also endangers the health of people. Reducing the accumulation of garbage and protecting the environment are necessary prerequisites and important guarantees for achieving sustainable development of society. It has been agreed upon both at home and abroad that we need to dispose of waste safely and efficiently to build a more comfortable ecological home and realize sustainable development. For example, in 2018, China issued the document Pilot Program for the Construction of "Waste-free Cities", aiming to reduce, recycle, and dispose of industrial and agricultural solid waste as well as domestic and hazardous waste to promote ecological civilization and build a more beautiful country.

To implement waste management efficiently, waste is classified into groups such as radioactive, hazardous, solid, and healthcare waste (HCW). Hazardous wastes with direct or indirect effects such as infectivity and toxicity, which occur during medical treatment, prevention, and other relevant procedures in health care and medical institutions, are collectively referred to as HCW [1]. As is known to all, HCW has a greater risk of infection than ordinary wastes. To dispose of HCW effectively, HCW is segmented into infectious, damaging, pathological, pharmaceutical, and chemical waste [2].

With the outbreak of COVID-19, routine nucleic acid tests to ensure public health led to a significant increase in the use of disposable gloves, cotton swabs, protective clothing, and surgical gloves [3]. As observed by China's Ministry of Ecology and Environment, in

2021, 1.4 million tons of HCW in total were collected, representing an 11.1% increase year on year. The national centralized HCW disposal volume in 2022 reached 2.8 million tons, which was more than 80% higher than in 2019 before COVID-19. COVID-19 has increased the pressure on HCW treatment invisibly.

HCW without timely treatment is extremely harmful. Take the novel coronavirus as an example, the virus can stably survive on the surface of objects for about 14 days. If not treated in time, the virus can be transmitted secondarily by respiratory droplets, close contact, and aerosols of patient excrement. Pathogens contaminated with HCW will infect medical personnel and sanitation workers, and it is highly likely to cause large-scale pollution at the social level [4]. Additionally, the HCW buildup can contaminate otherwise clean medical supplies, resulting in waste.

To prevent HCW from spreading and polluting the environment, appropriate and efficient technologies are needed for its disposal. The most common medical disposal technologies include incineration, microwave, steam sterilization, and landfill [5]. Incineration is the primary technology considered for HCW treatment [6], as the name suggests, waste is placed in an incinerator, where the virus is inactivated at very high temperatures, but incineration is prone to produce fumes containing dioxins, one of the most harmful chemicals with a high risk of carcinogenesis and mutagenesis, posing a threat to human health [7]. The landfill is also a common HCWTT, but it makes the conversion rate of resources extremely low, and waste such as plastic is not easily degraded in the ground and is prone to produce dangerous gases [8], which does not meet the original purpose of protecting the environment. Steam sterilization is suitable for the treatment of infectious and injurious waste, although the types of waste that can be disposed of by this technology are limited, its operation is simple, operating conditions are convenient, and it covers an area and faces fewer safety risks [9]. Microwaves can treat not only the waste that can be disposed of by steam sterilization but also pathological waste, which can treat HCW with maximum efficiency in a short period without generating environmentally unsafe elements such as dioxins and effluent [10]. In summary, each HCWTT has its advantages and disadvantages, and choosing an economical and environmentally friendly HCWTT can help with waste management.

Since multiple evaluation criteria and objects are involved, HCWTT selection can be thought of as a multi-criteria group decision-making (MCGDM) issue. Due to the vagueness of cognition and the complexity of the real world, people sometimes cannot use precise real numbers to give their evaluation opinions of HCWTT, in this regard, intuitionistic hesitation fuzzy sets [11] and intuitionistic fuzzy sets (IFSs) [12] were introduced. IFSs require the sum of membership and non-membership to be one; compared to Fermatean fuzzy sets (FFSs) [13], there is still some information here that cannot be described comprehensively. The research related to FFSs is gradually enriched in a great many areas. To assemble Fermatean fuzzy (FF) numbers, the FF Archimedean copula-based symmetric Maclaurin mean, soft aggregation, and Archimedean copula operators were proposed one after another [14–16]. Decision tools including TOPSIS, Measurement Alternatives and Ranking Based on Compromise Solution (MARCOS), and Elimination and Choice Transiting Reality (ELECTRE) in the FF environment were successfully extended to solve supplier selection [17], HCW treatment site selection [18], and biomedical material selection problems [19].

The following exact issues exist in the assessment and selection of HCWTT with MCGDM techniques:

(1) Due to a number of issues, including inadequate information disclosure and the inclusion of non-quantifiable attributes in the evaluation criteria, decision-makers (DMs) find it difficult to provide precise evaluation values for each alternative during the actual process of HCWTT selection and evaluation.
(2) The evaluation criteria of HCWTT are uncertain. The criteria currently used to evaluate HCWTT are centered on four dimensions: economic, environmental, technological, and social [20,21], but they are not unified.

(3) The evaluation criteria weights are unclear. Attribute weights, as a particularly important factor influencing scheme ranking, need to balance objective data and subjective perceptions of DMs. Meanwhile, the current weight determination methods [22–24] and integration methods [25,26] are too restricted and lack novelty.
(4) There are some restrictions on the single decision technique when ordering and selecting alternatives. For instance, the classic TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [27] and VIKOR (ViseKriterijumska Optimimizacija I Kompromisno Resenje) [28] methods are unable to express dynamic changes, simply the relative positions of the alternatives. Grey relational analysis (GRA) [29] can only reflect the degree of similarity but not the position relationship. How to use decision procedures to comprehensively create the best decisions is something that requires attention.

To fill the gap of integrated weighting and decision methods in the evaluation of HCWTTs under an uncertain environment, this study works towards designing a hybrid MCGDM framework combining an integrated weighting procedure (IWP) and TOPSIS-GRA method under an FF environment. After constructing the index system, the Decision Making Trial and Evaluation Laboratory (DEMATEL) and FF entropy are combined with game theory to determine the integrated weights of attributes. Then the TOPSIS-GRA framework is applied to sort the options and choose the best HCWTT.

The paper is organized into the following sections. Section 2 is the literature review part. In Section 3, a new index system for HCWTT selection is proposed after taking into account the current evaluation dimensions. Section 4 reviews the basics of FFSs. Section 5 presents the IWP combing DEMATEL and entropy weight method (EWM) based on game theory. Section 6 presents the specific MCGDM process of the FF IWP-TOPSIS-GRA method. Section 7 applies the proposed model to a specific case of HCWTT selection and gives a comparative and sensitivity study. The valuable conclusions are given in Section 8.

2. Literature Review

At present, research on waste treatment is spread over various fields. The selection of HCWTT may involve many experts, who are evaluated by considering a combination of factors and criteria. Therefore, the HCWTT selection is able to be considered an MCGDM problem at that point. The current research on waste management using the MCGDM method mainly focuses on HCW treatment sites [30,31], HCW treatment suppliers [32], and HCWTT selection. The evaluation index construction, index weight determination, and the ranking and choice of alternatives are all part of the HCWTT selection process.

2.1. Evaluation Index Systems for HCWTT Selection

Qian et al. [20] constructed an HCWTT evaluation index system considering social and environmental, technical, and economic dimensions. Adar and Delice [21] argued that in the evaluation of HCWTT, ergonomic criteria must be considered along with economic, social, environmental, and technical factors. However, the evaluation criteria in the current extensive literature on HCWTT mainly revolve around four dimensions: social, economic, environmental, and technological. Liu et al. [33] established an index system for HCWTT, in which net cost per ton was under the economic dimension, waste residuals, noise, and release with health effects under the environmental dimension, reliability, occupational hazards, and treatment effectiveness under technical dimension and public acceptance under social dimension. On this basis, Shi et al. [34] did not consider noise and occupational hazards under economic and technical dimensions, so a new set of HCWTT evaluation index systems was established. Hinduja and Pandey [35] broke down the cost into capital, operational and maintenance, and disposal costs, and summarized the economic criteria used to measure HCWTT. In addition, Ju et al. [36] believed that the evaluation index system of HCW treatment should also take processing costs into account. Manupati et al. [28] pointed out that at the social level, the safety of an HCWTT could also affect the final choice. Based on the reality of Fuzhou, Ling et al. [37] established an index system for HCWTT evaluation containing seven first-level attributes including emission, employment potential, energy recovery, etc.

2.2. Attribute Weight Determination Procedures for HCWTT Evaluation

It is important to determine the weights for the evaluation criteria as weights affect the alternative ranking. Zhang et al. [38] developed a projection model based on a hesitant 2-tuple environment to determine the weights of DMs for evaluating HCWTT by measuring the similarity between two individual evaluation matrices. On the basis of a sustainable development perspective, Li et al. [22] used DEMATEL to solve a decision problem with unknown weights in an interval-valued fuzzy situation, a preferred HCWTT in an emerging economy was selected. Voudrias [23] assessed the weights of the evaluation attributes of infectious waste treatment systems by the Analytic Hierarchy Process (AHP), so as to provide support for medical institutions to make reasonable choices. Inspired by the traditional best-worst method (BWM), Torkayesh et al. [39] improved it and proposed a stratified BWM, the superiority of which is supported by a practical case of municipal waste treatment technology selection in Tehran. Zarrinpoor [24] focused on the social factors that influence the selection of HCWTT and BWM was utilized to assess their importance. To help select a technology that can effectively dispose of the growing amount of HCW, Puška et al. [40] used the Full Consistency Method (FUCOM) to establish attribute weights based on four evaluation dimensions. Subjective weighting methods are widely used to solve the multi-criteria evaluation problems for unknown weights including HCWTT selection, while weighting methods that comprehensively consider subjective weights and the objectivity of evaluation data are ignored. Recognizing that, Narayanamoorthy et al. [25] proposed a new integrated weighting approach for the HCWTT evaluation index which combined Criteria Importance Through Inter Criteria Correlation (CRITIC) and the rank sum weight method. The subjectivity of DMs is not only respected, but also based on objective evaluation data. Coincidentally, Liu et al. [26] provided technical support for calculating the DMs' weights and obtained more comprehensive results for selecting the optimal HCW recycling channel combing BWM and EWM.

