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# A Hybrid Fuzzy AHP-TOPSIS Approach for Implementation of Smart Sustainable Waste Management Strategies

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**Abstract:** The integration of smart city technologies into waste management is a challenging field for decision makers due to its multivariate, multi-limiting, and multi-stakeholder structure, despite its contribution to the ecological and economic sustainability understanding of cities. The success of smart sustainable waste management strategies depends on many environmental, technical, economic, and social variables, and many stakeholders are involved in these processes. Using fuzzy multi-criteria decision-making (MCDM) methods helps decision makers determine effective, affordable, and acceptable smart waste management strategies. Although MCDM methods are widely used in various environmental engineering applications, the determination of smart sustainable waste management strategies using these methods has not yet received enough attention in the literature. This study aims to contribute to this gap in the literature by evaluating four different smart waste management strategies using a hybrid fuzzy MCDM method. The performance of the proposed strategy alternatives according to fifteen sub-criteria (under four main criteria selected from the literature) was evaluated using a combined application of fuzzy analytic hierarchy process (fuzzy AHP) and fuzzy technique for order preference by similarity to obtain the ideal solution (fuzzy TOPSIS). For this evaluation, the subjective opinions of ten different experts working in academia, in the private sector, or in the public sector were obtained using prepared questionnaires. As a result, the sub-criteria of fewer atmospheric emissions (0.42), operational feasibility (0.64), initial investment costs (0.56), and increased awareness of sustainable cities (0.53) had the highest weight values in their main criteria groups. The performance ranking of the alternatives according to the closeness coefficient ($CC_i$) values was obtained as A2 (0.458) > A3 (0.453) > A4 (0.452) > A1 (0.440), with A3 being slightly ahead of A4 due only to a 0.001 higher $CC_i$ value. To test the reliability and stability of the obtained performance ranking results, a sensitivity analysis was also performed using eighteen different scenarios, in which the weights of the different sub-criteria were increased by 25% or decreased by 50%, or they were assumed to be 1 and 0, or all sub-criteria in the same group had equal weight values. Since the performance ranking of the alternatives did not change, the ranking obtained at the beginning was found to be robust against the sub-criterion weight changes.

**Keywords:** smart sustainable waste management; multi-criteria decision making; fuzzy AHP; fuzzy TOPSIS; smart city technologies



**Citation:** Demircan, B.G.; Yetilmezsoy, K. A Hybrid Fuzzy AHP-TOPSIS Approach for Implementation of Smart Sustainable Waste Management Strategies. *Sustainability* **2023**, *15*, 6526. https://doi.org/10.3390/su15086526

Academic Editor: Agostina Chiavola

Received: 25 January 2023
Revised: 5 April 2023
Accepted: 11 April 2023
Published: 12 April 2023



## 1. Introduction

The high trend of urbanization makes cities key players in both the global climate crisis and the global water crisis. It has been reported that two-thirds of the world's energy is consumed in cities, and cities are responsible for 70% of global carbon emissions [1]. In addition to emissions from the use of large quantities of fossil fuels, cement-related emissions from the creation and use of urban infrastructure in cities are also serious (9.2 $GtCO_2e$ and 9.6 $GtCO_2e$, respectively) [2]. Increasing per capita water consumption, in parallel with rising income levels in cities, poses a drought threat. On the other hand, in cities where people's wealth levels are low, there are problems, such as unhygienic water consumption and inability to access improved water resources. According to a recent report [3], 700 million urban residents lack improved sanitation facilities, and 156 million urban residents lack improved water resources.

Another consequence of urban overcrowding is that issues, such as convenient travel without long waits in traffic, effortless parking of vehicles, fast and hygienic disposal of garbage and sewage, and lower electricity and water bills, require more attention from city authorities. They are expected to use existing natural and economic resources as efficiently as possible and to cause as little harm to the environment as possible while meeting the basic needs of people living in cities, such as water, housing, transportation, education, and health care. For this reason, it is more urgent than ever to use innovative and technological applications to deliver urban services faster and more efficiently. Since the 1990s, this urgency has brought a new concept known as "smart city" into urban life [4,5].

In smart cities, where it is essential to provide city services in a greener, more economical, and faster manner and to meet the expectations of citizens, the integration of cutting-edge technologies into sustainable waste management approaches is becoming increasingly important [6,7]. However, this integration is directly related to the climatic, geophysical, economic, and socio-cultural characteristics of cities. Therefore, the implementation and maintenance of smart sustainable waste management strategies depends on many technical, economic, political, and social variables. These variables affect and change each other, further complicating management processes. On the other hand, the number of stakeholders involved in the relevant processes is usually quite high. It is often difficult for public authorities, private sector managers, researchers, and residents to act in a coordinated and coherent manner in a seamless and interconnected structure.

A fuzzy multi-criteria decision-making approach can be used as a solution to all the above-mentioned problems, while identifying smart sustainable waste management strategies that are technically, scientifically, and economically feasible and responsive to the needs of residents. In this approach, it is possible to rank, compare, or prioritize different smart sustainable waste management strategy alternatives through various mathematical operations after subjective expert evaluation based on a predetermined set of criteria. Containing fuzzy sets that allow for partial membership degrees, fuzzy MCDM makes it possible to work with incomplete, unmeasurable, or imprecise information. In this respect, it would be more appropriate to use this approach instead of traditional MCDM methods, which are still being developed in the field of smart waste management strategies and have not yet reached a satisfactory level of knowledge.

Although different types of multi-criteria decision-making methods are widely used in various environmental engineering applications, the number of studies using these methods for the determination of smart sustainable waste management strategies is very limited. It is seen that studies applying multi-criteria decision-making techniques in this field focused on either smart waste collection or smart waste disposal strategies, or they examined various smart waste management approaches for a particular type of waste. The strategy alternatives proposed in this study cover all processes from waste reduction to waste collection and disposal for all waste types, with a holistic view of smart sustainable waste management. On the other hand, although there are studies using different AHP and TOPSIS methods in this area, a hybrid study integrating the results obtained by using these two methods simultaneously has not yet been conducted. This study aims to fulfill this gap in the literature by evaluating four different smart waste management strategies using a hybrid fuzzy AHP-TOPSIS approach that can support local authorities in determining sustainable waste management strategies in smart cities.

To construct the hierarchical structure of the problem, as a first step, four different smart sustainable waste management strategies, which combine different sustainable waste management strategies and smart waste management technologies in the literature and practice, are selected. Then, in order to evaluate the performance of the strategies, fifteen sub-criteria were determined under four main criteria from the relevant literature. After constructing the hierarchical structure of the problem, a decision-making expert group of ten experts from academia, the private sector, and the public sector was formed for linguistic assessments. A weight criterion was made by using the verbal and subjective evaluations of the decision makers through the questionnaires prepared in the fuzzy AHP procedure. Decision makers also evaluated the performance of each strategy alternative in the questionnaires verbally and subjectively according to each sub-criterion. Finally, the performance ranking of the alternatives was obtained with the fuzzy TOPSIS method, applied by using these evaluation results and the sub-criteria weights obtained by fuzzy AHP.

The study also performed a sensitivity analysis using eighteen different scenarios to explore whether different weightings of the sub-criteria would alter the ranking of the alternatives. In these scenarios, the existing sub-criteria weight values were increased or decreased by different amounts, assumed as 1 or 0, and assumed as equal in a main criteria group.

## 2. Literature Review

### 2.1. Sustainable Waste Management

The term sustainability has been used in relation to the environment since the 1970s, with an understanding of proactive solutions to environmental problems. It was first mentioned in the literature [8] as "sustainable development", which oversees the protection of ecological life and natural resources. Sustainable development has been shown to have three dimensions, namely social, economic, and environmental [9], and these dimensions have been examined separately or together in various studies.

Considering the environment from these three pillars, it is seen that environmental sustainability is defined as "a set of rules to be followed on the use of recyclable and non-recyclable resources and waste and pollution removal" by Goodland [10], who introduced this concept into the literature. Another perspective [11] on environmental sustainability defines the term as meeting the needs of resources and services for present and future generations without compromising the health of the ecosystems that provide them.

