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Urban Scenic Spot Activity Center Investment: Strategic Construction Company Selection Using the Grey System-II Thinking Compromise Ranking of Alternatives from Distance to Ideal Solution Multi-Criteria Decision-Making Method

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Abstract: Investing in urban scenic spots is a complex process that requires careful consideration of multiple criteria to ensure sustainability and efficiency. In the post-pandemic era, the uncertainty of future trends necessitates effective risk management and informed investment decisions. Revitalizing urban scenic spots while maintaining profitability, along with the construction of multi-purpose activity centers, requires a thorough evaluation of construction companies. This study addresses the selection of the most suitable contractor for constructing multi-purpose activity chain centers as a Multi-Criteria Decision-Making (MCDM) problem. We address the intricacies of contractor selection by integrating MCDM and system thinking approaches, emphasizing the alignment of investment strategies with broader urban development goals. First, a time delay was introduced between the first and second rounds of administering the weighting questionnaire to capture decision-makers' preferences for the evaluation criteria as System-2 thinking, then the Grey System-2 Thinking (GS2T) weighting method was proposed for group decision-making. Second, the Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) method was incorporated into the Grey Systems Theory (GST), resulting in the development of the Grey-CRADIS method, which was applied to rank seven contractors for constructing activity centers across four urban scenic spots. Using the proposed GS2T with the developed Grey-CRADIS method in conjunction with the decision-makers' preferences, Company-2 was found to be the best contractor for the construction project. Finally, classical MCDM methods such as the Weighted Sum Model (WSM) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) were employed to confirm the top-ranking contractor.

Keywords: multiplie criteria decision-making; MCDM; grey systems theory; system thinking; investment; contractor; scenic spot; CRADIS; TOPSIS

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1. Introduction

China boasts one of the world's longest continuous civilizations, with over 3700 years of rich history, and has established itself as a cultural powerhouse in East Asia [1–3]. The Chinese government has implemented various policies to preserve this heritage, including establishing museums to conserve artefacts and designating significant areas as cultural landmarks. However, the upkeep of these sites entails considerable costs, necessitating sustainable strategies to ensure their longevity. One approach has been the development of scenic spots, which not only serve as cultural preservation hubs but also attract tourism, providing economic support for their maintenance.

The deliberate decision to preserve Chinese culture over centuries reflects a process of long-term, thoughtful consideration. Kahneman's theory of decision-making [4] provides a valuable lens to understand the complexities of such choices. System-1 thinking, characterized by speed and intuition, contrasts with the slower, more analytical approach known as System-2 thinking. Both systems are relevant in supplier selection for urban construction projects, where decision-makers must balance urgency with meticulous planning to align infrastructure development with cultural and economic objectives. Undoubtedly, System-2 thinking is needed to preserve Chinese culture strategically and deliberately.

One common class of decision problems is the Multi-Criteria Decision-Making (MCDM) problem [5]. MCDM provides a systematic method for addressing decision challenges that involve multiple, often conflicting, criteria. To initiate this process, two key elements must first be established. First, the alternatives and potential solutions to the problem must be identified. Second, the criteria for evaluating these alternatives must be determined, which serve as the benchmark for measurement. Once the performance of each alternative is evaluated based on the evaluation criteria, the numerical analysis can proceed [6].

Every effective decision-maker (DM) recognizes that some criteria carry more weight than others in decision-making processes. Hence, expert opinions are crucial for assigning these weights to reflect the relative importance of each criterion [7]. However, a DM's decision environment can significantly influence their judgments, sometimes leading to bias or errors. A problem arises when decisions that should be logical and deliberative (System-2 thinking) are sometimes made emotionally and impulsively (System-1 thinking) due to time constraints or an unconducive environment [8]. In such cases, a DM may inadvertently assign weights based on instinctive reactions rather than careful evaluation.

Despite efforts to ensure that weights are derived from System-2 thinking, there remains inherent uncertainty in subjective group decision-making. This research applies Grey Systems Theory (GST) to manage the uncertainty that may arise when groups of DMs assign weights through a more deliberative process, as is required for solving Multi-Criteria Decision-Making (MCDM) problems. The uncertainty inherent in group decision-making is effectively addressed using GST. Deng [9] proposed GST as a bridge between complete and incomplete information. In this framework, a "white system" represents a situation where all information is fully known, while a "black system" refers to one where information is entirely unknown. Grey systems lie between these two extremes, where some information is known, yet uncertainty persists [10,11].

After the weighting process, the evaluation of alternatives is conducted. Classical methods such as the Weighted Sum Model (WSM) [12,13] and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method are commonly used MCDM approaches [14,15]. These foundational methods have paved the way for more advanced techniques, such as the Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) [16]. CRADIS is an MCDM method that ranks alternatives by evaluating their proximity to an ideal solution. However, a key limitation of the CRADIS method is its inability to account for uncertainties in the evaluation process. In real-world scenarios, uncertainty is an inherent aspect of decision-making that must be carefully considered [17]. To address this limitation, the CRADIS method has been enhanced through the integration of GST, which allows for a more robust assessment of uncertainty.

In this research, GST is used because it offers several advantages over fuzzy set theory for handling incomplete or uncertain data. It is highly effective with small sample sizes and does not require prior knowledge about data distribution, making it suitable for data-scarce scenarios [18]. Unlike fuzzy systems, GST eliminates the need for membership functions, reducing subjectivity and complexity [19]. Also, It supports interval and target-based data analysis, enabling strategic insights under significant uncertainty [20]. Additionally, GST offers precise encapsulation of uncertain data with minimal parameter configuration, making it more robust in environments of incomplete information with uncertainty [21] and suitable for integration with other models, such as neural networks, for enhanced performance [22].

The new methodology in this paper contributes to the broader field of decision science by offering practical solutions for improving the reliability and validity of expert judgment in MCDM contexts, ensuring that decisions are not only logical but also aligned with long-term strategic goals. Explicitly, the main contribution of this paper is the introduction of a new MCDM weighting method based on GST, termed the Grey System-2 Thinking (GS2T) weighting method. Additionally, this paper proposes a hybrid MCDM evaluation method that integrates GS2T weights with Grey-CRADIS, combining the strengths of both methodologies. Another significant contribution is the development of a hierarchical model for the construction of smart multi-purpose centers, which serves as a practical application of the proposed methods. More importantly, these contributions in this paper will provide answers to the two main research questions: (1) What are the key benefits of integrating reflective (System-2) thinking with GST for reducing cognitive biases in decision-making? And (2) How does GST compare with traditional decision-making methods like the Weighted Sum Model (WSM) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in addressing uncertainties?

The remainder of the paper is organized as follows: Section 2 presents a comprehensive literature review, providing an in-depth analysis of the relevant theories, methods, and previous work in this domain. Section 3 details the approaches employed in this research, including the application of GST and the integration of MCDM methods. Section 4 presents the results and analysis of the case. Section 5 discusses the research findings. Section 6 concludes the paper, summarizing the research contributions and suggesting potential future work.

2. Literature Review

Urban investment, particularly in scenic spots, requires strategic decision-making for ensuring long-term success. In this context, MCDM methods have emerged as essential tools to guide decision-makers through complex evaluations. However, classical MCDM methods often fall short in accounting for uncertainties inherent in real-world decision-making. This literature review is streamlined towards recent advances in the MCDM problem in construction, beginning by highlighting system thinking in group decision-making under uncertainty.

2.1. System Thinking in Group Decision-Making

In high-stakes decision-making scenarios, such as selecting contractors for urban scenic spots, decision-makers must rely on System-2 thinking, a concept introduced by Kahneman [4,23]. System-2 thinking is slow, deliberate, and logical, in contrast to the faster, more intuitive System-1 thinking. The combination of these two systems is known as the dual-system theory. Prior to Kahneman's book titled "Thinking, Fast and Slow" [24] in 2011, his foundational work on the dual-system theory was elaborated as the judgement under uncertainty, covering heuristics and biases that laid the groundwork for many concepts central to dual-process theories, including the role of heuristics and biases in intuitive judgment in the 1970s [25]. Then, in the 1980s, Kahneman introduced foundational ideas about how intuitive (System-1) and deliberative (System-2) thinking influence decision-making, particularly in the context of Prospect Theory, a precursor to the more formalized dual-system framework [26]. The importance of Kahneman's theory cannot be overemphasized [27].

In MCDM, System-2 thinking is particularly important because it ensures that decisions are based on careful analysis rather than impulsive judgments. Sahoo and Kumar [6] further examined how MCDM methods can be enhanced by incorporating system thinking. By introducing time delays between weighting and evaluation phases, they allowed decision-makers to engage more thoroughly with the criteria, ultimately resulting in more accurate and thoughtful decisions. Their work supports the idea that the evaluation of contractors for complex projects, such as urban scenic spot activity centers, should involve deliberate, systematic thinking rather than fast, intuitive judgments.

Recent studies have been conducted on decision-making processes involving weights and expert opinions influenced by both cognitive and behavioral factors. Bisht and Pal [28] introduced a decision-making framework that leverages fuzzy logic and expert trust relationships to assign weights to criteria in complex decision environments, such as green supplier selection. They emphasize the importance of both subjective and objective weights, integrating social network analysis to address biases in expert opinions. Rao [29] presented the Best Holistic Adaptable Ranking of Attributes Technique method, an MCDM approach that simplifies the process of assigning weights without relying on fuzzy logic. This method emphasizes the importance of assigning logical and consistent weights to attributes based on expert rankings. Paz and Pico [30] developed a hybrid MCDM method to assess firefighting hazards, which integrates subjective expert opinions with a fuzzy set approach to account for uncertainties and biases in judgment.

GST was introduced by Deng [9] to manage uncertainty by bridging the gap between complete and incomplete information. In GST, a "white system" refers to a situation where all information is known, while a "black system" denotes complete uncertainty. Most real-world decisions fall somewhere in between, within the "grey" area where some information is available but uncertainty remains. GST has proven effective in situations like urban project investments, where decisions often rely on incomplete data.

2.2. MCDM in Urban Construction Projects

Multi-Criteria Decision-Making (MCDM) methods provide a structured way to evaluate and compare alternatives based on various criteria. Classical approaches like the WSM and TOPSIS have been widely applied to contractor selection, where criteria such as cost and quality are considered [15,31]. Cao et al. [31] applied a hybrid method of the Stepwise Weight Analysis Ratio Assessment (SWARA) and the Full Consistent MCDM method to evaluate contractors. Also, SWARA combined with Grey Relational Analysis (GRA) can be used in evaluating the compensation and benefit of the construction worker [32]. WSM evaluates alternatives by assigning weights to criteria, while TOPSIS ranks alternatives based on their distance from an ideal solution. However, both methods assume certainty in the decision-making process, which is rarely true in real-world scenarios [33]. In a study on the prosperity performances of G7 countries, Altintas used the Logarithmic Percentage Change-driven Objective Weighting combined with the CRADIS method to rank alternatives, highlighting that decision-makers require more advanced tools to deal with uncertainties inherent in large-scale projects.

In urban construction projects, decision-makers face uncertainties stemming from incomplete or ambiguous data. While classical MCDM methods like WSM and TOPSIS offer a solid foundation, they do not sufficiently account for these uncertainties [34]. This is where GST comes into play. Studies such as the one by Abacioğlu et al. [35] on sustainability rankings across universities have demonstrated the utility of GST in decision-making processes involving uncertainty. The authors used GST to decode complex sustainability metrics, providing decision-makers with a clearer understanding of which factors contributed most to the rankings. Similarly, GST has been applied to contractor selection, helping urban planners manage the uncertainty inherent in assessing potential construction companies.

In construction and urban development projects, the application of GST is particularly valuable when evaluating contractor performance, as decision-makers often have incomplete information about contractors' abilities or future project risks. A significant advancement in this area was introduced by Puška et al. [16], who integrated the fuzzy TRUST method with CRADIS to assess sustainable suppliers in agribusiness. The fuzzy approach allowed for the incorporation of linguistic variables and the management of uncertainty in contractor evaluations. This method is particularly relevant for urban scenic spot activity center projects, where the uncertainty of future trends and market conditions necessitates flexible and robust decision-making tools.

Researchers have explored a variety of applications of the CRADIS method. Starcevic et al. [36] demonstrated that the years 2009, 2013, and 2016 were the most favorable for Bosnia and Herzegovina, while 2012, 2014, and 2016 were optimal for Serbia regarding macroeconomic performance. Their study employed data envelopment analysis, Principal Component Analysis, and an Improved Fuzzy Stepwise Weight Assessment Ratio Analysis model to comprehensively analyze and rank macroeconomic parameters, offering a robust framework for assessing the interdependencies of factors such as foreign direct investments, gross domestic product, and employment under conditions of uncertainty in complex economic environments. Yuan et al. [17] introduced a distance measure for MCDM based on the Jensen–Shannon divergence within a picture fuzzy environment. This measure, proven to satisfy the four properties of metric space, demonstrated superior differentiation compared to existing methods and was applied to determine attribute weights using a maximum deviation method, thereby creating an MCDM approach integrating the CRADIS framework. Qu et al. [37] investigated the supply chain risks faced by the sports supplies industry, highlighting the importance of effective risk management strategies. Their study demonstrated how Probabilistic Linguistic Term Sets, combined with MCDM, improved supply chain resilience and competitiveness. Demir et al. [38] applied the Fuzzy Preference Selection Index and Fuzzy-CRADIS methods to assess medical waste disposal technologies, with a case study in Sivas, Turkey, validating the efficacy of this approach.