2.3. Evaluation and Decision Methods for HCWTT Selection

The decision tools used in HCWTT selection have received much attention and interest from scholars. Mishra et al. [12] applied novel parametric divergence measures to the conventional Evaluation based on Distance from Average Solution (EDAS) and the decision results showed that steam sterilization was most suitable for sterilization. Makan and Fadili [41] used the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) to investigate the priority order of ten HCWTTs, the ranking results showed that the rotary kiln has the highest disposal sustainability. To choose the best HCWTT, Huang et al. [42] presented an integrated MCDM framework integrating BWM and PROMETHEE. Due to the fact that there are uncertain qualitative attributes in actual HCWTT evaluation, scholars have started to focus on the decision methods based on fuzzy evaluation information. Geetha et al. [11] used multiple objective optimizations based on MULTIMOORA to select the optimal one from four effective waste treatment technologies. The results showed that choosing different disposal methods for different types of waste was the best measure to protect the environment. To help government to choose the optimal HCWTT, Manupati et al. [28] used fuzzy VIKOR to rank the alternatives based on the 10 criteria constructed, and after a comparative analysis with TOPSIS, the results consistently showed that incineration was probably the most effective means of HCW treatment at present. To ensure that the best HCWTT can be selected under incomplete and uncertain information, EDAS applicable to the multi-granular linguistic environment [36] and generalized orthopair fuzzy environment [43] were proposed. To solve the HCWTT selection problem in q-rung orthopair fuzzy sets (QROFSs), Saha et al. [44] suggested an MCDM method that used extended double normalization-based multi-aggregation (DNMA) to establish alternative ranking. Wang and Wang [45] used a Bonferroni mean operator to fuse linguistic information and designed an MCDM framework for HCWTT based on Combined Compromise Solution (CoCoSo). Adar and Delice [21] presented a hybrid hesitant fuzzy linguistic assessment model for the HCWTT selection. Comparison with results produced by TOPSIS and VIKOR all revealed that steam sterilization was the most effective waste treatment procedure.

3. HCWTT Evaluation Index System

Due to the recent occurrence and ongoing intensification of COVID-19, the proportion of HCW in waste is greatly increased. The hazardous waste in HCW cannot enter landfills because of its corrosive nature, so it can only be disposed of by incineration, which inadvertently increases the disposal task of incinerators. However, the limited capacity of incinerators is not enough to dispose of all the HCW. Therefore, in addition to the most common incineration technology, other diverse disposal processes are emerging. It is necessary to provide decision support for selecting the best HCWTT. The efficiency and effectiveness of an HCWTT can be evaluated under various qualitative and quantitative criteria.

Based on the existing literature, this study constructs a set of attributes for HCWTT selection based on four dimensions: social, environmental, economic, and technological, which focus on the six aspects below.

(1) Economic: The economic cost of HCWTT consists of construction investment and operating costs. Under the economic dimension, we selected the attribute cost to evaluate the HCWTT.

Cost (C_1): The cost refers to the total cost required to dispose of HCW [34]. The construction investment cost is the total cost required from the beginning of the HCW treatment site project construction to the completion, specifically including the cost of purchasing and installing HCW disposal equipment and land occupied by the site [21]. Operating equipment requires a certain amount of human and material resources, the operating costs include electricity, labor, and maintenance costs [35]. In addition, the cost of storing and transporting the HCW is also included.

(2) Environmental: The purpose of selecting the best HCWTT is to minimize the emission of hazardous objects, achieve stable and standardized discharge of pollutants, and reduce environmental pollution and harm to health from residuals. Under the environmental dimension, we selected waste residuals and release with health effects as important evaluation attributes.

Waste residuals (C_2): There are liquid and gas emissions, solid residuals, and noise in the process of disposing of HCW [46]. Medical wastewater corrodes soil and pollutes rivers. Greenhouse gas emissions into the atmosphere, cause secondary pollution. We can describe the waste residuals by measuring the level of discomfort caused by noise to operators and surrounding residents, the number of solid residuals left behind, and liquid and gas emissions [45].

Release with health effects (C_3): This attribute is concerned with the impact of HCW treatment residuals on the health of operators and residents surrounding the disposal site. Residents living at incineration sites are exposed to higher concentrations of dioxins, facing a very high risk of carcinogenesis and mutagenesis [47]. Mercury from HCW incineration can damage the excretory, nervous, and reproductive systems [48]. Sterilizing HCW produces low levels of organic compounds that are not only detrimental to air quality but also cause dizziness and other discomforts in humans.

(3) Technical: The maturity of each technology is the key to measuring the HCW treatment effectiveness. The treatment effectiveness and technical performance can be examined from quantitative and qualitative perspectives, respectively. We selected reliability and treatment effectiveness as key attributes for assessing HCWTTs.

Reliability (C_4): This attribute focuses on the ease of operation, reliability, and stability of a disposal technology for disposing of HCW [46]. We can examine whether a treatment technology can operate properly and complete its task within the specified time [45]. Only when the maturity and feasibility of the technology for treating HCW are guaranteed can the requirements for HCW treatment be met and the purpose of protecting the environment be achieved.

Treatment effectiveness (C_5): It refers to whether a technology is suitable for a certain situation of HCW treatment, whether the realistic results of the implementation meet the expected scenario [45], whether it has considerable long-term applicability [28], and whether it can be extended to other areas of waste treatment. It can be measured by HCW removal rates and residual emissions.

(4) Social: The public is the most important external environmental stakeholder of hospitals and governments, and there is a mutual influence relationship between the public and HCW treatment. HCWTT of high quality can provide a better living environment for the public. The awareness improvement of environmental protection drives social progress and HCWTT innovation. We selected public acceptance as the sub-criterion.

Public acceptance (C_6): This attribute examines public acceptance of technology for HCW treatment, including the effectiveness, safety, and cost of disposal [28,44]. The influence technology has on employment potential can also be examined [37], and if the technology increases the potential for future employment, public acceptance will be increased. If the public is resistant to the technology, there is a high risk of complaints about it, leading to a suspension of the waste treatment process.

4. Fermatean Fuzzy Sets

The basics of FFSs will be briefly reviewed in this part.

Definition 1. *[13]. Let Δ be a non-empty set. An FFS is defined as follows:*

$$\Gamma = \{\langle \tau_j, \psi_\Gamma(\tau_j), \varphi_\Gamma(\tau_j)\rangle | \tau_j \in \Delta\}, \tag{1}$$

where $\psi : \Delta \to [0,1]$ is the membership $\psi_\Gamma(\tau_j)(0 \le \psi_\Gamma(\tau_j) \le 1)$ and $\varphi : \Delta \to [0,1]$ is the non-membership $\varphi_\Gamma(\tau_j)(0 \le \varphi_\Gamma(\tau_j) \le 1)$. For $\tau_j \in \Delta$, it satisfies the condition $0 \le (\psi_\Gamma(\tau_j))^3 + (\varphi_\Gamma(\tau_j))^3 \le 1$. If $\Phi_\Gamma(\tau_j) = \sqrt[3]{1 - (\psi_\Gamma(\tau_j))^3 - (\varphi_\Gamma(\tau_j))^3}$, then $\Phi_\Gamma(\tau_j)$ is defined to be the indeterminacy of the set Γ. Specially, $\Gamma = (\psi_\Gamma, \varphi_\Gamma)$ denotes an FFS.

Definition 2. *[13]. If there exists a positive real number σ, let $\Gamma_1 = (\psi_1, \varphi_1)$ and $\Gamma_2 = (\psi_2, \varphi_2)$ be and two FFSs. The algorithms between FFSs are as follows:*

(1) $\Gamma_1^c = (\varphi_1, \psi_1)$;

(2) $\Gamma_1 \oplus \Gamma_2 = \left(\sqrt[3]{\psi_1^3 + \psi_2^3 - \psi_1^3\psi_2^3}, \varphi_1\varphi_2\right)$;

(3) $\sigma\Gamma_1 = \left(\sqrt[3]{1 - (1 - \psi_1^3)^\sigma}, (\varphi_1)^\sigma\right)$;

(4) $\Gamma_1^\sigma = \left((\psi_1)^\sigma, \sqrt[3]{1 - (1 - \varphi_1^3)^\sigma}\right)$.

Definition 3. *[13]. Let $\Gamma = (\psi_\Gamma, \varphi_\Gamma)$ be an FFS; its score function $\mathbb{S}(\Gamma)$ and accuracy function $\mathbb{C}(\Gamma)$ are defined as:*

$$\mathbb{S}(\Gamma) = (\psi_\Gamma)^3 - (\varphi_\Gamma)^3; \tag{2}$$

$$\mathbb{C}(\Gamma) = (\psi_\Gamma)^3 + (\varphi_\Gamma)^3, \tag{3}$$

where $\mathbb{S}(\Gamma) \in [-1,1]$ and $\mathbb{C}(\Gamma) \in [0,1]$.

