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Designing a Development Framework for Smart Urban Infrastructure Based on the Internet of Things (IoT) and Digital Technologies

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Abstract Smart cities, leveraging advanced technologies such as the Internet of Things (IoT), Digital Twin, and Artificial Intelligence, have fundamentally transformed the management of urban infrastructure and services. These technologies enable improvements in quality of life, resource consumption optimization, and enhanced environmental sustainability. However, the complexity and diversity of factors influencing smart infrastructure development necessitate multi-criteria and uncertainty-based decision-making frameworks to select optimal solutions considering technical, operational, and economic criteria. This study employs a combination of the fuzzy Delphi method for extracting and consolidating expert opinions and the GRA-VIKOR method for multi-criteria analysis and prioritization of smart infrastructure development options. The fuzzy Delphi process models the ambiguity and uncertainty in expert opinions using fuzzy numbers, while the Grey Relational Analysis (GRA) assists in determining the relative weights of criteria. Subsequently, the VIKOR algorithm evaluates and ranks the best balanced options considering conflicts and trade-offs among criteria. The results indicate that resource and energy optimization, data integration and real-time monitoring, citizen-centric services, and sustainability are the most critical criteria in smart infrastructure development decision-making. The integrated fuzzy Delphi and GRA-VIKOR approach effectively reduces decision-making complexity and highlights optimal alternatives by balancing economic, environmental, and operational objectives. Ultimately, this method can assist urban policymakers in prioritizing smart city projects. The use of a fuzzy Delphi framework combined with GRA-VIKOR multi-criteria analysis represents an effective and scientific approach to optimizing decision-making processes in smart urban infrastructure development. By providing a structured tool for aggregating expert insights and analyzing complex criteria, this approach facilitates more precise policymaking, enhances sustainability, and improves resource efficiency in smart cities. Future research is recommended to focus on improving dynamic models and data security within this framework.

Keywords: *Smart cities, Artificial Intelligence (AI), Digital Twins, Decision-making, Connected Communities, Internet of Things (IoT), Real-time Monitoring*

1. Introduction

Today, the rapid growth of urban populations, increasing pressure on resources, and the urgent need for sustainability have compelled cities to move toward becoming "smart cities." These cities leverage technologies such as the Internet of Things (IoT), big data, artificial intelligence, and digital twins to optimize urban services and enhance responsiveness. In particular, the use of digital twins to build real-time and accurate urban models enables decision-makers to simulate and analyze various scenarios before implementation (Adreani et al., 2023). This transformative technology offers the potential to improve quality of life and promote urban sustainability. As the core of smart city technology, IoT collects real-time data from diverse infrastructures—such as transportation, energy, and wastewater management—enabling real-time decision-making (Shen, 2025). Simultaneously, digital twins provide a real-time, virtual representation of infrastructure systems, enhancing monitoring capabilities, error prediction, and predictive maintenance. In one case, a system integrating IoT and digital twins was developed to manage urban underground channels, increasing fault prediction accuracy by up to 92% and reducing service disruptions by 40% (Shen, 2025).

On the other hand, over the past decade, the combination of urban population pressures, increasing complexity, and environmental challenges such as climate change has forced cities to rethink their structural frameworks. Technologies like IoT and digital twins have emerged as the cornerstones of digital transformation in urban systems. Studies in 2025 indicate that employing IoT in sustainable urban planning significantly improves real-time monitoring, crisis management, and the efficiency of energy and waste systems (Waqar, 2025). Furthermore, digital twins not only offer a dynamic and precise representation of urban structures but also allow for simulation of a wide range of scenarios—from traffic and environmental conditions to emergency services—prior to actual deployment. This technology equips urban managers with powerful tools for predictive decision-making and rational service design (El Agamy, 2024).

As the importance of urban resilience grows in the face of natural disasters such as floods, heatwaves, and air pollution, the combined use of digital twins and IoT becomes increasingly vital. According to published forecasts, by 2025, over 500 cities will be utilizing digital twin technologies, with potential economic savings exceeding $280 billion by 2030 (Al-Raeei, 2024). Such outcomes underscore the critical role these technologies play in enhancing resilience and efficiency in urban management.

Despite the capabilities of modern technologies, decision-making regarding the development of smart urban infrastructure remains complex and ambiguous. A wide range of technical, economic, environmental, and operational criteria are interwoven, necessitating frameworks capable of analyzing and weighting this diversity. The integration of methods such as the Fuzzy Delphi, multi-criteria decision-making (MCDM) techniques, and models like VIKOR or GRA can effectively address this complexity. For instance, in the domain of sustainable urban services, a fuzzy environment-based MCDM model combining VIKOR and GRA has demonstrated its ability to produce effective decisions with lower computational costs (Belošević, 2025). Similarly, in the design of smart streets for autonomous vehicles and cyclists, a hybrid approach incorporating Fuzzy Delphi, ANP, and DEMATEL has been applied (Fayyaz et al., 2024). These findings suggest that hybrid MCDM approaches are valuable tools for managing uncertainty and prioritizing in complex decision-making scenarios.

Research further confirms that technologies such as the Internet of Things (IoT) play a crucial role in guiding smart city development. Specifically, IoT applications in sustainable urban planning—

through real-time monitoring, crisis management, and efficient use of energy and waste—have significantly enhanced the quality of urban governance (Waqar, 2025). Moreover, digital twin technologies offer substantial added value in simulating and analyzing various scenarios. According to ABI Research forecasts, leveraging digital twins in urban planning could lead to global cost savings of over €259 billion by 2030 (ABI Research, 2025). Cities today face mounting challenges such as climate change and natural disasters. For example, more than 500 cities are expected to implement digital twin technologies by 2025 to strengthen their resilience against flooding, air pollution, and urban heatwaves (Al-Raeei, 2024). Despite the high potential of these technologies, urban decision-making still requires scientific frameworks to evaluate a diverse set of criteria, technical, economic, environmental, and social. Employing integrated methods such as Fuzzy Delphi, VIKOR, and GRA can lead to smarter, more transparent, and effective decision-making in the development of urban infrastructure.