Public administrations and businesses, which play a major role in ensuring environmental sustainability, have, over time, moved away from traditional waste management approaches to plans and strategies that follow the principle of viewing the processes of waste generation, collection, and disposal as parts of a whole that influence each other. A strong sustainable waste management system focuses on processes rather than products, and its products, functions, and organizational structures must also be adaptable and versatile [12]. As a contribution to this view, it could be added that the most effective management of waste has to relate to local environmental, economic, and social priorities and must go beyond traditional consultative approaches that require the use of experts [13]. To put it more simply, for a waste management system to be sustainable, it must be environmentally effective, economically affordable, and socially acceptable [14].

### 2.2. Sustainable Waste Management in Smart Cities

In the literature, there are many studies that propose different approaches for sustainable waste management. It is possible to come across multidisciplinary studies in different fields, such as resource reduction, waste minimization, and energy recovery from waste. Although there have been many studies on the sustainable waste management topic, the concept of internet of things (IoT)-enabled waste management is quite new, and the number of publications in this field is still growing. It has been accepted by researchers through various studies that the integration of smart city technologies with sustainable waste management approaches contributes to the understanding of environmental sustainability in terms of the efficient use of resources, reducing pollution loads, and saving energy and time. Since environmental sustainability is one of the key features of smart cities, it is quite understandable that the use of smart city technologies for sustainable waste management is a valid trend that is becoming more widespread every day.

Looking at the literature, it is seen that IoT-based smart waste management studies mainly focus on the management of solid waste. However, there are studies using information communication technology tools for the separation, collection, transportation, and disposal of different types of waste. Depending on the technologies used and the scope of application, a classification can be found in [15] for smart sustainable solid waste management.

Dynamic route optimization applications for improvements in household waste collection are one of the oldest and most common solid waste management approaches in smart cities. They are based on the simultaneous transmission of data, produced by different types of sensors placed in containers, to a database via different communication protocols and processing using decision support tools and mathematical models.

Another common IoT-enabled waste management strategy is using smart containers to make waste collection and separation for source activities more effective. In a 2019 study [16], smart management of e-waste on campus was enabled by level sensors in smart collection boxes installed at Monash University in Malaysia and a mobile application connected to a cloud database and Wi-Fi module. The mobile application guides users to the nearest e-waste collection box on campus based on their current location using GPS.

IoT tools were used in a 2020 study [17] that aimed to contribute to the decision-making process by examining the consumption patterns of city residents according to the waste they throw away. Data, such as the amount of daily collected waste and incorrect waste sorting behaviors, are stored in the cloud system through QR codes owned by the residents of a neighborhood. To test the effectiveness of the approach, a case study was conducted in Shanghai. Significant results were obtained in terms of the frequency of waste disposal, hours of waste disposal per day, and the change in waste disposal behavior depending on weather conditions.

As can be seen from the examples, the integration of IoT technologies into waste management is mostly in the field of solid waste management. However, as mentioned before, it is possible to come across studies involving other types of waste. Two examples of this can be seen in 2020. The first one [18] aimed to manage landfill leachate using IoT technology and developed a mechanical waste segregator that segregates incoming waste according to whether it is dry or wet. The device includes an Arduino microcontroller, an infrared light proximity sensor, and a soil moisture sensor. In the study, a leachate reactor—upflow anaerobic sludge blanket reactor system—was proposed to treat the leachate-containing microchips for imaging and a Wi-Fi module for data transmission to a cloud server. A fuzzy control system was developed based on real-time data on turbidity, suspended solids, dissolved oxygen, and chemical oxygen demand collected by sensors. In a second study [19], an air quality monitoring system using fog computing-based IoT was proposed. The sensor module, the fog computing device, and the IoT cloud platform were integrated to evaluate the effectiveness. Experiments were conducted in different environments for 15 days. As an air quality metric, the air quality index was calculated by measuring six major pollutants.

Recently, it has become possible to come across deep-learning- and machine-learning-based waste management studies. An artificial intelligence tool was used to label the images based on a specific trained set. In a study conducted in Vietnam [20], the objective was to estimate the amount of waste generated in waste bins and to optimize the distance between bins and make the emptying of bins as short as possible. For this purpose, two different algorithms were used in machine learning for the waste data obtained from garbage cans with IoT tools. The performance of the proposed system was evaluated using operational tests at Ton Duc Thang University. In another study [21], deep learning enabled the smart bin to classify the waste to be disposed of and, thanks to servo motors, open the appropriate compartment for each type of waste (e.g., plastic, metal, paper, or general waste). Data received via the Long-Range communication protocol, object detection, and waste classification were utilized in the TensorFlow framework using a pre-trained object detection model. This object detection model was trained with waste images to generate a frozen inference graph used for object detection, which is performed using a camera connected to the Raspberry Pi 3 Model BCas, the main processing unit. A scrap-metalproducing company and a waste management company collaborated in a field study [22] as part of a European project aimed at making operations more efficient by developing an integrated information management system conducted in the same year. Thanks to the simultaneous monitoring and notification provided by the sensors installed in the containers, the elevator company's scrap metal waste management was more effective, while the private company's waste management activities were effectively planned thanks to the developed online analytics platform. With the help of the deep learning method, it was possible to make price estimates for possible future waste types based on past company data.

Currently, there are various initiatives aimed at further developing IoT-based applications for waste management through integration with blockchain technology. In a 2021 study [23], researchers created a framework based on blockchain technology combined with the IoT developed using smart contracts to improve the management of hospital waste and wastewater. Data from waste containers and a wastewater treatment plant were collected by smart IoT tools. They were transmitted to the blockchain through existing communication technologies. Peripheral nodes then grouped the collected information into data blocks, which were temporarily stored. After verification, they were added to the blockchain, allowing stakeholders to process these data and enabling real-time decisions. In another study [24] conducted in the same year, researchers proposed a smart waste management system and utilized smart contracts on the Ethereum blockchain while designing it. They aimed to prove the superiority of their proposed system over traditional waste management by developing different algorithms for each step, from the time the waste is thrown into the smart waste container to its collection and disposal, and rewarding the waste producer.

### *2.3. Multi-Criteria Decision Making in Sustainable Waste Management*

Problems that arise in academic research and in the public or private sector often complicate decision-making processes due to their multidimensional and complex nature. It is not always easy for decision makers to choose between different alternatives or scenarios, to rank them according to their expectations, or to compare them with each other. In such cases, regardless of the subject and area of the problem to be solved, the use of MCDM techniques helps decision makers reach the optimal result. In its most general definition, this method is the ranking, selection, or comparison of different scenarios, alternatives, or factors of a problem using various mathematical models according to the subjective evaluation of relevant stakeholders based on a predetermined set of criteria.

Although a variety of MCDM methods are used in the literature and in practice, and it is possible to classify them differently according to their distinct characteristics, a basic classification for MCDM according to the alternatives and criteria used would be multi-attribute decision making and multi-objective decision making. In multi-objective decision-making-based problems, the alternatives are infinite, and the selection among the available criteria is represented by continuous functions [25]. This method is generally used in operational applications such as route optimization studies that require taking action in a relatively short time. On the other hand, the multi-attribute decision-making approach requires choosing among decision alternatives defined according to their characteristics. There are a limited number of decision alternatives given in multi-attribute decision-making-related problems [26].

Multi-attribute decision making can be basically divided into four main categories as follows:

1. Value-based approaches:
    - Multi-attribute utility theory
    - Analytic hierarchy process
    - Weighted sum model
2. Outranking approaches:

   - Preference ranking organization and method for enrichment evaluation
   - Elimination and choice expressing reality
3. Goal-based approaches:
   - Technique for order preference by similarity
   - Data envelopment analysis
4. Evaluation-based approaches:
   - Structural equation modeling
   - Interpretive structural modeling
   - Decision-making trial and evaluation laboratory

In the field of sustainability, which is inherently multivariate, multirestrictive, and multi-stakeholder, researchers benefit from MCDM methods that allow them to address problems with a systematic approach. Transportation and logistics, energy, construction and infrastructure, and supply chain management are the most common areas where MCDM methods are used to find solutions to sustainability problems [27]. In addition to the supply chain in the manufacturing sector, MCDM methods are also used in the areas of sustainable product design, sustainable material, sustainable technology, or sustainable project selection.

A recent study [28] in the field of sustainable transport examined the barriers to sustainable transport systems in India using the gray-decision-making trial and evaluation laboratory approach. In another study [29], the preference ranking organization and method for enrichment evaluation method was used to try to identify composite indices that can be used to compare and monitor sustainability in seaport regions in the Mediterranean.