Definition 4. *[13]. Let $\Gamma_1 = (\psi_1, \varphi_1)$ and $\Gamma_2 = (\psi_2, \varphi_2)$ be two FFSs, then*

(1) *if $\mathbb{S}(\Gamma_1) > \mathbb{S}(\Gamma_2)$, then $\Gamma_1 > \Gamma_2$;*
(2) *if $\mathbb{S}(\Gamma_1) = \mathbb{S}(\Gamma_2)$, if,*
    (a) *if $\mathbb{C}(\Gamma_1) > \mathbb{C}(\Gamma_2)$, then $\Gamma_1 > \Gamma_2$;*
    (b) *if $\mathbb{C}(\Gamma_1) = \mathbb{C}(\Gamma_2)$, then $\Gamma_1 = \Gamma_2$.*

Definition 5. *[13]. Let $\Gamma_1 = (\psi_1, \varphi_1)$ and $\Gamma_2 = (\psi_2, \varphi_2)$ be two FFSs, then the Euclidean distance $d(\Gamma_1, \Gamma_2)$ between Γ_1 and Γ_2 is introduced as:*

$$d(\Gamma_1, \Gamma_2) = \sqrt{\frac{1}{2}\left[\left(\psi_1^3 - \psi_2^3\right)^2 + \left(\varphi_1^3 - \varphi_2^3\right)^2 + \left(\Phi_1^3 - \Phi_2^3\right)^2\right]}. \tag{4}$$

Definition 6. *[13]. Let $\Gamma_i = (\psi_i, \varphi_i)(i = 1, 2, \ldots, n)$ be a set of FFSs, where $w = (w_1, w_2, \ldots, w_n)^T$ is the weight vector of $\Gamma_i(i = 1, 2, \ldots, n)$, then*

$$FFWA(\Gamma_1, \Gamma_2, \ldots, \Gamma_n) = \left(\sqrt[3]{1 - \prod_{i=1}^{n}\left(1 - \psi_i^3\right)^{w_i}}, \prod_{i=1}^{n} \varphi_i^{w_i}\right) \tag{5}$$

is defined as the FF weighted average (FFWA) operator, where $w_i \geq 0$ and $\sum_{i=1}^{n} w_i = 1$.

5. The IWP Based on DEMATEL, FF Entropy, and Game Theory

Weights are divided into subjective and objective weights. Subjective weights indicate the different importance of attributes and are given based on the experience of evaluation experts, but the experts are highly subjective. Objective weights depend on reference data but ignore the different levels of importance brought by the attributes themselves. This section aims to provide an integrated weighting reference combing DEMATEL and entropy with game theory, which can remove the bias of findings produced by a single weighing method and obtain more idealized results.

5.1. Subjective Weights Determination Method Based on DEMATEL

DEMATEL is a decision method that combines graph theory and matrix theory for the analysis of complex system factors [49], which can identify factors in complex networks and is considered one of the best methods for exploring causal relationships. It is widely adopted to identify the evaluation attributes' importance. The idea of DEMATEL to determine subjective weights is to analyze the relationship between factors two by two, determine a comprehensive relationship matrix, analyze the influence and influenced degrees between factors, and determine the importance and attribute weight. Following are the precise processes for using DEMATEL to calculate the subjective weights.

Step 1. Determine the direct evaluation matrix $X = \left[x_{ij}\right]_{n\times n}$. Evaluate the influence degree of the attributes $C_j(j = 1, 2, \ldots, n)$ with linguistic variables represented in Table 1 after expert panel consultation. The direct influence matrix $X = \left[x_{ij}\right]_{n\times n}$ is determined by a two-by-two comparison, where x_{ij} indicates the influence degree of attribute C_i on C_j.

Table 1. Evaluation linguistic scale.

Linguistic Terms	Influence Scores	FFSs
Very good (VG)	6	(0.9, 0.15)
Good (G)	5	(0.85, 0.25)
Qualified (Q)	4	(0.7, 0.25)
Moderate (M)	3	(0.6, 0.6)
Ineligible (I)	2	(0.35, 0.7)
Bad (B)	1	(0.3, 0.85)
Very bad (VB)	0	(0.2, 0.9)

Step 2. Determine the normalized direct influence matrix $N = \left[n_{ij}\right]_{n\times n}$. Normalize the direct evaluation matrix $X = \left[x_{ij}\right]_{n\times n}$ to obtain the normalized direct influence matrix $N = \left[n_{ij}\right]_{n\times n}$ using Equation (6):

$$n_{ij} = \frac{x_{ij}}{\max\limits_{1\le i\le n}\sum\limits_{j=1}^{n} x_{ij}}. \tag{6}$$

Step 3. Calculate the total relation matrix $T = \left[t_{ij}\right]_{n\times n}$ using Equation (7):

$$T = N(E-N)^{-1}, \tag{7}$$

where E is an identity matrix.

Step 4. Compute the influence degree P_j and influenced degree Q_j of attributes using Equations (8) and (9):

$$P_j = \left[\sum_{i=1}^{n} t_{ji}\right]_{1\times n}; \tag{8}$$

$$Q_j = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n}. \tag{9}$$

Step 5. Calculate the importance degree W_j of attributes by Equation (10). Normalize importance degree w_j of attributes by Equation (11) to obtain objective weights of attributes.

$$W_j = \sqrt{\left(P_j - Q_j\right)^2 + \left(P_j + Q_j\right)^2}, \tag{10}$$

$$w_j = \frac{W_j}{\sum\limits_{j=1}^{n} W_j}. \tag{11}$$

where relation degree $P_j - Q_j$ indicates the influence degree of the attributes on others while prominence degree $P_j + Q_j$ indicates the level of importance of each attribute.

We can thus obtain subjective weights $w_j = (w_1, w_2, \ldots, w_n)^T$, where $w_j \in [0,1]$ and $\sum\limits_{j=1}^{n} w_j = 1$.

5.2. Objective Weights Determination Method Based on FF Entropy

Let $\Re = \left(\lambda_{ij}\right)_{m\times n}$ be a normalized comprehensive evaluation matrix under alternative sets $A = \{A_1, A_2, \ldots, A_m\}$ and attribute sets $C = \{C_1, C_2, \ldots, C_n\}$, where $\lambda_{ij} = \left(\psi_{ij}, \varphi_{ij}\right)$ is an FFS. Objective weights ω_j of each attribute $C_j(j = 1, 2, \ldots, n)$ can be calculated according to the formula of the FF entropy measure:

$$\omega_j = \frac{1 - \widetilde{S}_j}{n - \sum_{j=1}^{n} \widetilde{S}_j}, \tag{12}$$

where $\widetilde{S}_j = \frac{1}{m}\sum_{i=1}^{m} S(\lambda_{ij})$ and $S(\lambda_{ij})$ is the entropy value of λ_{ij}. The calculation formula is as follows [50]:

$$S(\lambda_{ij}) = 1 - \left[\left(\psi_{ij}^3 - \varphi_{ij}^3\right)\left({}_{ij}^3 + \varphi_{ij}^3\right)\right]^2. \tag{13}$$

We can thus can obtain the objective weights $\omega_j = (\omega_1, \omega_2, \ldots, \omega_n)^T$, where $\omega_j \in [0, 1]$ and $\sum_{j=1}^{n} w_j = 1$.

5.3. Game Theory-Based Integration Weighting Method

The game theory-based integration weighting method [51] seeks to investigate the optimum linear combination coefficients combining objective and subjective weights by minimizing the deviation of different types of weights from the optimal weights, which can assign the weights more reasonably and avoid the adverse effects of single weights. The steps for determining the IWP based on game theory are presented below.

Step 1. Construct the base weight vector set, this paper selects a total of two weight determination methods to obtain the weight of n attributes, then the constructed weight vector set is expressed as follows:

$$\begin{cases} w = (w_1, w_2, \ldots, w_n) \\ \omega = (\omega_1, \omega_2, \ldots, \omega_n) \end{cases}. \tag{14}$$

Step 2. Construct linear combinations of weight vectors q. The linear combination of the above different weight vectors is

$$q = a_1 w^T + a_2 \omega^T, \tag{15}$$

where $a_i(i = 1, 2)$ are linear combination coefficients and $a_i > 0$.

Step 3. Construct a multi-objective game geometric model to optimize the linear combination of coefficients a_i. Suppose there is a_i that minimizes the deviation of q from w^T and ω^T, so

$$\min||a_1 w^T + a_2 \omega^T - q||. \tag{16}$$

The following linear equation system can be obtained by differentiating Equation (16) in the first order

$$\begin{bmatrix} ww^T & w\omega^T \\ \omega^T w & \omega\omega^T \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} ww^T \\ \omega\omega^T \end{bmatrix} \tag{17}$$

The optimal linear combination coefficients a_i can be solved using MATLAB software.

Step 4. Normalize the optimal linear combination coefficients using Equation (18).

$$a_i^* = \frac{a_i}{\sum_{i=1}^{2} a_i}(i = 1, 2) \tag{18}$$

Step 5. Calculate integrated weights using Equation (19).

$$\varpi = a_1^* w^T + a_2^* \omega^T \tag{19}$$

We can thus obtain integrated weights $\varpi_j = (\varpi_1, \varpi_2, \ldots, \varpi_n)^T$, where $\varpi_j \in [0,1]$ and $\sum_{j=1}^{n} \varpi_j = 1$.

6. FF IWP-TOPSIS-GRA Framework for FF MCGDM Analysis

TOPSIS, a decision-making framework that selects the best solution by computing the alternatives' distance from the negative and ideal scheme, has been widely used in various fuzzy environments because of its simplicity and low workload [52–54]. However, it can only reflect relative positions and cannot show developmental changes, while GRA can exactly compensate for the shortcomings exhibited by TOPSIS. Therefore, scholars have combined TOPSIS and GRA to provide a more comprehensive evaluation technique. The TOPSIS-GRA framework has been extended to IFSs [55,56], interval-valued IFSs [57,58], QROFSs [59], single-valued neutrosophic sets [60], and spherical fuzzy sets [61]. It also provides technical support for dealing with MCGDM problems [62,63]. This section introduces the proposed FF IWP-TOPSIS-GRA model and presents its concrete steps.