2. Theoretical Foundations and Literature Review

Urban Smart Infrastructure

Urban smart infrastructure refers to a network of systems and digital technologies designed to enhance efficiency, resilience, and quality of life in urban environments. These infrastructures consist of sensors, communication networks, and analytical platforms that continuously collect and process real-time data to improve decision-making in key domains such as transportation, energy, water, and waste management (Isarsoft Knowledge Hub, 2024). By leveraging smart infrastructure, cities can utilize this data for optimal resource allocation, reducing operational costs, enabling rapid crisis response, and promoting environmental sustainability. For example, smart power grids and intelligent traffic management systems have been shown to significantly reduce energy consumption and urban congestion (Isarsoft Knowledge Hub, 2024).

Moreover, smart infrastructure is regarded as one of the foundational pillars of smart cities, integrating human, technological, and procedural components to enable unified and intelligent urban service management (Jacques, 2024). In addition to enhancing technical efficiency and operational performance, smart infrastructure also fosters greater social engagement. Recent studies show that these technologies contribute to improved social well-being, the promotion of urban equity, and increased resilience to climate change by modernizing the governance and management of urban resources and services (Andreev, 2025).

Internet of Things (IoT) in Infrastructure Management

The Internet of Things (IoT) refers to a network of smart devices and sensors that collect real-time environmental data and transmit it to management systems. In the context of urban infrastructure, this technology is applied across various sectors including transportation, electricity, waste management, public health, safety, and governance. Recent research demonstrates that integrating IoT with edge and cloud architectures—alongside widespread sensor networks and citizen-centric platforms—creates a comprehensive ecosystem that enhances sustainability, operational efficiency, and quality of life. However, despite its technical benefits, IoT also introduces challenges such as cybersecurity risks, interoperability issues, data governance concerns, and the need for active citizen engagement (Wairimu, 2025).

Recent literature reviews suggest that applying IoT in urban management has led to smarter resource distribution, reduced operational costs, faster crisis response, and improved environmental sustainability. Specifically, in sectors such as smart energy and transportation, IoT-based decision-making systems have significantly decreased energy consumption and traffic congestion (Zaman, 2024). Moreover, the integration of IoT with cloud computing plays a crucial role in enhancing urban decision-making, resource allocation, and the quality of public services (Das, 2024). While IoT promises a revolution in urban management, it also faces significant barriers such as managing a rapidly growing number of connected devices, addressing security threats, and ensuring system interoperability. For example, a 2025 study proposed a comprehensive solution for managing hundreds of IoT devices at the city scale (Sousa et al., 2025). Huzzat (2025) conducted an in-depth review of the role of digital twin technology in shaping smart cities, emphasizing its utility in providing a framework for urban analysis, simulation, and comprehensive planning. Similarly, Alvi (2025) explored the methodological landscape and innovations in infrastructure enabled by digital twins. From an academic perspective, El Agamy (2024) analyzed over 4,200 articles to examine digital twin architectures, performance metrics, and platform types in urban environments. Therias (2023) investigated how urban digital twins can serve as a foundation for enhancing resilience, particularly in times of crisis and environmental change. Additionally, a Reuters report (2024) highlighted that more than 500 cities are expected to adopt digital twin technologies by 2025, emphasizing their effectiveness in managing disasters such as flooding, air pollution, and urban heatwaves.

Zaman et al. (2024) provided a comprehensive review of IoT applications in urban management, covering fundamental architectures and prevailing standards, while also addressing key challenges and successful implementation strategies. Salih (2025) introduced a detailed framework examining the components of IoT in smart cities, highlighting implementation challenges and future research needs. In a systematic literature review, Ishaq and Farooq (2023) emphasized that technical uncertainties and concerns regarding security and privacy are particularly prominent in IoT-based smart infrastructure projects. Kumar et al. (2023) analyzed the challenges of developing and maintaining urban IoT testbeds, focusing on issues related to data security and management across endpoint, edge, and cloud layers. Dahmane (2025) reviewed data collection methods, urban issue prioritization techniques, and service performance measurement, offering a conceptual framework for methodological analysis. Finally, the UN-Habitat (2024) report highlighted key strategies, policies, and institutional capacities required for smart city development.

Table 1. Summary of Previous Research

No.	Authors & Year	Title of Study	Methodology	Key Findings	Identified Gap / Critique
1	El-Agamy et al. (2024)	A Comprehensive Review of Digital Twins in Smart Cities	Systematic review of over 4,200 articles	Identification of architectures, models, and performance metrics	Lack of localized frameworks for developing countries

No.	Authors & Year	Title of Study	Methodology	Key Findings	Identified Gap / Critique
2	Zaman et al. (2024)	IoT in Smart City Development	Literature review	Technical challenges, architectures, and implementation solutions	Limited focus on multi-criteria decision-making
3	Shen (2025)	IoT and Digital Twin Integration for Urban Sewage Infrastructure	Data-driven case study	Improved fault prediction accuracy up to 92%	No cost-benefit analysis provided
4	Waqar et al. (2025)	IoT's Role in Sustainable Urban Planning	Statistical analysis and surveys	Emphasis on sustainability and real-time monitoring	Lack of integration with other digital technologies
5	Huzzat et al. (2025)	Digital Twins in Future Smart Cities	Analytical review	Strategic role of digital twins in future urban planning	Absence of decision-making frameworks
6	Fayyaz et al. (2024)	Smart Street Design using MCDM Techniques	Hybrid: Fuzzy Delphi, ANP, DEMATEL	Prioritized model for urban street design	Focused solely on transportation context
7	Salih et al. (2025)	Challenges in IoT Implementation in Urban Infrastructure	Qualitative analysis & conceptual framework	Categorization of technical and implementation barriers	Requires further empirical investigations
8	Alvi et al. (2025)	Infrastructure Innovation via Digital Twins	Foresight-based review	Highlights data standards and open architectures	Lacks evaluation model development
9	Turek et al. (2024)	Digital Twin Applications in Urban Infrastructure	Multi-purpose case study	Enhancement of resilience and infrastructure efficiency	No cost-effectiveness evaluation
10	Kumar et al. (2023)	Urban IoT Testbed Infrastructure	Systematic literature review	Analysis of scalability constraints in technical deployment	No focus on localization strategies

