International Journal of Production Management and Engineering

https://doi.org/10.4995/ijpme.2025.21558

Received: 2024-10-16 Accepted: 2024-10-17

Decision making model for waste management: fuzzy group AHP-CoCoSo

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Abstract:

Waste collection represents critical strategic focal point in urban development planning. The establishment and maintenance of such systems contribute significantly to policymakers' pursuit of sustainable development objectives. The efficient collection, categorization, and disposal of diverse types of waste pose formidable challenges within urban governance. This study proposes a comprehensive framework for group decision analysis employing Analytic Hierarchy Process (AHP) and Combined Compromise Solution (CoCoSo) to address the optimal site selection problem for waste disposal facilities. In order to rigorously and scientifically address collective waste management issues, this paper engages ten experts to score and evaluate criteria for waste management and alternative site locations. Innovatively integrating fuzzy methodology, the authors optimize decision-makers' preference inputs. Through our proposed method, decision-makers' weights and criteria weights are calculated, while fuzzy CoCoSo is utilized to determine the final collective decision ranking. By synthesizing the ratings from the ten experts, ideal decision outcomes are obtained to aid cities in selecting the most suitable waste disposal sites. This study advances the urban waste management strategies, offering a systematic approach that accounts for the diverse perspectives of stakeholders and the complex dynamics inherent in waste management decision-making.

Key words:

AHP, CoCoSo, fuzzy group decision making, waste management, decision makers importance.

1. Introduction

Sustainable solutions for managing the global challenge of waste management involve integrating various disciplines and technologies. Artificial Intelligence, Nanotechnology, Omics, and Bioengineering can be leveraged to optimize anaerobic digestion processes and convert organic waste into biogas and nutrient-rich digestate (Chidi et al., 2022). Companies are transitioning towards sustainable waste management by transforming waste into energy and reusable products, but there is a need for innovative marketing initiatives and increased awareness among end users (Farooq et al., 2022). Waste-to-resource development plays a crucial role in managing waste that is not possible to handle through reduce, reuse, and recycle methods, and factors like economics, public engagement, and environmental impacts need to be considered in the design of waste-to-resource projects (You, 2022). Solid waste management is a global concern, and waste-to-energy technologies offer an eco-friendly solution for efficient waste disposal and energy generation (Gupta, 2023). Sustainable waste management strategies focus on the 3R principles (reduce, reuse, recycle) and utilize life cycle assessment and modeling tools for effective waste management and recycling (Das et al., 2019).

To cite this article: Yazdani, M., Ye, C., Shaayesteh, M.T., Zaraté, P. (2025). Decision making model for waste management: fuzzy group AHP-CoCoSo. *International Journal of Production Management and Engineering, 13*(1), 77-92. https://doi.org/10.4995/ijpme.2025.21558

Challenges and trends in waste management include low collection coverage, inadequate waste disposal procedures, and pollution caused by improper waste management systems (Shittu et al., 2021). Solid waste reduction is one of the fundamentals of sustainable goals (Gupta, 2023). The accumulation of waste in developing countries is a major concern for health and hygiene (Koraganji et al., 2022). India is facing challenges in solid waste management due to urbanization and industrialization (Sharma, 2022). These challenges highlight the need for improved waste management practices, such as smart waste management in smart cities, innovative waste degradation and recycling methods, and the adoption of waste-to-energy technologies. Efforts should also focus on implementing efficient strategies for waste disposal, improving collection and transportation systems, and involving informal sectors and private agencies in waste management.

Sustainable waste management is a crucial topic that requires in-depth research and consideration. The literature on sustainable waste management has seen a significant increase since 2015, with a focus on poorer countries facing environmental concerns (Waqas et al., 2023). Composting is a profitable and environmentally friendly practice for agricultural waste disposal, contributing to recycling farm and agricultural wastes (Mishra et al., 2022). Vermicompost, an organic fertilizer rich in nutrients and beneficial soil microbes, is a sustainable alternative to chemical fertilizers and promotes plant growth (Akram et al., 2021). Municipal solid waste (MSW) management is a global concern, with improper management leading to greenhouse gas emissions and adverse effects on socioeconomic status and ecological systems (Gautam & Agrawal, 2021). Mitigation strategies such as waste segregation, recycling, composting, and advanced modifications in waste management systems are essential for sustainable progression.

Waste management faces challenges due to increasing waste generation, inadequate infrastructure, and reliance on informal sectors for management (Adhikari, 2022). Common practices include open dumping and burning, leading to environmental and health risks (Awasthi et al., 2023). In contrast, modern waste management follows principles of "zero waste" and the "circular economy" (Vitenko et al., 2021). The EU has developed a regulatory framework for waste management, aiming to meet international environmental safety standards (Mahajan, 2023). Research gaps in waste management include biodiversity, hazardous waste, and vermicomposting (Zhang et al., 2019). To improve waste management, public awareness, reduction, reuse, and recycling concepts should be applied, along with modernization and scientific management. The study of waste management highlights the need for better frameworks to prevent adverse effects on the environment and public health (Erdem, 2022).

By this introduction, we design the rest of the paper as this order; study background and literature review are presented in section 2. At the end of the section 2, the research question, objectives and contribution are demonstrated. Section 3 releases the mathematical formulas and required equations for computation as fuzzy AHP and fuzzy CoCoSo. In section 4, Data collection and results generation, the numerical example are generated. Finally, Conclusion, implication, and future research works are explained in section 5.

2. Brief Study background and problem statement

2.1. Waste management and disposal system

Waste management is a critical environmental issue influenced by factors such as population growth, industrialization, and urbanization (Yang, 2022). Effective waste management strategies and policies are essential to minimize environmental hazards (Higgins, 2018). Key approaches include extended producer responsibility (EPR) for manufacturers and innovative technologies like shredding, drying, and extraction processes (Singh et al., 2014; Kanagamani et al., 2021).

A significant aspect of waste management is the selection of appropriate disposal locations, which plays a vital role in minimizing environmental and health risks. Effective disposal site selection requires careful planning, assessment of geographical factors, and consideration of both hazardous and non-hazardous waste types (LaGrega et al., 2010). Hazardous waste must be properly stored, segregated, and treated to reduce its impact, while non-hazardous waste should be managed efficiently to avoid unnecessary expenses (Blackman Jr, 2016; Drace et al., 2022).