In one of the latest MCDM studies in the field of sustainable energy, Dhiman and Deb [30] used fuzzy TOPSIS and fuzzy COPRAS methods to evaluate the performances of four different alternatives for a hybrid wind farm in terms of penalty costs. In India, researchers [31] evaluated seven different energy sources in terms of sustainability concepts by applying fuzzy AHP and fuzzy TOPSIS together. Spherical fuzzy AHP and TOPSIS were used simultaneously in another study [32] proposing a fuzzy MCDM model for sustainable energy source selection for an industrial complex in Vietnam.

Considering the studies in the field of sustainable construction and infrastructure; the preference ranking organization and method for enrichment evaluation and AHP methods were used together [33] to select the best-performing bridge in terms of sustainability among three different bridge alternatives planned for the construction of the intersection of a two-lane highway. Researchers used the decision-making trial and evaluation laboratory method [34] to identify and rank sustainability indicators for green building manufacturing assessment considering the green building index.

In one of the studies using MCDM techniques in the field of sustainable production, Chu and Lin [35] used fuzzy TOPSIS to select the most appropriate robot from three different alternatives. In another study [36] addressing the problem of selecting green suppliers with the goal of sustainability, researchers used the intuitionistic fuzzy TOPSIS model for selecting the most appropriate green supplier. For sustainable supplier selection in the food processing industry in Vietnam, researchers [37] proposed a hybrid model, and fuzzy AHP was used as the MCDM method. A hybrid MCDM approach, including data envelopment analysis, spherical fuzzy AHP, and spherical fuzzy weighted aggregated sum product assessment, was used, all together [38], for sustainable supplier selection in the steel industry.

When combining MCDM with sustainable waste management applications, researchers generally aim to [39]: (1) investigate optimal decision making among various alternative waste management strategies (e.g., landfill disposal, incineration, recycling, reuse, etc.); (2) explore possible technologies (e.g., mass incineration, pyrolysis, gasification, plasma incineration in cement kilns, etc.); and (3) determine the optimal location of a waste management facility (e.g., landfill, waste treatment facility, recycling facility, etc.).

A 2015 study [40] using fuzzy AHP and fuzzy TOPSIS together evaluated three different options for landfill sites in Istanbul, Turkey. Four criteria were used, including soil conditions, topography, and climatologic and hydrologic conditions. In a technology selection study [41] in the same year, ten different solid waste disposal technologies were evaluated with fuzzy TOPSIS according to eighteen criteria set by experts in order to determine the most suitable alternative for Istanbul, Turkey.

A hybrid fuzzy multi-criteria decision analysis method was applied in a 2017 study [42] evaluating six different wastewater treatment technologies, including membrane bioreactor, moving-bed bio-film reactor, and activated sludge process. Fuzzy AHP was used to weight the criteria, and fuzzy TOPSIS was used to rank the alternatives according to these criteria. In a 2021 study [43] aiming to determine the best disposal method for healthcare waste during and after the recent COVID-19 pandemic, the results obtained using fuzzy TOPSIS were compared with the results obtained with another fuzzy MCDM method. Four main criteria with ten subcategories were used to determine the most optimal one out of nine different disposal alternatives for healthcare waste.

In one of the most recent studies in this field [44], a hybrid fuzzy MCDM application was applied to evaluate eight different solid waste management scenarios for India. Fuzzy AHP was used for criterion weighting, and fuzzy TOPSIS was used to rank alternatives. Looking at recent MCDM studies in the field of sustainable waste management, it is seen that in addition to evaluating traditional waste management approaches, more specific waste management strategies adapted to socioeconomic conditions of the countries were also evaluated using this methodology. For example, in a study [45] conducted in Pakistan in 2022, fuzzy TOPSIS and fuzzy AHP were used together to identify the barriers that may be encountered in the transition to a circular economy (CE) in the management of food waste in that country.

In recent years, it has been observed that waste management strategies have been developed in accordance with the understanding of using waste for the benefit of a sustainable environment and economy, rather than seeing it as a problem that needs to be eliminated. It is seen that MCDM techniques are also used in the evaluation of these strategies. Two recent studies used fuzzy MCDM methods to determine the most suitable option for the location of a waste-to-energy plant. In the study of [46], which was used on a renewable energy project in Vietnam, fuzzy AHP was used to determine the solid waste-to-energy plant location in the country. In the second study [47], four possible waste-to-energy plant locations in Kırıkkale, Turkey, were evaluated using fuzzy AHP and fuzzy TOPSIS according to four criteria determined by expert opinion and literature research.

As can be seen from the above examples, fuzzy MCDM methods are applied to problems both in sustainability and waste management fields seperately. However, since smart sustainable waste management approaches are still a growing research area, the evaluation of these approaches with these methods is not very common in the literature. In a study [48] in which four different alternatives for smart solid waste collection using information and communication technologies were proposed for the Tepebasi region in Turkey, alternatives were evaluated using the type 2 fuzzy TOPSIS method, taking into account seven criteria set by experts. In another recent study [49], seven different smart strategies selected for medical waste disposal were prioritized using the decision-making trail and evaluation laboratory method. A hybrid MCDM method (modified entropy and combinative distance-based assessment under q-level interval-valued fuzzy sets) was used in a study [50] investigating different smart waste collection methods for a municipality in Istanbul, Turkey. In another study [51] covering smart waste management approaches in a more general way, researchers used the spherical AHP method to evaluate three different alternatives for smart waste management.

It should be noted that the examples given above are related to either the collection or disposal of waste. However, the present study covers broader strategies for smart waste management from production to disposal. It also differs from the above-mentioned studies using the fuzzy hybrid AHP-TOPSIS approach. A smart sustainable waste management strategy evaluation using this approach has not yet been reported.

It would be inaccurate to say that there is only one ideal method for solving a particular problem using fuzzy MCDM. By applying different methods for the same problem, different rankings of alternatives can occur. To overcome this shortcoming, a hybrid approach that integrates the results for final decision making was used in the study. The effectiveness and reliability of a hybrid fuzzy AHP-TOPSIS approach have been previously proven and are still used in current research, such as selecting cloud services [52], evaluating the service quality of hospitals [53], selecting suppliers for a construction company [54], evaluating hotel websites [55], evaluating the financial performance of banks [56], selecting computer-integrated manufacturing technologies [57], selecting aquaculture species [58], and studying the long-term growth in the online market for food delivery services [59].

## 3. Methodology

### 3.1. Constructing the Hierarchical Structure of the Problem

When working with a multi-criteria decision-making method, the problem to be solved must first be clearly defined. Then, the hierarchical structure of the problem in question is created. The hierarchical structure includes the alternatives, scenarios, or constraints of the problem to be evaluated or prioritized, as well as the criteria to be considered in the evaluation or prioritization. In determining the criteria, databases, expert opinions, or studies from the literature on the area in question may be consulted.

In this study, the problem was set to evaluate smart sustainable waste management strategies. Four smart waste management strategies were selected as alternatives for the present problem. Fifteen sub-criteria belonging to five main criteria were selected from the literature. The smart waste management strategy alternatives for the problem are presented in Table 1.

**Table 1.** Smart waste management strategy alternatives evaluated in the analysis.

| Alternative Number | Alternative Name |
|---|---|
| A1 | Integrating informal recyclable waste collection into a formal smart system |
| A2 | A pay as you throw application leveraging blockchain technology |
| A3 | IoT-Based community composting |
| A4 | Preventing illegal sewage discharge by utilizing IoT |

The main criteria and sub-criteria used in the evaluation of the strategy alternatives of the problem are given in Table 2.

**Table 2.** Main criteria and sub-criteria considered in the analysis.

| Main Criteria | Sub-Criteria No. | Sub-Criteria Name | Reference |
|---|---|---|---|
| Environmental criteria (C1) | C1.1 | Less atmospheric emissions | [60] |
| | C1.2 | Less soil pollution | [60] |
| | C1.3 | Less surface water pollution | [60] |
| | C1.4 | Energy recovery | [61] |
| | C1.5 | Natural resources recovery | [62] |
| Technical criteria (C2) | C2.1 | Operational feasibility | [48] |
| | C2.2 | Innovativeness | [48] |
| | C2.3 | Need for qualified personnel | [63] |
| Economic criteria (C3) | C3.1 | Maintenance costs | [64] |
| | C3.2 | Transportation costs | [63] |
| | C3.3 | Operational costs | [63] |
| | C3.4 | Initial invesment costs | [63] |
| Social criteria (C4) | C4.1 | Increased awareness on sustainable cities | [64] |
| | C4.2 | Increased quality of life in the city | [60] |
| | C4.3 | New employment opportunities | [65] |

### 3.2. Fuzzy Analytic Hierarchy Process (Fuzzy AHP)

Although there are various fuzzy AHP approaches in the literature, and van Laarhoven and Pedrycz [66] were the first to propose this approach, Chang's Extent Analysis [67], which is widely used due to its ease of implementation, was also used in this study. The method is based on pairwise comparisons of criteria and alternatives. For these comparisons, linguistic terms selected for this analysis and the corresponding triple fuzzy numbers are presented in Table 3. The steps of the extent analysis method [68–70] are summarized in Appendix A.