A review of recent literature reveals that numerous studies have explored the role of emerging technologies such as the Internet of Things (IoT) and digital twins in urban management. For example, the works of El Agamy et al. (2024), Huzzat et al. (2025), and Zaman et al. (2024) have effectively demonstrated the conceptual and practical potentials of these technologies in enhancing the resilience, sustainability, and efficiency of urban infrastructure. Additionally, studies such as those by Fayyaz et al. (2024) and Waqar et al. (2025) have employed multi-criteria and hybrid

decision-making methods to prioritize components of smart urban development.
However, a closer examination of the reviewed studies indicates that most of them either focus exclusively on a single technology, such as IoT or digital twins or rely primarily on qualitative and descriptive analyses. Furthermore, few studies have comprehensively addressed the integration of these two technologies within a structured framework for optimal decision-making in smart infrastructure development. Despite the widespread use of multi-criteria decision-making (MCDM) approaches in urban studies, many existing models remain one-dimensional and lack real-time analytical capabilities.
This reveals a significant gap in the literature: the absence of an integrated and reliable framework for prioritizing and making informed decisions on the development of smart urban infrastructure, one that effectively combines real-time IoT data with the analytical power of digital twins. The present study seeks to address this gap by developing a practical, multi-criteria framework—based on the integration of the Fuzzy Delphi method and GRA-VIKOR—to design and evaluate a development model for smart infrastructure. This model aims to assist urban policymakers in making transparent, data-driven, and balanced infrastructure decisions.

3. Research Methodology

Research is a systematic process for generating knowledge and uncovering relationships between phenomena through the collection, analysis, and interpretation of data using scientific methods. Employing an appropriate research methodology not only enhances the accuracy of results but also facilitates the generalizability of findings. The selection of a research method must be based on the objectives of the study, the nature of the problem, the type of data involved, and the desired level of analysis, enabling the researcher to achieve practical and insightful outcomes with optimal use of resources.
This study, aimed at designing a development framework for smart urban infrastructure based on digital technologies and the Internet of Things (IoT), is classified as applied research in terms of its objective, and as descriptive-survey in terms of its execution method. In the initial stage, theoretical data related to key concepts—including smart infrastructure, IoT technologies, digital twins, and multi-criteria decision-making (MCDM) methods—was collected through library-based research, including academic articles, specialized books, and credible international reports.
To localize the proposed framework, the Fuzzy Delphi method was employed to screen and consolidate expert opinions in identifying and prioritizing the most influential criteria. This step involved the participation of experts in smart cities, municipal IT managers, and specialists in urban infrastructure. Subsequently, for analyzing and prioritizing development options, a hybrid MCDM approach was used, incorporating the GRA (Grey Relational Analysis) to determine the relative weights of criteria and the VIKOR method to rank alternatives under conditions of conflicting criteria.
This methodological integration allowed the study to both minimize uncertainty in expert judgments through Fuzzy Delphi and optimize multi-criteria decisions in environments characterized by incomplete or ambiguous data (grey systems). For enhanced analytical precision, the decision-making environment was modeled using fuzzy and grey theory approaches.
Finally, the proposed development model was formulated based on the results of the MCDM analysis, validated, and supplemented with implementation strategies. In terms of data collection, the study employed a mixed-methods approach, combining desk research with field data gathered through expert questionnaires, semi-structured interviews, and expert panel analysis.

Best-Worst Method (BWM)

The Best-Worst Method (BWM) is a recent multi-criteria decision-making (MCDM) technique proposed by Rezaei (2015), which relies on pairwise comparisons to determine the weights of alternatives and related criteria. This method addresses several limitations of traditional pairwise comparison methods such as the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) most notably issues related to inconsistency.

One of the main advantages of BWM is its ability to significantly reduce the number of required pairwise comparisons by focusing on reference-based comparisons. In this approach, decision-makers only need to specify:

- the relative preference of the best criterion over all other criteria, and
- the relative preference of all criteria over the worst criterion.

By eliminating secondary comparisons, BWM is more efficient and faster than other existing methods for determining criteria weights in MCDM problems.

Definition 1: A comparison aij is considered a reference comparison if either i is the best criterion or j is the worst criterion.

Definition 2: A comparison aij is a secondary comparison if neither i nor j is the best or worst criterion, and aij≥1.

The BWM process consists of the following steps:

Step 1: Define the Set of Decision Criteria

Based on a review of the literature and expert opinions, a set of relevant criteria is identified and denoted as:

{c1,c2,…,cn}

Step 2: Identify the Best and Worst Criteria

The decision-maker selects the best criterion (e.g., the most important or desirable) and the worst criterion (e.g., the least important or desirable). In cases where multiple criteria are considered equally best or worst, a discretionary selection may be applied.

Step 3: Determine the Preferences of the Best Criterion over Others

Using a scale ranging from 1 to 9, the preference of the best criterion over each of the other criteria is expressed, as defined by a linguistic scale (see Table 4). The resulting preference vector is used to form the equations of the BWM model, as shown in Equation (2).

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad (2)$$

In this step, each comparison value aBjrepresents the preference of the selected best criterion B over criterion j. Clearly, the self-comparison value is:

aBB=1

Step 4: Determine the Preferences of All Criteria over the Worst Criterion

Similarly, using a scale from 1 to 9, the decision-maker assesses the preference of each criterion j over the worst criterion W. These comparisons are recorded to form the Worst-to-Others vector, denoted as:

ajW,where j=1,2,…,n

Again, the consistency rule applies such that:

aWW=1

These preference vectors (Best-to-Others and Others-to-Worst) are used to formulate the following set of optimization equations to derive the optimal weights for each criterion, as will be described in Step 5.

$$A_w = (a_{1W}, a_{2W}, \dots, a_{nW})^T \tag{3}$$

Each comparison value ajW represents the preference of criterion j over the selected worst criterion W. Clearly, the self-comparison yields:
aWW=1
These two sets of pairwise comparisons, Best-to-Others (aBj) and Others-to-Worst (ajW) form the basis for constructing an optimization model aimed at calculating the optimal weights for each criterion such that the maximum absolute deviation between derived weights and input comparisons is minimized.

formulation of the optimization model (Step 5):

Table 3. Linguistic Scale for Pairwise Comparisons in BWM

Linguistic Judgment	Numerical Value
Absolutely more important	9
Extremely more important	8
Very strongly more important	7
Strongly more important	6
Moderately more important	5
Slightly more important	4
Weakly more important	3
Very weakly more important	2
Equally important	1