Disposal location selection challenges include the need for sustainable waste management plans, technological advancements, and public participation (Kaczan et al., 2021). Additionally, integrated approaches in nuclear waste management highlight the importance of planning and facility needs assessment for long-term sustainability (S. Kumar et al., 2017). Effective planning in disaster waste management also emphasizes the importance of optimizing transportation routes to ensure urban resilience and minimize social costs (Habib et al., 2019).

Medical waste management and disposal pose unique challenges, particularly in site selection for disposal facilities. Methods such as autoclaving and anaerobic cracking offer environmentally friendly solutions for biomedical waste treatment (Amusa et al., 2020; Li et al., 2022). Moreover, the use of advanced technologies like decentralized blockchain for medical waste tracking enhances the efficiency and security of waste treatment processes (Le et al., 2022).

2.2. Models and algorithm for waste disposal location selection

The location of waste disposal facilities is a crucial aspect of waste management strategies. Several factors need to be considered when selecting a suitable location, including waste supply, transportation costs, environmental impact, and resource efficiency. Various methods and models have been developed to address the challenges of waste disposal location selection. These include robust facility location models that consider uncertain factors such as waste supply and transportation costs (Li et al., 2022). Multi-criteria decision-making (MCDM) methods, such as the CRITIC and DEVADA methods, have been extended to handle uncertainties using intuitionistic fuzzy sets (IFSs) and can be applied to waste disposal location selection problems (Alkan & Kahraman, 2022). The FSWARA-GISMAIRCA Hybrid Algorithm combines the fuzzy Delphi method, GIS, and multi-attribute decision-making methods to identify suitable locations for waste disposal sites (Pirbasti et al., 2020). An ecological and economic mechanism has been proposed for selecting land plots for waste disposal facilities, taking into account legislative criteria and optimizing the location based on efficiency and improvement (Yevsiukov & Petrovych, 2022). The Pythagorean Fuzzy REGIME (PF-REGIME) technique integrates Pythagorean fuzzy Sets with the REGIME method for waste disposal site selection (Oztaysi et al., 2021).

Waste disposal models in Europe vary in terms of their effectiveness and approach. Existing waste taxes are being assessed for their impact on waste generation and disposal (Ergun, 2022). The concept of sustainable development has been extended to waste management, with regulations in place for the safe handling and transport of hazardous waste (HW) (Callao et al., 2021). The proximity and self-sufficiency principles are followed in Europe for HW shipments (Salhofer et al., 2007). Different waste accumulation rates require different models for cost minimization in waste disposal (Tsai & Nagaraj, 2011). Integrated approaches that coordinate between manufacturing firms and disposal firms can provide cost-minimizing effects for both parties.

Multi-Criteria Decision-Making (MCDM) models have been proposed and applied in location modeling for various purposes, such as facility location selection, logistics center selection, and location-routing problems with fuzzy values. These models consider both qualitative and quantitative criteria, as well as the different importance weights of the criteria. The use of fuzzy sets allows for handling uncertainty and vagueness in decision-making. Several papers have presented different approaches and methodologies for fuzzy MCDM in location modeling. For example, Aditi et al. (2020) proposed an integrated approach using the fuzzy Analytical Hierarchy Process and fuzzy Technique for Order Performance by Similarity to Ideal Solution for evaluating facility locations based on Quality of Life (QOL) criteria. Yang et al. developed a fuzzy MCDM model for the evaluation and selection of logistics centers, considering multiple criteria and uncertain conditions (Unold & Cruz, 2019). Wang and Ying (2023) also proposed a fuzzy MCDM method for selecting logistics center locations, considering both qualitative and quantitative criteria (Torfi et al., 2016).

2.3. Contribution and objectives

This article addresses the allocation of criteria weights in collective decision-making through the utilization of fuzzy AHP. Furthermore, it integrates fuzzy CoCoSo analysis to examine the environmentally significant issue of waste disposal site selection. The study combines Multi-Criteria Decision-Making methods with fuzzy logic within the context of waste management.

The focus is on creating a robust approach that addresses the complexities inherent in selecting optimal waste disposal sites through a group decision-making process. By utilizing fuzzy logic, this framework seeks to incorporate the uncertainty and diverse perspectives of multiple decision-makers to arrive at a more nuanced and reliable outcome.

The choice of the two methodologies fuzzy AHP and CoCoSo was guided in one hand by the possibility for fuzzy AHP to have more flexibility to define preferences; in other hand for CoCoSo its ability to combe ideas of compromised solutions like mean evaluation weighting and power weight aggregation. These two methodologies seem very suitable to deal with fuzzy and compromised approaches.

The central research question guiding this study is: How can fuzzy AHP and CoCoSo methods be effectively combined to enhance the decision-making process for waste disposal site selection in a collaborative environment? Addressing this question aims to provide urban planners and policymakers with a systematic tool for sustainable waste management that is adaptable to varying conditions and stakeholder inputs.

Based on the literature, our research contribution falls into several points: first of all, in the literature there is no study to locate a municipal waste disposal site in a group decision making environment. Secondly is the utilization of a new version of group fuzzy AHP and fuzzy CoCoSo which adds value to the existing MCDM applications. The only study was presented by Lahane and Kant (2021) where a different fuzzy version of AHP and CoCoSo was used to rate the performance enablers in supply chain.

3. Methodology and mathematical equations

This section provides the required mathematical tools and equations to solve decision making problem. Firstly, we present fuzzy set theory requirements and fuzzy AHP and then the fuzzy CoCoSo will be explained.

3.1. Fuzzy Group AHP

Analyzing the multifaceted landscape of decision-making processes, the Analytic Hierarchy Process stands as a seminal Multiple Criteria Decision-Making method with widespread applications in both scientific research and industrial production. Initially developed to address the decision-making needs of the United States military, AHP has evolved into a fundamental algorithm employed across diverse domains.

The omnipresence of AHP is particularly evident in pivotal sectors such as energy, environment, and economics, where it plays a pivotal role in guiding strategic choices. However, the conventional AHP framework is not without its inherent limitations. Notably, the prescribed maximum limit of seven criteria poses a constraint on decision-makers, as surpassing this threshold makes it arduous for them to logically compare every pair of criteria, potentially resulting in an inconsistency ratio exceeding 0.1 and thus failing the consistency test.