**Table 3.** Linguistic terms and corresponding triple fuzzy numbers.

| Linguistic Term | Triangular Fuzzy Number Equivalent |
|---|---|
| Equally important | (1, 1, 1) |
| Slightly more important | (2/3, 1, 3/2) |
| Strongly more important | (3/2, 2, 5/2) |
| Very strongly more important | (5/2, 3, 7/2) |
| Definitely more important | (7/2, 4, 9/2) |

### 3.3. Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS)

This method, firstly introduced by Yoon and Hwang [71], is an example of multi-attribute decision making that is widely used in all fields. It is based on the assumption that the chosen alternative is closest to the positive ideal solution and farthest from the negative ideal solution.

In the first step of this method, a decision-maker group is formed of people who have expertise on the problem, and the cluster, consisting of K decision makers, is shown as $E = \{DM_1, DM_2, \ldots, DM_K\}$. The alternatives to the problem $A = \{A_1, A_2, \ldots, A_m\}$ and the criteria to be used in the evaluation of the alternatives $K = \{K_1, K_2, \ldots, K_n\}$ are determined. Then, the linguistic expressions that decision makers will use when weighting the criteria and evaluating the alternatives according to the relevant criteria are selected [61]. The steps in the fuzzy TOPSIS method [72] used in this study are summarized in Appendix B. The linguistic terms and corresponding triangular fuzzy number equivalents used in this method can be found in [73].

### 3.4. Obtaining Decision-Maker Opinions

In a fuzzy MCDM problem, subjective expert opinions are needed to determine the weighting of the selected criteria and to evaluate the proposed strategy alternatives according to these criteria. As long as there is at least one decision maker, there is no limit to the number of experts whose opinions are obtained [74]. In this study, a group of decision makers consisting of ten experts was formed. Eight of the experts work in the field of environmental engineering and two in the field of smart cities.

Three of the experts in the field of environmental engineering were working in academia (two professors and one research assistant). Among these, one professor and the research assistant were conducting studies that address waste management problems using various MCDM methods. The fourth specialist in the field was an environmental engineer working for the Ministry of Environment, Urbanization, and Climate in Turkey. The fifth expert was working as an environmental engineer at ÇEVKO (Environmental Protection and Packaging Waste Utilization Foundation), a non-profit foundation promoting recycling of packaging waste in Turkey. The sixth expert was an electrical and electronics engineer working at the Bursa Metropolitan Municipality, Turkey, and holds a master's degree in environmental engineering. The seventh professional worked as an environmental engineer in a private sustainability company in Turkey, and the last one was also an environmental engineer, working for a company that operates an airport in Istanbul, Turkey.

The first of the decision makers with smart city expertise was a geomatics engineer, working as a project manager in an international mapping and technology company in

Ghent, Belgium. The other was an electronics and communications engineer who was involved in the implementation of thirty different smart city projects in Turkey and is currently a project manager at a defense electronics company in the country.

Figure 1 shows the work areas of the experts who make up the decision-making group and the type of institution they work for.

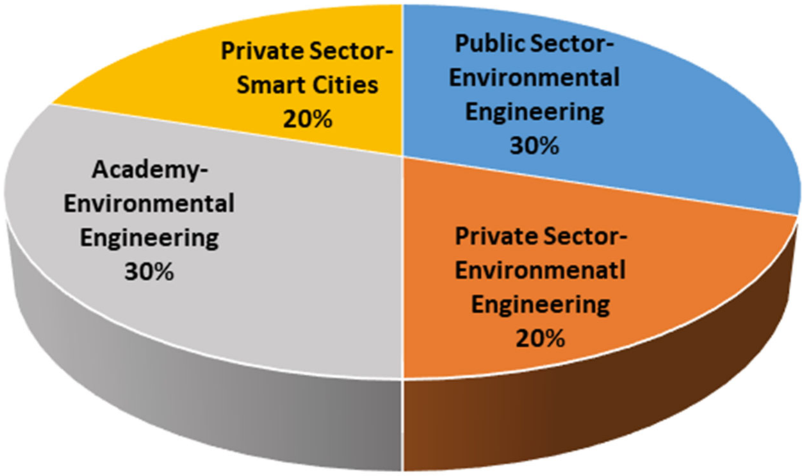


**Figure 1.** Distribution of expertise and work area of the decision-maker group.

In the first questionnaire prepared for the criteria weighting, the decision makers were asked to evaluate the 15 selected sub-criteria with linguistic expressions in the AHP method chosen in the study. In the second questionnaire, the decision makers were asked to rate the performance of the four proposed strategy alternatives for each criterion using verbal expressions in the TOPSIS method chosen in the study.

The experts were reached via e-mail and LinkedIn, and the questionnaire prepared with Google Forms was sent to them via the same means. The results of the linguistic expert evaluations were drawn from the survey in Google Forms. Microsoft® Excel® 2016 (Microsoft Inc., Redmond, WA, USA), running under Windows 10 system on a HP Pavilion (Intel® Core™ i5-7200U CPU, 2.50 GHz, 8 GB of RAM, 64-bit) PC platform, was used for the calculations of the fuzzy AHP and fuzzy TOPSIS.

### *3.5. Dealing with the Experts' Subjectivity*

In traditional multi-attribute decision-making approaches, the criteria present and their weights are given with precise and clear values. Thus, it is assumed that the selection or ranking of alternatives to be made with them is absolutely correct. In real problems, however, the nature of the problem makes it impossible to know exactly what the goals or constraints of the problem are. This uncertainty can be caused by reasons [75], such as unmeasurable information, incomplete information, inaccessible information, and partial ignorance. On the other hand, it would be unrealistic to claim that the decisions made by decision makers are absolutely correct or complete. Human subjectivity should also be taken into account in decision-making processes. One solution to these problems is to use fuzzy MCDM methods that allow for partial membership and work with uncertain and imprecise inputs or information. With the integration of fuzzy sets into the field of MCDM by Belman and Zadeh [76] and Zimmerman [77], fuzzy decision approaches now form a branch of fuzzy set theory. Another method that makes it possible to work with uncertain data is the grey numbers in the grey theory introduced by Deng [78]. As with fuzzy numbers, there are ambiguities in the data, but existing knowledge and experience allow the data in question to fall within a certain range of values. In other words, while subjective uncertainty is in question in fuzzy theory, objective uncertainty can be spoken of in grey theory [79].

The integration of smart city technologies into sustainable waste management complicates the administrative steps that need to be taken, especially in terms of increasing expertise and budgetary demands and difficulties in acceptance by city residents. Moreover, because this integration is a relatively new area of research, practical experience does not yet provide the desired level of data in the decision-making processes. Considering these difficulties, to avoid erroneous results, the data in this study were used in fuzzy form.

## 4. Results

### 4.1. Determination of Criterion Weights

The weights of the sub-criteria within each main criteria group were determined using pairwise comparison matrices based on verbal and subjective expert evaluations. These four comparison matrices were created through the experts' interpretation of the superiority of the sub-criteria over the others using the linguistic expressions. Since there were ten experts in the group of decision makers, the geometric mean of the triple fuzzy number equivalents of the linguistic expressions was taken to reduce the result to one. Then, the criteria weights were determined by following the calculations given below. Table 4 presents the pairwise comparison matrix obtained for environmental criteria.