In the context of this study, the Grey-CRADIS method is proposed, combining the strengths of GST with the CRADIS method. CRADIS ranks alternatives based on their proximity to an ideal solution, but its traditional form does not account for uncertainties in evaluation. By integrating GST, Grey-CRADIS addresses this limitation, offering a more robust framework for ranking contractors in complex urban projects. The Grey-CRADIS method proposed in this paper represents a further advancement in this area. By integrating GST with CRADIS, this method not only ranks contractors based on their proximity to an ideal solution but also accounts for the uncertainty in stakeholders' judgments. This hybrid approach identifies the most suitable contractor for constructing urban scenic spot activity centers, considering both known and uncertain factors.

To the best of our knowledge, this is the first study to combine the GST and System-2 thinking. The Grey System-2 Thinking (GS2T) weighing method introduced in this study builds on Kahneman's theory by introducing a time delay between rounds of weighting, allowing decision-makers to reflect more thoroughly on the criteria and their importance. This process helps mitigate the biases that can arise in group decision-making settings, where stakeholders may initially rely on System-1 thinking, leading to suboptimal decisions. The GS2T method encourages a more reflective and analytical approach, ensuring that decisions align with long-term strategic goals. Also, this research extends the CRADIS method with Deng's GST [9].

3. Methods

3.1. Evaluation Criteria

Urban construction projects, particularly those focusing on sustainable development and scenic spots, require an array of evaluation criteria to ensure that they meet environmental and societal goals [39,40]. These criteria help assess contractor suitability and project feasibility across multiple dimensions, such as resource conservation, health, strategic objectives, cost, and system integration, as shown in Figure 1. The following section provides a scientific explanation for each of the proposed evaluation criteria grounded in current research.

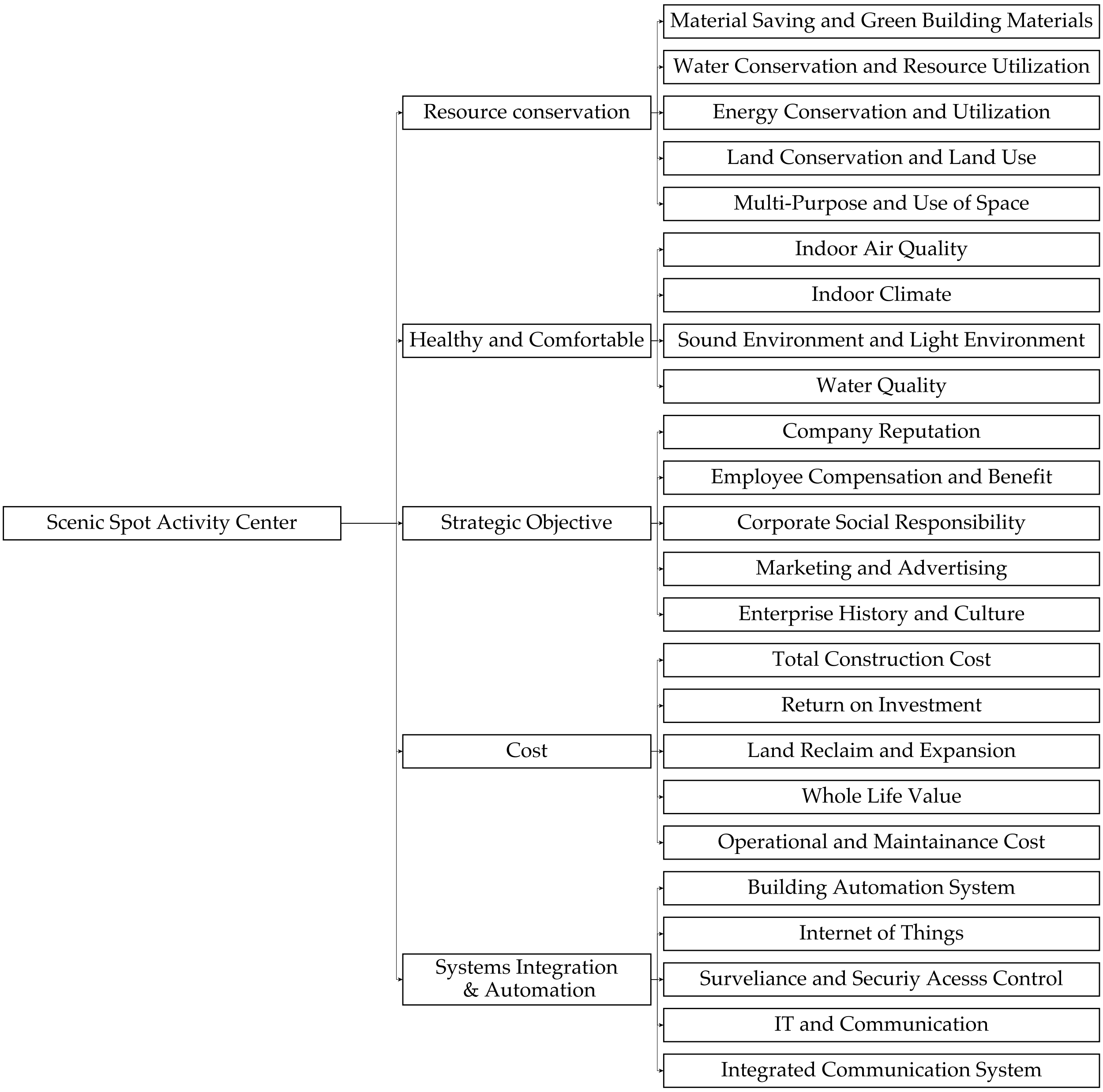

Figure 1. Hierarchical model for construction of urban scenic spot activity center.

3.1.1. Resource Conservation (C_1)

Resource conservation is critical in sustainable urban development, as it aims to minimize the environmental impact while maximizing resource efficiency. The following sub-criteria play an essential role. *Material Saving and Green Building Materials* ($C_{1\text{-}1}$): The use of sustainable and green building materials is increasingly prioritized in modern construction. These materials are often derived from recycled sources or possess properties that reduce environmental impact during their life cycle. Studies have shown that green building materials can reduce energy consumption by 24–50% and water consumption by 40% compared to conventional materials [41]. *Water Conservation and Resource Utilization ($C_{1\text{-}2}$)*: Water conservation strategies, such as rainwater harvesting and greywater recycling, are vital in reducing water usage in urban construction projects. Efficient water management systems can lower water demand by as much as 30% [42]. Integrating water-saving technologies is essential in addressing global water scarcity issues. *Energy Conservation and Utilization ($C_{1\text{-}3}$)*: Energy conservation measures, such as the use of renewable energy sources (solar, wind, etc.) and energy-efficient technologies (LED lighting, smart thermostats), can drastically reduce the energy footprint of construction projects. Buildings can achieve energy savings of up to 40% through effective energy management systems [43,44]. *Land Conservation and Land Use ($C_{1\text{-}4}$)*: Efficient land use involves strategies such as minimizing the development footprint, utilizing brownfield sites, and preserving green spaces. These measures are critical for reducing urban sprawl and maintaining biodiversity. Proper land-use planning can reduce deforestation and habitat destruction, contributing to environmental sustainability [45]. *Multi-Purpose and Use of Space ($C_{1\text{-}5}$)*: Multi-functional spaces allow for flexible use of buildings and facilities, optimizing space for various activities. This approach maximizes the utility of urban areas, reducing the need for additional construction. Multi-use spaces enhance social interaction and economic efficiency, promoting sustainable urban growth [46].

3.1.2. Healthy and Comfortable (C_2)

Creating healthy and comfortable environments within urban construction projects is a key factor in enhancing the quality of life for residents and users. The following criteria focus on indoor environmental quality and human health. *Indoor Air Quality ($C_{2\text{-}1}$)*: Good indoor air quality is critical for human health, particularly in densely populated urban areas. Poor air quality can lead to respiratory diseases and reduced cognitive performance. Ventilation systems and the use of low-emission building materials can improve indoor air quality significantly [47]. *Indoor Climate ($C_{2\text{-}2}$)*: Maintaining an optimal indoor climate (temperature, humidity) is essential for occupant comfort and productivity. Smart heating, ventilation, and air conditioning (HVAC) systems efficiently regulate indoor climates, reducing energy use while maintaining comfort [48]. *Sound and Light Environment ($C_{2\text{-}3}$)*: Noise pollution and inadequate lighting negatively impact well-being and productivity. Proper acoustic design and natural lighting solutions contribute to healthier and more comfortable indoor environments [40,46]. *Water Quality ($C_{2\text{-}4}$)*: Ensuring safe and clean water for drinking and other uses within buildings is a health priority. Filtration systems and water-monitoring technologies are essential for maintaining high water quality standards in urban construction projects [49].

3.1.3. Strategic Objectives (C_3)

The following strategic objectives of a construction company influence its long-term viability and alignment with sustainable development goals. *Company Reputation ($C_{3\text{-}1}$)*: A company's reputation can impact its ability to secure contracts and maintain stakeholder trust. Companies with strong reputations are often more committed to sustainability and social responsibility [50]. *Employee Compensation and Benefits ($C_{3\text{-}2}$)*: Fair compensation and employee benefits are critical for attracting and retaining skilled workers, leading to better project outcomes and long-term company success [51]. *Corporate Social Responsibility ($C_{3\text{-}3}$)*: CSR initiatives demonstrate a company's commitment to ethical practices, community engagement, and environmental stewardship. Companies with strong CSR programs often perform better financially in the long run [52]. *Marketing and Advertising ($C_{3\text{-}4}$)*: Effective marketing strategies can help a construction company stand out in a competitive market, particularly when promoting sustainable projects [53]. *Enterprise History and Culture ($C_{3\text{-}5}$)*: A company's history and organizational culture can impact its approach to project management and stakeholder relationships. Companies with a long history of successful projects often have stronger partnerships and more trust from clients [54].

3.1.4. Cost (C_4)

Cost-related criteria such as the following are fundamental to ensuring that urban construction projects are financially viable without sacrificing sustainability goals. *Total Construction Cost ($C_{4\text{-}1}$)*: The total cost of construction includes materials, labor, and administrative expenses. Reducing waste and improving efficiency can significantly lower construction costs [55,56]. *Return on Investment ($C_{4\text{-}2}$)*: ROI is a key measure of project success, ensuring that the financial outlay is justified by the long-term gains, both in economic terms and sustainability outcomes [57]. *Land Reclaim and Expansion ($C_{4\text{-}3}$)*: Efficient land reclamation and expansion are crucial for minimizing environmental impact while maximizing the utility of urban spaces [58]. *Whole Life Value ($C_{4\text{-}4}$)*: This refers to the total value generated by a project throughout its life cycle, taking into account both upfront costs and long-term benefits, such as energy savings and reduced environmental impact [59]. *Operational and Maintenance Cost ($C_{4\text{-}5}$)*: Efficient design and use of durable materials can reduce the long-term operational and maintenance costs of a project [60].

3.1.5. Systems Integration and Automation (C_5)

The integration of modern technologies and automation systems can enhance the functionality and sustainability of construction projects. *Building Automation System ($C_{5\text{-}1}$)*: Automated systems for heating, lighting, and ventilation can significantly improve energy efficiency and occupant comfort [45]. *Internet of Things ($C_{5\text{-}2}$)*: IoT-enabled devices allow for real-time monitoring and control of building systems, optimizing energy use and improving overall operational efficiency [55]. *Surveillance and Security Access Control ($C_{5\text{-}3}$)*: Advanced surveillance and security systems enhance building safety and can reduce costs associated with theft and vandalism [61]. *IT and Communication ($C_{5\text{-}4}$)*: Integrated communication systems allow for efficient coordination between stakeholders and contractors, reducing delays and ensuring smooth project execution [56].

3.2. Grey System-II Thinking Weights in Group Decision-Making

The common approach to determining weight in a group decision-making environment involves averaging preferences from decision-makers (DMs) based on System-1 thinking. By contrast, the main idea of the Grey System-2 Thinking (GS2T) group weighting method is to begin by discarding the data obtained through System-1 thinking and instead using the data derived from System-2 thinking. This is because System-2 thinking captures the rational preferences of DMs. Next, these preferences are represented as interval grey numbers, which are then whitened and converted into a global weight used to evaluate the alternatives. The steps for computing the GS2T method are as follows:

Step I. Obtain System-I data from DMs. A data collection instrument is developed to capture the DMs' preferences. Specifically, this can be a questionnaire in the form of a paper-based, electronic document or web-based. These data are put in a decision weighting table as given in Table 1, where the evaluation criteria are indexed $1 \leq i \leq p$, the alternatives are indexed $1 \leq j \leq q$, and the DMs are indexed $1 \leq k \leq s$.

Step II. Obtain System-II data from the DMs. The previously used measurement instrument in System-1, the questionnaire, is used again in the first round to gather the DMs' preferences. This time, the DMs are asked for their preferences after a significant amount of time has elapsed, allowing them to critically evaluate criteria and decide rationally. The data are then organized into a decision table, similar to Table 1, and called the System-2 thinking DM preference.

Table 1. Group decision-makers' weighting table.