Furthermore, the conventional AHP's reliance on a "Priority Matrix" to assign numerical values representing the relationships between criteria or alternatives can prove challenging for decision-makers. Subjectivity in choosing a singular numerical representation of the perceived importance of relationships between two criteria becomes a stumbling block. To address these challenges and enhance the robustness of decision inputs, the integration of fuzzy theory with AHP has emerged as a highly effective optimization strategy.

The amalgamation of fuzzy theory with AHP introduces a more nuanced approach, allowing decision-makers to express their preferences in a flexible and tolerant manner. Unlike the singular numerical representation in traditional AHP, fuzzy AHP employs three numbers to encapsulate the uncertainty associated with decision inputs. This augmentation provides decision-makers with a broader and more elastic space for objective analysis, thereby enhancing the adaptability and comprehensiveness of preference inputs. In light of these considerations, the utilization of fuzzy AHP emerges as a strategic paradigm for refining decision-making processes and accommodating the complexities inherent in real-world decision environments.

The fuzzy AHP methodology holds significant academic significance in the realm of collective decision-making. Numerous scholarly works have leveraged fuzzy AHP to amalgamate the preferences of multiple decision-makers, thereby deriving a consolidated ranking of alternatives. However, the current landscape of employing fuzzy AHP for collective decision-making is marked by diverse methodologies. This paper delineates a specific approach within this spectrum, elucidating the computation of the weight of criteria for each decision-maker and the determination of the overall weight of decision makers using fuzzy AHP.

The methodological exposition in this section serves as a precursor to the subsequent discussion on the integration of fuzzy CoCoSo, collectively contributing to the computation of the final ranking in collective decision-making scenarios. The forthcoming sections expound upon the intricate computations that synthesize fuzzy AHP with fuzzy CoCoSo to yield comprehensive and robust collective decision outcomes. The focal point of this section centers on the intricacies of calculating the importance of decision-makers and the weight of criteria for each decision-maker using the fuzzy AHP framework.

The steps to solve fuzzy AHP problem is provided here:

Step 1 – It involves delineating the definition and structure of the problem under analysis. The problem is systematically divided into a hierarchical structure, comprising overarching goals and criteria (sub-criteria). For instance, this study is centered on the selection of the most suitable location for waste disposal, necessitating the consideration of eight distinct criteria.

Step 2 - Decision-makers input their preferences for the eight criteria into a pairwise comparison utilizing the fuzzy scale of relative importance. Table 1 illustrates a comparative analysis between the traditional AHP Scale of relative importance and the fuzzy scale of relative importance, which incorporates fuzzy theory.

Since there are multiple decision-makers involved in the decision, the author uses n to stand in for the number of decision-makers. When the decision maker inputs information according to his PREFERENCE, the fuzzy pairwise matrix M_n is obtained.

$$M_n = \begin{bmatrix} m_{11}^n & \cdots & m_{1j}^n \\ \vdots & \ddots & \vdots \\ m_{i1}^n & \cdots & m_{i1}^n \end{bmatrix};$$
$$i = 1,2\cdots 8, j = 1,2\cdots 8;\ m_{ij}^n = \left(a^1, a^2, a^3\right),$$
$$m_{ij}^n = \left\{m_{ij}^n\right\}^{-1} \tag{1}$$

Step 3. Once we acquire the pairwise judgments from each expert (decision-maker), it is essential to calculate the weights for each criterion based on the expert matrix. The initial step in this process involves computing the fuzzy geometric mean, denoted as P_i, for each expert. The calculation formula for this step is as follows:

$$P_i^n = \sum_{j=1}^{n} m_{ij}^n \left[\sum_{i=1}^{n}\sum_{j=1}^{n} m_{ij}^n\right]^{-1} \tag{2}$$

$$P_i^n = \{p_i\},\ p_i = (p_1, p_2, p_3) \tag{3}$$

In fuzzy computation, a crucial step is the process of defuzzification. Therefore, in the subsequent step, it is necessary to perform defuzzification on P_i^n, transforming it from an array composed of three fuzzy elements into one-dimensional form $\bar{p}_i^n$.

$$\bar{P}_i^n = \frac{p_1^n + 2*p_2^n + p_3^n}{4} \tag{4}$$

Step 4. we normalize the defuzzified p_1^n values. According to the following formula, we derive the weight of criteria for each expert, denoted as W_i^n in this study.

$$W_i^n = \frac{\bar{P}_i^n}{\sum_{i=1}^{n} \bar{P}_i^n};\ w_i^n = (w_1^n, w_2^n, \ldots\ldots w_8^n) \tag{5}$$

Table 1. The scale of relative importance with the fuzzy number.

	The scale of relative importance	The fuzzy scale of relative importance
Equal importance	1	(1,1,1)
Moderate importance	3	(2,3,4)
Strong importance	5	(4,5,6)
Very strong importance	7	(6,7,8)
Extremely strong importance	9	(8,9,9)
Intermediate values	2,4,6,8	(1,2,3), (3,4,5), (5,6,7), (7,8,9)
Values for inverse comparison	1/3, 1/5, 1/7, 1/9	(1/3,1/2,1/1) ... (1/9,1/9,1/8)

After the decision makers have entered their preferences, the largest eigenvalue of the matrix needs to be calculated based on their pairwise matrix. The formula for calculating the characteristic root is described as follows: in fuzzy AHP we use λ_{max} to refer to it.

$$\lambda_{max} = \frac{\sum (AW)_i}{NW_i} \tag{6}$$

Step 5. Upon obtaining the maximum eigenvalue X, similar to the conventional AHP methodology, we need to utilize a table to determine the value of the Random Index (R.I), as illustrated in Table 2. The value of the Random Index is related to the number of criteria n.