Consider an MCGDM problem in the FF environment. Let $A = \{A_1, A_2, \ldots, A_m\}$ and $C = \{C_1, C_2, \ldots, C_n\}$ denote the set of alternatives and evaluation attributes, respectively. The set of DMs is $D = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_k)$ and the expert weight vector is $\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_k)$. Let the evaluation information of DMs $\varepsilon_\hbar(\hbar = 1,2,\ldots,k)$ about alternatives $A_i \in A$ under attribute $C_j \in C$ be denoted by $\lambda_{ij}^{\hbar} = \left(\psi_{ij}^{\hbar}, \varphi_{ij}^{\hbar}\right)$, where $\psi_{ij}^{\hbar}, \varphi_{ij}^{\hbar} \in [0,1]$ and $0 \leq \left(\psi_{ij}^{\hbar}\right)^3 + \left(\varphi_{ij}^{\hbar}\right)^3 \leq 1$. Thus, the FF evaluation matrix $\Re^{\hbar}$ of the DMs $\varepsilon_\hbar(\hbar = 1,2,\ldots,k)$ can be expressed as follows:

$$\Re^{\hbar} = \left(\lambda_{ij}^{\hbar}\right)_{m\times n} = \begin{pmatrix} \lambda_{11}^{\hbar} & \cdots & \lambda_{1n}^{\hbar} \\ \vdots & \ddots & \vdots \\ \lambda_{m1}^{\hbar} & \cdots & \lambda_{mn}^{\hbar} \end{pmatrix}. \tag{20}$$

The detailed phases of the proposed FF IWP-TOPSIS-GRA model are given below.

Step 1. The DMs $\varepsilon_\hbar(\hbar = 1,2,\ldots,k)$ assess the alternatives using the evaluation linguistic terms under each attribute, and then convert them to FFSs according to the transformation guidelines in Table 1. We can then obtain the evaluation matrix $\widetilde{\Re}^{\hbar} = \left(\widetilde{\lambda}_{ij}^{\hbar}\right)_{m\times n}$ of each expert, where $\widetilde{\lambda}_{ij}^{\hbar} = \left(\widetilde{\psi}_{ij}^{\hbar}, \widetilde{\varphi}_{ij}^{\hbar}\right)$.

Step 2. Integrate individual evaluation opinions using the FFWA operator to obtain a comprehensive evaluation matrix $\widetilde{\Re} = \left(\widetilde{\lambda}_{ij}\right)_{m\times n}$, where $\widetilde{\lambda}_{ij}$ is calculated as follows:

$$\widetilde{\lambda}_{ij} = \left(\widetilde{\psi}_{ij}, \widetilde{\varphi}_{ij}\right) = FFWA\left(\widetilde{\lambda}_{ij}^{1}, \widetilde{\lambda}_{ij}^{2}, \ldots, \widetilde{\lambda}_{ij}^{k}\right) = \left(\sqrt[3]{1 - \prod_{\hbar=1}^{k}\left(1 - \left(\widetilde{\lambda}_{ij}^{\hbar}\right)^3\right)^{\gamma_\hbar}}, \prod_{\hbar=1}^{k}\left(\widetilde{\lambda}_{ij}^{\hbar}\right)^{\gamma_\hbar}\right). \tag{21}$$

Step 3. Normalize comprehensive evaluation matrix. To ensure the consistency of attribute types, the cost-type attributes are transformed into benefit-type attributes according to Equation (22).

$$\lambda_{ij} = \left(\psi_{ij}, \varphi_{ij}\right) = \begin{cases} \left(\widetilde{\psi}_{ij}^{\hbar}, \widetilde{\varphi}_{ij}^{\hbar}\right), C_j \in J_b \\ \left(\widetilde{\varphi}_{ij}^{\hbar}, \widetilde{\psi}_{ij}^{\hbar}\right), C_j \in J_c \end{cases}, \tag{22}$$

where J_b and J_c stand for attribute sets of the benefit- and cost-types, accordingly.

Step 4. Determine indicators' weights based on IWP. The subjective weights $w = (w_1, w_2, \ldots, w_n)^T$ and objective weights $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ of attributes are calculated according to DEMATEL and EWM proposed in Section 5 of this paper, respectively. On this basis, the integrated weights $\varpi_j = (\varpi_1, \varpi_2, \ldots, \varpi_n)^T$ of attributes are calculated based on game theory.

Step 5. Find the negative ideal solution (NIS) A^- and positive ideal solution (PIS) A^+.

$$\begin{aligned} A^- &= \left\{ \lambda_j^-, \min_i S(\lambda_{ij}) \middle| j = 1, 2, \ldots, n \right\} \\ &= \left\{ \langle \lambda_1^-, (\psi_1^-, \varphi_1^-) \rangle, \langle \lambda_2^-, (\psi_2^-, \varphi_2^-) \rangle, \ldots, \langle \lambda_n^-, (\psi_n^-, \varphi_n^-) \rangle \right\} \end{aligned} \tag{23}$$

$$\begin{aligned} A^+ &= \left\{ \lambda_j^+, \max_i S(\lambda_{ij}) \middle| j = 1, 2, \ldots, n \right\} \\ &= \left\{ \langle \lambda_1^+, (\psi_1^+, \varphi_1^+) \rangle, \langle \lambda_2^+, (\psi_2^+, \varphi_2^+) \rangle, \ldots, \langle \lambda_n^+, (\psi_n^+, \varphi_n^+) \rangle \right\} \end{aligned} \tag{24}$$

where λ_j^+ and λ_j^- indicate the optimal and inferior solutions under attribute C_j.

Step 6. Compute the weighted Euclidean distance between d_i^+ and d_i^-, which denote the Euclidean distance between alternatives and the PIS A^+ and the NIS A^-, correspondingly.

$$\begin{aligned} d_i^+ &= \sum_{j=1}^{n} \varpi_j d\left(\lambda_{ij}, \lambda_j^+\right) \\ &= \sum_{j=1}^{n} \varpi_j \sqrt{\frac{1}{2}\left[\left((\psi_{ij})^3 - \left(\psi_j^+\right)^3 \right)^2 + \left((\varphi_{ij})^3 - \left(\varphi_j^+\right)^3 \right)^2 + \left((\Phi_{ij})^3 - \left(\Phi_j^+\right)^3 \right)^2 \right]} \end{aligned} \tag{25}$$

$$\begin{aligned} d_i^- &= \sum_{j=1}^{n} \varpi_j d\left(\lambda_{ij}, \lambda_j^-\right) \\ &= \sum_{j=1}^{n} \varpi_j \sqrt{\frac{1}{2}\left[\left((\psi_{ij})^3 - \left(\psi_j^-\right)^3 \right)^2 + \left((\varphi_{ij})^3 - \left(\varphi_j^-\right)^3 \right)^2 + \left((\Phi_{ij})^3 - \left(\Phi_j^-\right)^3 \right)^2 \right]} \end{aligned} \tag{26}$$

Step 7. Calculate the grey relational degree r_i^+ and r_i^- of alternative A_i with PIS and NIS using Equations (29) and (30).

$$r_{ij}^+ = \frac{\min_i \min_j d\left(\lambda_j^+, \lambda_{ij}\right) + \rho \max_i \max_j d\left(\lambda_j^+, \lambda_{ij}\right)}{d\left(\lambda_j^+, \lambda_{ij}\right) + \rho \max_i \max_j d\left(\lambda_j^+, \lambda_{ij}\right)}, \tag{27}$$

$$r_{ij}^- = \frac{\min_i \min_j d\left(\lambda_{ij}, \lambda_j^-\right) + \rho \max_i \max_j d\left(\lambda_{ij}, \lambda_j^-\right)}{d\left(\lambda_{ij}, \lambda_j^-\right) + \rho \max_i \max_j d\left(\lambda_{ij}, \lambda_j^-\right)}, \tag{28}$$

$$r_i^+ = \sum_{j=1}^{n} r_{ij}^+ \varpi_j, \tag{29}$$

$$r_i^- = \sum_{j=1}^{n} r_{ij}^- \varpi_j, \tag{30}$$

where r_{ij}^+ and r_{ij}^- represent the grey relational coefficient of alternatives A_i with PIS and NIS under attribute C_j. ρ is the recognition coefficient, which generally takes the value of 0.5.

Step 8. Normalize the weighted distance d_i^+ and d_i^- as well as grey relational degree r_i^+ and r_i^+ using the formula below:

$$\begin{cases} D_i^+ = \frac{d_i^+}{\max\limits_i d_i^+} \\ D_i^- = \frac{d_i^-}{\max\limits_i d_i^-} \end{cases}, \tag{31}$$

$$\begin{cases} R_i^+ = \frac{r_i^+}{\max\limits_i r_i^+} \\ R_i^- = \frac{r_i^-}{\max\limits_i r_i^-} \end{cases}. \tag{32}$$

Step 9. Combine the normalized weighted distance and grey relational degree, and then compute the relative closeness.

$$T_i^+ = \alpha D_i^- + (1-\alpha) R_i^+, \tag{33}$$

$$T_i^- = \alpha D_i^+ + (1-\alpha) R_i^-, \tag{34}$$

$$\xi_i = \frac{T_i^+}{T_i^+ + T_i^-}. \tag{35}$$

Larger D_i^- and R_i^- indicate an alternative is closer to a desirable one, meanwhile, larger D_i^+ and R_i^+ indicate that the alternatives stray from the best one. Therefore, T_i^+ and T_i^- denote the closeness of each alternative to the PIS and NIS, respectively. α and $1-\alpha$ indicate the degree of preference of the DMs for relative position and trend.