Decision-Makers	Criteria Index	Z_1	$\cdots$	Z_j	$\cdots$	Z_q
	C_1	r_{111}	$\cdots$	r_{1j1}	$\cdots$	r_{1q1}
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
DM_1	C_i	r_{i11}	$\cdots$	r_{ij1}	$\cdots$	r_{iq1}
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
	C_p	r_{p11}	$\cdots$	r_{pj1}	$\cdots$	r_{pq1}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
	C_1	r_{11k}	$\cdots$	r_{1jk}	$\cdots$	r_{1qk}
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
DM_k	C_i	r_{i1k}	$\cdots$	r_{ijk}	$\cdots$	r_{iqk}
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
	C_p	r_{p1k}	$\cdots$	r_{pjk}	$\cdots$	r_{pqk}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
	C_1	r_{11s}	$\cdots$	r_{1js}	$\cdots$	r_{1qs}
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
DM_s	C_i	r_{i1s}	$\cdots$	r_{ijs}	$\cdots$	r_{iqs}
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
	C_p	r_{p1s}	$\cdots$	r_{pjs}	$\cdots$	r_{pqs}

Step III. Scale the DMs' preferences. The weight is a relative measurement from the least to most important criteria, where the least is zero (0) on the preference scale, and the most important is one (1). Since the weights are given as score points, they are scaled from zero to one (0–1). This is computed using Equation (1):

$$x_{ij} = \frac{r_{ij} - \min\limits_{i} r_{ij}}{\max\limits_{i} r_{ij} - \min\limits_{i} r_{ij}} \tag{1}$$

Step IV. Convert the scaled group DMs to grey numbers. This conversion is performed using Equation (2):

$$\otimes x_{ij} = [\underline{x_{ij}}, \overline{x_{ij}}] = [\min_{k} x_{ijk}, \max_{k} x_{ijk}] \tag{2}$$

Step V. The grey number is whitened. To determine the number, a whitening coefficient (λ) between the range of zero (0) to one (1) is used:

$$\hat{w}_j = \underline{x_{ij}}(1-\lambda) + \overline{x_{ij}}\lambda \tag{3}$$

Step VI. Compute the local weight. This is obtained by normalizing the white number. For the research, the sum normalization is used:

- For first-level criteria (C_α),

$$w_\alpha = \frac{\hat{w}_\alpha}{\sum_{\alpha=1}^{m} \hat{w}_\alpha} \tag{4}$$

- For second-level criteria ($C_{\alpha\text{-}\beta}$),

$$w_{\alpha\text{-}\beta} = \frac{\hat{w}_{\alpha\text{-}\beta}}{\sum_{\beta=1}^{n} \hat{w}_{\alpha\text{-}\beta}} \tag{5}$$

Step VII. Compute the overall weight. This is the corresponding weight of each criterion to the fractional contribution by its parent criteria. This is obtained using Equation (6):

$$W_j = w_\alpha \times w_{\alpha\text{-}\beta} \tag{6}$$

The proposed Grey-System-2 Thinking (GS2T) and Grey-CRADIS methods represent significant advancements in the field, offering new tools for enhancing the reliability and validity of expert judgment in MCDM contexts.

3.3. CRADIS Method

While there are numerous MCDM evaluation methods, the CRADIS method and its extension to the GST are used in this research. The CRADIS can be considered as a hybrid method that incorporates aspects of each of the other three MCDM methods. It ranks alternatives by considering both their distance to an ideal solution (like TOPSIS) and compromise-based solutions (like Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS)), while also factoring in additive assessments similar to the Additive Ratio Assessment (ARAS) as shown in Figure 2. ARAS is based on a utility degree that evaluates each alternative by summing up weighted values for criteria. The method uses an additive approach to determine the overall preference of each alternative relative to an optimal solution [62]. Furthermore, MARCOS seeks a compromise solution, but it introduces a more detailed assessment of the alternatives' relative performance compared to a reference point. This method evaluates alternatives through a distance-based approach while incorporating the concept of utility functions to better handle diverse decision-making contexts [63]. TOPSIS ranks alternatives by calculating their distance to an ideal solution and a negative ideal solution. The best alternative is the one that is closest to the ideal solution and farthest from the negative ideal solution [64].

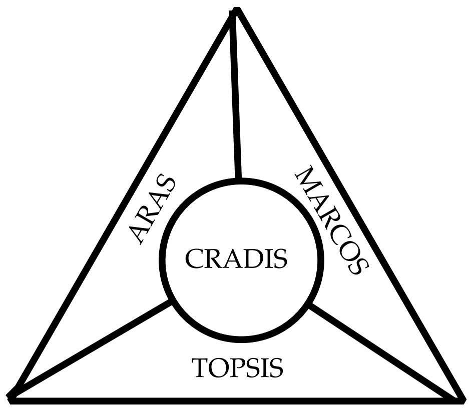

Figure 2. CRADIS method combines ARAS, MARCOS, and TOPSIS.

It should be noted that CRADIS has already been extended to a fuzzy set by Yuan et al. [17]. This paper presents a new extension.

3.3.1. Original CRADIS

The CRADIS method is a hybrid Multi-Criteria Decision-Making (MCDM) method that combines the strengths of three well-known MCDM techniques: ARAS, MARCOS, and TOPSIS. It aims to rank alternatives based on their proximity to an ideal solution while considering both beneficial and non-beneficial criteria. The CRADIS method integrates normalization, weighting, and distance computations to determine a compromise ranking for each alternative.

Step I. Construction of the Decision Matrix: First, a decision matrix is constructed that includes all alternatives and their associated criteria. The decision matrix, $D = [d_{ij}]$, consists of values that represent the performance of each alternative i with respect to each criterion j.

Step II. Normalization of the Decision Matrix: The decision matrix is normalized to bring all criteria onto a comparable scale. The *max normalization* method is used, which is suitable when the criteria have different units:

- For the beneficial criteria (where higher values are better),

$$d_{ij}^{\eta} = \frac{d_{ij}}{\max\limits_{i} d_{ij}} \tag{7}$$

Alternatively, the deviation from the minimum value can be used:

$$d_{ij}^{\eta} = 1 - \frac{\min\limits_{i} d_{ij}}{d_{ij}} \tag{8}$$

- For the non-beneficial criteria (where lower values are better),

$$d_{ij}^{\eta'} = \frac{\min\limits_{i} d_{ij}}{d_{ij}} \tag{9}$$

Alternatively, the deviation from the maximum value can be calculated:

$$d_{ij}^{\eta'} = 1 - \frac{d_{ij}}{\max\limits_{i} d_{ij}} \tag{10}$$

Step III. Computation of the Weighted Normalized Decision Matrix: After normalization, weights (w_j) are assigned to each criterion based on their importance. The weighted normalized decision matrix is calculated as

$$v_{ij} = n_{ij} \cdot w_j \tag{11}$$

Step IV. Determination of Ideal and Anti-Ideal Solutions: The *ideal solution* represents the best possible value for each criterion, while the *anti-ideal solution* represents the worst:

- For the ideal solution,

$$t_i = \max v_{ij} \tag{12}$$

- For the anti-ideal solution,

$$t_{ai} = \min v_{ij} \tag{13}$$

Step V. Computation of Deviation from Ideal and Anti-Ideal Solutions: The deviations of each alternative from the ideal and anti-ideal solutions are calculated as follows:

- Deviation from the ideal solution:

$$d^{+} = t_i - v_{ij} \tag{14}$$

- Deviation from the anti-ideal solution:

$$d^{-} = v_{ij} - t_{ai} \tag{15}$$

These deviations indicate the extent to which each alternative deviates from the ideal and anti-ideal solutions.

Step VI. Aggregation of the Degree of Deviation for Each Alternative: The total deviations for each alternative are aggregated across all criteria as follows:

- For the ideal solution,

$$s_i^{+} = \sum_{j=1}^{n} d^{+} \tag{16}$$

- For the anti-ideal solution,

$$s_i^{-} = \sum_{j=1}^{n} d^{-} \tag{17}$$

Step VII. Computation of the Alternative Utility Function: The *utility function* for each alternative is computed based on its deviation from the ideal and anti-ideal solutions:

- Utility with respect to the ideal solution:

$$K_i^{+} = \frac{s_0^{+}}{s_i^{+}} \tag{18}$$

- Utility with respect to the anti-ideal solution:

$$K_i^{-} = \frac{s_i^{-}}{s_0^{-}} \tag{19}$$

Here, s_0^{+} and s_0^{-} represent the deviations of the reference alternative (usually the ideal solution) from the ideal and anti-ideal points, respectively. The utility functions K_i^{+} and K_i^{-} indicate how closely each alternative aligns with the ideal and anti-ideal solutions.

Step VIII. Ranking of Alternatives: The final ranking of the alternatives is obtained by averaging the utility functions:

$$Q_i = \frac{K_i^{+} + K_i^{-}}{2} \tag{20}$$

The alternatives are ranked based on their Q_i values, where higher values indicate better performance.

3.3.2. CRADIS Extend to Grey Numbers

One limitation of the original CRADIS method is its inability to capture uncertainty; thus, we extend the CRADIS to grey numbers. The overall framework is extended with the introduction of GST, as shown in Figure 3. The triangle (comprising CRADIS, ARAS, MARCOS, and TOPSIS) is now enclosed within a large, dashed circle labeled "Grey System Theory", signifying the added dimension for managing uncertainty. This implies that the decision-making process can now handle incomplete or uncertain data, a fundamental aspect of GST. The dashed lines in the triangle emphasize flexibility and the ability to handle ambiguity, indicating that these methods, when applied under GST, are better suited for real-world scenarios where uncertainty exists. The GST provides an outer layer that encapsulates and strengthens the robustness of the CRADIS method by allowing for more flexible and adaptive decision-making processes in uncertain environments.

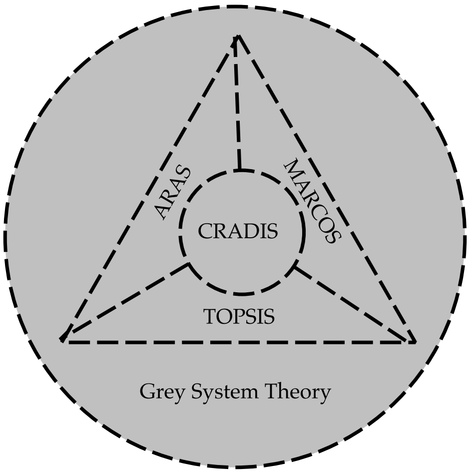

Figure 3. CRADIS method contained by the Grey System Theory.

Step I. Construction of the Grey Decision Matrix.
At different times, the performance of the alternative is different in a dynamic decision-making problem. This uncertainty is represented as a grey number by measuring the minimum and maximum values of the performance over a period. A decision matrix A by decision-maker k can be represented as

$$A_k = \begin{pmatrix} a_{11k} & \cdots & a_{1jk} & \cdots & a_{1nk} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1k} & \cdots & a_{ijk} & \cdots & a_{ink} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{m1k} & \cdots & a_{mjk} & \cdots & a_{mnk} \end{pmatrix}, \tag{21}$$

The grey decision matrix is represented as

$$\otimes A = \begin{pmatrix} \otimes a_{11} & \cdots & \otimes a_{1j} & \cdots & \otimes a_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes a_{i1} & \cdots & \otimes a_{ij} & \cdots & \otimes a_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \otimes a_{m1} & \cdots & \otimes a_{mj} & \cdots & \otimes a_{mn} \end{pmatrix}, \tag{22}$$

where

$$\otimes a_{ij} = [\underline{a_{ij}}, \overline{a_{ij}}] = \left[\min_d a_{ijd}, \max_d a_{ijd}\right] \tag{23}$$

Step II. Normalize the Decision Matrix. The researchers of [65] used maximization normalization as follows:

- For the beneficial criteria,

$$\otimes a'_{ij} = [\underline{a'_{ij}}, \overline{a'_{ij}}] = \left[\frac{\underline{a_{ij}}}{\max_i \overline{a_{ij}}}, \frac{\overline{a_{ij}}}{\max_i \overline{a_{ij}}}\right] \tag{24}$$

- For the non-beneficial criteria,

$$\otimes a'_{ij} = \left[\underline{a'_{ij}}, \overline{a'_{ij}}\right] = \left[\frac{\min_i \underline{a_{ij}}}{\overline{a_{ij}}}, \frac{\min_i \underline{a_{ij}}}{\underline{a_{ij}}}\right] \tag{25}$$

Step III. Compute the Weighted Normalized Grey Decision Matrix:

$$\otimes v_{ij} = \left[\underline{v_{ij}}, \overline{v_{ij}}\right] = \otimes a'_{ij}.w_j \tag{26}$$

Step IV. Obtain the Ideal (t_i) and Anti-ideal (t_{ai}) Solutions:

$$t_i = \max \overline{v_{ij}} \tag{27}$$

$$t_{ai} = \min \underline{v_{ij}} \tag{28}$$

Step V. Compute the Deviation From the Ideal and Anti-ideal Solutions:

$$\otimes d^+ = \left[t_i - \overline{v_{ij}}, t_i - \underline{v_{ij}}\right] \tag{29}$$

and

$$\otimes d^- = \left[\underline{v_{ij}} - t_{ai}, \overline{v_{ij}} - t_{ai}\right], \tag{30}$$

respectively.