Table 2. The value of the Random Index (R.I).

n	1	2	3	4	5	6	7	8	9
R.I	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Following the acquisition of the Random Index value, the calculation of the consistency index and consistency ratio for each decision-maker can be performed using the following formulas:

$$CI_n = \frac{(\lambda_{max}^n - n)}{(n-1)}, CR_n = \frac{CI_n}{RI_n} \tag{7}$$

Step 6. involves computing the weight of the decision-maker. The significance of this step lies in enhancing the decision quality of collective decision-making by assigning varying decision weights to different decision-makers. The consistency ratio value (CR_n) reflects the logical coherence of the decision-maker concerning the decision problem. Thus, in this paper, decision-makers with stronger logical coherence will be assigned greater decision weights. The formula for calculating the decision weight (WD_n) for decision-maker n is as follows:

$$Wd_n = \frac{1}{1 + aC_R^n}, a > 0, n = 1,2\ldots\ldots m \tag{8}$$

$$WD_n^* = \frac{Wd_n}{\sum_{n=1}^{m} Wd_n} \tag{9}$$

Up to this point, we have described how to use fuzzy AHP to calculate the weight of criteria and calculate the Weight of decision maker for each decision maker in collective decision support. Next, in the next section, we will show how to use fuzzy CoCoSo to calculate the ranking of Alternatives for each decision maker.

3.2. Fuzzy Group CoCoSo

In real world projects, when complex and multi variable condition exist, the role of decision-making will be vital to handle uncertainty and aid experts and policy makers to look for appropriate models and solutions. The decision makers require reliable methods that are understandable and easy for implementation. In this study, based on our model proposal and requirements we worked on a fuzzy MCDM approach, which allows to establish rankings the alternative (Yazdani et al., 2021). Integration of fuzzy approach and CoCoSo has been developed to ease decision makers participation find a compromise solution while facing uncertainty. The process of the solution to find the best alternative is applied based on the following steps:

Table 3. Linguistic assessment and the associated fuzzy values.

Performance	Abbreviation	Linguistic fuzzy values
Absolutely low	AL (1)	[1, 1.5, 2.5]
Very low	VL (2)	[1.5, 2.5, 3.5]
Low	L (3)	[2.5, 3.5, 4.5]
Medium Low	ML (4)	[3.5, 4.5, 5.5]
Equal	E (5)	[4.5, 5.5, 6.5]
Medium High	MH (6)	[5.5, 6.5, 7.5]
High	H (7)	[6.5, 7.5, 8.5]
Extremely high	EH (8)	[7.5, 8.5, 9.5]
Absolutely high	AH (9)	[8.5, 9.5, 10]

Source: (Demir et al., 2022).

Step 1- Identifying the decision-making matrix including criteria, alternatives, decision-making team, questionnaire preparation, etc.

Step 2- Evaluating the alternatives with regard to each decision criteria by expert opinion and fuzzy linguistic variable according to equation (10).

$$\tilde{X}_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{10}$$

for $i = 1,\ldots,m$ and $j = 1,\ldots,n$

Step 3- Normalizing the matrix in previous step as equations (11-12) indicate

$$\tilde{r}_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{11}$$

$$\tilde{r}_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{12}$$

where equation (11) is used for benefit criteria, and equation (12) is used for cost criteria.

Step 4- Finding the sum of the weighted comparability sequence (SW_i) and the power-weighted comparability sequences (PW_i) for each alternative using the following equations (13-14).

$$\tilde{SW}_i = \sum_{j=1}^{n} (\tilde{w}_j \tilde{r}_{ij}) \tag{13}$$

$$\tilde{PW}_i = \sum_{j=1}^{n} (w_j)^{r_{ij}} \tag{14}$$

Step 5- Developing the aggregated appraisal scores to calculate the relative weights of alternatives using three strategies:

$$\tilde{Q}_1 = \frac{\tilde{PW}_i + \tilde{SW}_i}{\sum_{i=1}^{m} (PW_i + \tilde{SW}_i)} \tag{15}$$

$$\tilde{Q}_2 = \frac{\tilde{SW}_i}{\min_i \tilde{SW}_i} + \frac{\tilde{PW}_i}{\min_i \tilde{PW}_i} \tag{16}$$

$$\tilde{Q}_3 = \frac{\lambda\left(\tilde{SW}_i\right) + (1-\lambda)(\tilde{PW}_i)}{\lambda \max_i \tilde{SW}_i + (1-\lambda)\max_i \tilde{PW}_i} \tag{17}$$

where $0 \geq \lambda \geq 1$ and is usually considered 0.5 ($\lambda = 0.5$ is taken in this study).

Step 6 – Computing the integrated value for each alternative as equation (18) addresses:

$$\tilde{Q}_i = (\tilde{Q}_1 \times \tilde{Q}_2 \times \tilde{Q}_3)^{\frac{1}{3}} + \frac{1}{3}\left(\tilde{Q}_1 + \tilde{Q}_2 + \tilde{Q}_3\right) \tag{18}$$

In Equation 17, varying the value of λ allows decision making process to test accuracy. In the results section, after finding the priority and alternative scores, some analysis and sensitivity tests will be performed to check how the results would change.

3.3. Group decision making based on Fuzzy AHP-CoCoSo

In this study, we have proposed a fuzzy AHP-CoCoSo group decision making structure to choose the most suitable location. The step-by-step process to reach the objective is stated here and Figure 1 exhibits those steps visually.

Step 1: After review the literature and setting and defining decision variables and alternatives, all decision-makers are required to provide pairwise comparison matrices for the criteria needed by fuzzy AHP. To ensure comprehensiveness and consistency, this step necessitates decision-makers to interactively consider and input their preferences regarding the importance relationships among the criteria.

Step 2: Employing fuzzy AHP for computation, determine the weights of criteria for each decision-maker and their decision weight throughout the entire decision-making process. The purpose of this step is to utilize the fuzzy analytic hierarchy process, ensuring a rational evaluation of each decision-maker's contribution to collective decision-making.

Step 3: All decision-makers must adhere to the rules of fuzzy CoCoSo and provide decision matrices. In this stage, decision-makers are required to adhere to the specifications of fuzzy CoCoSo, ensuring that the input of decision matrices meets the accuracy requirements.

Step 4: Integrate the fuzzy CoCoSo algorithm with the criteria weights obtained from fuzzy AHP in the second step to calculate the ranking of alternative solutions for each decision-maker, providing rankings for alternative solutions for each decision-maker.

Step 5: Consolidate the rankings of alternative solutions for all decision-makers using their decision weights. Ultimately, the rankings of alternative solutions obtained through collective decision-making will reflect the shared opinions and preferences of all decision-makers. This process ensures a comprehensive and rational final ranking in a complex decision-making environment.