Step 10. The options are ordered depending on how near they are to PIS. The relative closeness ξ_i indicates how close the alternative is to the PIS. The alternative is more in line with the PIS when ξ_i is larger while greater distance between the alternative and PIS is indicated by a smaller ξ_i.

The roadmap of decision-making techniques proposed in this section is shown in Figure 1.

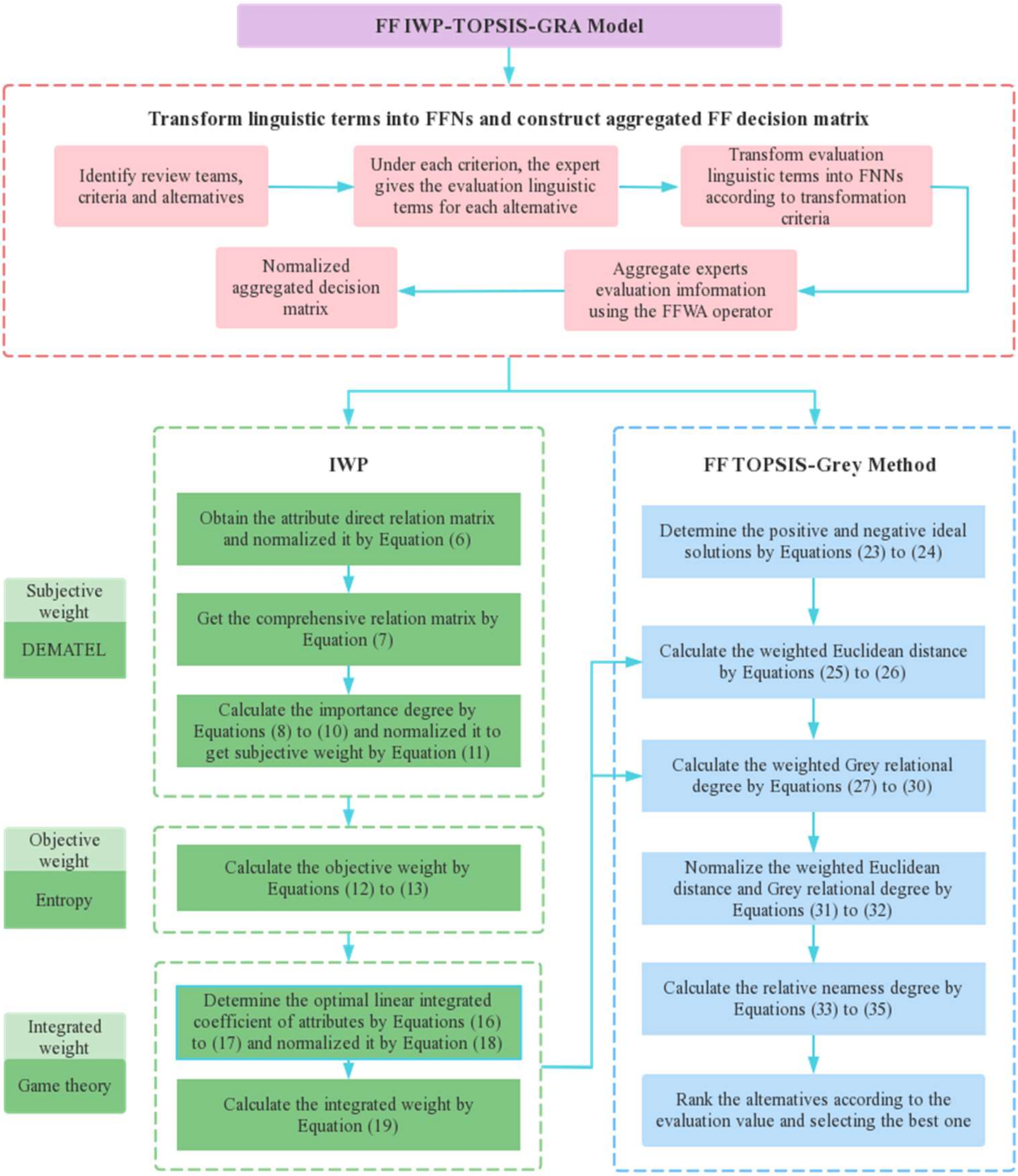

Figure 1. FF IWP-TOPSIS-GRA model.

7. Case Study

The suggested IWP-TOPSIS-GRA model will be used in the real case of HCWTT selection. Parameter and comparison analysis is utilized to demonstrate its validity.

Assuming that a hospital intends to select the optimal HCWTT from stream sterilization (A_1), microwave (A_2), landfill (A_3), and incineration (A_4). Four DMs $\varepsilon_\hbar(\hbar = 1,2,3,4)$ in the industry (expert weight vector is $(0.26, 0.2, 0.3, 0.24)^T$) are invited to evaluate the four HCWTT mentioned above and choose the best one by utilizing six attributes $C_j = (j = 1,2,3,4,5,6)$, shown in Figure 2, where C_1 is cost, C_2 is waste residuals, C_3 is release with health effects, C_4 is reliability, C_5 is treatment effectiveness, and C_6 is public acceptance. C_1, C_2, and C_3 are undoubtedly attributes of the beneficial type, whereas C_4, C_5, and C_6 are traits of the cost type.

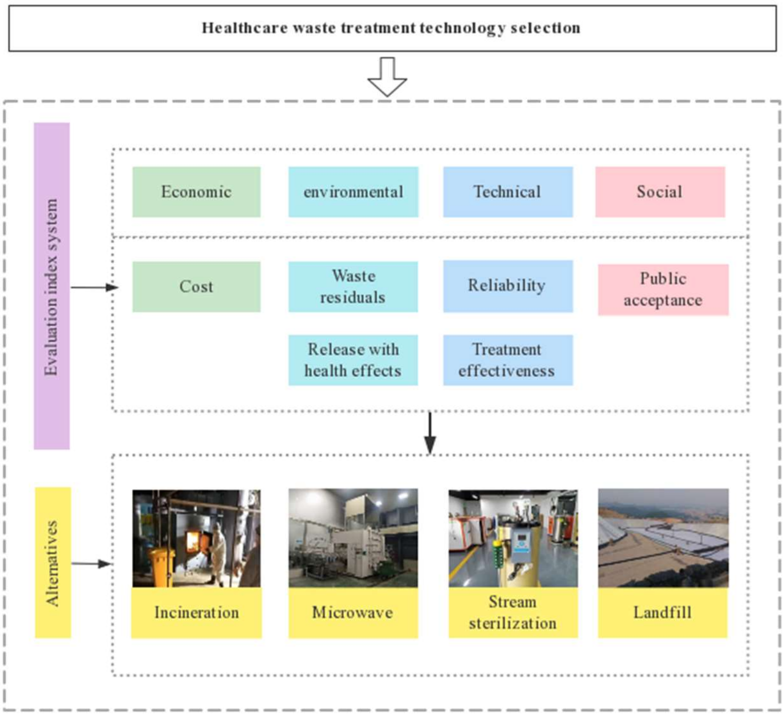

Figure 2. Evaluation index system and alternatives.

The following is the specific process for selecting the superior HCWTT.

Step 1. Construct a matrix for the FF evaluation. Four reviewers $\varepsilon_{\hbar}(\hbar = 1, 2, 3, 4)$ give evaluation linguistic terms for four HCWTT based on six attributes as displayed in Table 2.

Table 2. Evaluation linguistic terms of DMs.

DMs	Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
ε^1	A_1	B	G	VB	VG	G	VG
	A_2	M	M	B	B	VB	VG
	A_3	Q	G	G	M	Q	B
	A_4	M	G	G	M	G	B
ε^2	A_1	VB	M	B	G	G	G
	A_2	G	M	B	M	I	G
	A_3	M	G	Q	Q	M	I
	A_4	M	VG	G	M	VG	B
ε^3	A_1	B	G	B	G	G	G
	A_2	G	B	B	M	B	VG
	A_3	M	G	G	M	M	B
	A_4	G	M	VG	G	Q	B
ε^4	A_1	VB	I	B	VG	Q	Q
	A_2	G	M	I	G	B	G
	A_3	M	G	G	M	M	B
	A_4	M	G	G	M	M	B

The evaluation linguistic terms given by the experts are translated into FFSs based on the rules presented in Table 1. Table 3 includes a list of each expert's evaluation data.

Table 3. Evaluation information.

