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A Robust Evaluation Framework for Smart Cities in Egypt: Integrating Type-2 Neutrosophic Sets with LBWA and EDAS Methods

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Abstract

The rapid pace of urbanization has driven the global rise of smart cities, which leverage technology to improve the quality of life for citizens and address key challenges such as sustainability, livability, and economic growth. This paper presents a comprehensive framework for evaluating smart cities in Egypt using advanced Multi-Criteria Decision-Making (MCDM) methods, incorporating Type-2 Neutrosophic Numbers (T2NN), the Logarithmic Best-Worst Approach (LBWA), and the Evaluation Based on Distance from Average Solution (EDAS) method. These methods were chosen to effectively handle the uncertainties and imprecision that characterize decision-making in complex urban systems. The study identifies six key criteria—Cultural Interaction, Economy, Research & Development (R&D), Livability, Environment, and Accessibility—to assess the performance of smart cities in Egypt, including emerging projects. By applying T2NN to model uncertainty and indeterminacy, LBWA to determine the relative importance of criteria, and EDAS to rank alternatives, the study provides a robust, systematic evaluation framework. The findings underscore the potential of T2NN-LBWA-EDAS in smart city evaluation, providing valuable insights for policymakers and urban planners as they work towards creating sustainable, innovative, and livable urban environments. This approach can be extended to other domains of urban planning and applied to evaluate smart cities globally. Future research could integrate real-time data and other MCDM methods to further enhance the decision-making process in the smart city context.

Keywords: MCDM; T2NN; LBWA; EDAS; Smart City.

1 | Introduction

A smart city is an urban area that uses technology, data, and innovation to improve the quality of life for its citizens, enhance sustainability, and streamline public services (1). By integrating advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data, smart cities aim to create a more efficient, connected, and sustainable urban environment (2). The concept of smart cities revolves around key areas like transportation, energy management, public safety, healthcare, environmental sustainability, and infrastructure (3). These cities utilize information and communication technologies (ICT) to manage resources effectively, improve governance, and create better living conditions (4). Smart cities provide citizens with better access to healthcare, education, public services, and transportation, resulting in higher living standards and increased convenience (5). By optimizing resource management and promoting green practices, smart cities contribute to a cleaner, more sustainable environment. Energy-efficient buildings, reduced

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emissions, and smart waste management systems help mitigate environmental impact (6). Smart cities encourage innovation and entrepreneurship by providing the infrastructure for digital economies to thrive. They foster tech-driven industries, generate jobs, and boost overall economic productivity (7). Smart cities implement advanced surveillance systems, predictive policing, and real-time monitoring to improve public safety. AI-driven analytics help authorities respond more effectively to emergencies and crime prevention (8). With data-driven decision-making, city authorities can optimize traffic, manage utilities more efficiently, and enhance service delivery. This leads to cost savings, reduced waste, and better use of urban resources (9). With rapid urbanization, cities across the globe are adopting smart solutions to address challenges related to infrastructure, sustainability, and citizen services (10).

The concept of smart cities has emerged as a response to the challenges posed by rapid urbanization, environmental degradation, and resource depletion (11). The world's population is increasingly urbanized, with more than half of the population living in cities (12). This trend is expected to continue, with the United Nations predicting that the global urban population will reach 6 billion by 2045 (13). Urbanization has brought about numerous challenges, including traffic congestion, air and water pollution, and strain on resources such as energy and water (14). Egypt, with its growing population and urbanization, has also embarked on the journey of developing smart cities. The Egyptian government has launched several initiatives aimed at developing smart cities, including the New Administrative Capital and New Alamein. These cities are designed to be sustainable, efficient, and livable, with a focus on providing high-quality services to citizens. In Egypt, the development of smart cities is a key component of the government's long-term strategic plans, such as Egypt Vision 2030. As Egypt focuses on creating cities like the New Administrative Capital, it is crucial to evaluate their smart city attributes systematically focusing on key criteria such as economy, cultural interaction, research & development (R&D), livability, environment, and accessibility. However, evaluating the performance of these smart cities is a complex task that requires the consideration of multiple criteria. Smart cities are characterized by their use of technology and data to improve the quality of life for citizens, and their performance can be evaluated from various perspectives, including economy, cultural interaction, research & development (R&D), livability, environment, and accessibility (15). Evaluating the performance of smart cities is a complex task that requires the consideration of multiple criteria (16). Traditional evaluation methods often suffer from limitations, including the inability to handle uncertainty and imprecision, limited ability to consider multiple criteria, and Lack of transparency and accountability (17).