4. Data collection and results generation

4.1. Empirical example

In order to test our methodology, we have defined a multi criteria example for waste disposal location problem. In this stage we develop several tasks and follow them step by step to achieve the optimal solution. We utilize fuzzy AHP method to generate the weights of decision makers (DMs) and weights of each decision criteria simultaneously. Thereafter, CoCoSo will

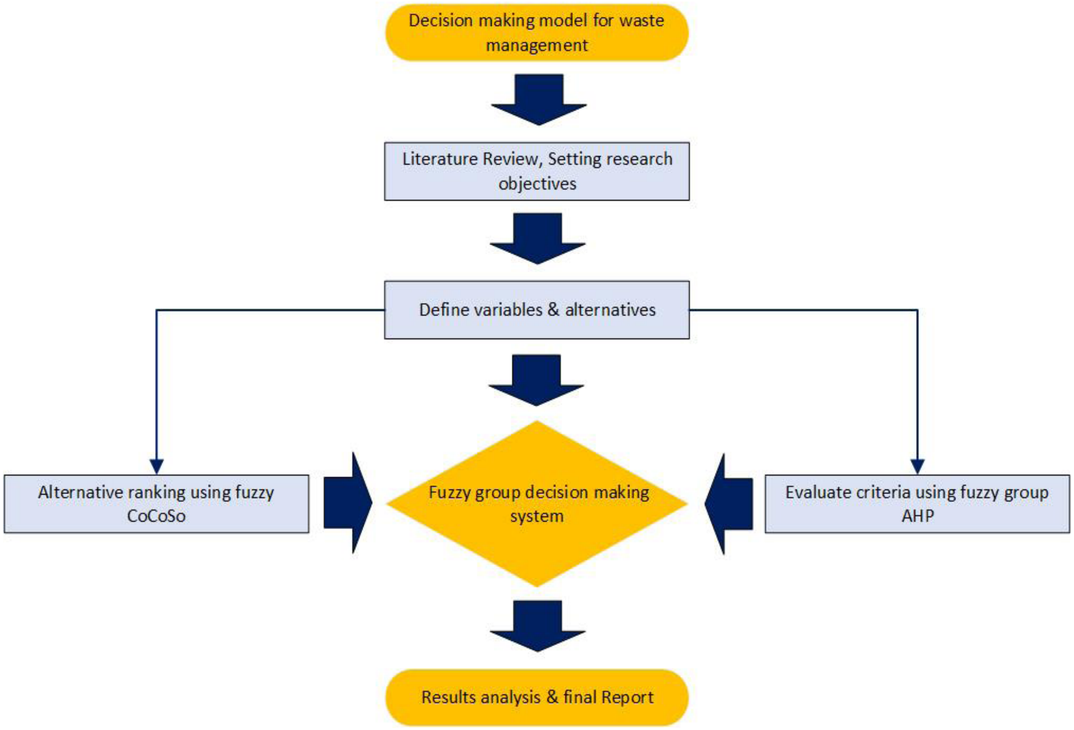

Figure 1. The schematic process of waste disposal location problem.

be applied to rank the location alternatives. Five possible locations are considered in the *Valencian metropolitan city* where the local government must take urgent action to dispose waste and find the best location. For that purpose, we have consulted to a team of 10 experts to participate and deliver us their opinion. These experts in charge are composed of regional government, municipal and relevant parties to discuss and offer their opinion anonymously. The expert profile is observed in the Table 4 below, as it is seen, there are various profiles from different sectors and profession with skills and experiences.

These five locations are chosen as decision alternatives (A1, … A5). A1 is selected as north zone, A2 and A3 are located closely as west zone, A4 as south zone and A5 is southwest. We designed a questionnaire and sent it to the experts through email to evaluate the five distinct locations under the eight decision variables (factors or criteria). They are used to express their opinions about each factor and the relative importance of the criteria and, in the second level, assessment of each alternative over the available criteria. The list below shows the relevant criteria for waste location objective. We divided them into three categories.

C1: Land Price (per square meter) in the specific zone (cost factor)

C2: Access to transportation, railroad, airports (benefit factor)

C3: Possibility of future expansion (benefit)

C4: Risk of the potential of intrusion and emission (degree of contamination) (cost factor)

C5: The proximity to the urban and city infrastructure (society) (benefit)

C6: Distance to a complex of waste sorting (cost)

C7: Operators, workforce resource (benefit)

C8: Local and territorial rules or regulations (cost)

4.2. Results and analysis

4.2.1. Fuzzy AHP

In the process of employing fuzzy AHP methodology, an initial step involves soliciting input from each decision maker regarding their individual preferences. Subsequently, each decision maker is prompted to reflect on the perceived

Table 4. Expert profiles and experiences.

	Sex	Experience	Education	Profession
Exp. 1	Male	12 years	PhD in sustainable supply chain	Chief office of logistics
Exp. 2	Male	8 years	Master in chemical engineering	Director of laboratory
Exp. 3	Female	15 years	Master in transport Engineering	Head of transport & logistics
Exp. 4	Male	10 years	Master in environmental sciences	Office of environmental protection.
Exp. 5	Male	12 years	Bachelor in Public affair	Chief executive officer, Valencia transport sector
Exp. 6	Female	20 years	Master in environmental and ecology	Environmental protection senior supervisor
Exp. 7	Male	5 years	PhD in information science	Research director
Exp. 8	Male	10 years	Bachelor, business analytics, master, Data sciences	Associate professor
Exp. 9	Male	15 years	PhD in finance and governmental administration	Researcher in politics and sustainable development
Exp. 10	Female	24 years	MBA	Teacher

importance of the relationships between every pair of criteria, thereby inputting corresponding fuzzy numbers to represent these considerations. The essential relationships, depicted in Table 1, are articulated through fuzzy numbers, providing a tangible representation of the nuanced qualitative assessments inherent in fuzzy AHP analysis.

Given the collaborative nature of decision-making in this study, where ten decision makers are involved, the individual preferences of each participant become pivotal inputs for the algorithm's functionality. Table 5 elucidates the scoring derived from the crucial relationship table generated through fuzzy AHP by the initial decision maker, offering insights into the decision-making process.