Step 5: Determining the Optimal Weights
The optimal weights for all criteria are represented as:
(W1∗,W2∗,…,Wn∗)
The objective is to calculate these weights in a way that minimizes the maximum absolute deviation between the computed weights and the input comparison values. Specifically, the goal is to minimize the largest discrepancy among all values from the following set:

$$\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$$

This leads to the following minimax optimization model, formulated as Equation (4):

$$\min \max_j \{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$$
$$\text{S.t.}$$
$$\sum_j w_j = 1$$
$$w_j \geq 0, \text{for all } j \tag{4}$$

Equation (4) can be transformed into the following linear programming model, presented as Equation (5):

$$\min \xi$$
$$\text{S.t.}$$

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \text{for all j}$$
$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \text{for all j}$$
$$\sum_j w_j = 1$$
$$w_j \geq 0, \text{for all j} \qquad (5)$$

By solving Model (5), the optimal weights$(w_1^*, w_2^*, \ldots, w_n^*)$^*) and ξ^* index are obtained.
The solution space of Model (5) includes all positive values of wj for j=1,…,n, such that the sum of weights must equal 1, and the maximum deviation from pairwise comparison ratios is minimized to ξ
However, in the original formulation proposed by Rezaei (2015), the model may produce multiple optimal solutions when dealing with decision problems involving more than three criteria. To address this limitation and ensure a unique solution, Rezaei (2016) proposed a revised linear model that reformulates the problem in a way that guarantees uniqueness of the weights.
The linear form of the BWM optimization model proposed in Rezaei's (2016) study is expressed as follows:
In this revised model, instead of minimizing the maximum deviation among the set:
$\left\{\left|\frac{w_B}{w_j} - a_{Bj}\right|, \left|\frac{w_j}{w_W} - a_{jw}\right|\right\}$,
the objective is to minimize the maximum absolute deviation among the alternative set:
$\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$
This formulation transforms the original nonlinear model into a linear programming problem, which ensures a unique optimal solution. Accordingly, the model is reformulated as Equation (6):

$$\min \max_j \{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$$
$$\text{S.t.}$$
$$\sum_j w_j = 1$$
$$w_j \geq 0, \text{for all j} \qquad (7)$$

Equation (7) can be further transformed into the following linear programming model, ensuring compatibility with standard optimization solvers and guaranteeing a unique solution:

$$\min \xi^L$$
$$\text{S.t.}$$
$$|w_B - a_{Bj}w_j| \leq \xi^L, \text{for all j}$$
$$|w_j - a_{jW}w_W| \leq \xi^L, \text{for all j}$$

$$\sum_{j} w_j = 1$$

$$w_j \geq 0, \text{for all } j \tag{8}$$

The above linear model yields a unique optimal solution. By solving Model (7), the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ as well as the linear consistency index ξ^{L*} are obtained.
In this formulation, the value of ξ^{L*} directly reflects the consistency of the pairwise comparisons made by the decision-maker. Therefore, there is no need to calculate a separate consistency ratio, as required in earlier versions of the model (e.g., Equation (5)).
In general, values of ξ^{L*} close to zero indicate a high level of consistency in the input judgments (Rezaei, 2016).

Introduction to the Fuzzy Integrated Approach: GRA Combined with VIKOR

In this section, the fundamental concepts of the VIKOR and GRA methods, as well as the newly developed fuzzy integrated GRA-VIKOR approach, are briefly introduced.
The VIKOR method was first introduced by Opricovic (1998) as a compromise ranking method, particularly useful in decision-making scenarios involving multiple conflicting criteria. VIKOR seeks to identify a compromise solution based on the principle of "closeness to the ideal solution and mutual consensus through aggregated scores." The method has been widely adopted by researchers for ranking alternatives in various multi-criteria decision-making (MCDM) problems.
Let us denote the alternatives as $a_1, a_2, \dots, a_m$. For each alternative ai, the performance with respect to the jth criterion is denoted by fij, where:
fij=the performance value of criterion j for alternative ai the performance value of criterion
The VIKOR ranking algorithm can be summarized in the following steps:
Step 1: Determine the Best and Worst Values
For each criterion j, determine the **best** value fj∗ and the **worst** value fj− across all alternatives.
For benefit-type criteria, the best and worst values are calculated as follows:

$$f_j^* = \max_i f_{ij}, \qquad i = 1,2,\dots,m$$

$$f_j^- = \min_i f_{ij}, \qquad i = 1,2,\dots,m \tag{8}$$

Step 2: Calculate Si and Ri for i=1,2,…,m

$$S_i = \sum_{j=1}^{n} w_j\left(f_j^* - f_{ij}\right)/(f_j^* - f_j^-)$$

$$R_i = \max\left[w_j\left(f_j^* - f_{ij}\right)/(f_j^* - f_j^-)\right] \tag{9}$$

Step 3: Calculate the Qi Values for i=1,2,…,m
In this step, the VIKOR index Qi is computed for each alternative using Equation (10):

$$Q_i = v\left[\frac{S_i - S^*}{S^- - S^*}\right] + (1 - v)\left[\frac{R_i - R^*}{R^- - R^*}\right] \quad (10)$$

Grey Relational Analysis (GRA) Technique

Grey Relational Analysis (GRA) was first introduced by Deng (1982). The grey systems theory is an algorithm designed to analyze the uncertain relationships between elements of a system and a reference sequence. It has been widely applied in multi-criteria decision-making (MCDM) problems.

A key strength of this approach lies in its ability to capture both qualitative and quantitative relationships among complex system factors. It measures the degree of similarity or closeness between alternatives using a distance-based metric (Kuo & Liang, 2011).

The following outlines the key concepts and computational procedure for the GRA model.

In an MCDM problem, let:

$X=\{x0,x1,x2,\ldots,xi,\ldots,xm\}$

denote a set of sequences (alternatives), where:

- x0 is the reference sequence,
- xi is the comparative sequence for alternative i.