To overcome these limitations, Multi-Criteria Decision Making (MCDM) methods have been widely used in evaluating smart cities (18). MCDM methods provide a structured approach to evaluating multiple criteria and can handle uncertainty and imprecision more effectively (19). However, traditional MCDM methods often suffer from the limitations of traditional fuzzy sets, which are unable to handle uncertainty and imprecision effectively (20). Type-2 Neutrosophic Sets (T2NN) have been proposed as an extension of traditional fuzzy sets to handle uncertainty and imprecision more effectively (21). T2NN is a powerful tool for handling uncertainty and imprecision in decision-making problems (22). They provide a more flexible and robust approach to modeling uncertainty, as they can handle both probabilistic and possibilistic uncertainty (23). T2NN has been applied in various fields, including image processing, natural language processing, and decision-making (21).

The increasing complexity of modern decision-making problems has led to the development of advanced methods to handle uncertainty and ambiguity (24). T2NN provides an advanced approach to handling uncertainty by offering three degrees: truth, indeterminacy, and falsity (22). This has led to their increasing application in MCDM problems where decisions are affected by ambiguity and vagueness (21). In MCDM problems, T2NN can be used to represent the uncertainty associated with different criteria and alternatives (23). LBWA is a novel method for calculating the relative weights of criteria in MCDM problems (25). The method is based on the idea of pairwise comparisons, where the decision-maker is asked to compare the importance of different criteria (26). However, unlike traditional pairwise comparison methods, LBWA uses a logarithmic scale to reduce the number of comparisons required (27). The EDAS method is a ranking method that evaluates alternatives based on their distance from the average solution (28). The EDAS method is particularly useful in complex decision-making scenarios, such as smart city evaluations, where there are multiple criteria and alternatives to evaluate (29). By ranking alternatives based on their distance from the average solution, the EDAS method provides a more comprehensive evaluation of the alternatives (30). The study applies the LBWA method to determine the relative importance of criteria and the EDAS method to rank the smart cities. By using T2NN, LBWA, and EDAS, the study aims to provide a more systematic and comprehensive evaluation of smart cities, taking into account the uncertainty and vagueness inherent in decision-maker judgments.

The motivation behind this paper is to develop a comprehensive framework for evaluating smart cities in Egypt using MCDM methods in a T2NN Environment. Egypt has embarked on the journey of developing smart cities, with several initiatives aimed at creating sustainable, efficient, and livable cities. Evaluating the performance of these smart cities is crucial to ensure that they meet the desired objectives and provide high-quality services to citizens. Traditional MCDM methods often suffer from the limitations of traditional fuzzy sets, which are unable to handle uncertainty and imprecision effectively. T2NN has been proposed as an extension of traditional fuzzy sets to handle uncertainty and imprecision more effectively. T2NS are effective in handling uncertainty and imprecision in decision-making problems. They provide a more flexible and robust approach to modeling uncertainty, as they can handle both probabilistic and possibility uncertainty. There is a need for a case study that applies the proposed framework to real-world data. The case study will provide valuable insights into the effectiveness of the proposed framework and its potential applications in evaluating smart cities in Egypt.

The objectives of this paper are:

- To develop a comprehensive framework, to handle the complexity of evaluating smart cities in Egypt, considering multiple criteria and uncertainty. The framework will be based on MCDM methods, specifically the LBWA and the EDAS method, in a T2NN environment.
- To apply the proposed framework to a case study of four smart cities in Egypt, to test the effectiveness of the proposed framework in a real-world setting.
- To develop a systematic approach, to evaluate smart cities based on key criteria such as economy, cultural interaction, R&D, livability, environment, and accessibility.
- To evaluate the effectiveness of the proposed framework in evaluating smart cities in Egypt, to assess the performance of the proposed framework in evaluating smart cities in Egypt.
- Provide a decision-making tool for policymakers and stakeholders in Egypt, to evaluate and compare the performance of smart cities. The tool will be based on the proposed framework and will provide a comprehensive evaluation of smart cities in Egypt.

