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Strategic classification of smart city strategies in developing countries

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ABSTRACT

Smart cities represent the forefront of combining technological innovation with urban management to enhance the quality of life and sustainability of urban environments. While existing studies have focused on individual smart city evaluations, there is a notable gap in systematic classification approaches that can handle uncertain and incomplete data in developing countries. As urban populations continue to grow, the strategic integration of smart technologies in city planning and management becomes crucial, necessitating more sophisticated evaluation methodologies. These technologies offer promising solutions to urban challenges by improving efficiency, economic growth, and citizen engagement. This research addresses this gap by proposing a novel framework that combines Interval Valued Neutrosophic Sets (IVNS) with the EDAS Method, specifically designed to handle the complexities and uncertainties inherent in developing country contexts.

The study extensively reviews existing literature and methodologies applied in similar contexts, identifying key limitations in current approaches and building a robust framework that incorporates both new and established criteria. Through the systematic application of IVNS-EDAS methodology across multiple urban environments, this study develops a comprehensive classification system that accounts for both quantitative metrics and qualitative assessments of smart city capabilities. The results showcase a dynamic classification framework that effectively handles data uncertainty while providing clear, actionable insights for urban planners and policymakers. The paper concludes by validating the effectiveness of the proposed approach through a detailed computational study involving diverse stakeholders, confirming its applicability and utility in refining smart city strategies globally, particularly in developing country contexts where data reliability and completeness may be challenging.

The study provides specific policy guidelines for each city classification, offering policymakers a structured framework for resource allocation and strategic planning, ranging from foundational infrastructure development in emerging cities to advanced technology integration in metropolitan areas.

1. Introduction

The ever-increasing population in cities makes it difficult to use limited resources effectively and efficiently. Since this leads to the failure to achieve the desired performance results in the services provided by local governments, local governments of cities are looking for new solutions in order not to cause disruptions in the sustainable service approach in urban life.

With the technological possibilities that have developed more rapidly in recent years, concepts such as artificial intelligence (AI) and big data (BD) have started to be used in different fields. IoT-based systems can quickly offer solutions for the effective and efficient use of resources with scientific methods and AI applications of BD created by instant data collected with IoT-based systems. With the implementation of this flexibility offered by technological developments in urban services, the services offered to cities have also started to improve. This situation has paved the way for the formation and development of the "Smart City" phenomenon.

When the definitions of smart cities are examined, Dameri and Benevolo [6] define smart cities as a new but emerging phenomenon that aims to improve existing living conditions in large cities by involving citizens in city management, and to increase the attractiveness of the city through sustainable economic development with advanced technology information and communication facilities [6]. T.R. Ministry

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of Environment and Urbanization [21] defines smart cities as Cities that are made more habitable and sustainable through collaborative efforts among stakeholders, leveraging cutting-edge technologies and inventive methods, offering rationale grounded in data and expertise, and generating solutions that enhance our lives by anticipating upcoming challenges and requirements (Urbanization, 2019). Smart cities enable more efficient and flexible provision of services in the city by using information technologies[15]. Table 1

As the policies for smart cities and the social gains obtained due to new technologies increase, smart city applications are also increasing. While the number of new cities defining themselves as smart is increasing, existing smart cities are renewing themselves[5]. However, since each of the cities that want to start this transformation by adopting smart city policies has different characteristics and priorities, each city needs to advance its work with different approaches. Making this requirement specific to each city creates the problem of non-standardization. For this reason, cities that adopt smart city policies should be classified according to certain criteria and smart city development strategies should be made in line with these classes. In this context, when past academic studies are examined, it is seen that evaluation and classification studies have been carried out by taking different criteria into account with different approaches.

1.1. Smart city rankings and evaluations literature

Anand et al [3] worked on the creation of sustainable indicators with fuzzy and fuzzy AHP in smart cities to be designed in developing countries [3]. Picioroaga et al (2018), using z-transformation and Analytic Hierarchy Process methods, developed a method that can be used in the evaluation of smart cities by considering energy and environmental issues (Picioroag et al., 2018). Kumar et al [12] developed an approach that evaluates the suitability of N cities for the smart city mission using the fuzzy MICMAC method [12]. Escolar et al [7] proposed a methodology for ranking the existing smart martyrs based on Multiple Attribute Decision Making to measure the degree of realization of the smart city concept and tested the methodology on the cities of New York, Seoul and Santander [7]. Zapolskyte et al (2020) developed a method that takes into account 5 criteria with the AHP method to evaluate the smartness of mobility activities within the city[27]. Ozkaya and Erdin [17] proposed an evaluation approach with ANP and TOPSIS methods for weighting and evaluating the criteria of sustainable smart cities. 44 cities were evaluated with this method and recommendations were developed for decision makers [17]. Villessuzanne et al (2021) conducted studies to create three different clusters for 40 different cities in Europe in order to develop their dynamic capabilities for smart city strategies. In the first cluster, developing cities are grouped, in the second cluster, metropolitan cities that have made some progress in smart city applications, and in the last cluster, cities with medium quality of life in the city are grouped (Villessuzanne et al., 2021). Mokarrari and Torabi (2021) created a smart city evaluation framework using six different CRM methods, taking into account subjective and objective criteria, and tested this method on 5 major cities in Iran (Mokarrari and Torabi, 2021). Hajduk and Lelonek (2021) presented an approach to measure the energy performance of smart cities with the TOPSIS method, which is one of the CRM methods[10]. Hajduk [9] evaluated and ranked 66 cities in Poland with TOPSIS method within the scope of smart city concept [9]. Sotirelis et al (2021) developed an approach that can analyze the PROMETHEE II method by considering 52 indicators for the evaluation and ranking of smart cities and analyzed 17 cities around the world with this approach (Sotirelis et al., 2021). Wu and Chen [24] created a three-stage approach to create a portfolio by selecting smart city projects by taking into account the needs of citizens in smart cities [24]. Adali et al [1] proposed a method that can measure the performance of 17 European cities with the EDAS-G method by using Level Based Weight Assessment (LBWA) and Distance from Average Solution (EDAS) methods together to compare smart cities [1]. Ye et al [26]

Table 1
Criteria included in the study and their references.