**Table 4.** Pairwise comparison matrix obtained for environmental criteria.

| Environmental Criteria | Less Atmospheric Emissions | Less Soil Pollution | Less Surface Water Pollution | Energy Recovery | Natural Resources Recovery |
|---|---|---|---|---|---|
| Less atmospheric emissions | (1.00, 1.00, 1.00) | (1.36, 1.69, 2.09) | (1.20, 1.58, 2.06) | (1.56, 1.97, 2.43) | (1.46, 1.74, 2.05) |
| Less soil pollution | (0.48, 0.59, 0.74) | (1.00, 1.00, 1.00) | (1.09, 1.32, 1.59) | (1.37, 1.76, 2.24) | (1.28, 1.52, 1.76) |
| Less surface water pollution | (0.49, 0.63, 0.84) | (0.63, 0.76, 0.92) | (1.00, 1.00, 1.00) | (1.50, 1.97, 2.54) | (1.35, 1.69, 2.08) |
| Energy recovery | (0.41, 0.51, 0.64) | (0.45, 0.57, 0.73) | (0.39, 0.51, 0.67) | (1.00, 1.00, 1.00) | (1.18, 1.52, 1.91) |
| Natural resources recovery | (0.49, 0.57, 0.69) | (0.57, 0.66, 0.78) | (0.48, 0.59, 0.74) | (0.52, 0.66, 0.84) | (1.00, 1.00, 1.00) |

In order to obtain the fuzzy synthetic extent value of a criterion, the vector obtained by the sum of the vectors in the row belonging to the relevant criterion and the inverse of the vector, which was the sum of all row sums, were multiplied as follows:

$S_{Less\ atmospheric\ emissions} = (6.57, 7.98, 9.63) \otimes (0.03, 0.04, 0.04) = (0.20, 0.29, 0.41)$
$S_{Less\ soil\ pollution} = (5.22, 6.19, 7.32) \otimes (0.03, 0.04, 0.04) = (0.16, 0.22, 0.31)$
$S_{Less\ surface\ water\ pollution} = (4.97, 6.05, 7.36) \otimes (0.03, 0.04, 0.04) = (0.15, 0.22, 0.32)$
$S_{Energy\ recovery} = (3.44, 4.10, 4.95) \otimes (0.03, 0.04, 0.04) = (0.10, 0.15, 0.21)$
$S_{Natural\ resources\ recovery} = (3.06, 3.48, 4.05) \otimes (0.03, 0.04, 0.04) = (0.09, 0.13, 0.17)$

Using these vectors, the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ were calculated according to Equation (A6) (see Appendix A). The results are summarized in Appendix C. Thus, the weight vector for the environmental criteria was calculated as follows: $W_{Environmental\ criteria} = (0.42, 0.27, 0.27, 0.04, 0.00)$.

The results showed that the most important criterion among environmental criteria was that of fewer atmospheric emissions. Less soil pollution and less surface water pollution criteria were equally important. The energy recovery criterion was of much lower importance than all these criteria. The weight value for the criterion of natural resources was given as 0, implying that the mentioned criterion was not important at all compared to the other environmental criteria. Table 5 presents the pairwise comparison matrix obtained for technical criteria.

**Table 5.** Pairwise comparison matrix obtained for technical criteria.

| Technical Criteria | Operational Feasibility | Innovativeness | Need for Qualified Personnel |
|---|---|---|---|
| Operational feasibility | (1.00, 1.00, 1.00) | (1.59, 2.08, 2.63) | (1.34, 1.62, 1.93) |
| Innovativeness | (0.38, 0.48, 0.63) | (1.00, 1.00, 1.00) | (1.52, 2.00, 2.56) |
| Need for qualified personnel | (0.52, 0.62, 0.75) | (0.39, 0.50, 0.66) | (1.00, 1.00, 1.00) |

The fuzzy synthetic extent values were obtained accordingly:

$S_{Operational\ feasibility}$ = (3.93, 4.71, 5.55) ⊗ (0.08, 0.10, 0.11) = (0.32, 0.46, 0.64)
$S_{Innovativeness}$ = (2.90, 3.48, 4.19) ⊗ (0.08, 0.10, 0.11) = (0.24, 0.34, 0.48)
$S_{Need\ for\ qualified\ personnel}$ = (1.91, 2.12, 2.41) ⊗ (0.08, 0.10, 0.11) = (0.16, 0.21, 0.28)

The values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are summarized in Appendix C. Thus, the weight vector for the technical criteria was calculated as follows: $W_{Technical\ criteria}$ = (0.64, 0.36, 0.00).

The results showed that operational feasibility was the most important criterion among the technical criteria. The criterion of innovativeness had lower importance compared to the criterion of operational feasibility. However, the weight value of the criterion for the need for qualified personnel was given as 0, indicating that the mentioned criterion in question was not important at all compared to the other technical criteria. Table 6 tabulates the pairwise comparison matrix obtained for economic criteria.

**Table 6.** Pairwise comparison matrix obtained for economic criteria.

| Economic Criteria | Initial Invesment Costs | Operational Costs | Maintenance Costs | Transportation Costs |
|---|---|---|---|---|
| Initial invesment costs | (1.00, 1.00, 1.00) | (1.37, 1.64, 1.96) | (1.25, 1.58, 1.97) | (1.53, 1.94, 2.41) |
| Operational costs | (0.51, 0.61, 0.73) | (1.00, 1.00, 1.00) | (1.35, 1.58, 1.82) | (1.25, 1.47, 1.73) |
| Maintenance costs | (0.51, 0.63, 0.80) | (0.55, 0.63, 0.74) | (1.00, 1.00, 1.00) | (1.25, 1.58, 1.97) |
| Transportation costs | (0.41, 0.51, 0.65) | (0.58, 0.68, 0.80) | (0.51, 0.63, 0.80) | (1.00, 1.00, 1.00) |

The fuzzy synthetic extent values were obtained accordingly:

$S_{Initial\ investment\ costs}$ = (5.15, 6.17, 7.35) ⊗ (0.05, 0.06, 0.07) = (0.25, 0.35, 0.49)
$S_{Operational\ costs}$ = (4.11, 4.66, 5.28) ⊗ (0.05, 0.06, 0.07) = (0.20, 0.27, 0.35)
$S_{Maintenance\ costs}$ = (3.30, 3.85, 4.52) ⊗ (0.05, 0.06, 0.07) = (0.16, 0.22, 0.30)
$S_{Transportation\ costs}$ = (2.50, 2.83, 3.26) ⊗ (0.05, 0.06, 0.07) = (0.12, 0.16, 0.22)

The values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are summarized in Appendix C. Thus, the weight vector for the economic criteria was calculated as follows: $W_{Economic\ criteria}$ = (0.56, 0.30, 0.14, 0.00).

The results revealed that the initial investment cost criterion is very important compared to other economic criteria. This criterion is followed by the operational cost criterion. The criterion of maintenance costs is insignificant compared to these two criteria. The criterion of transportation costs did not make any sense compared to other economic criteria. Table 7 shows the pairwise comparison matrix obtained for social criteria.

**Table 7.** Pairwise comparison matrix obtained for social criteria.

| Social Criteria | Increased Awareness on Sustainable Cities | Increased Quality of Life in the City | New Employment Opportunities |
|---|---|---|---|
| Increased awareness on sustainable cities | (1.00, 1.00, 1.00) | (1.48, 1.89, 2.35) | (1.10, 1.47, 1.95) |
| Increased quality of life in the city | (0.42, 1.00, 0.67) | (1.00, 1.00, 1.00) | (1.54, 2.02, 2.58) |
| New employment opportunities | (0.51, 0.68, 0.91) | (0.39, 0.49, 0.65) | (1.00, 1.00, 1.00) |

The fuzzy synthetic extent values were obtained accordingly:

$S_{Increased\ awareness\ on\ sustainable\ cities}$ = (3.59, 4.36, 5.31) $\otimes$ (0.08, 0.09, 0.12) = (0.30, 0.41, 0.63)
$S_{Increased\ quality\ of\ life\ in\ the\ city}$ = (2.97, 4.02, 4.26) $\otimes$ (0.08, 0.09, 0.12) = (0.24, 0.38, 0.50)
$S_{New\ employment\ opportunities}$ = (1.90, 2.17, 2.55) $\otimes$ (0.08, 0.09, 0.12) = (0.16, 0.21, 0.30)

The values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are summarized in Appendix C. Thus, the weight vector for the social criteria was calculated as follows: $W_{Social\ criteria}$ = (0.53, 0.46, 0.01).

Although the two criteria were very close to each other, it was seen that the criterion of increasing awareness about sustainable cities is slightly more important than the criterion of increasing the quality of life in the city. The new employment opportunities criterion was rather insignificant compared to the other two criteria.