The paper makes several contributions to the existing body of knowledge on smart cities and MCDM methods:

- This paper extends the application of MCDM methods to a T2NN Environment, which is a new and emerging area of research. The study demonstrates the effectiveness of MCDM methods in a T2NN Environment for evaluating smart cities.
- The study develops a comprehensive framework for evaluating smart cities in Egypt using MCDM methods in a T2NN. The framework considers multiple criteria and uncertainty, making it a valuable tool for policymakers and stakeholders.
- The study evaluates the performance of four smart cities in Egypt. This evaluation provides a comprehensive assessment of the smart cities in Egypt and identifies areas for improvement.
- The paper identifies the key criteria that should be considered when evaluating smart cities in Egypt, providing valuable insights for policymakers and stakeholders.

- The paper contributes to the existing body of knowledge on smart cities by providing new insights into the application of MCDM methods in a T2NN Environment for evaluating smart cities.
- The study develops a decision-making tool that can be used by policymakers and stakeholders in Egypt to evaluate and compare the performance of smart cities.

This paper is structured as follows: Section 2: Some literature Review about using MCDM to evaluate smart cities and some of studies about LBWA and EDAS methods. Section 3: propose some of the T2NN fundamental and the hybrid T2NN-LBWA-EDAS methodology. Section 4: Application: to evaluate Smart Cities in Egypt. Section 5: Discussion and Results. Section 6: Implications and future work. Section 7: Conclusions.

2 | Literature Review

The use of MCDM methods in smart city evaluations is increasingly significant due to their capacity to assess diverse criteria in areas such as IoT-based waste management, sustainable energy systems, and urban mobility (31). Studies explore various MCDM frameworks to address complex challenges like sustainability, resilience, security, and infrastructure performance. These methods help in balancing multiple factors under uncertainty, providing a systematic approach for evaluating and improving smart city performance across diverse domains (32). Irem Otay and her team ventured into the energy domain, using the BWM-TOPSIS method under Interval-Valued Pythagorean Fuzzy environments to evaluate sustainability in energy systems (33). Meanwhile, Thangaraj Manirathinam applied an innovative APPRESAL approach to explore micro-mobility, illustrating how transportation modes perform within smart cities (34). Ye et al. (31) proposed MCDM methods to rank China's smart cities. The development of smart cities has led to an increased focus on the resilience and sustainability of urban infrastructure, including metro systems. MCDM methods have been widely used in flood risk assessment due to their ability to handle multiple criteria and uncertainty (35). Adali et al. (15) aimed to assess the smartness of European cities using an integrated grey MCDM approach. Ozkaya et al. (36) evaluated the performance of smart and sustainable cities using an ANP and TOPSIS. A complex network-based approach is proposed to address security and governance issues in smart green cities, focusing on identifying influential spreaders and vulnerable IoT devices using the Modified Dynamic Weighted Sum Method framework is used to determine influential devices and spreaders (37). A novel fuzzy expert-based multi-criteria decision support model is proposed to evaluate the performance of 35 European smart cities based on sustainability, resilience, and livability (38).

In the context of decision-making, T2NN provides an advanced mechanism to handle uncertainty and indeterminacy more effectively than traditional fuzzy or Type-1 sets (21). When integrated with the EDAS method, T2NN decision-makers incorporate truth, indeterminacy, and falsity membership functions for a more accurate assessment of alternatives (39). This combined approach has been proven to significantly improve the evaluation process by managing complex, uncertain, and imprecise information. The EDAS method ranks alternatives by measuring their distances from positive and negative solutions (39). This method has gained traction in various decision-making environments, particularly when paired with other methods like AHP, TOPSIS, and MABAC to improve robustness. Farid et al. (40) applied EDAS within a q-rung orthopair fuzzy environment to evaluate sustainable approaches for smart waste management of automotive fuel cells, offering valuable insights into the sustainability of different waste management strategies. Similarly, Krishankumar et al.(41) used EDAS to assess urban mobility, demonstrating its flexibility across different smart city applications. Shah et al. (42) performed a comparative analysis using EDAS and TOPSIS to evaluate flood susceptibility in the Jhelum River Basin, providing a valuable case study on how EDAS can be used in environmental planning. Ersoy uses TOPSIS, EDAS, and CODAS methods to select e-commerce companies (43). I. Irvanizam et al.(44) compare MABAC with EDAS in Triangular Fuzzy Neutrosophic Numbers. Ayan et al.(45) analyze some MCDM methods with EDAS like WASPAS, MABAC, CODAS, COCOSO, and MARCOS.