Code	Criteria	Sub-Criteria	Covered by
A1	**Smart City**	Smart city awareness	This Paper
B1	**Society**	Society	[3,19]
B2		Population	[16,19,20]
B3		Population Growth Rate	This Paper
B4		Governance	[4,7,8,11,12,16,17,19,26],
B5		Net Migration	This Paper
B6		Public safety	[1,11,16,17,19]
C1	**Life Quality**	Life satisfaction	This Paper
C2		life cost	[1,7,12,19,22,23]
C3		Socioeconomic development	This Paper
C4		Life expectancy	
C5		Medical and health services	[4,8,9,11,16,17,19,20]
C6		Number of Applications per Physician	This Paper
D1	**Infrastructure**	infrastructure	[12,16,17,19,20,23]
D2		Fiber-Optic Cable Length	[20]
D3		Number of fiber internet subscribers	[20]
D4		Internet access	[4,16,19]
D5		Number of Mobile Phone Subscribers	This Paper
E2	**Mobility**	Mobility	[1,3,7,19]
E3		Traffic congestion	[4,11,16,22]
E4		Public transport	[1,4,11,16,17,19,22,23]
E5		Renewable Energy buses	[26,27]
E6		Number of motor vehicles	[9,20]
E7		Number of traffic accidents	[9,20]
E8		Mobility Mobil app	[16,19]
E9		Bicycle paths	This Paper
E10		Highways Length (km)	This Paper
F1	**Activities**	Cultural activities	[1,16,17,19]
F2		Number of Official Tourism Facilities	[1,20]
F3		Number of visitors to museums and ruins affiliated	[4,20]
G1	**Opportunies (Work & School)**	job opportunities	[1,4,8,11,16,19,22]
G2		Employment rate	[9,16,19,20,22]
G3		Education and learning opportunities	[4,8,9,11,16,17,19,20,22]
G4		Open Data	[19]
H1	**Smart Economy**	Gross national product	[9,11,19,22]
H2		Businesses	[1,11,16,19,23]
H3		Capital resources	[4,12]
H4		Economy	[3,7]
H5		information and communication technologies investment / company	[1,16,22,26]
H6		Number of venture	[9,16,17,20,22]
H7		E-commerce copmanies	[16]
J1	**Smart Environment**	Ecology and natural environment	[1,7,12,18]
J2		Air quality	[1,11,16,18,22,23]
J3		Noise pollution	[18,19]
J4		Light pollution	[19]
J5		Energy Consumption	[3,10,16–20]
J6		Renewable Energy Production	[10,16,18,22,27]
J7		Green spaces	[9,11,16,19,20,22,23]
J8		Water treatment	[19,22]
J9		Waste and Recycling	[9,11,16,19,20,22]

proposed a methodology using the Shannon Entropy Weighting Method, which is one of the multi-criteria decision-making methods, taking into account the criteria of digital infrastructure, smart living and digital economy within the scope of creating a smart city index. They tested their methodology using data from 9 cities [26]. Taş and Alptekin (2023) proposed a two-stage CRM approach for measuring smart city performance and focusing investments in developing countries. They used this approach in the evaluation of 30 different municipalities in Turkey (Taş and Alptekin, 2023). Baki [4] proposed a new approach for the evaluation of smart cities using CRITIC and CODAS in an integrated manner. With this method, 32 smart megacities were evaluated [4]. Ünal and Alptekin [22] developed a new approach for the evaluation of smart cities with the TOPSIS method using objective data. With this method, 48 smart cities were evaluated [22]. Gelmez and Özceylan [8] conducted the evaluation of 118 different cities in the globally accepted Smart City Index 2021 with the focus on health and safety, mobility, activities, opportunities (work and school) and governance with the COPRAS and ARAS method [8]. The current report of the Smart City Index was last published in 2023 without changing the evaluation criteria and the evaluations were updated [11].

1.2. Smart city rankings and evaluations

Smart city rankings and evaluations are comprehensive assessments that aim to measure how cities utilize technology, infrastructure, and policies to enhance the quality of life of their residents and promote sustainable urban development. These evaluations often encompass a wide array of criteria, each contributing to the overall effectiveness and efficiency of a city's smart initiatives. Criteria such as Smart City Awareness (A1), Society (B1), Population Growth Rate (B3), and Net Migration (B5), covered in this paper, reflect the city's readiness and public engagement towards smart initiatives. Governance (B4) and Public Safety (B6), sourced from multiple studies, highlight the administrative capacity and safety measures integral to maintaining and scaling smart city operations.

Further, life quality indicators like Life Satisfaction (C1), Socioeconomic Development (C3), and Health Services (C5) directly impact resident well-being and are essential for determining a city's livability. Infrastructure criteria including the breadth of Internet Access (D4) and the extent of Mobile Phone Subscribers (D5) gauge the technological framework supporting smart city functionalities. Mobility metrics such as Traffic Congestion (E3) and Public Transport (E4) evaluate the efficiency of transportation systems, which are vital for the environmental and operational efficiency of urban centers.

Additionally, the scope of Activities (F1) and Opportunities for Work and School (G1) provide insights into the cultural and educational aspects of city life, which are critical for attracting and retaining a skilled workforce. In the economic domain, factors such as the Gross National Product (H1), Business Ecosystem (H2), and Investments in Information and Communication Technologies (H5) offer a snapshot of the city's economic health and its capacity for sustaining growth.

Lastly, the Environmental segment, covering criteria like Air Quality (J2), Energy Consumption (J5), and Waste and Recycling (J9), underscores the importance of environmental sustainability in the smart city context. These criteria not only reflect the current status of a city's smart environment but also its potential for improvement and innovation.

Each of these criteria, documented across various referenced studies and this paper, together provide a holistic view of a city's smart city status. The collective analysis of these elements is crucial for understanding the multidimensional nature of smart cities and for guiding future urban development in a manner that is both sustainable and technologically advanced.

Our study's criteria align significantly with the Smart City Index 2024, while introducing additional dimensions particularly relevant for developing countries. The Smart City Index 2024 primarily focuses on health and safety, mobility, activities, opportunities, and governance – all of which are incorporated in our framework through criteria such as Health Services (C5), Traffic Congestion (E3), Activities (F1), and Governance (B4). However, our methodology extends beyond these standard metrics by including criteria specifically crucial for developing contexts, such as Smart City Awareness (A1), Population Growth Rate (B3), and Net Migration (B5). This expanded framework allows for a more comprehensive evaluation of cities in transitional stages of smart development. Additionally, while the Smart City Index 2024 relies heavily on concrete data points, our IVNS-EDAS methodology's ability to handle uncertainty makes it particularly valuable for regions where data may be incomplete or inconsistent. This adaptation makes our classification system more applicable to the realities of developing urban environments while maintaining alignment with globally recognized smart city evaluation standards.

1.3. Neutrosophic sets

As urban centers grow more complex and interconnected, the decision-making processes governing them require increasingly sophisticated mathematical models capable of handling ambiguity, uncertainty, and incomplete information. Traditional binary logic, with its clear-cut true or false dichotomies, is often inadequate for addressing the nuanced and multifaceted challenges of urban development. This has prompted urban planners and policymakers to explore more advanced decision-making frameworks that can better accommodate the complexity of urban systems.

Among these, multi-criteria decision-making (MCDM) methods have emerged as pivotal tools. MCDM encompasses a variety of techniques designed to handle complex decision processes where multiple conflicting criteria must be considered simultaneously. Techniques such as the Analytic Hierarchy Process (AHP) and Fuzzy Logic Systems extend beyond conventional decision-making models by allowing for more nuanced assessments that reflect the realities of urban planning. AHP, for instance, helps in decomposing decision problems into a hierarchy of more easily comprehended sub-problems, each of which can be analyzed independently before the results are consolidated into a global perspective. This is particularly useful in urban planning, where decisions often involve evaluating trade-offs between economic, environmental, and social factors.