Step VI. Aggregate the degree of deviation for all alternatives:

$$\otimes s_i^+ = \left[\underline{s_i^+}, \overline{s_i^+}\right] = \sum_{j=1}^{n} \otimes d^+ \tag{31}$$

and

$$\otimes s_i^- = \left[\underline{s_i^-}, \overline{s_i^-}\right] = \sum_{j=1}^{n} \otimes d^-, \tag{32}$$

respectively.

Step VII. Compute the alternative utility function. It is obtained by taking the quotient of the sum of the lower and upper bounds of all the alternatives to the sum of the lower and upper bounds of both the grey ideal and grey anti-ideal:

$$K_i^+ = \frac{\otimes s_0^+}{\otimes s_i^+} = \frac{\underline{s_0^+} + \overline{s_0^+}}{\underline{s_i^+} + \overline{s_i^+}} \tag{33}$$

and

$$K_i^- = \frac{\otimes s_i^-}{\otimes s_0^-} = \frac{\underline{s_i^-} + \overline{s_i^-}}{\underline{s_0^-} + \overline{s_0^-}} \tag{34}$$

Step VIII. Rank the alternatives:

$$Q_i = \frac{K_i^+ + K_i^-}{2} \tag{35}$$

4. Results and Analysis

At this post-pandemic stage, tourism has resumed, and the government is focused on increasing revenue at scenic spots. In response to these new realities, a multi-purpose activity center has been strategically planned for construction at these locations. Seven construction firms were invited to submit sustainable building plans with a consistent theme across four scenic locations. Four decision-makers evaluated the proposals and assigned scores based on predetermined evaluation criteria. This study draws insights from a diverse group of seasoned engineering professionals with extensive experience in the fields of construction, water conservancy, and infrastructure management. The participants include senior engineers with specialized credentials, such as First-Class Constructor certifications and additional registrations in HVAC, supervision, and project safety. Their professional tenures range from 15 to 32 years, with academic backgrounds from renowned institutions. The four experts have a combined total of 90 years of work experience and bring expertise in disciplines including engineering management, building environment and equipment engineering, industrial and civil construction, and hydraulic structures, making them representative of high-level industry practitioners. Their insights contribute valuable practical and theoretical perspectives to the field of engineering research.

Figure 4 presents the MCDM framework that integrates several methods—Grey System-II Thinking Weighting Method, Grey-CRADIS, Weighted Sum Model (WSM), and TOPSIS—to rank alternatives. It begins with group DMs assigning points to construction companies. Represented in green boxes are the data collected after System-1 (fast and instinctive) has undergone a time delay (of two weeks for this research) and System-2 (deliberative, logical) thinking data are collected. These points are transformed into grey numbers that are scaled and whitened, and local and global weights are calculated. The blue boxes denote steps specific to the Grey-CRADIS process, which involves creating a weighted grey normalized matrix, identifying ideal and anti-ideal solutions, computing deviation from these solutions, and calculating an alternative utility to rank the alternatives. The yellow boxes correspond to the WSM process, which involves maximum normalization and creating an aggregated weighted normalized decision matrix, leading to traditional WSM rankings. The orange boxes represent the TOPSIS method, where vector normalization is applied, closeness values to the ideal solutions are computed, and rankings are determined. Finally, the rankings from each method are compared, offering a comprehensive evaluation of alternatives and incorporating both certainty and uncertainty in decision-making.

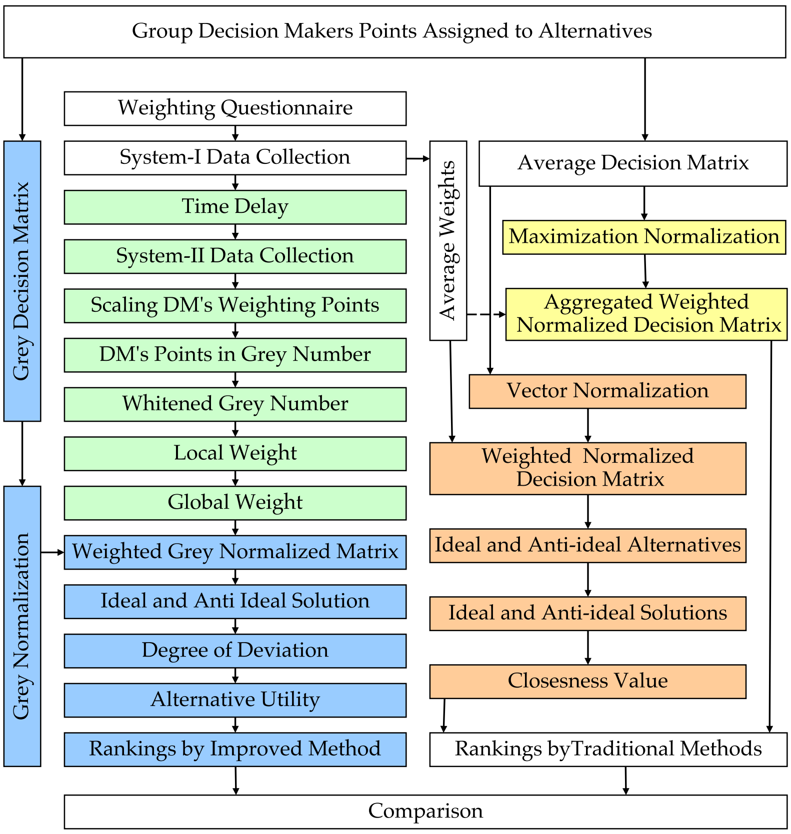

Figure 4. Flowchart of the research.

4.1. Application of Grey System-II for Evaluation Criteria Weighting

The Grey System-2 Thinking (GS2T) weighting approach is applied to calculate the weights for evaluation criteria based on the data provided by decision-makers (DMs) by introducing a time delay. This process involves discarding decision-maker inputs using System-1 thinking (quick, instinctive judgments) but using System-2 thinking (deliberate, logical analysis). The steps below outline the application of the GS2T approach to weighting the evaluation criteria:

Step I. Obtain System-I data from DMs. The decision-makers (DMs) were contacted to complete a questionnaire under time constraints, ensuring their responses reflected System-I thinking. The questionnaire was sent at the scheduled time and completed within 15 min. The responses, captured in Table 2, show the initial judgments of the DMs. For instance, DM_1 assigned 80% importance to *Resource Conservation* (C_1), while DM_4 assigned 70% to *Resource Conservation* (C_1) and 60% to *Integrated Communication System* ($C_{5\text{-}5}$).

Step II. Obtain System-II data from DMs. After the initial round, the DMs were notified that they would need to complete the same questionnaire 14 days later, allowing them time to reflect on the criteria. The responses collected after this time, representing System-2 thinking, are also presented in Table 2. For example, DM_1 still assigned 80% to *Resource Conservation* (C_1) in both rounds, while DM_4 assigned 60% to both *Resource Conservation* (C_1) and *Integrated Communication System* ($C_{5\text{-}5}$). It should be noted that the raw data collected were not directly used; they were further processed using the steps below.

Step III. Scale the DMs' preferences. The preferences provided by the DMs were then scaled using the following equation:

$$x_{ij} = \frac{r_{ij} - \min\limits_{1 \le i \le 29} r_{ij}}{\max\limits_{1 \le i \le 29} r_{ij} - \min\limits_{1 \le i \le 29} r_{ij}} \tag{36}$$

For example, the normalized preference of DM_1 for *Resource Conservation* (C_1) is

$$x_{1,1} = \frac{r_{1,1} - \min\limits_{1 \le i \le 29} r_{1,1}}{\max\limits_{1 \le i \le 29} r_{1,1} - \min\limits_{1 \le j \le 29} r_{1,1}} = \frac{80 - 70}{90 - 70} = 0.5 \tag{37}$$

Similarly, the normalized preference of DM_4 for *Integrated Communication System* ($C_{5\text{-}5}$) is

$$x_{4,29} = \frac{r_{4,29} - \min\limits_{1 \le i \le 29} r_{4,29}}{\max\limits_{1 \le i \le 29} r_{4,29} - \min\limits_{1 \le j \le 29} r_{4,29}} = \frac{80 - 60}{80 - 30} = 0.6 \tag{38}$$

The remaining normalized preferences were computed similarly and are shown in Table 3.

Step IV. Convert scaled DMs' preferences to grey numbers. The scaled preferences for each criterion were converted to grey numbers to capture the range of variability in DMs' inputs. This was performed using Equation (2), having

$$\otimes x_j = [\underline{x_{ij}}, \overline{x_{ij}}] = \left[\min\limits_{1 \le j \le 4} x_{ij}, \max\limits_{1 \le j \le 4} x_{ij}\right] \tag{39}$$

For instance, the grey preference for *Resource Conservation* (C_1) is

$$\otimes x_1 = [\underline{x_{1,1}}, \overline{x_{1,1}}] = \left[\min\limits_{1 \le j \le 4} x_{1,1}, \max\limits_{1 \le j \le 4} x_{1,1}\right] = [0, 0.75] \tag{40}$$

Similarly, the grey preference for *Integrated Communication System* ($C_{5\text{-}5}$) is

$$\otimes x_{29} = [\underline{x}_{29,j}, \overline{x}_{29,j}] = \left[\min_{1\le j\le 4} x_{29,j}, \max_{1\le j\le 4} x_{29,j}\right] = [0.5, 0.75] \tag{41}$$

Step V. Whitening the grey numbers. A whitening coefficient $\lambda = 0.5$ was applied to convert the grey numbers into white values using the following equation:

$$w_j = \underline{x_{ij}} \times 0.5 + \overline{x_{ij}} \times 0.5 \tag{42}$$

Thus, the white value of the grey weights for *Resource Conservation* (C_1) and *Integrated Communication System* ($C_{5\text{-}5}$) are

$$\hat{w}_1 = 0.375 \quad \text{and} \quad \hat{w}_{29} = 0.625$$

Step VI. Compute local weights. The local weights were computed by normalizing the white numbers using sum normalization. For first-level criteria, the formula is

$$w_\alpha = \frac{\hat{w}_\alpha}{\sum_{\alpha=1}^{5} \hat{w}_\alpha} = \frac{\hat{w}}{2.65} \tag{43}$$

For instance, the local weight for *Resource Conservation* (C_1) is

$$w_1 = \frac{0.375}{2.65} = 0.1415$$

For the second-level criterion *Material Saving and Green Building Materials* (C_{1-1}), the local weight is calculated as

$$w_{1-1} = \frac{\hat{w}_{1-1}}{\sum_{\beta=1}^{5} \hat{w}_{1\text{-}\beta}} = \frac{0.5}{2.375} = 0.2105 \tag{44}$$

Similarly, the local weight for *Integrated Communication System* (C_{5-5}) is

$$w_{5-5} = \frac{\hat{w}_{5-5}}{\sum_{\beta=1}^{5} \hat{w}_{5-5}} = \frac{0.625}{3.125} = 0.2 \tag{45}$$

Step VII. Compute global weights.
The overall or global weight was computed by multiplying the local weights for each criterion level using Equation (6):
For *Material Saving and Green Building Materials* (C_{1-1}), the global weight is

$$W_{1-1} = 0.1415 \times 0.2105 = 0.0298 \tag{46}$$

For *Integrated Communication System* (C_{5-5}), the global weight is

$$W_{5-5} = 0.2830 \times 0.2 = 0.0566 \tag{47}$$

The weight obtained here is used in the subsequent section in computing the weighted decision matrix.

Table 2. Points assigned by DMs for weighting.

Index (j)	Class Criteria	System-1 DM_1	System-1 DM_2	System-1 DM_3	System-1 DM_4	System-2 DM_1	System-2 DM_2	System-2 DM_3	System-2 DM_4
1	C_1	80	90	70	70	80	80	80	60
2	C_2	90	80	80	60	90	90	90	70
3	C_3	75	75	60	40	80	80	80	50
4	C_4	80	70	70	60	80	80	80	70
5	C_5	70	70	80	80	80	90	90	60
6	$C_{1\text{-}1}$	60	85	60	70	70	80	90	60
7	$C_{1\text{-}2}$	70	80	40	60	70	85	80	50
8	$C_{1\text{-}3}$	80	80	70	80	70	85	90	70
9	$C_{1\text{-}4}$	80	85	65	60	80	80	80	60
10	$C_{1\text{-}5}$	80	80	40	70	80	85	70	80
11	$C_{2\text{-}1}$	100	100	80	80	70	100	80	70
12	$C_{2\text{-}2}$	90	90	60	40	80	95	80	50
13	$C_{2\text{-}3}$	90	90	55	50	80	95	80	50
14	$C_{2\text{-}4}$	80	80	50	60	80	85	80	60
15	$C_{3\text{-}1}$	80	80	70	60	80	85	90	60
16	$C_{3\text{-}2}$	90	80	70	70	80	85	80	50
17	$C_{3\text{-}3}$	90	90	60	60	90	95	60	30
18	$C_{3\text{-}4}$	70	80	45	40	80	85	70	50
19	$C_{3\text{-}5}$	80	90	60	30	80	95	60	50
20	$C_{4\text{-}1}$	90	90	80	60	80	95	90	80
21	$C_{4\text{-}2}$	85	80	60	50	90	85	80	70
22	$C_{4\text{-}3}$	70	90	60	40	80	85	50	60
23	$C_{4\text{-}4}$	80	80	70	40	80	80	80	70
24	$C_{4\text{-}5}$	80	80	80	70	80	90	50	80
25	$C_{5\text{-}1}$	85	90	70	60	80	95	80	60
26	$C_{5\text{-}2}$	85	90	70	50	80	95	80	70
27	$C_{5\text{-}3}$	70	80	80	70	80	90	70	60
28	$C_{5\text{-}4}$	85	90	70	70	85	95	80	60
29	$C_{5\text{-}5}$	80	80	80	60	80	90	80	60

Table 3. Local weights of the criteria.