Using the T2NN-LBWA-EDAS model is particularly beneficial for evaluating criteria in situations where there are multiple conflicting objectives, as they can simultaneously handle vague, imprecise, and incomplete information, which is a common scenario in real-world applications like smart city assessment. On the other hand, LBWA simplifies the weighting process by using logarithmic functions, identifying the most and least important criteria with greater computational ease (25). Korucuk et al.(46) applied LBWA in a fuzzy environment to evaluate smart network strategies for logistics companies, showcasing the method's practical applicability. Pamucar et al.(47) used LBWA also in fuzzy environments to enhance decision-making for urban planning projects. Recent studies have demonstrated the effectiveness of combining EDAS with LBWA for more reliable and insightful decision-making. Adali et al. (15) Evaluated 17 European smart cities using the LBWA-EDAS framework, employing grey extensions to account for uncertainty. Integrating T2NN-LBWA-EDAS is particularly beneficial for evaluating scenarios with multiple conflicting objectives, such as smart city assessments, where decision-makers must navigate complex datasets with imprecise and incomplete information. This combination can effectively handle the vagueness and indeterminacy of real-world data, offering more robust and comprehensive evaluations for sustainable urban development.

3 | Methodology

3.1 | T2NN Basics

In the T2NN environment, each criterion's performance is expressed in terms of three membership functions: truth (T), indeterminacy (I), and falsity (F). These values provide flexibility in modeling uncertainties by allowing a higher degree of information fuzziness.

Definition 3.1 (21). Consider that Y is a limited universe of discourse, and D [0,1] is the set of all triangular neutrosophic numbers on F [0,1].

A T2NNS $\tilde{A}$ in Y is represented by:

$$\tilde{A} = \left\langle \left(T_{T_{\tilde{A}}}(y), T_{I_{\tilde{A}}}(y), T_{F_{\tilde{A}}}(y)\right), \left(I_{T_{\tilde{A}}}(y), I_{I_{\tilde{A}}}(y), I_{F_{\tilde{A}}}(y)\right), \left(F_{T_{\tilde{A}}}(y), F_{I_{\tilde{A}}}(y), F_{F_{\tilde{A}}}(y)\right) \right\rangle \quad (1)$$

Where $\breve{T}_{\tilde{A}}(y) : Y \rightarrow D[0,1]$, $\tilde{I}_{\tilde{A}}(y) : Y \rightarrow D[0,1]$, $\breve{F}_{\tilde{A}}(y) : Y \rightarrow D[0,1]$.

The T2NNS $\breve{T}_{\tilde{A}}(y) = \left(T_{T_{\tilde{A}}}(y), T_{I_{\tilde{A}}}(y), T_{F_{\tilde{A}}}(y)\right)$, $\tilde{I}_{\tilde{A}}(y) = \left(I_{T_{\tilde{A}}}(y), I_{I_{\tilde{A}}}(y), I_{F_{\tilde{A}}}(y)\right)$, $\breve{F}_{\tilde{A}}(y) = \left(F_{T_{\tilde{A}}}(y), F_{I_{\tilde{A}}}(y), F_{F_{\tilde{A}}}(y)\right)$ defined as the truth, indeterminacy and falsity member-ships of y in $\tilde{A}$ respectively.