Fuzzy logic provides another layer of complexity, offering a way to mathematically represent uncertainty and imprecision. This approach is invaluable in urban planning, where precise data may be unavailable or variable over time. Fuzzy systems convert qualitative aspects of human thought and natural language into quantitative analysis, bridging the gap between numerical data and human-like decision-making.

Introduced by Florentin Smarandache in the 1990 s, Neutrosophic Sets (NS) are a sophisticated mathematical tool developed to tackle the challenges of uncertainties, imprecisions, and incomplete knowledge—areas where traditional binary and fuzzy logic systems fall short. Neutrosophic Sets enhance the framework of fuzzy systems by incorporating three degrees of truth: truth, indeterminacy, and falsehood. This tripartite division makes NS especially effective in scenarios characterized by incomplete, inconsistent, or vague information that cannot be precisely quantified by traditional or fuzzy systems.

In the realm of smart city evaluations and planning, where data often stems from qualitative expert opinions rather than quantitative sensor readings, the application of Neutrosophic Sets proves particularly valuable. Urban environments are inherently complex, with many variables and outcomes that are not easily quantifiable. The flexibility of Neutrosophic Sets allows urban planners to navigate this complexity by providing a methodological framework that can accommodate the ambiguity and fluidity of urban data. This adaptability is crucial for developing accurate and effective smart city strategies that must operate efficiently under varying degrees of uncertainty and incomplete knowledge.

Neutrosophic sets are characterized by three membership degrees:

- Truth Membership (T): The degree to which an element belongs to a set.
- Indeterminacy Membership (I): The degree to which it is indeterminate whether an element belongs to a set.
- Falsity Membership (F): The degree to which an element does not belong to a set.

Each membership degree is independently mapped in the interval [0,1], allowing for a more nuanced representation of real-world phenomena. The flexibility to have values greater than 0 for all three memberships simultaneously makes neutrosophic sets particularly suited to scenarios where information is contradictory or incomplete.

Neutrosophic sets have found applications across various fields, from decision-making and engineering to computer science and AI. In urban planning and smart cities, these sets help model and analyze complex systems where data may be uncertain or conflicting. These methodologies are particularly well-suited for addressing the intricate and often ambiguous data scenarios typical in urban environments, where traditional binary logic systems may not provide sufficient depth or flexibility.

By leveraging these sophisticated mathematical frameworks, urban planners can more effectively synthesize and analyze the vast arrays of data required for smart city initiatives. These tools facilitate a deeper understanding of complex urban dynamics and enhance the decision-making processes that underpin the development of sustainable, efficient, and responsive urban environments.

1.4. Research Design

In the context of smart city development and classification in developing countries, this research aims to answer several key questions:

- How should smart cities be quantitatively assessed and categorized when such of the data requires is uncertain and incomplete as often represented in developing countries?
- What are the best metrics to evaluate city readiness and capacity to implement smart city solutions in developing country contexts?
- How can a smart city classification system best take account of multiple stakeholder perspectives?

To answer these research questions, this study aimed to achieve the followings:

- To create a broad assessment framework capable of integrating the uncertainty and uncertainty existing in smart city evaluation by using interval valued neutrosophic sets (IVNS) and EDAS method.
- To determine and justify the most important criteria for resolving smart city classification in the context of developing countries, by using existing as well as new metrics and comparison measures.
- To develop a systematic classification method that can assist policymakers and urban planners in designing focused smart city policies according to the differentiated attributes and availabilities among different cities.
- To test the methodology with a case study of Turkiye's 81 cities to assess its application relevance and real-world feasibility.

This research contributes to the existing literature by addressing the gap in systematic smart city classification methodologies, particularly in developing country contexts where traditional evaluation methods may be insufficient due to data uncertainty and incompleteness. The proposed IVNS-EDAS methodology offers a novel approach to handling these challenges while providing practical guidance for smart city development strategies.

2. Methodology

2.1. Preliminaries for Neutrosophic sets

Definition 1. *$xj = \langle [T_j^L.T_j^U].[I_j^L.I_j^U].[F_j^L.F_j^U] \rangle$ denotes a set of interval-valued neutrosophic numbers (IVNN) associated with a particular decision-maker, indexed by 'j' ($j = 1, 2, \dots n$). Equation (1). aggregates the interval-valued neutrosophic values assigned by the decision makers and computes the weighted average interval-valued neutrosophic numbers.*

$(x_1.x_2.\cdots.x_n) = \sum_{k=1}^{n} y_k x_j.$
Where

$$\langle \left[1-\prod_{k=1}^{n}\left(1-T_j^L\right)^{y_k}.1-\prod_{k=1}^{n}\left(1-T_j^U\right)^{y_k}\right]\left[\prod_{k=1}^{n}\left(I_j^L\right)^{y_k}.\prod_{k=1}^{n}\left(I_j^U\right)^{y_k}\right].\left[\prod_{k=1}^{n}\left(F_j^L\right)^{y_k}.\prod_{k=1}^{n}\left(F_j^U\right)^{y_k}\right]\rangle \tag{1}$$

and y_k shows the degree of importance (weights) of decision makers.

Definition 2. *Eq. (2) defines the mathematical expression used to rank alternatives.*

$$K(x) = \frac{\left(T_x^L*\left(2-I_x^L-I_x^U\right)\right)+\left(T_x^U*\left(2-I_x^L-I_x^U\right)\right)+\left(1-F_x^L\right)*\left(2-I_x^L-I_x^U\right)+\left(1-F_x^U\right)*\left(2-I_x^L-I_x^U\right)}{8} \tag{2}$$

$$x = \langle [T_x^L.T_x^U].[I_x^L.I_x^U].[F_x^L.F_x^U] \rangle$$

Definition 3. *X represents a universe of discourse with three membership functions which are a truth membership function $T_N(x)$, an indeterminacy membership function $I_N(x)$ and a falsity membership function $F_N(x)$.*

$T_N = \left[T_{N(x)}^L.T_{N(x)}^U \subseteq [0.1]\right].\mathrm{I_N(x)} = \left[\mathrm{I}_{N(x)}^L.\mathrm{I}_{N(x)}^U \subseteq [0.1]\right].$ and $.F_N(x) = \left[F_{N(x)}^L.F_{N(x)}^U \subseteq [0.1]\right]$

The sum of the membership functions for truth, indeterminacy and falsity should be between 0 and $3.0 \leq T_{N(x)}^L + I_{N(X)}^L + F_{N(x)}^L \leq 3$.

The IVNS should be defined as:

$$N = \{\langle x.[T^L_{N(x)}.T^U_{N(x)}].[I^L_{N(x)}.I^U_{N(x)}].[F^L_{N(x)}.F^U_{N(x)}]\rangle | x \in X\} \quad (3)$$

IVNS can be represented as equation (3). However, due to the complex notation structure, it will be used as follows. $[T^L_N.T^U_N].[I^L_N.I^U_N].[F^L_N.F^U_N]$.