Criteria	DM_1	DM_2	DM_3	DM_4	Grey Preference	White Preference	Local Weight	Global Weight
C_1	0.5	0	0.75	0.6	[0, 0.75]	0.375	0.1415	0.1415
C_2	1	0.5	1	0.8	[0.5, 1]	0.75	0.2830	0.2830
C_3	0.5	0	0.75	0.4	[0, 0.75]	0.375	0.1415	0.1415
C_4	0.5	0	0.75	0.8	[0, 0.8]	0.4	0.1509	0.1509
C_5	0.5	0.5	1	0.6	[0.5, 1]	0.75	0.2830	0.2830
$C_{1\text{-}1}$	0	0	1	0.6	[0, 1]	0.5	0.2105	0.0298
$C_{1\text{-}2}$	0	0.25	0.75	0.4	[0, 0.75]	0.375	0.1579	0.0223
$C_{1\text{-}3}$	0	0.25	1	0.8	[0, 1]	0.5	0.2105	0.0298
$C_{1\text{-}4}$	0.5	0	0.75	0.6	[0, 0.75]	0.375	0.1579	0.0223
$C_{1\text{-}5}$	0.5	0.25	0.5	1	[0.25, 1]	0.625	0.2632	0.0372
$C_{2\text{-}1}$	0	1	0.75	0.8	[0, 1]	0.5	0.2326	0.0658
$C_{2\text{-}2}$	0.5	0.75	0.75	0.4	[0.4, 0.75]	0.575	0.2674	0.0757
$C_{2\text{-}3}$	0.5	0.75	0.75	0.4	[0.4, 0.75]	0.575	0.2674	0.0757
$C_{2\text{-}4}$	0.5	0.25	0.75	0.6	[0.25, 0.75]	0.5	0.2326	0.0658
$C_{3\text{-}1}$	0.5	0.25	1	0.6	[0.25, 1]	0.625	0.2500	0.0354
$C_{3\text{-}2}$	0.5	0.25	0.75	0.4	[0.25, 0.75]	0.5	0.2000	0.0283
$C_{3\text{-}3}$	1	0.75	0.25	0	[0, 1]	0.5	0.2000	0.0283
$C_{3\text{-}4}$	0.5	0.25	0.5	0.4	[0.25, 0.5]	0.375	0.1500	0.0212
$C_{3\text{-}5}$	0.5	0.75	0.25	0.4	[0.25, 0.75]	0.5	0.2000	0.0283
$C_{4\text{-}1}$	0.5	0.75	1	1	[0.5, 1]	0.75	0.2913	0.0440
$C_{4\text{-}2}$	1	0.25	0.75	0.8	[0.25, 1]	0.625	0.2427	0.0366
$C_{4\text{-}3}$	0.5	0.25	0	0.6	[0, 0.6]	0.3	0.1165	0.0176
$C_{4\text{-}4}$	0.5	0	0.75	0.8	[0, 0.8]	0.4	0.1553	0.0234
$C_{4\text{-}5}$	0.5	0.5	0	1	[0, 1]	0.5	0.1942	0.0293
$C_{5\text{-}1}$	0.5	0.75	0.75	0.6	[0.5, 0.75]	0.625	0.2000	0.0566
$C_{5\text{-}2}$	0.5	0.75	0.75	0.8	[0.5, 0.8]	0.65	0.2080	0.0589
$C_{5\text{-}3}$	0.5	0.5	0.5	0.6	[0.5, 0.6]	0.55	0.1760	0.0498
$C_{5\text{-}4}$	0.75	0.75	0.75	0.6	[0.6, 0.75]	0.675	0.2160	0.0611
$C_{5\text{-}5}$	0.5	0.5	0.75	0.6	[0.5, 0.75]	0.625	0.2000	0.0566

4.2. *Application of Grey-CRADIS Method for Contractor with Design Selection*

Step I. Construction of the decision matrix. The decision matrix is constructed by drawing the performance values of construction companies from Table 4. These performance values are scored by experts and represented as a tensor, as shown in Equation (21). For example, the first expert's evaluation matrix is shown in Equation (48), where the evaluation criteria range from the second-level criteria $1 \leq i \leq 24$:

$$A_1 = \begin{pmatrix} a_{1,1,1} & a_{1,2,1} & a_{1,3,1} & \cdots & a_{1,24,1} \\ a_{2,1,1} & a_{2,2,1} & a_{2,3,1} & \cdots & a_{2,24,1} \\ a_{3,1,1} & a_{3,2,1} & a_{3,3,1} & \cdots & a_{3,24,1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{7,1,1} & a_{7,2,1} & a_{7,3,1} & \cdots & a_{7,24,1} \end{pmatrix} = \begin{pmatrix} 76 & 75 & 85 & 83 & \cdots & 78 \\ 85 & 83 & 90 & 85 & \cdots & 80 \\ 90 & 79 & 88 & 83 & \cdots & 70 \\ 83 & 81 & 83 & 70 & \cdots & 70 \\ 78 & 80 & 84 & 76 & \cdots & 81 \\ 80 & 88 & 82 & 86 & \cdots & 85 \\ 70 & 85 & 81 & 75 & \cdots & 75 \end{pmatrix} \tag{48}$$

The fourth expert's scores are presented in Equation (49). These scores are then aggregated into a grey decision matrix, $\otimes A_4$, representing the minimum and maximum bounds for each performance evaluation:

$$A_4 = \begin{pmatrix} a_{1,1,4} & a_{1,2,4} & a_{1,3,4} & \cdots & a_{1,24,4} \\ a_{2,1,4} & a_{2,2,4} & a_{2,3,4} & \cdots & a_{2,24,4} \\ a_{3,1,4} & a_{3,2,4} & a_{3,3,4} & \cdots & a_{3,24,4} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{7,1,4} & a_{7,2,4} & a_{7,3,4} & \cdots & a_{7,24,4} \end{pmatrix} = \begin{pmatrix} 82 & 84 & 88 & 75 & \cdots & 83 \\ 94 & 93 & 93 & 92 & \cdots & 92 \\ 93 & 92 & 92 & 96 & \cdots & 90 \\ 90 & 90 & 89 & 92 & \cdots & 80 \\ 94 & 90 & 92 & 92 & \cdots & 92 \\ 82 & 85 & 89 & 92 & \cdots & 92 \\ 82 & 84 & 92 & 92 & \cdots & 90 \end{pmatrix} \tag{49}$$

$$\otimes A_4 = \begin{pmatrix} \otimes a_{1,1} & \otimes a_{1,2} & \cdots & \otimes a_{1,24} \\ \otimes a_{2,1} & \otimes a_{2,2} & \cdots & \otimes a_{2,24} \\ \otimes a_{3,1} & \otimes a_{3,2} & \cdots & \otimes a_{3,24} \\ \vdots & \ddots & \vdots & \vdots \\ \otimes a_{7,1} & \otimes a_{7,2} & \cdots & \otimes a_{7,24} \end{pmatrix} = \begin{pmatrix} [62,82] & [65,84] & [72,88] & [65,83] & \cdots & [72,83] \\ [75,94] & [68,93] & [73,93] & [70,92] & \cdots & [78,92] \\ [75,93] & [63,92] & [62,92] & [72,96] & \cdots & [70,90] \\ [72,90] & [75,90] & [68,89] & [68,92] & \cdots & [70,80] \\ [70,94] & [75,90] & [70,92] & [70,92] & \cdots & [78,92] \\ [70,82] & [75,88] & [68,89] & [71,92] & \cdots & [70,92] \\ [65,82] & [68,85] & [66,92] & [68,92] & \cdots & [75,90] \end{pmatrix} \tag{50}$$

This grey decision matrix encapsulates uncertainty in the experts' evaluations, reflecting the range of possible values for each criterion.

Step II. Normalize the grey decision matrix. The grey decision matrix is normalized using maximum normalization since all criteria are beneficial (higher values indicate better performance). The normalization is carried out using Equation (24):

$$\begin{aligned} \otimes a'_{ij} = [\underline{a'_{ij}}, \overline{a'_{ij}}] &= \left[\frac{\underline{a_{ij}}}{\max\limits_{1\leq i\leq 7} \overline{a_{ij}}}, \frac{\overline{a_{ij}}}{\max\limits_{1\leq i\leq 7} \overline{a_{ij}}} \right] \\ &= \begin{pmatrix} [0.6596, 0.8723] & [0.6989, 0.9032] & [0.7742, 0.9462] & [0.6771, 0.8646] & \cdots & [0.7826, 0.9022] \\ [0.7979, 1] & [0.7312, 1] & [0.7849, 1] & [0.7292, 0.9583] & \cdots & [0.8478, 1] \\ [0.7979, 0.9894] & [0.6774, 0.9892] & [0.6667, 0.9892] & [0.75, 1] & \cdots & [0.7609, 0.9783] \\ [0.766, 0.9574] & [0.8065, 0.9677] & [0.7312, 0.957] & [0.7083, 0.9583] & \cdots & [0.7609, 0.8696] \\ [0.7447, 1] & [0.8065, 0.9677] & [0.7527, 0.9892] & [0.7292, 0.9583] & \cdots & [0.8478, 1] \\ [0.7447, 0.8723] & [0.8065, 0.9462] & [0.7312, 0.957] & [0.7396, 0.9583] & \cdots & [0.7609, 1] \\ [0.6915, 0.8723] & [0.7312, 0.914] & [0.7097, 0.9892] & [0.7083, 0.9583] & \cdots & [0.8152, 0.9783] \end{pmatrix} \end{aligned} \tag{51}$$

Normalization ensures that all performance criteria are scaled uniformly, allowing for a fair comparison across all alternatives.

Step III. Compute the weighted normalized grey decision matrix. While there are numerous MCDM weighting methods, this research applies the GS2T method. The weights are given in Equations (46) and (47) as shown in Table 4. The weighted normalized grey decision matrix is computed using Equation (26):

$$\otimes v_{ij} = \begin{pmatrix} [0.0196, 0.026] & [0.0156, 0.0202] & [0.0231, 0.0282] & [0.0151, 0.0193] & \cdots & [0.0443, 0.0511] \\ [0.0238, 0.0298] & [0.0163, 0.0223] & [0.0234, 0.0298] & [0.0163, 0.0214] & \cdots & [0.048, 0.0566] \\ [0.0238, 0.0295] & [0.0151, 0.0221] & [0.0199, 0.0295] & [0.0168, 0.0223] & \cdots & [0.0431, 0.0554] \\ [0.0228, 0.0285] & [0.018, 0.0216] & [0.0218, 0.0285] & [0.0158, 0.0214] & \cdots & [0.0431, 0.0492] \\ [0.0222, 0.0298] & [0.018, 0.0216] & [0.0224, 0.0295] & [0.0163, 0.0214] & \cdots & [0.048, 0.0566] \\ [0.0222, 0.026] & [0.018, 0.0211] & [0.0218, 0.0285] & [0.0165, 0.0214] & \cdots & [0.0431, 0.0566] \\ [0.0206, 0.026] & [0.0163, 0.0204] & [0.0211, 0.0295] & [0.0158, 0.0214] & \cdots & [0.0461, 0.0554] \end{pmatrix} \quad (52)$$

Table 4. Performance value of the construction companies with design proposal.