Definition 3.2 (21) Let

$$\tilde{A} = \left\langle \left(T_{T_{\tilde{A}}}(y), T_{I_{\tilde{A}}}(y), T_{F_{\tilde{A}}}(y)\right), \left(I_{T_{\tilde{A}}}(y), I_{I_{\tilde{A}}}(y), I_{F_{\tilde{A}}}(y)\right), \left(F_{T_{\tilde{A}}}(y), F_{I_{\tilde{A}}}(y), F_{F_{\tilde{A}}}(y)\right) \right\rangle,$$

$$\tilde{A}_1 = \left\langle \left(T_{T_{\tilde{A}1}}(y), T_{I_{\tilde{A}1}}(y), T_{F_{\tilde{A}1}}(y)\right), \left(I_{T_{\tilde{A}1}}(y), I_{I_{\tilde{A}1}}(y), I_{F_{\tilde{A}1}}(y)\right), \left(F_{T_{\tilde{A}1}}(y), F_{I_{\tilde{A}1}}(y), F_{F_{\tilde{A}_1}}(y)\right) \right\rangle \text{ and}$$

$$\tilde{A}_2 = \left\langle \left(T_{T_{\tilde{A}2}}(y), T_{I_{\tilde{A}2}}(y), T_{F_{\tilde{A}2}}(y)\right), \left(I_{T_{\tilde{A}2}}(y), I_{I_{\tilde{A}2}}(y), I_{F_{\tilde{A}2}}(y)\right), \left(F_{T_{\tilde{A}2}}(y), F_{I_{\tilde{A}2}}(y), F_{F_{\tilde{A}_2}}(y)\right) \right\rangle$$

by three T2NN and $\lambda > 0$. Their operations are defined as follows:

T2NN Addition:

$$\tilde{A}_1 \oplus \tilde{A}_2 = \left\langle \begin{matrix} \begin{pmatrix} T_{T_{\widetilde{A1}}}(y) + T_{T_{\widetilde{A2}}}(y) - T_{T_{\widetilde{A1}}}(y).T_{T_{\widetilde{A2}}}(y),\ T_{I_{\widetilde{A1}}}(y) + T_{I_{\widetilde{A2}}}(y) - T_{I_{\widetilde{A1}}}(y).T_{I_{\widetilde{A2}}}(y), \\ T_{F_{\widetilde{A1}}}(y) + T_{F_{\widetilde{A2}}}(y) - T_{F_{\widetilde{A1}}}(y).T_{F_{\widetilde{A2}}}(y) \end{pmatrix}, \\ \left(I_{T_{\widetilde{A1}}}(y).I_{T_{\widetilde{A2}}}(y), I_{I_{\widetilde{A1}}}(y).I_{I_{\widetilde{A2}}}(y), I_{F_{\widetilde{A1}}}(y).I_{F_{\widetilde{A2}}}(y)\right), \\ \left(F_{T_{\widetilde{A1}}}(y).F_{T_{\widetilde{A2}}}(y), F_{I_{\widetilde{A1}}}(y).F_{I_{\widetilde{A2}}}(y), F_{F_{\tilde{A}1}}(y).F_{F_{\tilde{A}2}}(y)\right) \end{matrix} \right\rangle \quad (2)$$

T2NN Multiplication:

$$\tilde{A}_1 \otimes \tilde{A}_2 =$$

$$\left\langle \begin{matrix} \left(\left(T_{T_{\widetilde{A1}}}(y).T_{T_{\widetilde{A2}}}(y), T_{I_{\widetilde{A1}}}(y).T_{I_{\widetilde{A2}}}(y), T_{F_{\widetilde{A1}}}(y).T_{F_{\widetilde{A2}}}(y)\right)\right), \\ \left(\left(I_{T_{\widetilde{A1}}}(y) + I_{T_{\widetilde{A2}}}(y) - I_{T_{\widetilde{A1}}}(y).I_{T_{\widetilde{A2}}}(y)\right), \left(I_{I_{\widetilde{A1}}}(y) + I_{I_{\widetilde{A2}}}(y) - I_{I_{\widetilde{A1}}}(y).I_{I_{\widetilde{A2}}}(y)\right), \begin{pmatrix} I_{F_{\widetilde{A1}}}(y). + I_{F_{\widetilde{A2}}}(y) - \\ I_{F_{\widetilde{A1}}}(y).I_{F_{\widetilde{A2}}}(y) \end{pmatrix}\right) \\ \left(\left(F_{T_{\widetilde{A1}}}(y) + F_{T_{\widetilde{A2}}}(y) - F_{T_{\widetilde{A1}}}(y).F_{T_{\widetilde{A2}}}(y)\right), \left(F_{I_{\widetilde{A1}}}(y) + F_{I_{\widetilde{A2}}}(y) - F_{I_{\widetilde{A1}}}(y).F_{I_{\widetilde{A2}}}(y)\right), \begin{pmatrix} F_{F_{\tilde{A}1}}(y) + F_{F_{\tilde{A}2}}(y) - \\ F_{F_{\tilde{A}1}}(y).F_{F_{\tilde{A}2}}(y) \end{pmatrix}\right) \end{matrix} \right\rangle \quad (3)$$