$a = [T^L_a.T^U_a].[I^L_a.I^U_a].[F^L_a.F^U_a]$ and $b = [T^L_b.T^U_b].[I^L_b.I^U_b].[F^L_b.F^U_b]$ denotes the two IVNN and mathematical operations using these a and b are shown below:

$a^c = \langle [T^L_a.T^U_a].[1 - I^L_a.1 - I^U_a].[F^L_a.F^U_a]\rangle$

$a \subseteq b$ if and only if $a \subseteq b$ and only if $T^L_a \le T^L_b.T^U_a \le T^U_b; I^L_a \ge I^L_b.I^U_a \ge I^U_b; F^L_a \ge F^L_b.F^U_a \ge F^U_b$

$a = b$ if and only if $a \subseteq b$ and $b \subseteq a$.

$a \oplus b = \langle [T^L_a + T^L_b - T^L_a T^L_b.T^U_a + T^U_b - T^U_a T^U_b].[I^L_a I^L_b.I^U_a I^U_b].[F^L_a F^L_b.F^U_a F^U_b]\rangle$

$a \otimes b = \langle [T^L_a T^L_b.T^U_a T^U_b].[I^L_a + I^L_b - I^L_a I^L_b.I^U_a + I^U_b - I^U_a I^U_b].[F^L_a + F^L_b - F^L_a F^L_b.F^U_a + F^U_b - F^U_a F^U_b]\rangle$

Definition 5. *Eq. (4) is used to subtract two interval-valued neutrosophic sets.*

$$x \ominus y = \langle \left[T^L_x - T^U_y.T^U_x - T^L_y\right].\left[Max\left(I^L_x.I^L_y\right).Max\left(I^U_x.I^U_y\right).\right]\left[F^L_x.F^U_y.F^U_x - F^L_y\right]\rangle \quad (4)$$

$$x = \langle [T^L_x.T^U_x].[I^L_x.I^U_x][F^L_x.F^U_x]\rangle and y = \langle \left[T^L_y.T^U_y\right].\left[I^L_y.I^U_y\right]\left[F^L_y.F^U_y\right]\rangle$$

Definition 6. *$A = \langle [T^L.T^U].[I^L.I^U].[F^L.F^U]\rangle$ is the IVNN and Eq. (5) is used for the computation of the deneutrosophicated value (x):*

$$K(A) = \frac{T^L + T^U + 2 - F^L - F^U + T^L * T^U + \sqrt{(1-F^L)*(1-F^U)}}{6} * \left[\left(1 - \frac{I^L + I^U}{2}\right) - (\sqrt{I^L * I^U}\right] \quad (5)$$

2.2. Interval valued Neutrosophic EDAS method

This section shows the steps of the interval-valued neutrosophic EDAS method. After applying these steps, the ranking of alternatives can be found.

Step 1: Each expert j evaluates each alternative in linguistic terms according to each decision criterion. For each expert, a decision IVN creates a decision matrix. The columns of the matrix contain the alternatives (n), the rows contain the criteria (m) and the cells are assigned linguistic terms. The nine linguistic terms and the IVNN corresponding to the linguistic terms are shown in Table 2. The IVN decision matrix D_j, is converted into IVN numbers (Table 3).

Step 2: In this step, all decision matrices are combined to produce the average decision matrix. The average decision matrix is shown in Table 4.

Step 3: In this step, decision makers assign the linguistic terms of the weights for each criterion using the IVN criteria weights. After the IVN weight matrices are created, these linguistic terms are converted into IVN numbers. The linguistic terms to be used and the corresponding IVN values are shown in Table 5.

Step 4: The IVN values assigned by the decision makers for the weight are aggregated with the arithmetic mean operator to access the average criterion weight matrix. The resulting average criteria weight matrix is shown in Table 6.

Step 5: Positive and negative distances from the mean (PDA and NDA) are determined according to the cost and profit criteria.

$$PDA = [pda_{mn}]_{m*n} \quad (7)$$

$$NDA = [nda_{mn}]_{m*n} \quad (8)$$

PDA represents the positive distance of criterion m of alternative n from the average solution, while NDA represents the negative distance of criterion m of alternative n from the average solution. The equation by which the distance to the mean solution is calculated depends on whether the criterion is a benefit or a cost. If the criterion is benefit, the first equation in Equation (9) should be used to access the positive distances from the mean solution. Otherwise, the second equation in Equation 19 should be used. Eq. (10) should be used for negative

Table 2
IVN Decision Matrix Scales.

Linguistic Terms		$\langle T.I.F\rangle$
CL	Certainly Low	⟨[0.15. 0.25]. [0.15. 0.25]. [0.85. 0.95]⟩
VL	Very Low	⟨[0.25. 0.35]. [0.35. 0.45]. [0.75. 0.85]⟩
L	Low	⟨[0.35. 0.45]. [0.45. 0.55]. [0.65. 0.75]⟩
BA	Below Average	⟨[0.45. 0.55]. [0.55. 0.65]. [0.55. 0.65]⟩
A	Average	⟨[0.55. 0.60]. [0.65. 0.75]. [0.45. 0.55]⟩
AA	Above Average	⟨[0.55. 0.65]. [0.55. 0.65]. [0.45. 0.55]⟩
H	High	⟨[0.65. 0.75]. [0.45. 0.55]. [0.35. 0.45]⟩
VH	Very High	⟨[0.75. 0.85]. [0.25. 0.35]. [0.25. 0.35]⟩
CH	Certainly High	⟨[0.85. 0.95]. [0.15. 0.25]. [0.15. 0.25]⟩

Table 3
IVN decision matrix as per DM's.

Criterion	Type	AL1	…	ALN
C1	Cost	$\langle[T^L_j.T^U_j].[I^L_j.I^U_j].[F^L_j.F^U_j]\rangle$	…	$\langle[T^L_j.T^U_j].[I^L_j.I^U_j].[F^L_j.F^U_j]\rangle$
C2	Cost	$\langle[T^L_j.T^U_j].[I^L_j.I^U_j].[F^L_j.F^U_j]\rangle$	…	$\langle[T^L_j.T^U_j].[I^L_j.I^U_j].[F^L_j.F^U_j]\rangle$
⋮	⋮	⋮	⋮	⋮
Cm	Benefit	$\langle[T^L_j.T^U_j].[I^L_j.I^U_j].[F^L_j.F^U_j]\rangle$	…	$\langle[T^L_j.T^U_j].[I^L_j.I^U_j].[F^L_j.F^U_j]\rangle$

Table 4
IVN Decision Matrix (Aggregated).