### *4.2. Ranking of the Strategy Alternatives according to the Weighted Criteria*

In this part of the study, the performance ranking of the strategy alternatives was performed using the fuzzy TOPSIS method. For this purpose, weighted criteria with the fuzzy AHP method from the previous section were used. Expert opinions were taken to evaluate the performance of each proposed strategy alternative according to each sub-criterion using linguistic terms [80]. Since there were ten experts in the decision-making group, the arithmetic mean of the triple fuzzy number equivalents of linguistic terms was taken, and the result was reduced to one. The fuzzy decision matrix (not shown here due to space constraints) was obtained accordingly.

Equations (A13) and (A14) were used to obtain a normalized fuzzy decision matrix (see Appendix B). The normalization was performed differently depending on whether the criterion is a benefit criterion or a cost criterion. For example, since C1.3 is a benefit criterion, normalization of the corresponding vector to the second alternative (A2) ((5.70, 7.20, 8.30)) is performed by dividing the vector elements by 8.90, which is the third-largest element in the vectors in the relevant column, and the new vector is obtained as (5.70/8.90, 7.20/8.90, 8.30/8.90) = (0.64, 0.81, 0.93).

Let us take the C3.1 criterion. Since the criterion is a cost criterion, the first vector element with the smallest value in the column is determined. This value is 5.80. Accordingly, the normalization of the vector (6.60, 8.30, 9.40) corresponding to the second alternative (A2) of this criterion is calculated as (5.80/9.40, 5.80/8.30, 5.80/6.60) = (0.62, 0.70, 0.88). Accordingly, the normalized fuzzy decision matrix (not shown here due to the lack of space) was created within the scope of the present analysis.

To obtain the weighted normalized fuzzy decision matrix, the matrix elements were multiplied by the sub-criteria weights obtained by the fuzzy AHP method in the previous section. The weighted normalized fuzzy decision matrix (not shown here due to space limitations) was obtained by multiplying the vectors in the column of each criterion by the weight of that criterion.

When determining the fuzzy positive ideal solution values ($A^*$), the vector elements were assigned a value of 1 if the criterion in question was a benefit criterion and 0 if it was a cost criterion. The opposite was considered as true when determining the fuzzy negative ideal solution values ($A^-$). The fuzzy positive/negative ideal solution values were determined using the weighted fuzzy decision matrix as follows:

$A^*$ = [(1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (1, 1, 1), 1, 1, 1), 1, 1, 1)]

$A^-$ = [(0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (1, 1, 1), (0, 0, 0), (0, 0, 0), (0, 0, 0))]

The distances ($d^*$ and $d^-$) (not presented here due to limited place) of the alternatives from $A^*$ and $A^-$ were calculated using Equations (A20) and (A21), respectively. Based on the above values, the closeness coefficient ($CC_i$) and the ranking of the alternatives were determined using Equation (A22) (see Appendix B). The ranking of the proposed smart waste management strategy alternatives according to the above closeness coefficients (values are given in the respective parentheses) was A2 (0.458) > A3 (0.453) > A4 (0.452) > A1 (0.440).

The results indicated that considering the selected criteria, the application pay as you throw (PAYT), which uses blockchain technology, had the best performance among the proposed smart sustainable waste management strategies. Among the two strategies with very close $CC_i$ values, IoT-based community composting was slightly ahead of IoT-based illegal sewage discharge prevention by only 0.001. The strategy of integrating illegal waste collection workers into a formal smart system came in last with the lowest $CC_i$ value compared to others.

### *4.3. Sensitivity Analysis*

In multi-criteria decision making, sensitivity analysis was used to test the consistency of the ranking obtained and to be sure of the result obtained. It is noted that in studies where hybrid MCDM is used, researchers usually perform sensitivity analysis using scenarios in which the original criteria weights are changed to varying degrees [81].

In this study, a sensitivity analysis was performed with eighteen different scenarios, in which the weighting of the criteria was changed [82]. In the first ten scenarios, the weight of each of the ten benefit criteria was increased by 25%. In Scenarios 11–15, the weight of each of the five cost criteria was increased by 25%. In Scenario 16, the weight of the criterion with the highest weight in each main criteria group was reduced by 50%. In Scenario 17, the weight of the criterion with the highest weight in each main criterion group was assumed to be 1, and all other criterion weights were assumed to be 0. Finally, in Scenario 18, the weights of the criteria were chosen to be the same in each main criteria group. Accordingly, the new closeness coefficient values ($CC_i$) of the alternatives after the sensitivity analysis were obtained. The results of the sensitivity analysis showed that the ranking of the alternatives obtained with the fuzzy AHP-fuzzy TOPSIS hybrid approach remained unchanged when the criteria weights were varied. The obtained $CC_i$ values of the alternatives are summarized in Appendix D, Table A1.

In all eighteen scenarios, the application PAYT, which uses blockchain technology, (A1) took first place in the ranking of alternatives, with the highest closeness coefficient value. It was followed by IoT-based community composting (A2). Although they had very close $CC_i$ values, as in the present results, preventing illegal sewage discharge by utilizing IoT (A3) performed slightly better than integrating informal recyclable waste collection into an Iot-based formal system (A4). Although no significant change in the closeness coefficients occurred in the first sixteen scenarios in which the criterion weights were increased or decreased at specific rates, it was found that the weights changed in the 16th scenario, in which the criterion weights were assigned values of 1 and 0, and in the 17th scenario, in which the criterion weights were assigned values of 1 and 0. However, this situation did not affect the ranking of the alternatives. This confirmed the reliability and the stability of the results obtained from the hybrid fuzzy AHP-TOPSIS approach.

## 5. Discussion

### *5.1. Managerial Implication*

The results of this research will assist decision makers in determining the sustainable waste management strategies to be implemented. It also motivates and guides managers and researchers in conducting pilot studies that will place smart sustainable waste management concepts on a more realistic footing.

The operational feasibility (C2.1) and initial investment costs (C3.4) criteria had the highest weighting values after the criterion weighting. This result confirmed the necessity of conducting detailed and realistic feasibility and budget studies before implementing smart sustainable waste management strategies.

Among the four proposed strategy alternatives, a PATY application leveraging blockchain technology took first place, with the highest closeness coefficient ($CC_i$). The long-term success and acceptance of this strategy are directly related to the conditions and needs of the region in which the strategy is implemented. The main disadvantage of such a system may be the illegal dumping of waste. To prevent this, legal regulations and strict controls are needed. On the other hand, detailed cost analysis is required depending on the blockchain infrastructure to be used (e.g., public or private blockchain).

The second-ranked strategy alternative (IoT-based community composting (A3)) has a closeness coefficient value that is only 0.001 higher than the third-ranked alternative (preventing illegal sewage discharge by utilizing IoT (A4)). In such cases where the two alternatives have very close closeness coefficient values, a multi-tiered approach in decision making can be carried out by the decision makers. Just as Multi-Group Confirmatory Factor Analysis used in the social sciences helps researchers [83] confirm the accuracy of results obtained with MCDM, the use of methods, such as Life Cycle Assesment (LCA) and/or SWOT (strengths, weaknesses, opportunities, threats), in combination with a hybrid fuzzy MCDM method can do the same for smart sustainable waste management problems.

### *5.2. Limitations of the Study*

Although the smart sustainable waste management strategies proposed in the study are comprehensive and multi-level, no specific city, residential area, or pilot region was chosen as the application site for the strategies. For this reason, the proposed strategies were determined to encompass more general approaches without sharp boundaries. However, the needs and expectations of city residents, as well as local government plans and goals for a sustainable environment and economy, require that these strategies be implemented at different scales and with different adaptations.

Since the proposed strategies in the study were handled in a more general way, the evaluations of the decision makers were also made in this way. However, take, for example, the inclusion of illegal waste collection workers in a formal smart system. Since the human factor is involved here, the data obtained through preliminary interviews with potential workers to be included in the system will help make the expert evaluations in the decision-making processes healthier. Alternatively, consider the PAYT application based on blockchain. Before implementing this strategy, knowing the main goals of the authorities (e.g., reducing the amount of household waste generated annually, increasing the amount of waste recycled annually, etc.) could put the decision makers' assessments on a more realistic footing in terms of costs, operational feasibility, and acceptance.

Local governments are primarily responsible for ensuring environmental and economic sustainability in cities. In addition, most waste management services are provided by municipalities. This makes them among the most important stakeholder groups in the integration of smart city technologies into sustainable waste management. In forming the decision-making group in the study, experts working in the smart city departments of various municipalities were reached, but although some of the experts provided positive feedback, they did not participate in the mailed questionnaires. For this reason, in the part of the study where the criteria and alternatives are evaluated verbally, there is no opinion of a smart city expert for working in the public sector.