Let x0j and xij represent the values of the jth criterion for the reference and comparative sequences, respectively, with $j=1,2,\ldots,n$

Then, the grey relational coefficient $\gamma(x0j,xij)$, which reflects the relationship between the reference and comparative values at criterion jj, is calculated using Equation (11):

$$\gamma(x_{0j}, x_{ij}) = \frac{\min_i \min_j \Delta_{ij} + \xi \max_i \max_j \Delta_{ij}}{\Delta_{ij} + \xi \max_i \max_j \Delta_{ij}} \quad (11)$$

where:

$\Delta ij=|x0j-xij|$

and $\xi\in[0,1]$ is the distinguishing coefficient, used to mitigate the effect of extreme values and enhance stability in the analysis. The typical value for ξ is 0.5, unless specified otherwise.

- $i\in I=\{1,2,\ldots,m\}$ denotes the set of alternatives
- $j\in J=\{1,2,\ldots,n\}$ denotes the set of **criteria**

After computing all the grey relational coefficients $\gamma(x0j,xij)$, the Grey Relational Grade (GRG), which represents the overall similarity between the reference sequence x0x_0x0 and each comparative sequence xi , is calculated using Equation (12):

$$\gamma(x_{0j}, x_{ij}) = \sum_{j=1}^{n} w_j \gamma(x_{0j}, x_{ij}), \qquad \sum_{j=1}^{n} w_j = 1 \quad (12)$$

where wj denotes the weight of the criterion or attribute j.

Fuzzy GRA-VIKOR Hybrid Method

In this section, a novel fuzzy multi-criteria decision-making (MCDM) technique is introduced to address complex decision problems under uncertainty and ambiguity. This approach is based on the integration of the VIKOR and GRA methods within a fuzzy environment, aiming to effectively

handle vague, imprecise, or linguistic data in real-world MCDM scenarios.
The proposed fuzzy GRA-VIKOR method leverages the strengths of both VIKOR (compromise ranking) and GRA (grey relational analysis) to improve decision quality in situations where precise information is lacking or judgments are subjective.
The linguistic scale used in this method for evaluating alternatives is shown in Table 4.

Table 4. Fuzzy Rating Scale

Fuzzy Number	Linguistic Term	Triangular Fuzzy Scale
9	Complete Importance	(8, 9, 10)
8	Absolute Importance	(7, 8, 9)
7	Very High Importance	(6, 7, 8)
6	Fairly High Importance	(5, 6, 7)
5	Moderate Importance	(4, 5, 6)
4	Slight Preference	(3, 4, 5)
3	Low Importance	(2, 3, 4)
2	Very Low Importance	(1, 2, 3)
1	Equal Importance	(1, 1, 1)

General Steps of the Fuzzy GRA-VIKOR Method *(Adapted from Li & Zhao, 2016)*

Step 1: Constructing the Fuzzy Decision Matrix
In this step, a pairwise fuzzy decision matrix is formed, representing the evaluation of each alternative with respect to each criterion.
Assume the decision problem involves m potential alternatives and n evaluation criteria. The performance rating of each alternative with respect to a given criterion is expressed using triangular

$$\tilde{x}_{ij} = \frac{1}{k}\left[\tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \cdots + \tilde{x}_{ij}^{k}\right] = \frac{1}{k}\sum_{k=1}^{K} \tilde{x}_{ij}^{k} \qquad (13)$$

where $\tilde{x}_{ijk}$ denotes the fuzzy rating assigned by decision-maker k for alternative i with respect to criterion j.
Accordingly, a multi-criteria decision-making (MCDM) problem for group decision-making in a fuzzy environment can be represented as follows:

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} = \left[\tilde{x}_{ij}\right]_{m\times n} \qquad (14)$$

Where x~ij, ∀i,j represents the fuzzy rating (fuzzy performance value) of the potential alternative Ai, for i=1,2,...,m with respect to the criterion Cj, for j=1,2,...,n.
To ensure consistency among the evaluation criteria, the initial fuzzy decision matrix must be converted into a comparable scale. Therefore, the normalized fuzzy decision matrix is denoted as $R^{\sim}$ (Chen, 2000).

$$\tilde{R} = [\tilde{r}_{ij}]_{m\times n}$$
$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right), \qquad j \in B$$
$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right), \qquad j \in C$$
$$u_j^+ = \max_i u_{ij} \ \text{ if } j \in B$$
$$l_j^- = \min_i l_{ij} \quad \text{if } j \in C \tag{15}$$

Where B denotes the set of benefit criteria, and C represents the set of cost criteria.
Step 2: Determining the Positive and Negative Ideal Reference Series
After calculating the normalized values of various criteria, two reference series are defined:

- The positive ideal solution A+
- The negative ideal solution A−

These are determined according to Equations (16) and (17).

$$A^+ = [\tilde{r}_{01}^+, \tilde{r}_{02}^+, \dots, \tilde{r}_{0n}^+] \tag{16}$$

$$A^- = [\tilde{r}_{01}^-, \tilde{r}_{02}^-, \dots, \tilde{r}_{0n}^-] \tag{17}$$

Where $\tilde{r}_{0j}^+ = \max_i(\tilde{r}_{ij})$, $\quad \tilde{r}_{0j}^- = \min_i(\tilde{r}_{ij})$, and j=1,2,...,n
Step 3: Calculating the Fuzzy Grey Relational Coefficient
The positive and negative ideal solutions are treated as reference series, and each alternative is considered a comparative series.
The fuzzy grey relational coefficient of each alternative with respect to the positive and negative ideal solutions is calculated based on Equations (18) and (19).

$$\gamma(\tilde{r}_{0j}^+, \tilde{r}_{ij}) = \frac{\min_i \min_j \tilde{d}_{ij}^+ + \xi \max_i \max_j \tilde{d}_{ij}^+}{\tilde{d}_{ij}^+ + \xi \max_i \max_j \tilde{d}_{ij}^+} = \frac{\min_i \min_j d(\tilde{r}_{0j}^+, \tilde{r}_{ij}) + \xi \max_i \max_j d(\tilde{r}_{0j}^+, \tilde{r}_{ij})}{d(\tilde{r}_{0j}^+, \tilde{r}_{ij}) + \xi \max_i \max_j d(\tilde{r}_{0j}^+, \tilde{r}_{ij})} \tag{18}$$

$$\gamma(\tilde{r}_{0j}^-, \tilde{r}_{ij}) = \frac{\min_i \min_j \tilde{d}_{ij}^- + \xi \max_i \max_j \tilde{d}_{ij}^-}{\tilde{d}_{ij}^- + \xi \max_i \max_j \tilde{d}_{ij}^-} = \frac{\min_i \min_j d(\tilde{r}_{ij}, \tilde{r}_{0j}^-) + \xi \max_i \max_j d(\tilde{r}_{ij}, \tilde{r}_{0j}^-)}{d(\tilde{r}_{ij}, \tilde{r}_{0j}^-) + \xi \max_i \max_j d(\tilde{r}_{ij}, \tilde{r}_{0j}^-)} \tag{19}$$

Where ξ∈[0,1] is the distinguishing coefficient.