			Decision-Maker 1				…	Decision-Maker 4				Grey Performance			
Index (*i*)	**Criteria**	**Weights**	Z_1	Z_2	…	Z_7	…	Z_1	Z_2	…	Z_7	Z_1	Z_2	…	Z_7
1	$C_{1\text{-}1}$	0.0298	76	85	…	70	…	82	94	…	82	[62, 82]	[75, 94]	…	[65, 82]
2	$C_{1\text{-}2}$	0.0223	75	83	…	85	…	84	93	…	84	[65, 84]	[68, 93]	…	[68, 85]
3	$C_{1\text{-}3}$	0.0298	85	90	…	81	…	88	93	…	92	[72, 88]	[73, 93]	…	[66, 92]
4	$C_{1\text{-}4}$	0.0223	83	85	…	75	…	75	92	…	92	[65, 83]	[70, 92]	…	[68, 92]
5	$C_{1\text{-}5}$	0.0372	80	70	…	60	…	90	94	…	84	[63, 90]	[68, 94]	…	[60, 84]
6	$C_{2\text{-}1}$	0.0658	81	85	…	85	…	90	93	…	92	[68, 90]	[65, 93]	…	[72, 92]
7	$C_{2\text{-}2}$	0.0757	81	75	…	85	…	90	89	…	91	[67, 90]	[66, 89]	…	[70, 91]
8	$C_{2\text{-}3}$	0.0757	70	70	…	80	…	85	92	…	93	[70, 85]	[70, 92]	…	[67, 93]
9	$C_{2\text{-}4}$	0.0658	70	85	…	75	…	82	94	…	89	[70, 82]	[68, 94]	…	[68, 89]
10	$C_{3\text{-}1}$	0.0354	81	96	…	90	…	92	94	…	96	[80, 92]	[83, 96]	…	[85, 96]
11	$C_{3\text{-}2}$	0.0283	81	90	…	60	…	87	96	…	91	[81, 87]	[83, 96]	…	[60, 91]
12	$C_{3\text{-}3}$	0.0283	78	65	…	50	…	91	94	…	82	[78, 91]	[65, 94]	…	[50, 82]
13	$C_{3\text{-}4}$	0.0212	70	75	…	65	…	84	92	…	84	[70, 84]	[75, 92]	…	[65, 84]
14	$C_{3\text{-}5}$	0.0283	70	80	…	88	…	92	93	…	92	[70, 92]	[75, 93]	…	[80, 92]
15	$C_{4\text{-}1}$	0.0440	80	70	…	60	…	93	95	…	94	[78, 93]	[70, 95]	…	[60, 94]
16	$C_{4\text{-}2}$	0.0366	60	60	…	75	…	89	95	…	90	[60, 89]	[60, 95]	…	[75, 90]
17	$C_{4\text{-}3}$	0.0176	60	85	…	75	…	86	94	…	80	[60, 86]	[78, 94]	…	[66, 80]
18	$C_{4\text{-}4}$	0.0234	70	80	…	60	…	92	92	…	90	[70, 92]	[72, 92]	…	[60, 90]
19	$C_{4\text{-}5}$	0.0293	70	60	…	70	…	82	95	…	85	[70, 82]	[60, 95]	…	[70, 85]
20	$C_{5\text{-}1}$	0.0566	78	78	…	75	…	82	94	…	92	[78, 83]	[78, 94]	…	[75, 92]
21	$C_{5\text{-}2}$	0.0589	60	78	…	80	…	84	89	…	91	[60, 84]	[76, 89]	…	[76, 91]
22	$C_{5\text{-}3}$	0.0498	75	85	…	81	…	86	93	…	94	[75, 86]	[83, 93]	…	[75, 94]
23	$C_{5\text{-}4}$	0.0611	80	80	…	75	…	90	92	…	92	[80, 90]	[80, 92]	…	[70, 92]
24	$C_{5\text{-}5}$	0.0566	78	80	…	75	…	83	92	…	90	[72, 83]	[78, 92]	…	[75, 90]

Step IV. Obtain the ideal and anti-ideal solutions. The ideal solution, representing the best possible performance for each criterion, is computed using Equation (27): t_i = 0.0298, 0.0223, 0.0298, 0.0223, 0.0372, 0.0658, 0.0757, 0.0757, 0.0658, 0.0354, 0.0283, 0.0283, 0.0212, 0.0283, 0.0440, 0.0366, 0.0176, 0.0234, 0.0293, 0.0566, 0.0589, 0.0498, 0.0611, 0.0566.

The anti-ideal solution, representing the worst possible performance for each criterion, is obtained using Equation (28): t_{ai} = 0.0196, 0.0151, 0.0199, 0.0151, 0.0238, 0.0450, 0.0535, 0.0529, 0.0455, 0.0276, 0.0177, 0.0147, 0.0134, 0.0181, 0.0278, 0.0231, 0.0112, 0.0127, 0.0185, 0.0434, 0.0384, 0.0344, 0.0427, 0.0431.

Step V. Compute the deviation from the ideal and anti-ideal solutions. The deviation from the ideal solution for each alternative is calculated using Equation (29):

$$\otimes d^{+} = \begin{pmatrix} [0.0038, 0.0101] & [0.0022, 0.0067] & [0.0016, 0.0067] & [0.003, 0.0072] & \cdots & [0.0055, 0.0123] \\ [0, 0.006] & [0, 0.006] & [0, 0.0064] & [0.0009, 0.0061] & \cdots & [0, 0.0086] \\ [0.0003, 0.006] & [0.0002, 0.0072] & [0.0003, 0.0099] & [0, 0.0056] & \cdots & [0.0012, 0.0135] \\ [0.0013, 0.007] & [0.0007, 0.0043] & [0.0013, 0.008] & [0.0009, 0.0065] & \cdots & [0.0074, 0.0135] \\ [0, 0.0076] & [0.0007, 0.0043] & [0.0003, 0.0074] & [0.0009, 0.0061] & \cdots & [0, 0.0086] \\ [0.0038, 0.0076] & [0.0012, 0.0043] & [0.0013, 0.008] & [0.0009, 0.0058] & \cdots & [0, 0.0135] \\ [0.0038, 0.0092] & [0.0019, 0.006] & [0.0003, 0.0086] & [0.0009, 0.0065] & \cdots & [0.0012, 0.0105] \end{pmatrix} \quad (53)$$

The deviation from the anti-ideal solution is computed using Equation (30):

$$\otimes d^{-} = \begin{pmatrix} [0, 0.0063] & [0.0005, 0.005] & [0.0032, 0.0083] & [0, 0.0042] & \cdots & [0.0012, 0.008] \\ [0.0041, 0.0101] & [0.0012, 0.0072] & [0.0035, 0.0099] & [0.0012, 0.0063] & \cdots & [0.0049, 0.0135] \\ [0.0041, 0.0098] & [0, 0.007] & [0, 0.0096] & [0.0016, 0.0072] & \cdots & [0, 0.0123] \\ [0.0032, 0.0089] & [0.0029, 0.0065] & [0.0019, 0.0086] & [0.0007, 0.0063] & \cdots & [0, 0.0062] \\ [0.0025, 0.0101] & [0.0029, 0.0065] & [0.0026, 0.0096] & [0.0012, 0.0063] & \cdots & [0.0049, 0.0135] \\ [0.0025, 0.0063] & [0.0029, 0.006] & [0.0019, 0.0086] & [0.0014, 0.0063] & \cdots & [0, 0.0135] \\ [0.001, 0.0063] & [0.0012, 0.0053] & [0.0013, 0.0096] & [0.0007, 0.0063] & \cdots & [0.0031, 0.0123] \end{pmatrix} \quad (54)$$

Step VI. Aggregate the degree of deviation for each alternative. The aggregated degree of deviation from the ideal solution is computed using Equation (31):

$$\otimes s_i^{+} = \begin{pmatrix} [0.0731, 0.2484] \\ [0.0103, 0.2287] \\ [0.0283, 0.2472] \\ [0.0619, 0.2534] \\ [0.0295, 0.2613] \\ [0.0351, 0.2203] \\ [0.0383, 0.2587] \end{pmatrix} \quad (55)$$

The aggregated deviation from the anti-ideal solution is computed using Equation (32):

$$\otimes s_i^{-} = \begin{pmatrix} [0.0742, 0.2495] \\ [0.094, 0.3124] \\ [0.0754, 0.2943] \\ [0.0692, 0.2607] \\ [0.0614, 0.2932] \\ [0.1023, 0.2875] \\ [0.0639, 0.2843] \end{pmatrix} \quad (56)$$

Step VII. Compute the alternative utility function. The utility function for each alternative is computed by taking the ratio of the aggregated deviations from the ideal and anti-ideal solutions. The utility function for the ideal solution is given by Equation (33):

$$K_i^{+} = \begin{pmatrix} 5.2173 & 7.0206 & 6.0886 & 5.3198 & 5.7697 & 6.5670 & 5.6466 \end{pmatrix}^{\mathrm{T}} \quad (57)$$

The utility function for the anti-ideal solution is given by Equation (34):

$$K_i^{-} = \begin{pmatrix} 0.1930 & 0.2422 & 0.2204 & 0.1967 & 0.2114 & 0.2324 & 0.2076 \end{pmatrix}^{\mathrm{T}} \quad (58)$$

Step VIII. Rank the alternatives. Finally, the alternatives are ranked based on their utility values, using Equation (35):

$$Q_i = \begin{pmatrix} 2.7052 \\ 3.6314 \\ 3.1545 \\ 2.7583 \\ 2.9905 \\ 3.3997 \\ 2.9271 \end{pmatrix} = \begin{pmatrix} 7^{\mathrm{th}} \\ 1^{\mathrm{st}} \\ 3^{\mathrm{rd}} \\ 6^{\mathrm{th}} \\ 4^{\mathrm{th}} \\ 2^{\mathrm{nd}} \\ 5^{\mathrm{th}} \end{pmatrix} \quad (59)$$

The ranking process allows decision-makers to identify the best-performing contractor for the design selection.

The application of the Grey-CRADIS method allows for a robust selection of contractors, taking into account both the inherent uncertainty of DMs' evaluations and the multi-criteria nature of the problem. The integration of GST with CRADIS ensures that decision-making is both comprehensive and adaptable to real-world complexities in the selection process. This approach offers urban planners and developers a powerful tool for making informed, strategic decisions in contractor selection aligned with broader sustainability and profitability goals.

4.3. Weighting Comparison

We compare the traditional approach to weightings with the GS2T presented here. First, each DM is singled out, and their System-I and System-II thinking weights are compared to the GS2T weights. Second, the average weights of the DMs are compared to the GS2T.

4.3.1. Comparison of System-I Thinking, System-II Thinking, and the GS2T Weighting

The critical role of GS2T wieighting in MCDM for a group of DMs was analyzed. Figure 5 shows a comparison of System-1 and System-2 thinking weights with the GS2T weights across DM_1, DM_2, DM_3, and DM_4. The black dots represent System-1 thinking weights, the red dots represent System-2 thinking weights, and the blue dots represent GS2T weights based on the expert's perspective.

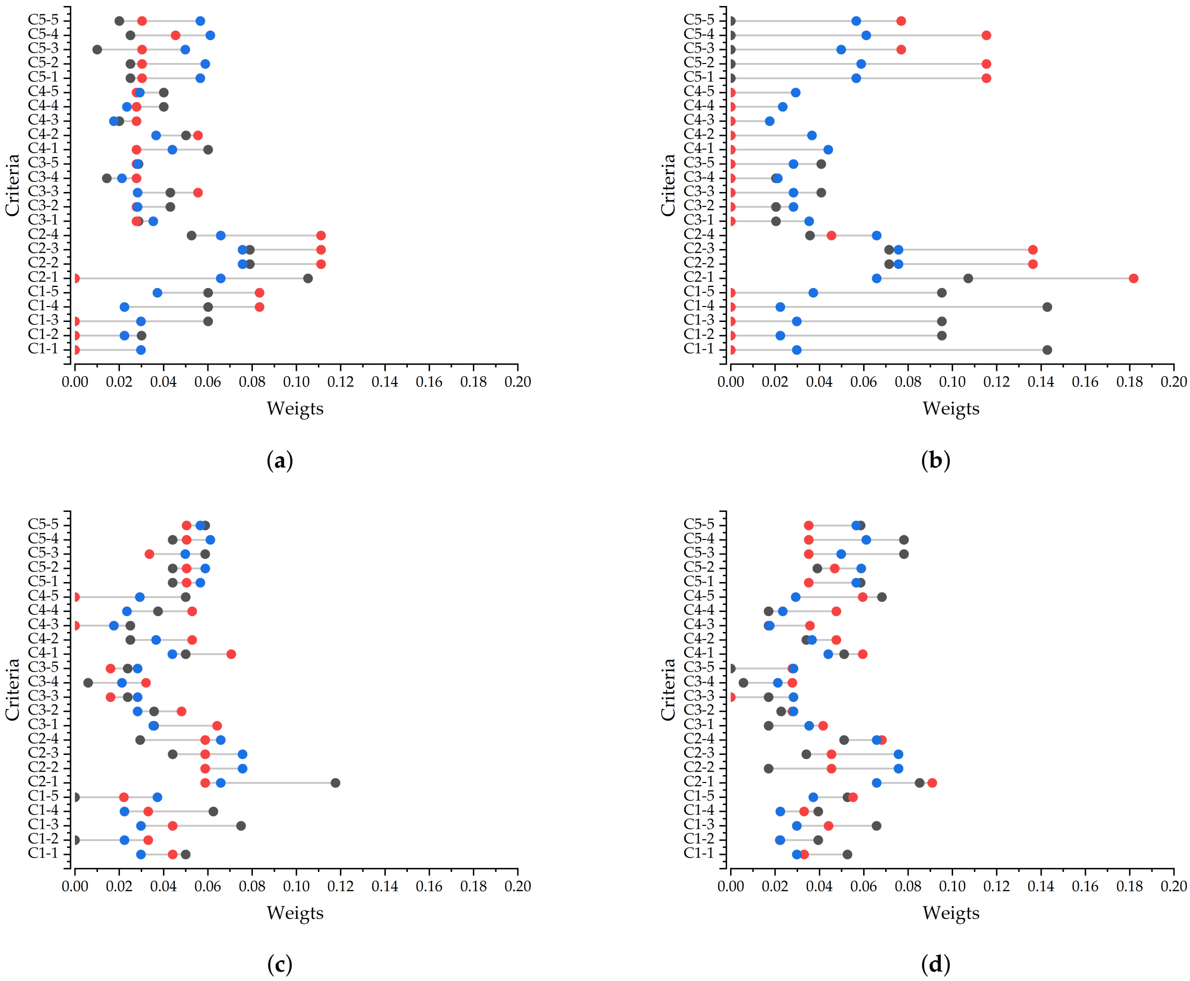

Figure 5. System-I (black) and System-II (red) thinking weight comparison with Grey System-II (blue) weights: (**a**) DM_1, (**b**) DM_2, (**c**) DM_3, and (**d**) DM_4.