## 6. Conclusions

The long-term success of smart sustainable waste management strategies depends on the extent to which they meet the needs and expectations of the city in which they are implemented and how compatible they are with the sustainability goals of local governments. This makes these strategies multivariate, multi-restrictive, and multi-stakeholder, which complicates the determination processes. In this study, it was shown that decision makers can benefit from a hybrid fuzzy AHP-TOPSIS approach when determining sustainable waste management strategies in smart cities. The present study also revealed that authorities should give due consideration to operational feasibility and initial investment costs before implementing such strategies. In future studies, piloting the proposed smart waste management strategies will allow decision makers to make more concrete assessments by identifying the strengths and weaknesses of the strategies and testing their applicability. Furthermore, decision-making processes can be more strongly supported in this way by applying an LCA or SWOT analysis in parallel with a hybrid fuzzy AHP-TOPSIS approach.

**Author Contributions:** Conceptualization, B.G.D. and K.Y.; methodology, B.G.D. and K.Y.; software, B.G.D.; validation, B.G.D. and K.Y.; formal analysis, B.G.D.; investigation, B.G.D.; resources, B.G.D. and K.Y.; data curation, B.G.D.; writing—original draft preparation, B.G.D. and K.Y.; writing—review and editing, K.Y.; visualization, B.G.D. and K.Y.; supervision, K.Y. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** This work was carried out as a part of an M.Sc. thesis by Bihter Gizem Demircan, completed under the supervision of Kaan Yetilmezsoy. The authors also acknowledge the valuable insights of the reviewers and academic editor who contributed extensively to improving the article's quality.

**Conflicts of Interest:** The authors declare that there are no conflicts of interest, including any financial, personal, or other relationships, with other people or organizations.

## Appendix A. Methodological Steps Used in Fuzzy AHP

The steps in the extent analysis method are summarized below:

Step 1: The value of fuzzy synthetic extent with respect to the $i$-th object is defined as in Equation (A1):

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[ \sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} \tag{A1}$$

To obtain $\sum_{j=1}^{m} M_{g_i}^{j}$, the fuzzy addition operation of $m$ extent analysis values for a particular matrix is performed as in Equation (A2):

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left( \sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \tag{A2}$$

and to obtain $\left[ \sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1}$, the fuzzy edition operation of $m$ extent analysis values for a particular matrix is performed as in Equation (A3):

$$\left[ \sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} = \left( \sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \tag{A3}$$

and then the inverse of the vector in Equation (A3) is computed as in Equation (A4):

$$\left[ \sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} = \left( \frac{1}{\sum_{i=1}^{n} u_i} \right), \left( \frac{1}{\sum_{i=1}^{n} m_i} \right), \left( \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{A4}$$

Step 2: The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as in Equation (A5):

$$V(M_2 \geq M_1) = \sup_{y \geq x}[\min(\mu_{M1}(x), \mu_{M2}(y))] \tag{A5}$$

and is equivalently shown as in Equation (A6):

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M1}(d)\begin{cases} 1, & if\ m_2 \geq m_1 \\ 0, & if\ \ l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & other \end{cases} \tag{A6}$$

where $hgt$ and $d$ represent the highest intersection point and $x$ coordinate of the intersection point $D$, respectively, between $\mu_{M1}$ and $\mu_{M2}$ (Figure A1). To compare two fuzzy numbers, $M_1$ and $M_2$, both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are needed.

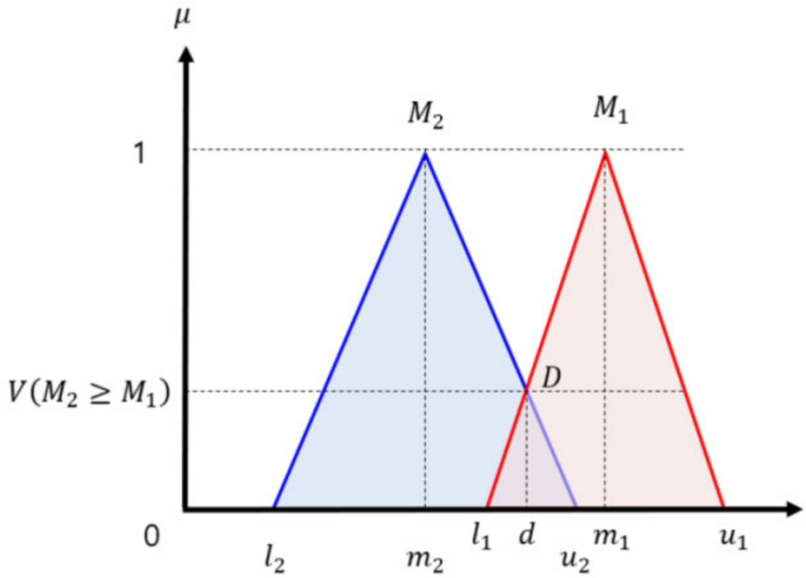


**Figure A1.** The intersection between $M_1$ and $M_2$.

Step 3: The degree possibility for a convex fuzzy number to be greater than convex fuzzy numbers $M_i$ ($i$ = 1, 2, . . . , $k$) can be defined as in Equation (A7):

$$\begin{aligned} V(M \gg M_1, M_2, \ldots, M_k) &= V[(M \gg M_1)\ and\ \ (M \gg M_2)\ and\ \ldots\ \ and\ (M \gg M_k)] \\ &= minV(M \gg Mi), \qquad i = 1,\ 2, \ldots, k \end{aligned} \tag{A7}$$

Assume that $d\prime(A_i) = min\ V(S_i \gg S_k)$ for $k = 1, 2, \ldots, n;\ k \neq 1$. Then, the weight factor for $k_i$ is shown by Equation (A8):

$$W' = \left(d'(A_1), d'(A_2), \ldots, d'(A_n)\right)^T, \tag{A8}$$

where $A_i(i = 1, 2, \ldots, n)$ are $n$ elements.

Step 4: Via normalization, the normalized weight vectors would be as in shown Equation (A9):

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \tag{A9}$$

where $W$ is a non-fuzzy number.

## Appendix B. Methodological Steps Used in Fuzzy TOPSIS

In the group consisting of K decision makers, where $\tilde{x}_{ij}$ represents the criterion value of the alternative, which was evaluated by the decision makers, and where $\tilde{w}_j$ represents the criterion weight, the criterion values and criteria weights, respectively, are calculated as in Equations (A10) and (A11):

$$\tilde{x}_{ij} = \frac{1}{K}\left[\ \tilde{x}_{ij}{}^{1} + \tilde{x}_{ij}{}^{2} + \ldots + \ \tilde{x}_{ij}{}^{K}\right] \tag{A10}$$

$$\tilde{w}_{j} = \frac{1}{K}\left[\tilde{w}_{j}{}^{1} + \tilde{w}_{j}{}^{2} + \ldots + \tilde{w}_{j}{}^{K}\right] \tag{A11}$$

A fuzzy multi-criteria group decision-making problem that can be succinctly expressed in matrix form as follows:

$$\tilde{\boldsymbol{D}} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{A12}$$

$$\tilde{\boldsymbol{W}} = [\tilde{w}_1,\ \tilde{w}_2, \ldots, \tilde{w}_n] \tag{A13}$$

where $\tilde{x}_{ij}\ \forall\ i, j$ and $\tilde{w}_j,\ j = 1,\ 2,\ \ldots, n$ are linguistic variables. They could be described by triangular fuzzy numbers, $\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$ and $\tilde{w}_j = \left(w_{j1}, w_{j2}, w_{j3}\right)$.