However, due to the inherent complexity arising from the interplay of eight criteria, decision makers may encounter instances where the Consistency Ratio surpasses the acceptable threshold of 0.1. In response to such occurrences of inconsistency, the decision support system initiates corrective measures by prompting decision makers to revise their inputs. This iterative process continues until the achieved Consistency Ratio aligns with the predetermined threshold, ensuring the robustness and reliability of the decision-making framework.

Once all ten decision makers have completed inputting their preferences and achieved Consistency Ratios below 0.1, the algorithm of fuzzy AHP can be employed to calculate the weight of criteria for each decision maker, along with their individual

Table 5. Fuzzy pairwise matrix for (comparisons between criteria) from DM1.

	C1	C2	C3	C4	C5	C6	C7	C8
C1	(1,1,1)	(1,2,3)	(4,5,6)	(2,3,4)	(3,4,5)	(2,3,4)	(4,5,6)	(5,6,7)
C2	(1/3,1/2,1/1)	(1,1,1)	(2,3,4)	(2,3,4)	(1,2,3)	(1,2,3)	(4,5,6)	(4,5,6)
C3	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1,1,1)	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1/6,1/5,1/4)	(2,3,4)	(3,4,5)
C4	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(3,4,5)	(1,1,1)	(1/4,1/3,1/2)	(1,2,3)	(3,4,5)	(1,2,3)
C5	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1,2,3)	(2,3,4)	(1,1,1)	(2,3,4)	(2,3,4)	(3,4,5)
C6	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(4,5,6)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1,1,1)	(1,2,3)	(1,2,3)
C7	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1,1,1)	(1/3,1/2,1/1)
C8	(1/7,1/6,1/5)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1,2,3)	(1,1,1)

Table 6. The criteria and decision makers weights.

	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	DM9	DM10
C1	0,3102	0,2025	0,2581	0,3	0,316	0,1892	0,192	0,2464	0,2288	0,2016
C2	0,2085	0,2605	0,2646	0,188	0,2234	0,3206	0,2833	0,2506	0,2699	0,2773
C3	0,0596	0,0628	0,0657	0,131	0,053	0,0882	0,0795	0,1216	0,0948	0,0637
C4	0,1068	0,1088	0,0978	0,1219	0,1104	0,1505	0,1338	0,0789	0,0948	0,1236
C5	0,1486	0,1678	0,1403	0,1086	0,1407	0,0797	0,1407	0,1447	0,139	0,1449
C6	0,0903	0,1072	0,0929	0,0679	0,0696	0,0882	0,0784	0,0621	0,0797	0,1025
C7	0,0349	0,0402	0,053	0,0498	0,0568	0,0475	0,0574	0,0542	0,0528	0,0401
C8	0,0412	0,0502	0,0275	0,0328	0,0301	0,0363	0,0349	0,0416	0,0402	0,0463
C.R-Fuzzy	0,0914	0,088	0,0894	0,0922	0,0926	0,0888	0,0848	0,0873	0,0863	0,0962
Weight of DM	0,099092	0,100871	0,100139	0,098674	0,09846	0,100445	0,102604	0,101256	0,101787	0,096673

Consistency Ratios, as illustrated in Table 6. In order to harmonize the preferences of all decision makers more effectively, it becomes necessary to assign distinct decision weights to each participant. Given that Consistency Ratio serves as a proxy for the logical coherence of decision makers' inputs, those exhibiting higher levels of logical consistency are allocated greater decision weights. Consequently, after meticulous computation, the decision weights for each decision maker are delineated in Table 6.

This process not only facilitates the integration of diverse preferences but also ensures that decision-making authority is distributed in accordance with the demonstrated logical coherence of each participant. By leveraging the Consistency Ratio as a guiding metric, the allocation of decision weights becomes not merely an exercise in uniform distribution but a reflection of the varying degrees of reliability and consistency inherent in individual decision-making processes. Thus, the resulting distribution of decision weights reflects a nuanced calibration that optimizes the synthesis of diverse perspectives while upholding the integrity of the decision-making framework.

4.2.2. Fuzzy CoCoSo

The fuzzy CoCoSo computation starts with the decision makers opinion and forming the initial fuzzy based matrix. Because we have 10 decision makers, so we have 10 different weights, and the computation

Table 7. Decision maker opinion for alternatives evaluation.

				DM1				
Alternative	C1	C2	C3	C4	C5	C6	C7	C8
A1	6	3	5	5	5	4	5	1
A2	4	3	5	5	1	7	3	8
A3	2	4	1	3	5	5	2	5
A4	2	2	6	2	5	7	3	1
A5	5	3	3	1	3	3	4	2

Table 8. Initial fuzzy decision matrix from (DM1).

	C1	C2	C3	C4	C5	C6	C7	C8
A1	(5, 6, 7)	(6, 7, 2)	(7, 2, 3)	(2, 3, 4)	(3, 4, 4)	(4, 4, 5)	(4, 5, 6)	(5, 6, 4)
A2	(3, 4, 5)	(4, 5, 2)	(5, 2, 3)	(2, 3, 4)	(3, 4, 4)	(4, 4, 5)	(4, 5, 6)	(5, 6, 4)
A3	(1, 2, 3)	(2, 3, 3)	(3, 3, 4)	(3, 4, 5)	(4, 5, 1)	(5, 1, 1)	(1, 1, 1)	(1, 1, 2)
A4	(1, 2, 3)	(2, 3, 1)	(3, 1, 2)	(1, 2, 3)	(2, 3, 5)	(3, 5, 6)	(5, 6, 7)	(6, 7, 1)
A5	(4, 5, 6)	(5, 6, 2)	(6, 2, 3)	(2, 3, 4)	(3, 4, 2)	(4, 2, 3)	(2, 3, 4)	(3, 4, 1)

here is set for the first DM weights, the rest will be calculated in the same process. The initial step in CoCoSo is to convert the main fuzzy decision matrix to numerical values. Experts delivered their opinion and comparison using linguistic variables in Table 3 and generated Table 7. These linguistic variables should be converted to fuzzy triangular values. We performed this process from Table 7 to Table 8 for 1th decision maker (DM1). Indeed, now we have an initial fuzzy matrix showed in formula 10.