Criterion	Type	AL1	…	ALN
C1	Cost	$\langle[T^L_A.T^U_A].[I^L_A.I^U_A].[F^L_A.F^U_A]\rangle$	…	$\langle[T^L_A.T^U_A].[I^L_A.I^U_A].[F^L_A.F^U_A]\rangle$
C2	Cost	$\langle[T^L_A.T^U_A].[I^L_A.I^U_A].[F^L_A.F^U_A]\rangle$	…	$\langle[T^L_A.T^U_A].[I^L_A.I^U_A].[F^L_A.F^U_A]\rangle$
⋮	⋮	⋮	⋮	⋮
Cm	Benefit	$\langle[T^L_A.T^U_A].[I^L_A.I^U_A].[F^L_A.F^U_A]\rangle$	…	$\langle[T^L_A.T^U_A].[I^L_A.I^U_A].[F^L_A.F^U_A]\rangle$

Table 5
Criteria Weighing Scales.

Linguistic Terms		$\langle T.I.F\rangle$
CLI	Certainly Low Importance	⟨[0.08. 0.24]. [0.69. 0.80]. [0.85. 1.00]⟩
VLI	Very Low Importance	⟨[0.24. 0.35]. [0.58. 0.69]. [0.4. 0.85]⟩
LI	Low Importance	⟨[0.35. 0.46]. [0.46. 0.58]. [0.63. 0.74]⟩
BAI	Below Average Importance	⟨[0.46. 0.58]. [0.35. 0.46]. [0.52. 0.63]⟩
AI	Average Importance	⟨[0.52. 0.58]. [0.13. 0.24]. [0.46. 0.52]⟩
AA	Above Average Importance	⟨[0.52. 0.63]. [0.35. 0.46]. [0.46. 0.58]⟩
HI	High Importance	⟨[0.63. 0.74]. [0.46. 0.58]. [0.35. 0.46]⟩
VHI	Very High Importance	⟨[0.74. 0.85]. [0.58. 0.69]. [0.24. 0.35]⟩
CHI	Certainly High Importance	⟨[0.85. 1.00]. [0.69. 0.80]. [0.08. 0.24]⟩

Table 6
Average criteria weights for scores.

Linguistic Terms		$\langle T.I.F\rangle$
C1	Linguistic cost	$\langle[T^L_{AV}.T^U_{AV}].[I^L_{AV}.I^U_{AV}].[F^L_{AV}.F^U_{AV}]\rangle$
C2	Numerical cost	$\langle[T^L_{AV}.T^U_{AV}].[I^L_{AV}.I^U_{AV}].[F^L_{AV}.F^U_{AV}]\rangle$
.	.	.
.	.	.
Cm	Linguistic Benefit	$\langle[T^L_{AV}.T^U_{AV}].[I^L_{AV}.I^U_{AV}].[F^L_{AV}.F^U_{AV}]\rangle$

distances from the mean solution according to criterion status.

$$pda_{mn} = \begin{cases} \dfrac{z(x_{mn} \ominus av_n)}{K(av_n)} . if m \in B \\ \dfrac{z(av_n \ominus x_{mn})}{K(av_n)} . if m \in C \end{cases} \tag{9}$$

$$nda_{mn} = \begin{cases} \dfrac{z(av_n \ominus x_{mn})}{K(av_n)} . if m \in B \\ \dfrac{z(x_{mn} \ominus av_n)}{K(av_n)} . if m \in C \end{cases} \tag{10}$$

Step 6: The weighted sum of the positive (sp_n) and negative distances (np_n) for all alternatives can be calculated using Equation (11) and Equation (12):

$$sp_n = \sum\nolimits_{n=1}^{l} (wj \otimes pda_{mn}) \tag{11}$$

$$np_n = \sum\nolimits_{n=1}^{l} (wj \otimes nda_{mn}) \tag{12}$$

Step 7: Eqs. (13) and (14) normalize the weighted total positive and negative distance for each alternative and spn_n and npn_n are obtained.

$$nsp_n = \frac{sp_n}{Max(K(sp_n))} \tag{13}$$

$$nsn_n = 1 - \frac{sn_n}{Max(K(sp_n))} \tag{14}$$

Step 8: In the last step, the evaluation score of each alternative is calculated.

$$as_n = \frac{1}{2}(nsp_n \oplus nsp_{n)} \tag{15}$$

Step 9: The assessment scores obtained are ranked from highest to lowest.

3. Computational study

In this study, the decision-making panel includes a diverse group of experts, each bringing a unique perspective and expertise to the evaluation and classification of smart city strategies. The decision-making panel was composed of three different groups of experts selected from the public sector, academia and the private sector. Public sector experts are experienced people who are actively involved in urban management and smart city projects, working in municipalities of different scales. Academics are selected from both theoretical and practical knowledge, specialising in smart city architecture, IoT and digital transformation, and having consultancy experience in national projects. Private sector experts are professionals who develop commercial solutions for smart cities and are experienced in technological and commercial viability. This diversity aims to ensure that the study is evaluated from a multi-dimensional perspective..

Public City Experts:

The public city experts selected for this study are drawn from three different scales of cities and are actively engaged in units specializing in smart city projects within their respective municipalities. These individuals are chosen based on their direct involvement in city management and smart city strategies at various levels of government. Each has substantial experience, often exceeding 15 years, in macro planning and the development of urban management strategies, providing invaluable insights into the public sector's challenges and opportunities in implementing smart city solutions.

Academicians:

The academic contributors to this panel are experts with broad knowledge and extensive publication records in smart city architecture, Internet of Things (IoT), and digital transformation. Their expertise is grounded in both theoretical frameworks and practical applications, having worked as consultants on various national-level projects. These academicians are familiar with national legislation and administrative processes, which enriches their contributions to the study with a deep understanding of the regulatory and educational aspects of smart city initiatives.

Private Sector Experts:

The private sector experts involved in this study come from companies that develop commercial solutions for smart cities, including software development and technology deployment. These professionals have experience in fostering partnerships with ministries and municipal governments through different levels of joint collaboration projects. Their practical experience in the field of smart city data architecture and project implementation offers a pragmatic perspective on the technological and commercial viability of smart city applications.

Together, this panel of experts ensures a well-rounded approach to decision-making in the study, combining in-depth knowledge of policy, academic research, and real-world application. This diverse expertise is crucial for addressing the complex issues associated with smart city evaluations and strategies, aiming to foster environments that are not only more technologically integrated but also sustainable and responsive to the needs of their inhabitants.

The weights of the decision makers whose evaluations were taken within the scope of this study are given in Table 7.

A total of 50 criteria were identified for smart city classification. By using these criteria, all cities of Turkey were considered and evaluated. Due to the large number of criteria and alternatives, only the first three and the last three alternatives will be evaluated according to the first three criteria and the last three criteria in all tables. The IVN-valued tables will show the results of the first alternative and the last alternative according to the first three criteria and the last three criteria. The results of the other alternatives and criteria in the tables are given in the s upplementary data file.

Step 1: Decision makers evaluated alternatives according to the criteria (Table 8).

Step2: All the IVN decision matrixes are aggregated to determine the average IVN decision matrix.