Step 4: Calculating Si and Ri Values

The values of Si and Ri, for i=1,2,...,m, are calculated based on Equations (20) and (21).

$$S_i = \sum_{j=1}^{n} w_j \gamma\left(\tilde{r}_{0j}^{+}, \tilde{r}_{ij}\right) \tag{20}$$

$$R_i = \max_j w_j \gamma\left(\tilde{r}_{0j}^{-}, \tilde{r}_{ij}\right) \tag{21}$$

Where Si represents the distance of alternative ii from the positive ideal solution, and Ri indicates the distance of alternative i from the negative ideal solution.

Also, wj denotes the weights of the criteria, obtained through the Best-Worst Method (BWM).

Step 5: Calculating the Qi Value

The value of Qi, for i=1,2,...,m, is calculated according to Equation (22).

$$Q_i = v\left(\frac{S^* - S_i}{S^* - S^-}\right) + (1 - v)\left(\frac{R_i - R^*}{R^- - R^*}\right) \tag{22}$$

Where $S^* = \max_i S_i$ ، $S^- = \min_i S_i$ ، $R^* = \min_i R_i$ ، $R^- = \max_i R_i$.

The parameter v is introduced as the weight of the group utility strategy, while (1−v) represents the weight of the individual regret.

Step 6: Ranking Alternatives Based on Qi Values

Based on the calculated Qi values, the alternatives are ranked in ascending order, such that the alternative with the smallest Qi receives the highest (first) rank.

The alternatives are ranked according to the minimum values of Qi, under the condition that the following two criteria are simultaneously satisfied:

- Condition 1 (Acceptable Advantage):
  Alternative A1 is selected if:

Q(A2)−Q(A1)≥1/m−1

where A2 is the second-ranked alternative, and mm is the total number of alternatives.

- Condition 2 (Acceptable Stability in Decision-Making):
  Alternative A1 must also be ranked first based on either Si or Ri values.
-

4. Research Findings

In general, the research process consists of two main phases: qualitative and quantitative. The essential steps of the study are presented as follows:

Many researchers have examined the components involved in various projects across different industries. Subsequently, through expert sessions, interviews with key stakeholders, and the use of brainstorming techniques, a list of relevant factors was identified, as reported in Table 5. In total, 19 key components were identified for the development of smart urban infrastructure based on the Internet of Things (IoT) and digital technologies.

Table 5. Key Components for Smart Urban Infrastructure Development

No.	Component	Brief Description	Source
1	Sensors and Actuators	Collecting environmental data and enabling automated response	MoonTechnolabs (2025)

2	Network Connectivity	Transmitting data from sensors to systems	Digi.com (2025)
3	Edge Computing	Fast, low-latency data processing	MDPI (2025)
4	Cloud Computing	Scalable data analysis and storage	TechTarget (2025)
5	Security and Privacy	Data and system protection	Deloitte Report (2025)
6	Analytics and AI	Data-driven decision-making and forecasting	Reuters (2024)
7	Digital Twin	Urban model simulation and monitoring	Georgia Tech (2024)
8	Data Management	Data warehousing and integrated analytics	Digi.com (2025)
9	Centralized Management	Unified control of all devices	Digi.com (2025)
10	Smart Utilities	Smart electricity, water, and gas systems	Digi.com (2025)
11	Intelligent Transportation (ITS)	Traffic and road safety management	Wikipedia ITS (2025)
12	Environmental Sensors	Air quality, temperature, pollution monitoring	Digi.com (2025)
13	Parking Sensors	Parking guidance and reduced traffic	Digi.com (2025)
14	Public Surveillance	Cameras and event detection	DeviceAuthority (2025)
15	Exchange Standards	Facilitating interoperability among systems	Wikipedia TALQ & NGSI-LD (2025)
16	Open Data / Participation	Transparency and public collaboration	EcoRenewableEnergy (2025)
17	5G Communications	High-speed broadband for time-sensitive systems	MDPI (2025)
18	Urban Operations Center	Optimized urban management control	SmartCitySS (2025)
19	Resilience and Sustainability	Crisis response and climate change adaptation	Reuters (2024)

4.3. Determining the Weights of Evaluation Indicators

In the process of designing a smart urban infrastructure development model, determining the weight (relative importance) of the indicators plays a crucial role, as these weights ultimately guide the analysis and prioritization of implementation options. The selected indicators are typically diverse and multidimensional, encompassing technical, economic, social, environmental, and managerial components. Given the multi-criteria nature of decision-making in smart infrastructure contexts, traditional statistical weighting methods are insufficient to address the complexity and interdependencies among criteria. To overcome this challenge, the present study adopts a modern and structured multi-criteria decision-making (MCDM) approach.

In the first step, the fuzzy Delphi method was employed to gather expert opinions and reduce uncertainty in judgments. By leveraging fuzzy logic, this method enables the modeling of uncertainty inherent in human assessments and leads to a consensus-based extraction of indicator importance. Subsequently, the Grey Relational Analysis (GRA) method was applied to determine the final weights of the indicators. Based on numerical comparisons of indicator behavior across various scenarios, GRA calculates the degree of influence each indicator has on the entire system. The integration of the fuzzy Delphi and GRA methods offers the advantage of combining qualitative expert insights with quantitative precision, resulting in numerically derived weights for the evaluation criteria. The results of this process indicate that indicators such as "resource sustainability," "data integration and AI," "real-time monitoring," and "citizen participation" hold the highest priority. These weights were subsequently used as inputs to the VIKOR model to enable balanced final decision-making and prioritization of infrastructure development options, while accounting for conflicts among criteria.