The next step in process of solving decision problem is normalization process. Based on formula 11 and 12. The produced results are observed in Table 9 for DM1. In CoCoSo to affect the decision-making weights, two strategies are applied as seen in Equations 13 and 14. The weighted fuzzy matrix and Si values are demonstrated in Table 10. In addition, the power weighted fuzzy matrix and Pi values can be checked in Table 11. To look for an aggregated result, appraisal scores according to formulas 15, 16 and 17 are computed to determine the relative weights of alternatives. The three values as Q1, Q2 and Q3 in fuzzy environment plus the final Q value (Equation 18) are observed in Table 12 accompanying to crisp or standard values for each alternative with respect to DM1 opinion. We carried out the same process for all other

Table 9. The normalized fuzzy decision matrix (DM1).

	C1	C2	C3	C4	C5	C6	C7	C8
A1	(0, 0.167, 0.333)	(0.167, 0.333, 0.25)	(0.333, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 0.5)	(0.75, 0.5, 0.667)	(0.5, 0.667, 0.833)	(0.667, 0.833, 0)
A2	(0.333, 0.5, 0.667)	(0.5, 0.667, 0.25)	(0.667, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 0.5)	(0.75, 0.5, 0.667)	(0.5, 0.667, 0.833)	(0.667, 0.833, 0)
A3	(0.667, 0.833, 1)	(0.833, 1, 0.5)	(1, 0.5, 0.75)	(0.5, 0.75, 1)	(0.75, 1, 0)	(1, 0, 0)	(0, 0, 0)	(0, 0, 0.4)
A4	(0.667, 0.833, 1)	(0.833, 1, 0)	(1, 0, 0.25)	(0, 0.25, 0.5)	(0.25, 0.5, 0.667)	(0.5, 0.667, 0.833)	(0.667, 0.833, 1)	(0.833, 1, 0.6)
A5	(0.167, 0.333, 0.5)	(0.333, 0.5, 0.25)	(0.5, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 0.167)	(0.75, 0.167, 0.333)	(0.167, 0.333, 0.5)	(0.333, 0.5, 1)

Table 10. The weighted fuzzy matrix and Si values.

	C1	C2	C3	C4	C5	C6	C7	C8	Si
A1	(0, 0.052, 0.103)	(0.052, 0.104, 0.156)	(0.03, 0.04, 0.05)	(0, 0.021, 0.043)	(0.089, 0.119, 0.149)	(0.045, 0.06, 0.075)	(0.021, 0.028, 0.035)	(0.041, 0.041, 0.041)	(0.278, 0.465, 0.652)
A2	(0.103, 0.155, 0.207)	(0.052, 0.104, 0.156)	(0.03, 0.04, 0.05)	(0, 0.021, 0.043)	(0, 0, 0)	(0, 0.015, 0.03)	(0.007, 0.014, 0.021)	(0, 0.005, 0.01)	(0.192, 0.355, 0.517)
A3	(0.207, 0.258, 0.31)	(0.104, 0.156, 0.208)	(0, 0, 0)	(0.043, 0.064, 0.085)	(0.089, 0.119, 0.149)	(0.03, 0.045, 0.06)	(0, 0.007, 0.014)	(0.015, 0.021, 0.026)	(0.488, 0.671, 0.853)
A4	(0.207, 0.258, 0.31)	(0, 0.052, 0.104)	(0.04, 0.05, 0.06)	(0.064, 0.085, 0.107)	(0.089, 0.119, 0.149)	(0, 0.015, 0.03)	(0.007, 0.014, 0.021)	(0.041, 0.041, 0.041)	(0.448, 0.635, 0.822)
A5	(0.052, 0.103, 0.155)	(0.052, 0.104, 0.156)	(0.01, 0.02, 0.03)	(0.107, 0.107, 0.107)	(0.03, 0.059, 0.089)	(0.06, 0.075, 0.09)	(0.014, 0.021, 0.028)	(0.031, 0.036, 0.041)	(0.355, 0.526, 0.697)

Table 11. The power weighted fuzzy matrix and Pi values.

	C1	C2	C3	C4	C5	C6	C7	C8	Pi
A1	(0, 0.574, 0.711)	(0.749, 0.865, 0.942)	(0.96, 0.976, 0.989)	(0, 0.842, 0.907)	(0.927, 0.967, 1)	(0.939, 0.964, 0.984)	(0.982, 0.992, 1)	(1, 1, 1)	(5.557, 7.181, 7.533)
A2	(0.711, 0.807, 0.882)	(0.749, 0.865, 0.942)	(0.96, 0.976, 0.989)	(0, 0.842, 0.907)	(0, 0, 0)	(0, 0.851, 0.906)	(0.945, 0.969, 0.982)	(0, 0.918, 0.945)	(3.365, 6.227, 6.552)
A3	(0.882, 0.945, 1)	(0.865, 0.942, 1)	(0, 0, 0)	(0.907, 0.947, 0.976)	(0.927, 0.967, 1)	(0.906, 0.939, 0.964)	(0, 0.945, 0.969)	(0.96, 0.972, 0.981)	(5.447, 6.658, 6.89)
A4	(0.882, 0.945, 1)	(0, 0.749, 0.865)	(0.976, 0.989, 1)	(0.947, 0.976, 1)	(0.927, 0.967, 1)	(0, 0.851, 0.906)	(0.945, 0.969, 0.982)	(1, 1, 1)	(5.677, 7.446, 7.753)
A5	(0.574, 0.711, 0.807)	(0.749, 0.865, 0.942)	(0.899, 0.937, 0.96)	(1, 1, 1)	(0.787, 0.873, 0.927)	(0.964, 0.984, 1)	(0.969, 0.982, 0.992)	(0.988, 0.995, 1)	(6.929, 7.347, 7.627)

Table 12. Aggregation strategies for CoCoSo

	Fuzzy Q1	Crisp Q1	Fuzzy Q2	Crisp Q2	Fuzzy Q3	Crisp Q3	Q value
A1	(0.146, 0.204, 0.285)	0.212	(3.099, 4.553, 5.63)	4.427	(0.678, 0.888, 0.951)	0.8392	2.749
A2	(0.089, 0.175, 0.246)	0.170	(2, 3.695, 4.635)	3.443	(0.413, 0.765, 0.821)	0.6665	2.158
A3	(0.149, 0.195, 0.269)	0.205	(4.159, 5.466, 6.482)	5.369	(0.69, 0.852, 0.9)	0.8136	3.092
A4	(0.154, 0.215, 0.298)	0.222	(4.016, 5.514, 6.577)	5.369	(0.712, 0.939, 0.996)	0.8824	3.176
A5	(0.183, 0.21, 0.29)	0.227	(3.907, 4.918, 5.889)	4.905	(0.846, 0.915, 0.967)	0.9095	3.019

Table 13. Decision makers final score for all the alternatives.