Scaler function:

$\lambda\tilde{A}$ = ((1 - (1-$T_{T_{\tilde{A}}}(y))^{\lambda}$, 1 - (1 $- T_{I_{\tilde{A}}}(y))^{\lambda}, 1 - \left(1 - T_{F_{\tilde{A}}}(y)\right)^{\lambda}\big)$,

($(I_{T_{\tilde{A}}}(y))^{\lambda}, I_{I_{\tilde{A}}}(y))^{\lambda}, I_{F_{\tilde{A}}}(y))^{\lambda}$), $(F_{T_{\tilde{A}}}(y))^{\lambda}, F_{I_{\tilde{A}}}(y))^{\lambda}, F_{F_{\tilde{A}}}(y))^{\lambda}$)) (4)

Definition 3.3 (21).

Suppose that $\widetilde{A_s} = \left\langle \left(T_{T_{\tilde{A}s}}(y), T_{I_{\tilde{A}s}}(y), T_{F_{\tilde{A}s}}(y)\right), \left(I_{T_{\tilde{A}s}}(y), I_{I_{\tilde{A}s}}(y), I_{F_{\tilde{A}s}}(y)\right), \left(F_{T_{\tilde{A}s}}(y), F_{I_{\tilde{A}s}}(y), F_{F_{\tilde{A}s}}(y)\right) \right\rangle$

Where S = 1, 2, …, m is a group of T2NNs and w = (w1, w2, … wm)T

Denotes the weight vector with $\mathcal{W}_j \in [0,1]$ and $\sum_{m=1}^{m} w_s = 1$ the following equation is used to calculate a Type 2 neutrosophic number weighted averaging (T2NNWA) operator:

$$T2NNWA\left(\widetilde{A_1}, \dots \widetilde{A_s}, \dots, \widetilde{A_m}\right) = w_1\widetilde{A_1} \oplus w_s\widetilde{A_s} \oplus \dots .\oplus w_m\widetilde{A_m} = \oplus_{s=1}^{m}\left(w_s\widetilde{A_s}\right)$$

$\big((1 - \prod_{s=1}^{m}(1 - T_{T_{\tilde{A}s}}(y))^{w_s}$, $1 - \prod_{s=1}^{m}(1 - T_{I_{\tilde{A}s}}(y))^{w_s}, 1 - \prod_{s=1}^{m}(1 - T_{F_{\tilde{A}s}}(y))^{w_s}$),

$\left(\prod_{s=1}^{m} I_{T_{\tilde{A}s}}(y))^{w_s}, \prod_{s=1}^{m} I_{I_{\tilde{A}s}}(y))^{w_s}, \prod_{s=1}^{m} I_{F_{\tilde{A}s}}(y))^{w_s}\right)$,

$\left(\prod_{s=1}^{m} F_{T_{\tilde{A}s}}(y))^{w_s}, \prod_{s=1}^{m} F_{I_{\tilde{A}s}}(y))^{w_s}, \prod_{s=1}^{m} F_{F_{\tilde{A}s}}(y))^{w_s}\right)$). (5)

Definition 3.4 (21). Suppose that

$\tilde{A} = \left\langle \left(T_{T_{\tilde{A}}}(y), T_{I_{\tilde{A}}}(y), T_{F_{\tilde{A}}}(y)\right), \left(I_{T_{\tilde{A}}}(y), I_{I_{\tilde{A}}}(y), I_{F_{\tilde{A}}}(y)\right), \left(F_{T_{\tilde{A}}}(y), F_{I_{\tilde{A}}}(y), F_{F_{\tilde{A}}}(y)\right) \right\rangle$ is T2NN Score function is calculated as follows:

$$S(\tilde{A}) = \frac{1}{12}\left\langle 8 + \left(T_{T_{\tilde{A}}}(y) + 2\left(T_{I_{\tilde{A}}}(y)\right) + T_{F_{\tilde{A}}}(y)\right) - \left(I_{T_{\tilde{A}}}(y) + 2\left(I_{I_{\tilde{A}}}(y)\right) + I_{F_{\tilde{A}}}(y)\right) - \left(F_{T_{\tilde{A}}}(y) + 2\left(F_{I_{\tilde{A}}}(y)\right) + F_{F_{\tilde{A}}}(y)\right)\right\rangle \quad (6)$$