Table 6. Most and Least Important Criteria Identified by Experts

Criterion (Indicator)	Identified as "Most Important"	Identified as "Least Important"
Feasibility	1, 5, 8	–
Implementation Cost	3, 7	6, 10
Impact on Sustainability	9	1, 4, 5
Contribution to Citizen Services	2, 10	8
Flexibility and Scalability	4, 6	–
Level of Innovation and Technology	–	2, 3, 7, 9

In the following stage, the prioritization of the best criterion relative to all other criteria is conducted. This information is derived from the distribution and collection of Best-Worst Method (BWM) questionnaires, in which the respondents (experts) were asked to determine the priority of the best criterion over the remaining ones.

It should be noted that in cases where multiple criteria were perceived as the best by an expert, the selection of the "best" criterion was entirely discretionary. Accordingly, the pairwise comparison vectors of the best criterion versus other criteria are presented in Table 9.

Table 9. Pairwise Comparison Vectors of the Best Criterion vs. Other Criteria (BWM)

Expert No.	Best Criterion	Feasibility	Implementation Cost	Impact on Sustainability	Contribution to Citizen Services	Flexibility & Scalability	Innovation & Technology
1	Feasibility	1	3	9	2	4	2
2	Implementation Cost	4	1	3	1	2	8
3	Impact on Sustainability	2	1	1	2	2	9
4	Contribution to Citizen Services	2	3	8	1	1	4
5	Flexibility & Scalability	1	2	9	3	1	2

6	Innovation & Technology	2	8	2	4	1	1

In a similar manner, the prioritization of all other criteria relative to the worst criterion is conducted. This information was also obtained through the distribution and collection of Best-Worst Method (BWM) questionnaires, in which the experts were asked to determine the priority of all other criteria with respect to the identified worst criterion.

It is important to note that in cases where more than one criterion was perceived as the worst by the experts, the selection of the "worst" criterion was made entirely at their discretion. Accordingly, the pairwise comparison vectors of other criteria versus the worst criterion are presented in Table 10.

Table 10. Pairwise Comparison Vectors of Other Criteria Relative to the Worst Criterion (Expert Judgment via BWM)

Worst Criterion	**Innovation & Technology**	**Flexibility & Scalability**	**Contribution to Citizen Services**	**Impact on Sustainability**	**Implementation Cost**	**Executability**	**Expert**
Executability	2	9	2	2	2	9	1
Implementation Cost	8	2	4	9	3	2	2
Impact on Sustainability	3	1	1	3	2	1	3
Contribution to Citizen Services	4	2	2	5	8	2	4
Flexibility & Scalability	1	4	8	2	3	3	5
Innovation & Technology	2	3	5	1	1	4	6

Ultimately, the Best-Worst Method (BWM) was employed to determine the consistency ratios of the pairwise comparisons as well as the weights of the influencing criteria. The respective criterion weights were obtained by solving the linear programming model of the BWM (Equation 7) for 10 expert respondents, using GAMS software version 24.3 and the CPLEX solver. The resulting weights represent the average values derived from the experts' judgments, consolidated into a single normalized weight vector, as presented in Table 11.

Table 11. Final Weights of Key Evaluation Criteria (Using BWM Method)

Criterion	**Expert 1**	**Expert 2**	**Expert 3**	**Expert 4**	**Expert 5**	**Expert 6**	**Expert 7**	**Expert 8**	**Expert 9**	**Expert 10**	**Final Weight**
Feasibility	0.356	0.100	0.148	0.151	0.326	0.149	0.139	0.400	0.121	0.205	**0.210**
Implementation Cost	0.138	0.175	0.352	0.137	0.137	0.043	0.353	0.146	0.106	0.038	**0.163**
Impact on Sustainability	0.046	0.125	0.102	0.048	0.042	0.191	0.145	0.121	0.394	0.128	**0.134**
Contribution to Citizen Services	0.149	0.375	0.205	0.103	0.126	0.106	0.185	0.042	0.212	0.359	**0.186**

Flexibility and Scalability	0.103	0.175	0.148	0.356	0.189	0.362	0.139	0.204	0.121	0.103	**0.190**
Innovation and Technological Level	0.207	0.050	0.045	0.205	0.179	0.149	0.040	0.088	0.045	0.167	**0.118**
ξL* (Consistency Index)	0.056	0.025	0.057	0.055	0.053	0.064	0.064	0.038	0.030	0.051	**0.049**

The value of ξL∗represents the consistency ratio for the pairwise comparisons. As shown in Table 11, the comparisons demonstrate a high level of consistency, with a value of 0.049, which is close to zero, indicating reliable judgments (Rezaei, 2016). Furthermore, the criteria "Risk Severity" and "Implementation Cost" exhibit relatively higher importance and weight compared to other indicators.

Next Step – Calculation of SiS_i, Ri, and the Compromise Indicator Qi

In this section, the distance of each alternative Ai from the positive ideal solution Si, the distance from the negative ideal solution Ri, and the compromise indicator Qi for each alternative are calculated using Equations (20) through (23).

These computations are summarized in Table 12.

It should be noted that the parameter v, which represents the weight assigned to the strategy of maximum group utility, is set to 0.5 in this study.

Table 12. Values of SiS_i, RiR_i, and QiQ_i for Each Alternative

Alternative	Si	Ri	Qi
R_1	0.539	0.185	0.744
R_2	0.499	0.138	0.618
R_3	0.574	0.131	0.341
R_4	0.472	0.173	0.895
R_5	0.542	0.151	0.550
R_6	0.531	0.139	0.520
R_7	0.551	0.119	0.347
R_8	0.486	0.135	0.647
R_9	0.604	0.102	0.088
R_{10}	0.545	0.153	0.548
R_{11}	0.613	0.125	0.182
R_{12}	0.596	0.124	0.230
R_{13}	0.596	0.100	0.100
R_{14}	0.627	0.100	0.000
R_{15}	0.543	0.125	0.410
R_{16}	0.523	0.193	0.835
R_{17}	0.593	0.152	0.393
R_{18}	0.517	0.130	0.518
R_{19}	0.607	0.132	0.237

Final Step – Ranking the Alternatives Based on Si, Ri, and Qi Values

According to the Fuzzy GRA-VIKOR methodology, alternatives are ranked based on the values of Si (group utility), Ri (individual regret), and the composite Qi index. The alternative with the lowest values across all three indicators is considered the top-ranked option.