Step 3- Step 4: Decision makers assign the linguistic terms of the weights for each criterion and the aggregate IVN weights matrix is found (Table 10).

Step 5–6: In this step, positive and negative distances from the average solution are calculated. and PDA and NDA are found. After computing the PDA and NDA, the weighted sum of the positive (sp_n) and negative distances (np_n) for all alternatives can be calculated (Table 11).

Step 7: Normalization of np_n and sp_n values.

Step 8: In this step, the evaluation score of each alternative are computed for each alternative.

Step 9: In the last step, the assessment scores obtained are ranked from highest to lowest.

With the results obtained in the last step, the final ranking of the provinces was obtained in line with the weights of the determined criteria. These ranking results were also evaluated by the experts whose opinions were consulted in determining the weights of the criteria and a common decision was reached that the results were meaningful.

Table 7
Decision-makers and their weights.

Decision-makers and their weights on a project		
Code	Explanation	Weights
DM1	Academic Expert	35
DM2	Public Administrator	40
DM3	Smart City Sector Expert	25

Table 8
IVN Decision Matrix of the Decision Maker 1 (DM1).

	City1	City2	City3	……	City79	City80	City81
Cri1	AA	BA	AA	……	L	L	L
Cri2	A	L	BA	……	BA	L	BA
Cri3	VH	BA	BA	……	L	L	BA
……	……	……	……	……	……	……	……
Cri48	CL	VL	CH	……	L	CH	CH
Cri49	VL	CL	CL	……	CL	CL	CL
Cri50	VL	CL	CL	……	CL	CL	CL

Table 13
The Evaluation Scores.

	TL	TU	IL	IU	FL	FU
City1	0.499	0.503	0.038	0.056	−0.004	0.005
City2	0.497	0.502	0.04	0.059	−0.002	0.009
City3	0.498	0.502	0.039	0.057	−0.003	0.007
……						
City79	0.498	0.502	0.04	0.058	−0.002	0.01
City80	0.498	0.502	0.04	0.059	−0.003	0.008
City81	0.498	0.502	0.039	0.058	−0.002	0.009

4. Discussion

This research employed the Interval Valued Neutrosophic EDAS Method, a sophisticated multi-criteria decision-making approach, within the framework of Interval Valued Neutrosophic Sets (IVNS) to evaluate and categorize smart city strategies in developing countries. A major strength of this study is its comprehensive evaluation framework, which not only revisits criteria used in previous studies but also introduces new criteria to enhance the robustness of smart city assessments. This method ensures a thorough examination of various factors critical to urban development and smart city implementation.

The detailed analysis, supported by extensive data from Tables 7 through 14, offers an exhaustive classification and evaluation of smart cities based on a myriad of criteria essential for sustainable urban development. Table 7 outlines the weights assigned to different decision-makers, reflecting a comprehensive input system that balances

Table 9
IVN Decision Matrix (Aggregated- Alternative 1&Alternative 7).

	City1						City81					
	TL	TU	IL	IU	FL	FU	TL	TU	IL	IU	FL	FU
Cri1	0.450	0.600	0.300	0.400	0.35	0.500	0.292	0.442	0.357	0.457	0.508	0.658
Cri2	0.413	0.600	0.132	0.238	0.387	0.573	0.363	0.527	0.228	0.336	0.437	0.600
Cri3	0.613	0.765	0.457	0.558	0.184	0.337	0.462	0.615	0.337	0.437	0.334	0.487
……	……	……	……	……	……	……	……	……	……	……	……	……
Cri48	0.050	0.200	0.600	0.700	0.750	0.900	0.728	0.881	0.573	0.674	0.066	0.221
Cri49	0.260	0.411	0.385	0.487	0.538	0.690	0.050	0.200	0.600	0.700	0.750	0.900
Cri50	0.216	0.367	0.432	0.533	0.583	0.733	0.050	0.200	0.600	0.700	0.750	0.900

Table 10
Criteria weights and aggregated IVN weights.

	DM1	DM2	DM3		Aggregated IVN weights TL	TU	IL	IU	FL	FU
Cri1	H	H	VH	**Cri1**	0.577	0.780	0.423	0.523	0.220	0.423
Cri2	VH	H	CH	**Cri2**	0.644	0.860	0.479	0.580	0.140	0.356
Cri3	VH	H	CH	**Cri3**	0.644	0.860	0.479	0.580	0.140	0.356
……	……	……	……	……	……	……	……	……	……	……
Cri48	VH	H	CH	**Cri48**	0.644	0.860	0.479	0.580	0.140	0.356
Cri49	VH	H	CH	**Cri49**	0.644	0.860	0.479	0.580	0.140	0.356
Cri50	VH	H	CH	**Cri50**	0.644	0.860	0.479	0.580	0.140	0.356

Table 11
Table of the positive (sp_n) and negative distances (np_n).

	sp_n						np_n					
	TL	TU	IL	IU	FL	FU	TL	TU	IL	IU	FL	FU
Cri1	−0.013	0.042	0.076	0.114	−0.009	0.009	0.998	1.007	0.987	0.981	0.999	1.001
Cri2	−0.029	0.019	0.081	0.120	−0.005	0.019	0.995	1.003	0.987	0.980	0.999	1.003
Cri3	−0.022	0.029	0.078	0.116	−0.006	0.015	0.996	1.005	0.987	0.981	0.999	1.002
……	……	……	……	……	……	……	……	……	……	……	……	……
Cri48	−0.028	0.020	0.08	0.119	−0.004	0.019	0.995	1.003	0.987	0.980	0.999	1.003
Cri49	−0.026	0.023	0.081	0.120	−0.005	0.017	0.996	1.004	0.986	0.980	0.999	1.003
Cri50	−0.026	0.024	0.08	0.118).	−0.005	0.017	0.996	1.004	0.987	0.980	0.999	1.003

Table 12
Normalized nsp_n and nsn_n values.

	nsp_n						nsn_n					
	TL	TU	IL	IU	FL	FU	TL	TU	IL	IU	FL	FU
City1	−10.977	36.654	66.113	98.875	−7.614	7.819	10.977	−36.654	66.113	98.875	7.614	−7.819
City2	−25.367	16.770	70.262	103.847	−3.962	16.192	25.367	−16.770	70.262	103.847	3.962	−16.192
City3	−19.466	24.850	67.971	101.078	−5.528	12.676	19.466	−24.850	67.971	101.078	5.528	−12.676
……	……	……	……	……	……	……	……	……	……	……	……	……
City79	−24.61	17.232	69.75	103.261	−3.07	16.851	24.61	−17.232	69.75	103.261	3.070	−16.851
City80	−22.962	19.958	70.518	104.186	−4.719	14.592	22.962	−19.958	70.518	104.186	4.719	−14.592
City81	−22.303	20.823	69.324	102.736	−4.285	14.905	22.303	−20.823	69.324	102.736	4.285	−14.905

Table 14
The Assessment Scores.