A notable benefit of the GS2T weights is their capacity to address cognitive divergence. In instances where weights deviate sharply, the grey system effectively reconciles disparities by approximating a compromise. For example, for criteria like *Indoor Air Quality* ($C_{2\text{-}1}$) and *Company Reputation* ($C_{3\text{-}1}$), where variability is pronounced, the GS2T weights reduce the gaps, providing a harmonized and more stable assessment. This harmonization ensures that critical criteria are neither overlooked due to underestimation nor exaggerated beyond practical relevance.

Across all four DMs, the GS2T weights demonstrate their adaptability. In decision contexts with high variability (e.g., DM_3 and DM_4), the GS2T weights show a strong alignment with analytical reasoning while still moderating excess deviations. This trend reflects their capacity to accommodate DMs' analytical preferences without introducing bias or extremes. By acting as a stabilizing factor, the GS2T weights ensure that the decision-making process remains consistent, balanced, and methodologically sound. While DM_1 shows a common pattern, DM_2 displays some variation in weights. Regardless, their subjective opinions are respected.

In addition to their stabilizing role, the GS2T weights enhance the robustness of decision evaluations. By reconciling divergent perspectives, the GST provides a structured, compromise-driven framework that accounts for both cognitive tendencies and practical priorities. This is particularly evident for criteria such as *Water Quality* ($C_{2\text{-}4}$) and *Surveillance and Security Access Control* ($C_{5\text{-}3}$), where grey weights capture the essence of analytical priorities while moderating extreme values to produce more actionable and balanced outcomes.

4.3.2. Comparison of Average Weighting and the Grey System-II Weighting

The common approach to aggregating the group DMs' points for weighting is to normalize the sum or average of the points they assign. This average weighting approach contrasts with the more concise GS2T weighing method, which accounts for uncertainty and reflects both fast (System-1) and deliberative (System-2) thinking. In this section, we compare the average System-1 points with the Grey System-II weights.

The average of the DMs' System-I assigned points, representing their initial instinctive judgments, is computed and used as the weight. These average weights are then compared to the Grey System-II weights. The average System-I points for all criteria, drawn from Table 2 are calculated using Equation (63):

$$\overline{dm_j} = \sum_{i=1}^{m} dm_{ij} = \sum_{i=1}^{4} dm_{ij} = 77.50, 77.50, 62.50, \cdots 75.00 \tag{60}$$

The local weight of the average points is obtained through a sum-normalization process as in Equations (4) and (45). This ensures that the sum of the weights for all criteria equals 1. The formula for normalizing the average weights of the first-level criteria is given by

$$\overline{DM}_\alpha = \frac{\overline{dm}_\alpha}{\sum_{\alpha=1}^{5} \overline{dm}_\alpha} = \frac{\overline{dm}_\alpha}{362.5} \tag{61}$$

For the second-level criteria, normalization follows a similar process as shown in Equation (45):

$$\overline{DM}_{\alpha\text{-}\beta} = \frac{\overline{dm}_{\alpha\text{-}\beta}}{\sum_{\beta=1}^{n} \overline{dm}_{\alpha\text{-}\beta}} = 0.21380.2138, 0.1724, 0.1931, 0.2069, \cdots 0.2160 \tag{62}$$

The global weight is then obtained by multiplying the local weights of the first-level and second-level criteria:

$$\overline{W_j} = \overline{DM}_\alpha \times \overline{DM}_{\alpha\text{-}\beta} \tag{63}$$

These computations lead to a set of global weights that are used to rank alternatives, yielding the following results:

$\overline{W}_j = \overline{DM}_\alpha \times \overline{DM}_{\alpha\text{-}\beta}$ = 0.0430, 0.0430, 0.0347, 0.0389, 0.0417, 0.0476, 0.0433, 0.0537, 0.0502, 0.0365, 0.0487, 0.0378, 0.0385, 0.0365, 0.0432, 0.0462, 0.0447, 0.0350, 0.0388, 0.0442, 0.0379, 0.0359, 0.0373, 0.0428.

In contrast, the GS2T method adopts a more structured approach, taking into account both System-1 and System-2 thinking, which captures the uncertainties in DMs' judgments over time. The Grey-CRADIS method (see Section 3.3.2) uses grey numbers to represent the variability in DMs' inputs, refining the weights through a more robust process. The grey normalization and subsequent calculation of weighted grey normalized matrices ensure that the weights reflect both the central tendency (as in the average approach) and the range of uncertainty.

Figure 6 illustrates the comparison between the traditional average weighting and the GS2T methods. The traditional method offers a simplified view of DMs' preferences, while the GS2T method provides a more refined weighting system that integrates both rapid (System-1) and reflective (System-2) thinking. By accounting for uncertainty, the GS2T weighting approach delivers a more nuanced and reliable framework for decision-making in complex scenarios, such as the selection of contractors for urban scenic spot development.

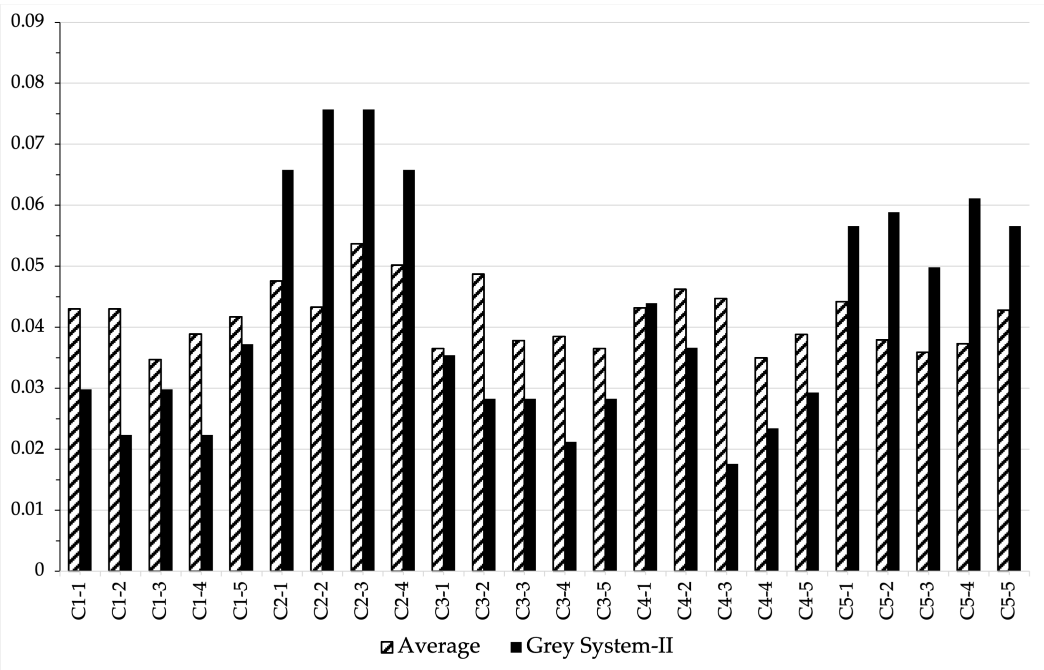

Figure 6. Comparison between average and GS2T weights.

4.4. Ranking Comparison

The Weighted Sum Model (WSM), also known as the Simple Additive Weighting (SAW) method, provides an efficient means of ranking alternatives using the average weights obtained in Section 4.3.2. Given the average performance value of each alternative, as described in Equation (22), the decision matrix $\overline{A}$ contains the aggregated values based on multiple DMs' evaluations, as computed from the individual DMs' performance values using Equations (48) and (49):

$$\overline{A}=\begin{pmatrix}\overline{a}_{11} & \cdots & \overline{a}_{1j} & \cdots & \overline{a}_{1n}\\ \vdots & \ddots & \vdots & \ddots & \vdots\\ \overline{a}_{i1} & \cdots & \overline{a}_{ij} & \cdots & \overline{a}_{in}\\ \vdots & \ddots & \vdots & \ddots & \vdots\\ \overline{a}_{m1} & \cdots & \overline{a}_{mj} & \cdots & \overline{a}_{mn}\end{pmatrix} = \begin{pmatrix}a_{1,1,1} & a_{1,2,1} & a_{1,3,1} & \cdots & a_{1,24,1}\\ a_{2,1,1} & a_{2,2,1} & a_{2,3,1} & \cdots & a_{2,24,1}\\ a_{3,1,1} & a_{3,2,1} & a_{3,3,1} & \cdots & a_{3,24,1}\\ \vdots & \ddots & \vdots & \ddots & \vdots\\ a_{7,1,1} & a_{7,2,1} & a_{7,3,1} & \cdots & a_{7,24,1}\end{pmatrix} = \begin{pmatrix}72 & 74.5 & 80 & 74 & \cdots & 77.5\\ 84.5 & 80.5 & 83 & 81 & \cdots & 85\\ 84 & 77.5 & 77 & 84 & \cdots & 80\\ 81 & 82.5 & 78.5 & 80 & \cdots & 75\\ 82 & 82.5 & 81 & 81 & \cdots & 85\\ 76 & 81.5 & 78.5 & 81.5 & \cdots & 81\\ 73.5 & 76.5 & 79 & 80 & \cdots & 82.5\end{pmatrix} \quad (64)$$

where $\overline{a}_{ij}$ represents the aggregated performance for alternative i and criterion j, calculated as follows:

$$\overline{a}_{ij} = \frac{1}{p}\sum_{k=1}^{p} a_{ijk} = \frac{1}{4}\sum_{k=1}^{4} a_{ijk}. \quad (65)$$

The decision matrix is then normalized using maximum normalization, as shown in Equations (7) and (8), to bring all performance values onto a common scale. The normalized matrix $\overline{A}^*$ is computed as follows:

$$\overline{A}^* = \begin{pmatrix}0.8521 & 0.903 & 0.9639 & 0.881 & \cdots & 0.9118\\ 1 & 0.9758 & 1 & 0.9643 & \cdots & 1\\ 0.9941 & 0.9394 & 0.9277 & 1 & \cdots & 0.9412\\ 0.9586 & 1 & 0.9458 & 0.9524 & \cdots & 0.8824\\ 0.9704 & 1 & 0.9759 & 0.9643 & \cdots & 1\\ 0.8994 & 0.9879 & 0.9458 & 0.9702 & \cdots & 0.9529\\ 0.8698 & 0.9273 & 0.9518 & 0.9524 & \cdots & 0.9706\end{pmatrix} \quad (66)$$

Finally, the WSM score for each alternative Q_i is calculated by summing the product of normalized scores and the respective criterion weights, as shown in Equation (67):

$$Q_i = \sum_{j=1}^{n} \overline{W}_j \overline{a}^*_{ij}. \quad (67)$$

The resulting scores Q_i are

$$Q_i = \begin{pmatrix}0.9235 & 0.9710 & 0.9486 & 0.9314 & 0.9401 & 0.9581 & 0.9296\end{pmatrix}^{\mathrm{T}} \quad (68)$$

These scores are ranked as

$$\begin{pmatrix}7^{\text{th}} & 1^{\text{st}} & 3^{\text{rd}} & 5^{\text{th}} & 4^{\text{th}} & 2^{\text{nd}} & 6^{\text{th}}\end{pmatrix}^{\mathrm{T}} \quad (69)$$

This means that the company with the highest value is the best, where Company A_2 ranks first, A_6 ranks second, A_3 ranks third, A_5 ranks fourth, A_4 ranks fifth, A_7 ranks sixth, and A_1 ranks seventh position.