As illustrated in the results, Alternative R_{14} achieves Rank 1, as it demonstrates the lowest Q value (Q = 0.000) and simultaneously satisfies both of the acceptability conditions of the Fuzzy GRA-VIKOR method:

1. Acceptable Advantage Condition:

Q(R9)−Q(R14)=0.088−0.000=0.088≥1m−1=118≈0.055

2. Acceptable Stability in Decision-Making:

   R14 also ranks first in terms of the R index (individual regret), confirming the stability of the ranking result.

Hence, R_{14} is a unique optimal solution, offering the most balanced and desirable option under the given decision criteria and uncertainty environment.

These results are summarized in Table 17, which presents the final ranking of all alternatives.

Table 17. Final Ranking of Alternatives Based on S, R, and Q Values

Ris	S	S Rank	R	R Rank	Q	Q Rank
R_1	0.539	7	0.185	18	0.744	17
R_2	0.499	3	0.138	12	0.618	15
R_3	0.574	12	0.131	9	0.341	7
R_4	0.472	1	0.173	17	0.895	19
R_5	0.542	8	0.151	14	0.550	14
R_6	0.531	6	0.139	13	0.520	12
R_7	0.551	11	0.119	4	0.347	8
R_8	0.486	2	0.135	11	0.647	16
R_9	0.604	16	0.102	3	0.088	2
R_{10}	0.545	10	0.153	16	0.548	13
R_{11}	0.613	18	0.125	6	0.182	4
R_{12}	0.596	15	0.124	5	0.230	5
R_{13}	0.596	14	0.100	2	0.100	3
R_{14}	**0.627**	**19**	**0.100**	**1**	**0.000**	**1**
R_{15}	0.543	9	0.125	7	0.410	10
R_{16}	0.523	5	0.193	19	0.835	18
R_{17}	0.593	13	0.152	15	0.393	9
R_{18}	0.517	4	0.130	8	0.518	11
R_{19}	0.607	17	0.132	10	0.237	6

4.4. Analysis of VIKOR Model Results

The results derived from the VIKOR decision-making model reveal that component R_{14} ranks first, with a Q value of 0.000, and is identified as the most balanced and optimal alternative across all evaluation criteria. Despite holding the lowest rank in the S index (with the highest value S =

0.627), it secures the top rank in both the R and Q indices. This outcome indicates that while R_{14} may not have the closest overall distance (S) to the ideal solution, it demonstrates exceptional performance in terms of maximum individual regret (R) and in the final compromise solution index (Q). This suggests that R_{14} achieves a well-balanced and stable performance across all criteria without relying heavily on any specific strength, an indicator of robustness and decision-making consistency.

Furthermore, components R_9 *(Q = 0.088)* and R_{13} *(Q = 0.100)* are ranked second and third, respectively. Notably, these components also perform very well in the R index, ranking second and third. This illustrates that these alternatives not only score high on average across all criteria but also maintain resilience under the worst-case conditions, making them reliable choices.

In contrast, components such as R_4 and R_1, despite achieving favorable ranks in the S index (1st and 7th, respectively), rank very low in the final Q ranking (19th and 17th), primarily due to high R values. This reveals that over-reliance on average performance (S) without considering the maximum deviation (R) can result in unstable or misleading decisions.

Components such as R_3, R_{12}, and R_{17}, which appear in the middle range of the ranking (7th to 11th), reflect moderate, yet not outstanding performance, lacking distinctive competitive advantages.

Additionally, alternatives R_4, R_{16}, and R_1 are ranked at the bottom of the Q index, indicating significant imbalance across evaluation criteria. Specifically, R_4 while ranking first in the S index—holds the lowest overall Q ranking (19th), exemplifying a clear trade-off imbalance in decision-making. This contrast reinforces the strength of the VIKOR method, which, by accounting for both group utility and individual regret, and emphasizing compromise solutions, provides a more balanced and comprehensive ranking approach compared to other MCDM techniques.

5. Discussion and Conclusion

The findings of this study highlight that the development of smart urban infrastructure requires a multidimensional and integrative perspective, one that simultaneously addresses technical, economic, social, environmental, and managerial aspects. By utilizing technologies such as the Internet of Things (IoT), Digital Twin, real-time data analytics, and intelligent algorithms, not only can the quality of urban services be enhanced, but the effectiveness of urban planning can also be significantly improved.

The results from the weighting of evaluation criteria and ranking of components revealed that some elements, such as real-time data management, security and privacy, resource sustainability, and urban operations centers carry greater importance and should be prioritized in strategic planning.

Moreover, the VIKOR analysis, as a multi-criteria decision-making method, demonstrated that balancing between evaluation criteria plays a critical role in identifying the optimal alternative. While some components performed well in isolation (based on S or R indices), they did not rank highly in the final Q index due to a lack of overall balance. This underscores the necessity of employing hybrid approaches like GRA-VIKOR, which can distinguish between average performance and critical deviation, providing a more precise and holistic evaluation.

The use of the Fuzzy Delphi Method during the criteria extraction phase also contributed significantly by reducing ambiguity in expert judgments and thereby increasing the overall accuracy of the analysis.

A comparison of this study's findings with the existing literature reveals that the research has addressed a notable scientific gap particularly by operationalizing the integration of IoT and

Digital Twin technologies within a structured decision-making framework. Whereas prior studies have often focused solely on conceptual analyses or isolated applications of these technologies, the proposed model in this study offers a unified approach for data aggregation, real-time analysis, and intelligent decision-making. This is especially beneficial in crisis situations, environmental changes, or rapid urban expansion, where it can offer a competitive advantage for urban authorities and policymakers.

From a practical perspective, the outcomes of this research can serve as a strategic foundation for the development of policies and action plans by municipalities, urban planning agencies, and technology firms. Based on the derived rankings, decision-makers can allocate financial and technical resources according to well-defined priorities while minimizing risks related to uncertainty and system misalignment. Finally, the proposed framework is designed with scalability and adaptability in mind, making it suitable for various urban contexts and capable of being deployed in both pilot programs and large-scale smart city initiatives.

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