Alt.	City Name	Score	Alt.	City Name	Score	Alt.	City Name	Score
40	İstanbul	0.7218	37	Hatay	0.7127	2	Adıyaman	0.7111
41	İzmir	0.7206	31	Erzurum	0.7127	16	Bilecik	0.7111
7	Ankara	0.7201	24	Çorum	0.7124	64	Osmaniye	0.7111
21	Bursa	0.7188	61	Nevşehir	0.7123	30	Erzincan	0.7111
53	Konya	0.7177	44	Karaman	0.7122	71	Şanlıurfa	0.7111
8	Antalya	0.7171	77	Uşak	0.7121	74	Tokat	0.711
52	Kocaeli	0.717	63	Ordu	0.7121	23	Çankırı	0.7109
66	Sakarya	0.716	29	Elazığ	0.7121	10	Artvin	0.7108
1	Adana	0.7155	70	Sivas	0.7121	13	Bartın	0.7107
47	Kayseri	0.7154	28	Edirne	0.7121	35	Gümüşhane	0.7103
25	Denizli	0.7148	27	Düzce	0.712	78	Van	0.7102
58	Mersin	0.7148	5	Aksaray	0.712	69	Sinop	0.7101
73	Tekirdağ	0.7148	65	Rize	0.712	9	Ardahan	0.7098
67	Samsun	0.7147	81	Zonguldak	0.7119	76	Tunceli	0.7098
33	Gaziantep	0.7146	26	Diyarbakır	0.7119	15	Bayburt	0.7095
59	Muğla	0.7145	20	Burdur	0.7118	45	Kars	0.7094
42	Kahramanmaraş	0.7145	6	Amasya	0.7117	17	Bingöl	0.7094
56	Manisa	0.7144	46	Kastamonu	0.7117	14	Batman	0.7094
32	Eskişehir	0.7142	49	Kırklareli	0.7117	57	Mardin	0.7093
11	Aydın	0.7141	34	Giresun	0.7116	51	Kilis	0.7093
12	Balıkesir	0.7141	48	Kırıkkale	0.7116	60	Muş	0.7089
55	Malatya	0.7134	50	Kırşehir	0.7115	18	Bitlis	0.7088
22	Çanakkale	0.7132	43	Karabük	0.7115	68	Siirt	0.7088
3	Afyonkarahisar	0.7132	80	Yozgat	0.7115	72	Şırnak	0.7083
75	Trabzon	0.7132	19	Bolu	0.7112	38	Iğdır	0.7081
54	Kütahya	0.7131	79	Yalova	0.7112	4	Ağrı	0.7081
39	Isparta	0.7128	62	Niğde	0.7112	36	Hakkari	0.708

insights from public administrators, academics, and industry experts. This diversity in perspectives ensures a holistic assessment of smart city initiatives. The decision matrices presented in Tables 8 and 9 detail the evaluation of cities against specific criteria, revealing the complex interactions between various urban development factors.

Furthermore, Table 10 highlights the significant emphasis on essential urban services and infrastructure through aggregated IVN weights, pinpointing areas that are critical for smart city evolution. The computation of positive and negative distances from the average solution, documented in Tables 11 and 12, provides a nuanced understanding of each city's relative performance, which is instrumental in identifying both strengths and areas requiring attention within each urban setting. Table 13′s normalization of these distances transforms raw scores into a standardized format that enhances comparability across diverse urban environments, facilitating easier interpretation and application by urban planners.

Finally, the rankings presented in Table 14 offer a clear snapshot of which cities are leading in smart technology integration, with Istanbul, Izmir, and Ankara emerging as the top performers. These metropolitan cities, which represent 30 out of the 81 provinces evaluated, naturally scored higher due to their enhanced capabilities in areas such as education, economy, industry, and social infrastructure. They demonstrate a higher readiness and capacity for implementing sophisticated smart city solutions, indicative of their larger infrastructural and economic frameworks. Since metropolitan cities have more opportunities such as population, education, economy, industry, job opportunities, infrastructure, social etc. than other cities, they are ranked at the top according to the weighted evaluation result.

The method used in this study produces rankings with values close to each other. These values were normalized by consulting expert opinions

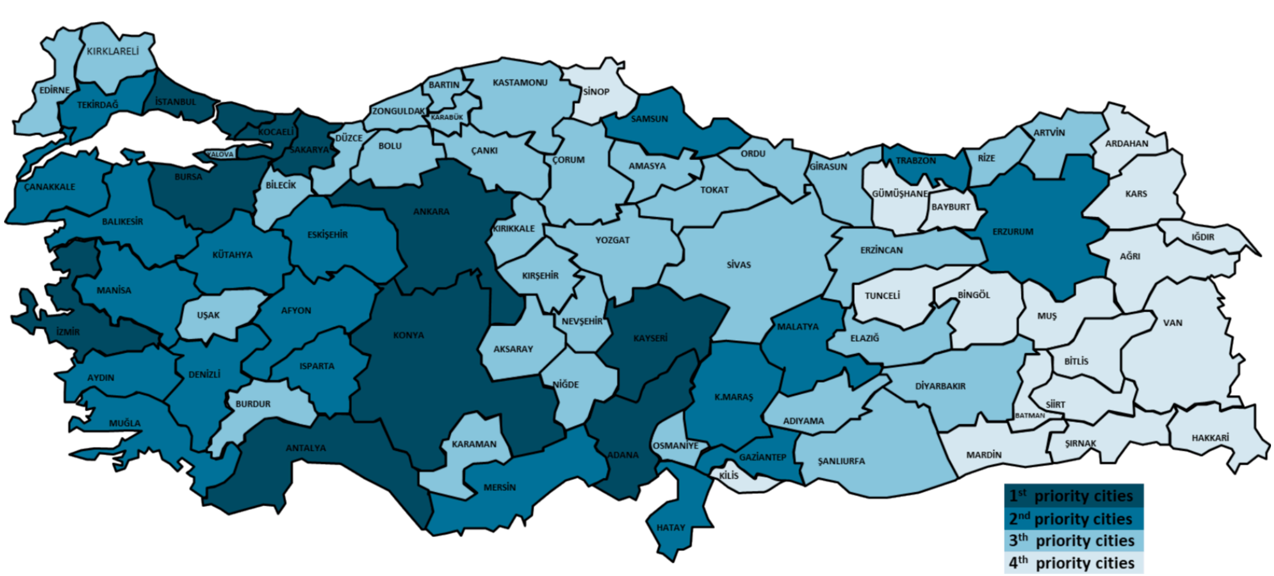

Fig. 1. Map representation of provinces categorized according to smart city strategy.

and 4 groups were formed. It was observed that there were 10 provinces in the 1st group, 19 in the 2nd group, 34 in the 3rd group and 18 in the 4th group. Fig. 1 shows the map representation of the classification of these provinces.