4.4.1. TOPSIS for Ranking Alternatives

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a classical method that ranks alternatives based on their relative closeness to an ideal solution (best case) and an anti-ideal solution (worst case). The decision matrix, $\overline{A}$, from Equation (64), is normalized using vector normalization:

$$\overline{a}_{ij}^{*} = \frac{\overline{a}_{ij}}{\sqrt{\sum_{i=1}^{n} \overline{a}_{ij}^{2}}}. \tag{70}$$

The normalized matrix is represented as

$$\overline{A}^{*} = \begin{pmatrix} 0.3439 & 0.3546 & 0.3799 & 0.3485 & \cdots & 0.3619 \\ 0.4036 & 0.3831 & 0.3941 & 0.3814 & \cdots & 0.397 \\ 0.4012 & 0.3689 & 0.3657 & 0.3956 & \cdots & 0.3736 \\ 0.3868 & 0.3927 & 0.3728 & 0.3767 & \cdots & 0.3503 \\ 0.3916 & 0.3927 & 0.3846 & 0.3814 & \cdots & 0.397 \\ 0.363 & 0.3879 & 0.3728 & 0.3838 & \cdots & 0.3783 \\ 0.351 & 0.3641 & 0.3752 & 0.3767 & \cdots & 0.3853 \end{pmatrix} \tag{71}$$

Once the normalized matrix is computed, the Weighted Normalization Matrix $\overline{A}'$ is calculated by multiplying the normalized values by their respective weights:

$$\overline{a}'_{ij} = w_j \times \overline{a}_{ij}^{*} = \begin{pmatrix} 0.0169 & 0.0141 & 0.0174 & 0.0176 & \cdots & 0.0153 \\ 0.0163 & 0.015 & 0.0177 & 0.0167 & \cdots & 0.0144 \\ 0.0165 & 0.015 & 0.0183 & 0.017 & \cdots & 0.0163 \\ 0.0153 & 0.0149 & 0.0177 & 0.0171 & \cdots & 0.0155 \\ 0.0148 & 0.014 & 0.0178 & 0.0167 & \cdots & 0.0158 \\ 0.017 & 0.015 & 0.0187 & 0.0176 & \cdots & 0.0163 \\ 0.0145 & 0.0136 & 0.0174 & 0.0155 & \cdots & 0.0144 \end{pmatrix}. \tag{72}$$

The ideal and anti-ideal solutions are computed as per Equations (73) and (74), respectively:

$$\overline{A}^{+} = \left(\max_{i} v_{ij} \mid j \in J^{+} \right) = \begin{pmatrix} 0.017 & 0.015 & 0.0187 & 0.0176 & \cdots & 0.0163 \end{pmatrix} \tag{73}$$

$$\overline{A}^{-} = \left(\min_{i} v_{ij} \mid j \in J^{-} \right) = \begin{pmatrix} 0.0145 & 0.0136 & 0.0174 & 0.0155 & \cdots & 0.0144 \end{pmatrix} \tag{74}$$

The distances from the ideal and anti-ideal solutions are calculated using Equations (75) and (77):

$$\overline{S}_{i^{+}} = \sqrt{\sum_{j=1}^{n} \left(\overline{a}'_{ij} - \overline{a}_{j}^{+} \right)^{2}} \tag{75}$$

$$\overline{S}^{+} = \begin{pmatrix} 0.0073 & 0.0038 & 0.0055 & 0.0071 & 0.0062 & 0.0053 & 0.0071 \end{pmatrix}^{\mathrm{T}} \tag{76}$$

$$\overline{S}_{i^{-}} = \sqrt{\sum_{j=1}^{n} \left(\overline{a}'_{ij} - \overline{a}_{j}^{-} \right)^{2}} \tag{77}$$

$$\overline{S}^{-} = \begin{pmatrix} 0.0061 & 0.0087 & 0.0074 & 0.0065 & 0.0066 & 0.0079 & 0.0055 \end{pmatrix}^{\mathrm{T}} \tag{78}$$

Finally, the closeness value for each alternative is determined and used for ranking using Equation (79):

$$\overline{C}_{i^{*}} = \frac{\overline{S}_{i^{-}}}{(\overline{S}_{i^{+}} + S_{i^{-}})} \tag{79}$$

The alternatives are ranked according to their closeness values, with the best alternative having the highest value:

$$\overline{C}^{+} = \begin{pmatrix} 0.4550 \\ 0.6993 \\ 0.5726 \\ 0.4797 \\ 0.5160 \\ 0.6014 \\ 0.4351 \end{pmatrix} = \begin{pmatrix} 6^{\text{th}} \\ 1^{\text{st}} \\ 3^{\text{rd}} \\ 5^{\text{th}} \\ 4^{\text{th}} \\ 2^{\text{nd}} \\ 7^{\text{th}} \end{pmatrix} \tag{80}$$

The company with the highest closeness value is the best, where Company A_2 placed first, A_5 placed second, A_3 placed third, A_4 placed fourth, A_5 placed fifth, A_1 placed sixth, and A_7 placed seventh position.

4.4.2. Grey-CRADIS Comparison

The Grey-CRADIS method, in contrast to WSM and TOPSIS, extends the ranking process by considering uncertainties in DMs' evaluations through grey numbers. This method, outlined in earlier sections, adjusts for the uncertainty in performance values by computing grey decision matrices, ideal and anti-ideal solutions, and deviation from ideal solutions (Equations (27) and (30)). Unlike WSM and TOPSIS, Grey-CRADIS provides a more robust solution when uncertainty in the data is significant, as it accounts for both the best- and worst-case scenarios while weighting DMs' preferences in a more dynamic way.

Based on Figure 7, the seven alternatives (A_1 to A_7) using the Grey-CRADIS, WSM, and TOPSIS methods reveal a strong consensus across all three methods. Company-2 (A_2) is consistently ranked 1$^{\text{st}}$ by Grey-CRADIS, WSM, and TOPSIS, indicating that it is the best-performing alternative. Similarly, Company A_3 is uniformly ranked third, while Companies A_1 and A_7 consistently rank at the lower end (sixth or seventh), reflecting their lower performance. There are minor variations in the rankings for Companies A_4 and A_6, with WSM and TOPSIS ranking Company-4 (A_4) the fourth position and Company-6 (A_6) the second position, while Grey-CRADIS ranks Company-4 (A_4) the fifth position and Company-6 (A_6) is ranked in the third position. Despite these small differences, the results demonstrate strong alignment among the three methods, confirming their reliability in evaluating the alternatives.

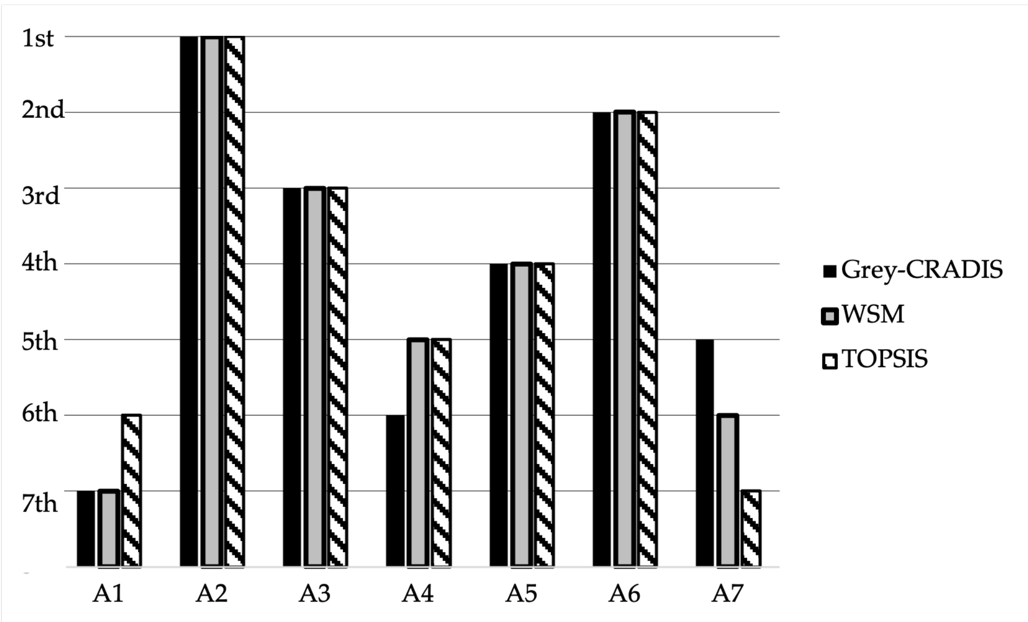

Figure 7. Comparison ranking bar chart of evaluation methods.

5. Discussion

The analysis results derived from integrating GST to MCDM methodologies provide critical insights into the proposed framework's robustness, applicability, and limitations. GST proved effective in addressing incomplete and ambiguous data, showcasing its capability to process incomplete information. By transforming DMs' preferences into grey numbers, the framework reduced biases introduced by uncertain or conflicting data. This approach enhanced decision accuracy and ensured that evaluations were consistent even under partial information. The use of a two-level hierarchical criteria model for evaluation enables the structured prioritization of the criteria under *Health and Comfort* (C_2) as a key influence in the ranking of the contractors. System-2 thinking inputs improved the reliability of weights assigned to these criteria, ensuring that the final rankings aligned closely with logical decision-making principles drawn from the wealth of experts.

The Grey-CRADIS method demonstrated superior performance compared to traditional decision-making techniques like WSM and TOPSIS because it provided more nuanced results, particularly in scenarios involving high uncertainty or incomplete datasets. The GST-based approach enabled multi-dimensional analysis, effectively balancing qualitative judgments with quantitative data. The analysis underscores Grey-CRADIS as the most advanced and reliable evaluation method, outperforming the older techniques, WSM and TOPSIS, in both robustness and adaptability. The results indicate that DMs can confidently use GS2T and Grey-CRADIS frameworks to address complex multi-criteria problems. The transparency and adaptability of the methodology ensure that stakeholder preferences and priorities are adequately reflected in the decision-making process.

A correlation of the evaluation methods is presented in Table 5. The Grey-CRADIS demonstrates a near-perfect Spearman's Rho correlation of 0.964 with WSM, reflecting its ability to align with traditional principles while introducing modern, innovative methodologies that address the complexities of contemporary decision-making. While its correlation with TOPSIS (0.893) is slightly lower, this deviation highlights Grey-CRADIS's nuanced approach to ranking, which surpasses TOPSIS's more rigid reliance on ideal-solution principles. Kendall's Tau further reinforces this, with Grey-CRADIS achieving a high concordance of 0.905 with WSM and a strong 0.810 with TOPSIS, indicating its capacity to maintain ranking stability while addressing multifaceted evaluation criteria. Weighted correlation results mirror this dominance, confirming that Grey-CRADIS seamlessly integrates traditional methods' strengths while overcoming their limitations. In comparison, WSM and TOPSIS, though historically significant, adhere to older frameworks that lack the flexibility required for modern, data-driven decision-making. The slightly weaker agreement with TOPSIS emphasizes Grey-CRADIS's superiority in handling complex criteria without oversimplification. These findings establish Grey-CRADIS as the best choice for decision-makers, offering unmatched reliability, innovation, and precision, making it a clear advancement over WSM and TOPSIS, which, while valuable in their time, now serve more as legacy methods in a field increasingly driven by complexity and modern demands.

Table 5. Correlation of CRADIS, WSM, and TOPSIS.

	Correlation	Grey-CRADIS	WSM	TOPSIS
Grey-CRADIS	Spearman's rho	–		
	Kendall's Tau B	–		
	Weighted Correlation (r_w)	–		
WSM	Spearman's rho	0.9643	–	
	Kendall's Tau B	0.9048	–	
	Weighted Correlation (r_w)	0.9643	–	
TOPSIS	Spearman's rho	0.8929	0.9643	–
	Kendall's Tau B	0.8095	0.9048	–
	Weighted Correlation (r_w)	0.8929	0.9643	–

6. Conclusions

This research effectively demonstrates the strength of integrating multiple MCDM methods—Grey-CRADIS, WSM, and TOPSIS—for evaluating alternatives in complex environments. This study's core strength lies in its robust methodological framework, combining these established techniques while leveraging GST to address uncertainties inherent in real-world Decision-Making. This approach Ensures a greater reliability of results by providing consistent rankings across different methods, thereby minimizing reliance on a single technique and reinforcing the confidence in identifying the best alternative, such as Company-2 (A_2). the inclusion of both ideal and anti-ideal solutions further enhances the evaluative process by offering a more comprehensive analysis that accounts for both optimal and worst-case scenarios.

A key contribution of this paper is its structured framework for decision-making, which emphasizes reflective, analytical, and systematic deliberation (System-2 thinking) over instinctive, impulsive judgments (System-1 thinking). By integrating extended time frames for reflection and organized group discussions, the study creates an environment where DMs can accurately assign weights to criteria, reducing biases and ensuring a balanced, consistent evaluation process. Furthermore, the proposed Grey-CRADIS method extends conventional decision-making by incorporating GST, making it capable of handling the ambiguities and uncertainties often encountered in complex decision environments. This hybrid approach not only ranks contractors based on proximity to an ideal solution but also accommodates uncertainties in stakeholders' judgments, providing a more reliable selection process for constructing urban scenic spot activity centers.

Despite its contribution of the GS2T and Grey-CRADIS methods in this paper, this research does have limitations. The reliance on subjective judgments for weighting criteria can introduce biases that may affect the accuracy of the outcomes. Additionally, the static nature of the model does not account for dynamic changes over time, which could limit its applicability in rapidly evolving scenarios. While GST excels in handling incomplete data, its reliance on grey numbers may require additional validation through cross-method comparisons in certain contexts. Regardless, the research provides a significant and well-rounded framework for MCDM in uncertain and complex environments, advancing the field by incorporating reflective decision-making and uncertainty management through GST. Furthermore, while the integration of GST mitigates uncertainties associated with subjective judgments, the final outcomes remain sensitive to the quality and consistency of expert input. This reliance can introduce cognitive biases or lead to over-reliance on domain-specific expertise. Additionally, the accessibility of the framework for non-specialist practitioners may be hindered without appropriate computational tools or technical expertise. The flexibility of GST, particularly in addressing uncertainty, makes it applicable to a wide range of industries, including environmental management, industrial decision-making, and urban development. However, customizing the criteria and their weights is essential to ensure alignment with domain-specific priorities. Differences in organizational structures, regulatory frameworks, and cultural norms may also necessitate modifications in the application of the framework. These factors should be carefully considered to preserve the validity of results across diverse settings.

Future studies can build upon the foundation laid by this research in several important ways, such as expanding the application of the Grey-CRADIS method to other domains beyond urban development, such as healthcare, supply chain management, or renewable energy projects, which could demonstrate its versatility and effectiveness in different fields. Lastly, future iterations of the model could integrate advanced algorithms to refine grey number computations further and enhance prediction accuracy; additionally, longitudinal studies and comparative analyses with other MCDM methods would enhance the framework's reliability and provide its relevance for broader applications.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/systems13010067/s1, Table S1: Decision-maker 1; Table S2: Decision-maker 2; Table S3: Decision-maker 3; Table S4: Decision-maker 4.

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