DMs	Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
ε^1	A_1	(0.3, 0.85)	(0.85, 0.25)	(0.2, 0.9)	(0.9, 0.15)	(0.85, 0.25)	(0.9, 0.15)
	A_2	(0.6, 0.6)	(0.6, 0.6)	(0.3, 0.85)	(0.3, 0.85)	(0.2, 0.9)	(0.9, 0.15)
	A_3	(0.7, 0.25)	(0.85, 0.25)	(0.85, 0.25)	(0.6, 0.6)	(0.7, 0.25)	(0.3, 0.85)
	A_4	(0.6, 0.6)	(0.85, 0.25)	(0.85, 0.25)	(0.6, 0.6)	(0.85, 0.25)	(0.3, 0.85)
ε^2	A_1	(0.2, 0.9)	(0.6, 0.6)	(0.3, 0.85)	(0.85, 0.25)	(0.85, 0.25)	(0.85, 0.25)
	A_2	(0.85, 0.25)	(0.6, 0.6)	(0.3, 0.85)	(0.6, 0.6)	(0.35, 0.7)	(0.85, 0.25)
	A_3	(0.6, 0.6)	(0.85, 0.25)	(0.7, 0.25)	(0.7, 0.25)	(0.6, 0.6)	(0.35, 0.7)
	A_4	(0.6, 0.6)	(0.9, 0.15)	(0.85, 0.25)	(0.6, 0.6)	(0.9, 0.15)	(0.3, 0.85)
ε^3	A_1	(0.3, 0.85)	(0.85, 0.25)	(0.3, 0.85)	(0.85, 0.25)	(0.85, 0.25)	(0.85, 0.25)
	A_2	(0.85, 0.25)	(0.3, 0.85)	(0.3, 0.85)	(0.6, 0.6)	(0.3, 0.85)	(0.9, 0.15)
	A_3	(0.6, 0.6)	(0.85, 0.25)	(0.85, 0.25)	(0.6, 0.6)	(0.6, 0.6)	(0.3, 0.85)
	A_4	(0.85, 0.25)	(0.6, 0.6)	(0.9, 0.15)	(0.85, 0.25)	(0.7, 0.25)	(0.3, 0.85)
ε^4	A_1	(0.2, 0.9)	(0.35, 0.7)	(0.3, 0.85)	(0.9, 0.15)	(0.7, 0.25)	(0.7, 0.25)
	A_2	(0.85, 0.25)	(0.6, 0.6)	(0.35, 0.7)	(0.85, 0.25)	(0.3, 0.85)	(0.85, 0.25)
	A_3	(0.6, 0.6)	(0.85, 0.25)	(0.85, 0.25)	(0.6, 0.6)	(0.6, 0.6)	(0.3, 0.85)
	A_4	(0.6, 0.6)	(0.85, 0.25)	(0.85, 0.25)	(0.6, 0.6)	(0.6, 0.6)	(0.3, 0.85)

Step 2. Integrate individual evaluation opinions using the FFWA operator to achieve a comprehensive assessment matrix $\widetilde{\Re}$. Table 4 summarizes the situation.

Table 4. Comprehensive assessment matrix $\widetilde{\Re}$.

	C_1	C_2	C_3
A_1	(0.2654, 0.8716)	(0.7646, 0.3813)	(0.2961, 0.8234)
A_2	(0.8123, 0.3139)	(0.5468, 0.6661)	(0.3136, 0.8113)
A_3	(0.6310, 0.4779)	(0.8500, 0.2500)	(0.7183, 0.4011)
A_4	(0.7154, 0.4614)	(0.8219, 0.2935)	(0.8675, 0.2145)
	C_4	C_5	C_6
A_1	(0.8779, 0.1936)	(0.8250, 0.2500)	(0.8435, 0.2189)
A_2	(0.6698, 0.5324)	(0.2936, 0.8299)	(0.8808, 0.1878)
A_3	(0.6342, 0.5036)	(0.6310, 0.4779)	(0.3114, 0.8176)
A_4	(0.7154, 0.4614)	(0.7937, 0.2785)	(0.3000, 0.8500)

Step 3. Normalize the comprehensive evaluation matrix using Equation (22). Table 5 represents the normalized comprehensive evaluation matrix.

Table 5. Normalized evaluation matrix $\Re$.

	C_1	C_2	C_3
A_1	(0.8716, 0.2654)	(0.3813, 0.7646)	(0.8234, 0.2961)
A_2	(0.3139, 0.8123)	(0.6661, 0.5468)	(0.8113, 0.3136)
A_3	(0.4779, 0.6310)	(0.2500, 0.8500)	(0.4011, 0.7183)
A_4	(0.4614, 0.7154)	(0.2935, 0.8219)	(0.2145, 0.8675)
	C_4	C_5	C_6
A_1	(0.8779, 0.1936)	(0.8250, 0.2500)	(0.8435, 0.2189)
A_2	(0.6698, 0.5324)	(0.2936, 0.8299)	(0.8808, 0.1878)
A_3	(0.6342, 0.5036)	(0.6310, 0.4779)	(0.3114, 0.8176)
A_4	(0.7154, 0.4614)	(0.7937, 0.2785)	(0.3000, 0.8500)

Step 4. PIS and NIS are established. PIS and NIS for each attribute are determined by calculating and comparing the scores in accordance with Equation (2).

$$A^{+} = \left\langle \begin{array}{c} (0.8716, 0.2654), (0.6661, 0.5468), (0.8234, 0.2961), \\ (0.8779, 0.1936), (0.8250, 0.2500), (0.8808, 0.1878) \end{array} \right\rangle, \quad (36)$$

$$A^{+} = \left\langle \begin{array}{c} (0.3139, 0.8123), (0.2935, 0.8219), (0.2145, 0.8675), \\ (0.6342, 0.5036), (0.2936, 0.8299), (0.3000, 0.8500) \end{array} \right\rangle. \quad (37)$$

Step 5. Determine the integrated weights of attributes.

Step 5.1. The linguistic formulations listed in Table 1 are used to determine the influence degree between the attributes, which are listed in Table 6.

Table 6. Influence degree between the attributes.

	C_1	C_2	C_3	C_4	C_5	C_6
C_1	-	VG	G	Q	I	M
C_2	G	-	VG	G	Q	G
C_3	Q	G	-	G	M	Q
C_4	M	VG	Q	-	Q	B
C_5	M	G	G	I	-	B
C_6	B	G	Q	B	M	-

Step 5.2. Normalize the direct influence matrix using Equation (6).

$$N = \begin{pmatrix} 0.00 & 0.24 & 0.20 & 0.16 & 0.08 & 0.12 \\ 0.20 & 0.00 & 0.24 & 0.20 & 0.16 & 0.20 \\ 0.16 & 0.20 & 0.00 & 0.20 & 0.12 & 0.16 \\ 0.12 & 0.24 & 0.16 & 0.00 & 0.16 & 0.04 \\ 0.12 & 0.20 & 0.20 & 0.08 & 0.00 & 0.04 \\ 0.04 & 0.20 & 0.16 & 0.04 & 0.12 & 0.00 \end{pmatrix} \quad (38)$$

Step 5.3. Calculate the total relation matrix using Equation (7).

$$T = \begin{pmatrix} 0.4531 & 0.8591 & 0.7807 & 0.6218 & 0.5088 & 0.5163 \\ 0.6915 & 0.7789 & 0.9121 & 0.7258 & 0.6422 & 0.6394 \\ 0.5945 & 0.8434 & 0.6232 & 0.6542 & 0.5477 & 0.5478 \\ 0.5285 & 0.8056 & 0.7045 & 0.4462 & 0.5371 & 0.4166 \\ 0.4887 & 0.7177 & 0.6804 & 0.4819 & 0.3589 & 0.3847 \\ 0.3713 & 0.6434 & 0.5832 & 0.3904 & 0.4210 & 0.2990 \end{pmatrix} \quad (39)$$

Step 5.4. Compute the influence degree P_j, influenced degree Q_j, importance degree W_j, and subjective weight w_j of attributes using Equations (8)–(11). Table 7 provides a summary of the computation findings.

Table 7. Calculation results of the DEMATEL model.

	$\mathbf{P_j}$	$\mathbf{Q_j}$	$\mathbf{W_j}$	$\mathbf{w_j}$
C_1	3.1276	3.7399	6.8947	0.163
C_2	4.6482	4.3899	9.0418	0.213
C_3	4.2841	3.8109	8.1088	0.191
C_4	3.3203	3.4384	6.7597	0.159
C_5	3.0157	3.1123	6.1288	0.144
C_6	2.8038	2.7083	5.5130	0.130

Step 5.5. Calculate the objective weights of attributes.

According to Equations (12) and (13), the objective weight vector of the attributes $\omega = (0.144, 0.138, 0.186, 0.114, 0.133, 0.285)^T$ can be obtained.

Step 5.6. Compute and normalize the optimal linear combination coefficients $a_i(i = 1, 2)$ of attributes.

According to Equations (16) and (17), the optimal linear combination coefficients $a_i = [0.2960, 0.7415](i = 1, 2)$ can be obtained. By normalizing them using Equation (18), we can obtain $a_i^* = [0.2853, 0.7147](i = 1, 2)$.

Step 5.7. Determine the integrated weights of attributes.

The integrated weight vector $\varpi = (0.149, 0.159, 0.187, 0.127, 0.137, 0.241)^T$ is determined by utilizing Equation (19).

Table A1 displays the integrated, subjective, and objective weights of attributes. The relationship between them can be observed in Figure 3.

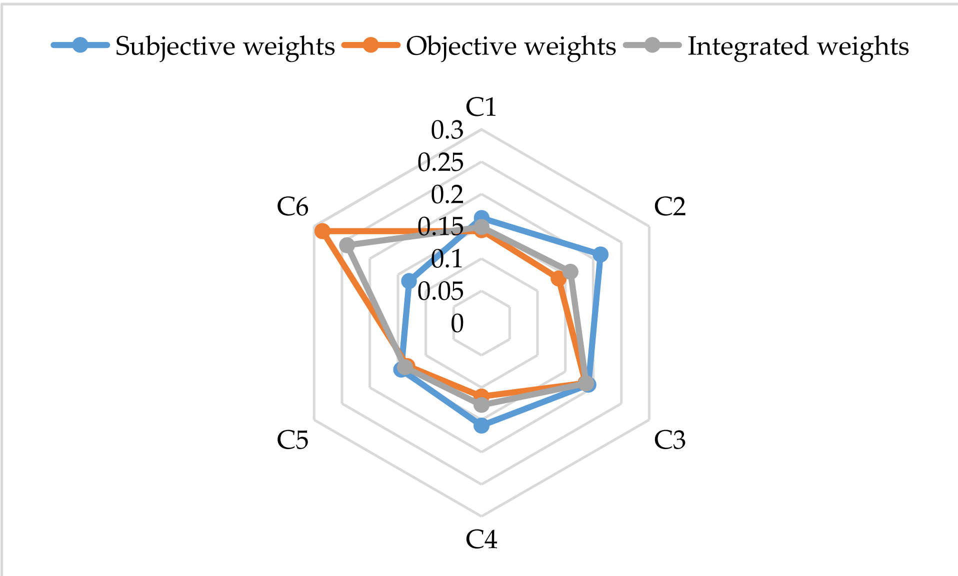

Figure 3. Attribute weights under different weight types.