The results of this research are important for future sustainable development of Turkish cities and provide valuable information to policymakers. The classification system created in this research can be a way of strategic roadmap, to be used while Turkey is heading towards 2053 carbon neutrality and smart city transformation targets. On the other hand, for metropolitan cities (among them top-ranked cities) such as Istanbul, Izmir and Ankara, İzmit (Kocaeli), the recommended focus areas to address include advanced technology integration and innovative solutions, autonomous transportation systems supporting sustainable mobility options; AI-driven urban services; smart grid implementations. Second-tier cities, in contrast, need to focus on digital infrastructure and smart mobility solutions as priorities. The third and fourth group cities need basic infrastructure development and capacity building with digital literacy and primitive smart city services. Development plans within local governments should reflect these classifications; and spending and prioritization of projects should follow strategy. In addition, the methodology established in this study can be periodically applied to track progress and amend strategies through changing times of their cities. Such a dynamic way of urban development will be very important for Turkish mega-cities with increasing pressure from urbanization, climate change and technological progress in the next decades. It shows that national and local governments should take a nuanced approach to developing smart cities, accounting for where each city falls today, as well its potential growth based on the classification system we facilitated. All the strategies proposed for smart cities are presented in a Table 15..

After determining the SC rankings for provinces in Turkey, it became necessary to develop general strategies tailored to these classifications. Considering the varying levels of SC awareness and existing capacities among provinces, designing policies within a systematic framework specific to SC will contribute to more effective and efficient investment outcomes.

The Metaverse has significant potential in developing and transforming smart cities [25]. This is because the Metaverse enables the use of emerging innovative technologies such as Artificial Intelligence, Big Data, Internet of Things, and Digital Twins with comprehensive datasets, helping to increase urban productivity and performance [2]. This has paved the way for an increased awareness of the social, economic and technological improvements offered by SCs and the creation of guidelines to guide decision-makers in the process of transforming existing cities into smart [14]. With the proliferation of SC applications, the integration of real and virtual life has increased, creating new economic opportunities and enabling the development of the MetaOmniCity concept that will lead to a new era of digital transformation [13].

Similarly, with the classification made within the scope of this study, after the situation analysis of the existing provinces, the strategies that these provinces should follow in the process of transformation into smart cities were revealed.

This study provides a unique framework that combines comprehensive criteria and modern methodologies, enabling practitioners to conduct similar analyses in diverse regions. The proposed strategies offer actionable insights for cities to evaluate their current positions in smart city policies and develop step-by-step plans for future improvements. By bridging the gap between theoretical approaches and practical applications, this research contributes to advancing urban planning and smart city implementations.

5. Conclusion

The findings from this research offer valuable insights for city planners and policymakers engaged in developing smart city strategies. By employing the Interval Valued Neutrosophic EDAS Method, this study not only advanced the analytical frameworks used in urban development but also contributed significantly to the practical aspects of urban planning. The detailed classification system developed provides a clear and actionable guide for enhancing urban environments through targeted technological integration and strategic planning.

The rankings and classifications derived from this study, underscore the effectiveness of the IVNS and EDAS methods in capturing the complex interplay of factors that define a smart city. The ability of these methods to accommodate diverse expert opinions and quantitative data ensures that the resulting strategies are comprehensive and well-suited to the specific needs and potential of each city.

As urban areas continue to grow and evolve, the methodologies and findings of this study will serve as a robust foundation for future research and the implementation of smart city initiatives. This research not only enriches the academic discourse on urban development but also

Table 15
Strategies of SC groups.

Main Criteria	Sub-Criteria (Examples)	1st Group (Leaders)	2nd Group (Developing)	3rd Group (Emerging)	4th Group (Newcomers)
Society	Population, Growth Rate, Governance, Net Migration, Public Safety	Fully integrated governance, high public safety systems	Strong governance with advanced public safety projects	Basic governance projects and public safety awareness	Building governance awareness and safety frameworks
Life Quality	Life Satisfaction, Life Cost, Health Services, Life Expectancy	Excellent life satisfaction, accessible healthcare services	Good life satisfaction, expanding healthcare capacity	Moderate life satisfaction and improving health services	Raising awareness on healthcare and life satisfaction
Infrastructure	Fiber Optic Length, Internet Access, Mobile Phone Subscribers	Advanced infrastructure with high-speed internet coverage	Improving internet infrastructure and mobile access	Limited but growing internet and mobile infrastructure	Initiating pilot internet and mobile connectivity projects
Mobility	Traffic Congestion, Public Transport, Bicycle Paths, Accidents	Seamless mobility with zero congestion and green transport	Reducing congestion with expanded public transport	Focused on reducing traffic and improving public transport	Basic public transport and traffic management programs
Activities	Cultural Activities, Tourism Facilities, Museum Visitors	Dynamic cultural activities and tourism hubs	Growing tourism facilities and cultural events	Building cultural infrastructure for tourism growth	Promoting cultural awareness and pilot tourism projects
Opportunities (Work & School)	Job Opportunities, Employment Rate, Learning Opportunities	Diverse job markets and advanced education programs	Expanding employment opportunities and education programs	Initial job creation programs and education platforms	Pilot programs for job creation and digital education
Smart Economy	GDP, Businesses, ICT Investment, E-Commerce Companies	Globally competitive businesses and robust e-commerce	Growing startups and digital transformation initiatives	Emerging local businesses and digital investments	Introducing foundational business ecosystems
Smart Environment	Air Quality, Renewable Energy, Green Spaces, Recycling	Sustainable ecosystems with advanced recycling systems	Moderate adoption of renewable energy and green projects	Initial steps in renewable energy and green spaces	Awareness campaigns for environmental sustainability

provides a practical framework for fostering more connected, sustainable, and resilient urban environments across developing countries.

This study's comprehensive criteria and the use of up-to-date methods provide a foundation for other practitioners to conduct similar analyses in their respective regions. Furthermore, the strategies developed in this research serve as a guiding framework, enabling cities to assess their current position in smart city policies and to identify incremental steps required for further advancement.

The planning of smart cities, particularly in the context of sustainability and advanced analytical approaches, becomes increasingly crucial as the global push towards digital transformation and carbon neutrality gains momentum. Proper classification and strategic planning of urban spaces are essential to effectively manage these transitions. As cities worldwide strive towards these ambitious goals, leveraging detailed and scientifically grounded methodologies like those explored in this study will be vital in guiding urban evolution in a sustainable and efficient manner. This holistic approach to smart city development not only supports immediate urban management needs but also aligns with broader global sustainability and resilience objectives, marking a critical step forward in urban planning disciplines.

CRediT authorship contribution statement

Mesut Samasti: Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Emre Çakmak:** Writing – review & editing, Writing – original draft, Methodology. **Alper Özpınar:** Writing – review & editing, Writing – original draft, Visualization, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contribution

The contribution of the authors to the present study is equal. All the authors read and approved the final manuscript. All the authors verify that the Text, Figures, and Tables are original and that they have not been published before.

Ethical approval

Ethics committee approval is not required.

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