The normalized fuzzy decision matrix ($\tilde{\boldsymbol{R}}$) is shown as in Equation (A14):

$$\tilde{\boldsymbol{R}} = \left[\tilde{r}_{ij}\right]_{m\times n} \tag{A14}$$

With $B$ and $C$ being the benefit and cost criteria, respectively, the normalization is performed as in Equations (A15) and (A16):

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), j \in B; \qquad c_j^* = \max_i c_{ij} \text{ if } j \in B \tag{A15}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), j \in C; \qquad a_j^- = \min_i a_{ij} \text{ if } j \in C \tag{A16}$$

Considering the different importance of each criterion, the weighted normalized fuzzy decision matrix is constructed as in Equation (A17):

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{mxn} \qquad i = 1, 2, \ldots, m \qquad j = 1,\ 2, \ldots, n \tag{A17}$$

where $\tilde{v}_{ij} = \tilde{r}_{ij}\ (\cdot)\ \tilde{w}_j$. Fuzzy positive ideal solution ($A^*$) and fuzzy negative ideal solution ($A^-$) are defined as in Equations (A18) and (A19):

$$A^* = (\tilde{v}_1{}^*, \tilde{v}_2{}^*, \ldots, \tilde{v}_n{}^*) \tag{A18}$$

$$A^- = \left(\tilde{v}_1{}^-, \tilde{v}_2{}^-, \ldots, \tilde{v}_n{}^-\right) \tag{A19}$$

where $\tilde{v}_j^* = (1,\ 1,\ 1)$ and $\tilde{v}_j^- = (0,\ 0,\ 0)$, $j = 1,\ 2, \ldots, n$. The distance of the alternatives from $A^*$ and $A^-$ is calculated as in Equations (A20) and (A21):

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij},\ \tilde{v}_j^*),\ i = 1,\ 2, \ldots, m, \tag{A20}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij},\ \tilde{v}_j^-),\ i = 1,\ 2, \ldots, m, \tag{A21}$$

where $d(.\ ,.)$ is the measurement of distance between two fuzzy numbers. After the $d_i^*$ and $d_i^-$ of alternatives have been calculated, the closeness coefficient of each alternative is calculated as in Equation (A22). The ranking of the alternatives is determined with this value.

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \quad \text{(A22)}$$

## Appendix C. Summary of the Values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$

For the "environmental criteria", the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are presented as follows:

$V(S_{Less\ atmospheric\ emissions} \geq S_{Less\ soil\ pollution})$ = 1.00
$V(S_{Less\ atmospheric\ emissions} \geq S_{Less\ surface\ water\ pollution})$ = 1.00
$V(S_{Less\ atmospheric\ emissions} \geq S_{Energy\ recovery})$ = 1.00
$V(S_{Less\ atmospheric\ emissions} \geq S_{Natural\ resources\ recovery})$ = 1.00
$V(S_{Less\ soil\ pollution} \geq S_{Less\ atmospheric\ emissions})$ = 0.65
$V(S_{Less\ soil\ pollution} \geq S_{Less\ surface\ water\ pollution})$ = 1.00
$V(S_{Less\ soil\ pollution} \geq S_{Energy\ recovery})$ = 1.00
$V(S_{Less\ soil\ pollution} \geq S_{Natural\ resources\ recovery})$ = 1.00
$V(S_{Less\ surface\ water\ pollution} \geq S_{Less\ atmospheric\ emissions})$ = 0.63
$V(S_{Less\ surface\ water\ pollution} \geq S_{Less\ soil\ pollution})$ = 1.00
$V(S_{Less\ surface\ water\ pollution} \geq S_{Energy\ recovery})$ = 1.00
$V(S_{Less\ surface\ water\ pollution} \geq S_{Natural\ resources\ recovery})$ = 1.00
$V(S_{Energy\ recovery} \geq S_{Less\ atmospheric\ emissions})$ = 0.10
$V(S_{Energy\ recovery} \geq S_{Less\ soil\ pollution})$ = 0.43
$V(S_{Energy\ recovery} \geq S_{Natural\ resources\ recovery})$ = 0.48
$V(S_{Energy\ recovery} \geq S_{Natural\ resources\ recovery})$ = 1.00
$V(S_{Natural\ resources\ recovery} \geq S_{Less\ atmospheric\ emissions})$ = 0.00
$V(S_{Natural\ resources\ recovery} \geq S_{Less\ soil\ pollution})$ = 0.15
$V(S_{Natural\ resources\ recovery} \geq S_{Less\ surface\ water\ pollution})$ = 0.21
$V(S_{Natural\ resources\ recovery} \geq S_{Energy\ recovery})$ = 0.76

For the "technical criteria", the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are presented as follows:

$V(S_{Operational\ feasibility} \geq S_{Innovativeness})$ = 1.00
$V(S_{Operational\ feasibility} \geq S_{Need\ for\ qualified\ personnel})$ = 1.00
$V(S_{Innovativeness} \geq S_{Operational\ feasibility})$ = 0.57
$V(S_{Innovativeness} \geq S_{Need\ for\ qualified\ personnel})$ = 1.00
$V(S_{Need\ for\ qualified\ personnel} \geq S_{Operational\ feasibility})$ = 0.00
$V(S_{Need\ for\ qualified\ personnel} \geq S_{Innovativeness})$ = 0.22

For the "economic criteria", the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are presented as follows:

$V(S_{Initial\ investment\ costs} \geq S_{Operational\ costs})$ = 1.00
$V(S_{Initial\ investment\ costs} \geq S_{Maintenance\ costs})$ = 1.00
$V(S_{Initial\ investment\ costs} \geq S_{Transportation\ costs})$ = 1.00
$V(S_{Operational\ costs} \geq S_{Initial\ investment\ costs})$ = 0.53
$V(S_{Operational\ costs} \geq S_{Maintenance\ costs})$ = 1.00
$V(S_{Operational\ costs} \geq S_{Transportation\ costs})$ = 1.00
$V(S_{Maintenance\ costs} \geq S_{Initial\ investment\ costs})$ = 0.26
$V(S_{Maintenance\ costs} \geq S_{Operational\ costs})$ = 0.68
$V(S_{Maintenance\ costs} \geq S_{Transportation\ costs})$ = 1.00
$V(S_{Transportation\ costs} \geq S_{Initial\ investment\ costs})$ = 0.00
$V(S_{Transportation\ costs} \geq S_{Operational\ costs})$ = 0.12

$V(S_{Transportation\ costs} \geq S_{Maintenance\ costs}) = 0.48$

For the "social criteria", the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are presented as follows:

$V(S_{Increased\ awareness\ on\ sustainable\ cities} \geq S_{Increased\ quality\ of\ life\ in\ the\ city}) = 1.00$
$V(S_{Increased\ awareness\ on\ sustainable\ cities} \geq S_{New\ employment\ opportunities}) = 1.00$
$V(S_{Increased\ quality\ of\ life\ in\ the\ city} \geq S_{Increased\ awareness\ on\ sustainable\ cities}) = 0.87$
$V(S_{Increased\ quality\ of\ life\ in\ the\ city} \geq S_{New\ employment\ opportunities}) = 1.00$
$V(S_{New\ employment\ opportunities} \geq S_{Increased\ awareness\ on\ sustainable\ cities}) = 0.03$
$V(S_{New\ employment\ opportunities} \geq S_{Increased\ quality\ of\ life\ in\ the\ city}) = 0.25$

## Appendix D. Summary of New Closeness Coefficient Values

**Table A1.** New closeness coefficient values ($CC_i$) of the alternatives after the sensitivity analysis.

| Scenario | $CC_i$ (A1) | $CC_i$ (A2) | $CC_i$ (A3) | $CC_i$ (A4) |
|---|---|---|---|---|
| 1 | 0.440 | 0.458 | 0.454 | 0.451 |
| 2 | 0.441 | 0.458 | 0.453 | 0.452 |
| 3 | 0.440 | 0.458 | 0.453 | 0.452 |
| 4 | 0.441 | 0.459 | 0.455 | 0.453 |
| 5 | 0.440 | 0.458 | 0.453 | 0.452 |
| 6 | 0.440 | 0.458 | 0.453 | 0.451 |
| 7 | 0.440 | 0.458 | 0.454 | 0.453 |
| 8 | 0.439 | 0.458 | 0.453 | 0.451 |
| 9 | 0.440 | 0.457 | 0.453 | 0.452 |
| 10 | 0.440 | 0.458 | 0.453 | 0.452 |
| 11 | 0.440 | 0.458 | 0.453 | 0.452 |
| 12 | 0.440 | 0.458 | 0.453 | 0.452 |
| 13 | 0.440 | 0.458 | 0.454 | 0.452 |
| 14 | 0.440 | 0.458 | 0.453 | 0.452 |
| 15 | 0.440 | 0.458 | 0.453 | 0.452 |
| 16 | 0.410 | 0.423 | 0.419 | 0.417 |
| 17 | 0.437 | 0.458 | 0.450 | 0.443 |
| 18 | 0.408 | 0.422 | 0.417 | 0.413 |

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