Step 6. The weighted distance between each alternative and the positive and negative ideal one can be determined by Equations (25) and (26).

$$d^+ = \langle 0.0617, 0.2076, 0.4491, 0.4351 \rangle, \tag{40}$$

$$d^- = \langle 0.4788, 0.3253, 0.1659, 0.1069 \rangle. \tag{41}$$

Step 7. Calculate the grey relational coefficient matrix r_{ij}^+ and r_{ij}^- using Equations (27) and (28). Then compute the grey relational degree r_i^+ and r_i^- using Equations (29) and (30).

$$\left(r_{ij}^+\right)_{4\times6} = \begin{pmatrix} 1.0000 & 0.5208 & 1.0000 & 1.0000 & 1.0000 & 0.7953 \\ 0.3521 & 0.6687 & 0.9342 & 0.4906 & 0.3670 & 1.0000 \\ 0.3970 & 0.4566 & 0.4192 & 0.4497 & 0.5345 & 0.3427 \\ 0.3912 & 0.4709 & 0.3486 & 0.5340 & 0.8434 & 0.3333 \end{pmatrix}, \tag{42}$$

$$\left(r_{ij}^-\right)_{4\times6} = \begin{pmatrix} 0.3521 & 0.7906 & 0.3486 & 0.4497 & 0.3670 & 0.3497 \\ 1.0000 & 0.4848 & 0.3534 & 0.8154 & 1.0000 & 0.3333 \\ 0.5541 & 0.7182 & 0.5498 & 1.0000 & 0.4416 & 0.8276 \\ 0.6813 & 0.7941 & 1.0000 & 0.7401 & 0.3801 & 1.0000 \end{pmatrix}; \tag{43}$$

$$r_i^+ = \langle 0.8745, 0.6871, 0.4233, 0.4634 \rangle, \tag{44}$$

$$r_i^- = \langle 0.4350, 0.6131, 0.6865, 0.8019 \rangle. \quad (45)$$

Step 8. Normalized d_i^+, d_i^-, r_i^+, and r_i^- to obtain D_i^+, D_i^-, R_i^+, and R_i^- using Equations (31) and (32). The detailed computed results are listed in Appendix A.

Step 9. Equations (33)–(35) are employed to rank the solutions and identify their relative closeness. Table 8 shows the relative closeness and ranking in detail.

Table 8. Relative closeness and ranking.

	T_i^+	T_i^-	ξ_i	**Ranking**
A_1	1.0000	0.3400	0.7463	1
A_2	0.7325	0.6134	0.5442	2
A_3	0.4253	0.9281	0.3092	3
A_4	0.3766	0.9845	0.2767	4

Table 8 shows that each alternative and the optimum solution are relatively close together, with values of 0.7463, 0.5442, 0.3092, and 0.2767, respectively. The alternatives have a grade of $A_1 \succ A_2 \succ A_3 \succ A_4$, and the best option is undoubtedly A_1, which means that stream sterilization is recommended by the DMs as the optimal HCWTT that can be used in hospitals.

7.1. Comparative Analysis

The weights of evaluation indicators are the key for DMs to make a reasonable choice among the alternative HCWTT. In this paper, the subjective, objective, and integrated weighting methods based on DEMATEL, EWM, and game theory have been introduced, respectively. To balance the subjectivity of DMs and the objectivity of evaluation data, we apply the integrated weights to obtain the final results in the above research.

The model proposed in this study was substituted for comparison using the subjective and objective weights obtained using DEMATEL and FF entropy proposed in Section 5, respectively. Tables 9 and 10 present a summary of the calculation results for the various weight types, Figure 4 allows us to compare the calculated findings further.

Table 9. Calculation results and ranking under the subjective weight.

	D_i^+	D_i^-	R_i^+	R_i^-	T_i^+	T_i^-	ξ_i	**Ranking**
A_1	0.1571	1.0000	1.0000	0.5974	1.0000	0.3773	0.7261	1
A_2	0.5403	0.6249	0.7335	0.8412	0.6792	0.6907	0.4958	2
A_3	1.0000	0.3794	0.4995	0.8770	0.4394	0.9385	0.3189	3
A_4	0.9437	0.2608	0.5534	1.0000	0.4071	0.9719	0.2952	4

Table 10. Calculation results and ranking under the objective weight.

	D_i^+	D_i^-	R_i^+	R_i^-	T_i^+	T_i^-	ξ_i	**Ranking**
A_1	0.1303	1.0000	1.0000	0.5216	1.0000	0.3259	0.7542	1
A_2	0.4324	0.7000	0.8069	0.7345	0.7534	0.5834	0.5636	2
A_3	1.0000	0.3345	0.4780	0.8477	0.4062	0.9239	0.3054	3
A_4	0.9790	0.2087	0.5201	1.0000	0.3644	0.9895	0.2692	4

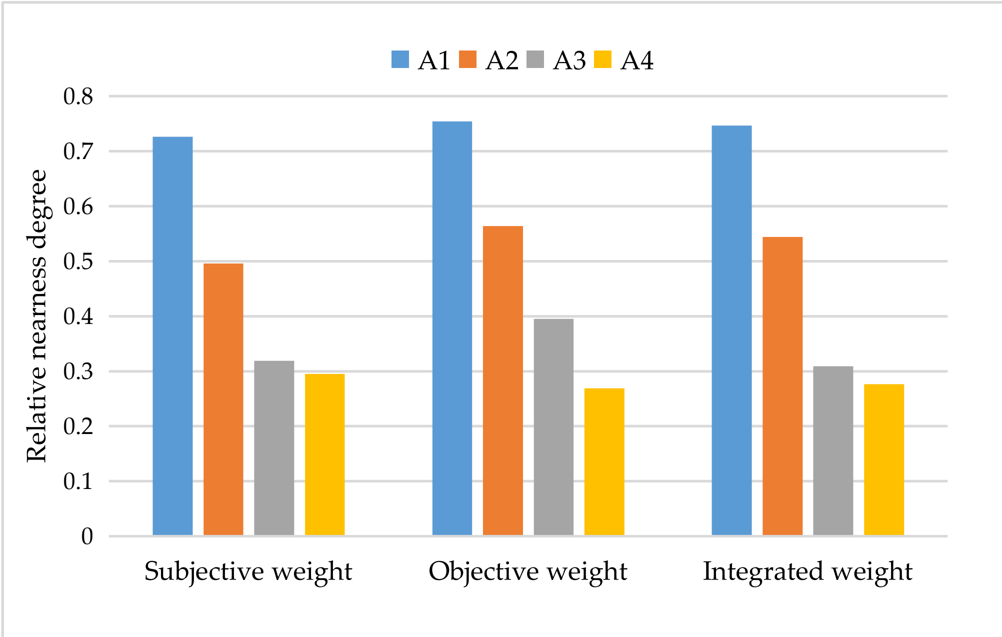

Figure 4. Comparison of alternative ranking under different weight types.

According to the calculation results, depending on the type of weights used, the relative nearness between each alternative and the optimum solution varies. Under objective weights, the alternatives' relative closeness concerning the optimal solution is the greatest, while their relative closeness to the worst solution is the smallest. The alternatives have the biggest relative closeness to the worst solution and the least relative closeness to the optimal solution under subjective weights. This is thus because, whereas subjective weights partially reflect the DMs' subjective opinions, which are highly ambiguous, computation outcomes under objective weights transmit the decision information of DMs. In this paper, we use game theory to calculate the optimal linear combination coefficients of the two weights. To establish integrated weights, which more successfully implement the benefits of subjective and objective weights, objective weights and subjective weights are merged. We can further find that no matter what type of weights are taken, the final ranking results of HCWTT obtained are always $A_1 \succ A_2 \succ A_3 \succ A_4$, and the most suitable technique for disposing of HCW is still steam sterilization. Therefore, there is some stability in the weight estimation approach suggested in this study. When solving complex MCDM problems, the existence of integrated weights cannot be ignored, which can help us to make rational and effective decisions and obtain the desired results.

Next, representative methods are selected for comparative analysis with the proposed model in the FF environment to verify its validity and accuracy. Firstly, the comparison with the TOPSIS method based on the FF hybrid weighted distance (FFHWD) measure [64] is conducted, thus illustrating the impact of different distance measures and single decision methods on the evaluation results; secondly, the comparison with VIKOR [65] and EDAS [66] can illustrate the impact of different decision methods and distance standards on the evaluation results. The final ranking results obtained by the above four methods on the same data set and equally weighted information are shown specifically in Table 11.

Table 11. Sorting values and rankings under different decision methods.