	Fuzzy CoCoSo score									
Alternatives	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	DM9	DM10
A1	2.749	3.208	3.054	2.696	2.813	3.086	3.151	3.002	3.088	3.1619
A2	2.158	3.303	3.228	2.887	3.045	3.297	3.340	3.126	3.222	3.2997
A3	3.092	3.422	3.293	2.983	3.147	3.270	3.404	3.217	3.291	3.3804
A4	3.176	3.789	3.705	3.388	3.516	3.749	3.820	3.697	3.749	3.7682
A5	3.019	2.701	2.663	2.548	2.575	2.653	2.693	2.659	2.674	2.6817

DMs and the final score for the alternatives are found in Table 13. In this stage, as we mentioned beforehand, the weight of decision makers (see the Table 6, lowest row) must be integrated to the CoCoSo process. With a geometric multiplication, the cumulative final score of each alternative can be produced. The corresponding information is defined in Table 14. The results show the following ranking:

A4 > A3 > A2 > A1 > A5

Table 14. The aggregated and group final ranking of Alternatives.

Alternatives	Score	Ranking
A1	3.002	4
A2	3.092	3
A3	3.251	2
A4	3.637	1
A5	2.687	5

5. Conclusion, implication, and future research works

An effective waste management process is fundamental for maintaining environmental sustainability and public health worldwide. As populations grow and urbanize, the volume of waste generated continues to increase, posing significant challenges such as pollution, resource depletion, and health risks. Sustainable waste management practices, encompassing strategies like recycling, composting, waste-to-energy technologies, and proper disposal methods, play a vital role in mitigating these challenges. Additionally, the integration of interdisciplinary approaches and advanced technologies further enhances the efficiency and effectiveness of waste management systems. Addressing waste management issues not only safeguards ecosystems and human well-being but also promotes economic prosperity through resource conservation and innovative solutions. Therefore, prioritizing research, policy development, and implementation efforts in waste management is imperative for fostering a cleaner, healthier, and more sustainable future for generations to come.

In this study, the methodology employed revolves around the integration of group Analytic Hierarchy Process (AHP) and CoCoSo methods under fuzzy parameter estimation to address the challenge of waste disposal site selection. Fuzzy AHP, a variant of the traditional AHP, enables decision-makers to express their preferences in a more flexible and tolerant manner by incorporating fuzzy logic. This approach allows for a nuanced assessment of criteria weights, particularly beneficial in complex decision-making scenarios where traditional AHP may fall short. Furthermore, the utilization of fuzzy CoCoSo adds another layer of analysis, contributing to the computation of the final ranking in collective decision-making scenarios. One of the specific contributions of this work is that we conducted a group decision process to produce the weights of decision-makers and then incorporated it into the CoCoSo final score. This approach allows for a much more comprehensive and global ranking system, which is scarce in several studies.

The weighting process involves several key steps. Firstly, the problem under analysis is structured hierarchically, delineating overarching goals and criteria. Secondly, decision-makers provide their preferences for each criterion through pairwise comparisons using the fuzzy scale of relative importance. This scale incorporates fuzzy theory, allowing decision-makers to express uncertainty in their judgments. The resulting fuzzy pairwise comparison matrices are then aggregated to derive the weight of criteria and decision-makers, facilitating a comprehensive analysis of the decision space. This integration of fuzzy AHP with the fuzzy CoCoSo methodology offers a robust framework for addressing the complexities inherent in waste disposal site selection, providing decision-makers with a systematic approach to evaluate and prioritize potential locations.

The fuzzy CoCoSo methodology provides a systematic approach to collective decision-making by integrating the opinions of multiple decision-makers. Starting with the formation of an initial fuzzy decision matrix based on the linguistic variables provided by each decision-maker, the process involves converting these linguistic variables into fuzzy triangular values and then normalizing the matrix. Subsequently, weighted fuzzy matrices are computed using two strategies to affect decision-making weights, leading to the determination of appraisal scores for each alternative. The final scores for the alternatives are aggregated considering the weights of decision-makers, resulting in a ranking of alternatives based on their overall suitability. This approach offers valuable insights for decision-makers in prioritizing alternatives in waste management practices, ensuring a comprehensive evaluation of potential solutions based on collective input from experts (Fernández-Portillo et al., 2023).

One of the limitations in waste management research is the lack of real-time data integration. Dynamic logistics systems, which are crucial for effective waste management, require constant processing of data in real time to adapt to changing market demands, inventory information, community engagement, and other factors influencing decision-making. However, existing research often neglects this aspect, relying on static or outdated data for analysis and decision-making processes. As a result, there is a need for future research to address this limitation by integrating the proposed methodologies into online decision-making services that enable continuous updating of data in the initial decision-making matrix. Additionally, further research should focus on integrating other theories of uncertainty into a multi-criteria framework, allowing for the processing of neutral information with dynamic interval values. This approach would enable more accurate and timely decision-making in waste management practices, ultimately leading to improved efficiency and effectiveness in handling waste disposal and recycling processes.

Future directions could be influenced by the utilization of advanced methodologies such as fuzzy Extended Z-numbers (Zafaranlouei et al., 2023; Haseli et al., 2024). These methods offer promise but also pose challenges due to their computational complexity, particularly when handling large datasets. Moreover, the integration of fuzzy sets and numbers, including fuzzy Extended Z-numbers, into machine learning techniques presents an avenue for addressing uncertainty and imprecision in waste management. Additionally, exploring the application of interval-valued fuzzy numbers could deliver innovative methods like the Combined Compromise Solution (CoCoSo) for handling interval-valued fuzzy Extended Z-numbers in decision-making and data analysis. These advancements have the potential to improve waste management practices, enhancing efficiency and sustainability efforts for the benefit of global environmental health and public well-being.

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