	Proposed Methodology		**FFHWD-TOPSIS [64]**		**VIKOR [65]**		**EDAS [66]**	
	ξ_i	**Ranking**	ς_i	**Ranking**	Q_i	**Ranking**	$\mathbb{C}_i$	**Ranking**
A_1	0.7463	1	0.0000	1	0.0000	1	1.0000	1
A_2	0.5442	2	−2.7540	2	0.2996	2	0.2888	2
A_3	0.3092	3	−7.7487	4	0.9620	4	0.1766	3
A_4	0.2767	4	−7.1639	3	0.9594	3	0.0284	4

As can be seen in Table 11, the four decision techniques mentioned above differ in their specific choices but there is still some similarity in the decision results. The worst alternative obtained by both the EDAS and our proposed model is A_4, and the worst alternative obtained based on FFWHD-TOPSIS and VIKOR is A_3. However, the top-ranked alternatives determined by these four methods remain the same. They all judge A_1 as the optimal alternative, which further illustrates the effectiveness and accuracy of the method proposed in this paper. The main reasons for the partial identities as well as minor differences in the specific rankings are:

(1) Different from the Euclidean distance measure we used, the FFWHD measure proposed in [64] reflected the importance of its own data as well as its location, which proves that different distance measures do have an impact on the decision results.
(2) Taking the closeness between the evaluation scheme and the ideal method as the basis of the optimal solution is the decision logic of references [64,65], the optimal choice of [66] corresponds to the distance from the average solution. All of these single decision methods focus only on the relative position relationship and ignore the intrinsic trend of the data series.
(3) When there are goal differences within the organization, using the average solutions in place of extremely positive and negative ideal solutions is more in line with the actual interests of the decision group. The rich practical implications of [66] make the rankings it obtains consistent with the model proposed in this paper.

7.2. Sensitivity Analysis

Due to the presence of parameters α in the FF IWP-TOPSIS-GRA model presented in this paper, the parameters α and $1-\alpha$ represent the DMs' preference degree for TOPSIS and GRA. The previous case study solely looked at case $\alpha = 0.5$, suggesting that DMs view TOPSIS and GRA as equally significant. The existence of parameters may somewhat influence the outcomes. For the stability of the suggested model to be completely validated, this one case is insufficient. As a result, we also covered the impact of the alteration of parameters on the order list of solutions and the best option.

Now we let α take different real values from $[0,1]$ and Table 12 displays the relative closeness and the rating of each choice. Figure 5 helps us to observe more visually the trend of relative closeness variation with the change of parameters.

Table 12 and Figure 5 provide evidence that the relative closeness of A_1 and A_2 gradually increases with the positive change of the parameters, and the increase rate of A_1 is obviously faster than that of A_2, while the relative closeness of A_3 and A_4 gradually decreases with the positive change of the parameters, and the decrease rate of A_3 is slower than that of A_4. As parameter α increases, the increasing rate of the relative closeness of A_1 becomes faster and faster, which indicates that A_1 becomes more and more desirable; on the contrary, the decreasing rate of the relative closeness of A_4 becomes faster and faster, which indicates that A_4 becomes less and less desirable.

In summary, the alteration of the parameter has a substantial impact on how close the alternative solution is to the optimal solution. That is because parameter α expresses the special fondness of DMs for TOPSIS, which measures how near the solution is to the ideal solution in terms of location. When parameter α is larger, TOPSIS has an increasing proportion in the whole decision model, and the solution is getting closer to the ideal one.

Meanwhile, we can see from Table 12 and Figure 5 that the ranking as well as the optimal alternative have remained stable even though the relative closeness has been changing, indicating that our proposed solution has extremely strong stability.

Table 12. Relative closeness and rankings under different values of parameter α.

Parameter α	ξ_1	ξ_2	ξ_3	ξ_4	Ranking
0.1	0.6658	0.5135	0.3508	0.3337	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.2	0.6842	0.5205	0.3404	0.3204	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.3	0.7037	0.5280	0.3300	0.3066	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.4	0.7244	0.5359	0.3196	0.2920	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.5	0.7463	0.5442	0.3092	0.2767	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.6	0.7696	0.5531	0.2988	0.2607	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.7	0.7943	0.5626	0.2884	0.2438	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.8	0.8207	0.5727	0.2781	0.2260	$A_1 \succ A_2 \succ A_3 \succ A_4$
0.9	0.8490	0.5835	0.2677	0.2072	$A_1 \succ A_2 \succ A_3 \succ A_4$

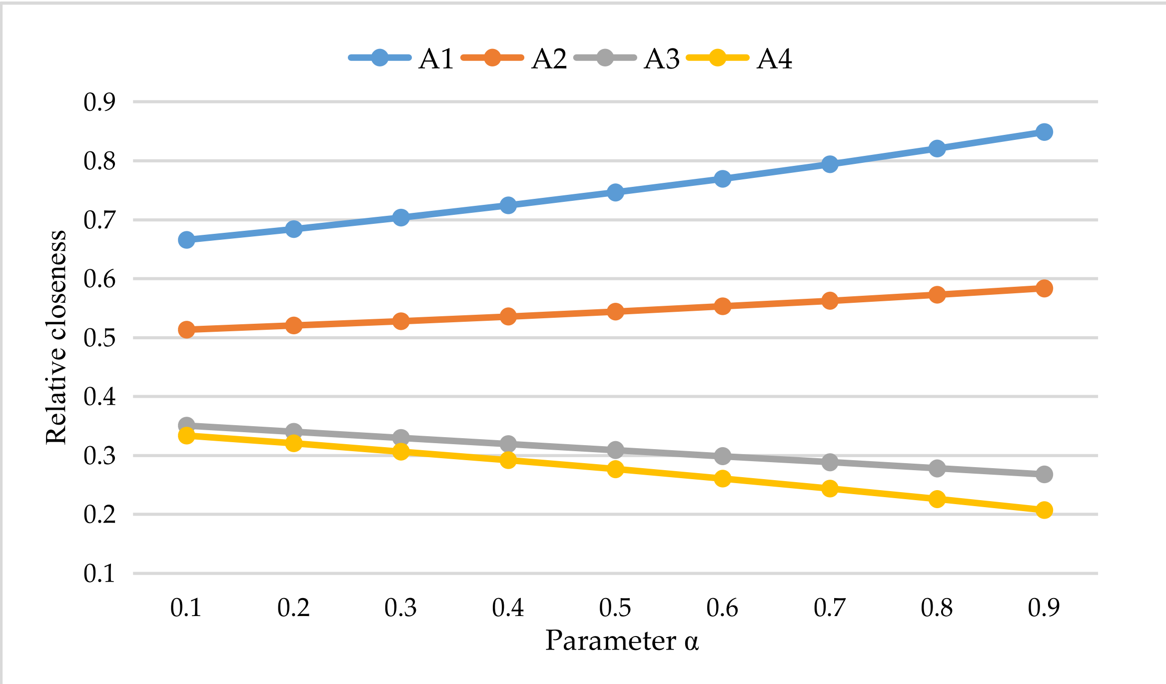

Figure 5. Comparison under different values of parameter α.

8. Conclusions

Choosing the right technology for HCW treatment is an important part of waste management. In this study, an FF IWP-TOPSIS-GRA model was proposed, aiming to offer technical assistance for the HCWTT selection under a complex environment. A complete and streamlined index system for evaluating HCWTT was first established, which considered four aspects: economic, social, environmental, and technological. Then, an IWP based on DEMATEL and FF entropy was applied to determine the integrated weights, which not only ensured the objectivity of the evaluation data but also conveyed the subjective perception of the evaluation experts. Finally, the IWP-TOPSIS-GRA model was applied to the actual case of HCWTT selection in FF situations. At the same time, the analyses of comparison and sensitivity were carried out. The numerical findings showed that different types of weights and parameters always gave stable ranking results, although they produced different relative closeness, which reflected the suggested model's stability and efficacy. This suggested strategy can not only compensate for the shortcomings of single weight determination and decision methods, but can also address a variety of disciplines, including green development, smart cities, and online teaching and learning.

With the outbreak of COVID-19 and the explosive growth of HCW, disposing of HCW timely and environmentally is a critical component. This study provides management recommendations for healthcare administrators and environmental policymakers who need to determine the best HCWTT. First, when examining HCWTTs, whether the technology will cause contamination residues that could endanger human health needs to be prioritized. When conflicts of interest arise, the relationship between the technology and the public should be properly coordinated to enhance social acceptance. The inclusion of operating costs and the reliability of the technology in the evaluation is also necessary. Second, a reference for determining the set of technologies that meet the needs of HCW disposal is provided. Steam sterilization is an optimal means of disposing of HCW with high disposal efficiency and capacity, which can effectively remove waste while minimizing contamination. Microwave can be an alternative to the best HCWTT by reducing costs and improving operational efficiency. The incineration of HCW emits toxic gases and inorganic substances that harm the environment and human health, and installation of purification devices will help. Landfills, on the other hand, are a poor overall performance HCWTT and should not be the primary means to be considered when disposing of HCW.

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Appendix A

Table A1. Attribute weights.

	C_1	C_2	C_3	C_4	C_5	C_6
Subjective weight	0.163	0.213	0.191	0.159	0.144	0.130
Objective weight	0.144	0.138	0.186	0.114	0.133	0.285
Integrated weight	0.149	0.159	0.187	0.127	0.137	0.241

Table A2. Normalized weighted distance and grey relational degree.

	$\mathbf{D_i^+}$	$\mathbf{D_i^-}$	$\mathbf{R_i^+}$	$\mathbf{R_i^-}$
A_1	0.1374	1.0000	1.0000	0.5425
A_2	0.4623	0.6794	0.7857	0.7646
A_3	1.0000	0.3465	0.4841	0.8561
A_4	0.9689	0.2333	0.5299	1.0000

Table A3. Calculation results comparison under different weight types.

Methods	ξ_1	ξ_2	ξ_3	ξ_4	**Ranking**
Subjective weight	0.7261	0.4958	0.3189	0.2952	$A_1 \succ A_2 \succ A_3 \succ A_4$
Objective weight	0.7542	0.5636	0.3954	0.2692	$A_1 \succ A_2 \succ A_3 \succ A_4$
Integrated weight	0.7463	0.5442	0.3092	0.2767	$A_1 \succ A_2 \succ A_3 \succ A_4$

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