Table 1. T2NN linguistic variables to distinct experts.

Experiences (years)	Linguistic variables	T2NN scale
5 <	Poor (P)	((0.20,0.30,0.20),(0.60,0.70,0.80),(0.45,0.75,0.75))
[5,15]	Medium Poor (MP)	((0.40,0.30,0.25),(0.45,0.55,0.40),(0.45,0.60,0.55))
[15,25]	Medium (M)	((0.65,0.55,0.55),(0.40,0.45,0.55),(0.30,0.40,0.35))
[25,30]	Good (G)	((0.80,0.75,0.70),(0.20,0.15,0.30),(0.15,0.10,0.20))
> 30	Very Good (VG)	((0.90,0.85,0.95),(0.10,0.15,0.10), (0.05,0.05,0.10))

Table 2. T2NN linguistic variables to distinct experts.

Linguistic variables	T2NN scale
Very Bad (VB)	((0.20,0.20,0.10),(0.65,0.80,0.85),(0.45,0.80,0.70))
Bad (B)	((0.35,0.35,0.10),(0.50,0.75,0.80),(0.50,0.75,0.65))
Medium Bad (MB)	((0.50,0.30,0.50),(0.50,0.35,0.45),(0.45,0.30,0.60))
Medium (M)	((0.40,0.45,0.50),(0.40,0.45,0.50),(0.35,0.40,0.45))
Medium Good (MG)	((0.60,0.45,0.50),(0.20,0.15,0.25),(0.10,0.25,0.15))
Good (G)	((0.70,0.75,0.80),(0.15,0.20,0.25,),(0.10,0.15,0.20))
Very Good (VG)	((0.95,0.90,0.95),(0.10,0.10,0.05), (0.05,0.05,0.05))

3.2 | Hybrid T2NN-LBWA-EDAS

LBWA is used to determine the weights of the criteria. It starts by identifying the best and worst criteria, followed by pairwise comparisons between them and the other criteria. The logarithmic scale offers a more refined method to derive the relative importance of the criteria (25). The EDAS method ranks alternatives by comparing them to an average solution based on positive distance from average (PDA) and negative distance from average (NDA). It is effective in decision-making problems with multiple alternatives and criteria (30).

Phase 1. T2NN expert reputation rating:

In this phase, the reputation of experts is assessed using T2NN, accounting for their experiences and expertise. The process is essential for determining the credibility of the experts involved in decision-making.

Step 1.1: Construct the T2NN Expert Reputation

In this first phase, the reputation of experts is assessed under the T2NN, accounting for their experiences and expertise. The process is essential for determining the credibility of the experts involved in decision-making.

Construct the T2NN expert reputation matrix. $\breve{U}$ as: Let

- A = {A1, A2, …Am} be the set of alternatives.
- C = {C1, C2, …, Cn} represent a set of criteria.
- D = {DM1, DM2, … DMk} is a set of decision-makers group.

The T2NN reputation matrix $\breve{U}$ is constructed using linguistic assessments of expert experiences and expertise. The reputation matrix elements Where $\breve{U}_e^{(1)} = \left(T_{T_{\tilde{U}1}(1)}(z), T_{I_{\tilde{U}1}(1)}(z), T_{F_{\tilde{U}1}(1)}(z)\right), \left(I_{T_{\tilde{U}1}(1)}(z), I_{I_{\tilde{U}1}(1)}(z), I_{F_{\tilde{U}1}(1)}(z)\right), \left(F_{T_{\tilde{U}1}(1)}(z), F_{I_{\tilde{U}1}(1)}(z), F_{F_{\tilde{U}1}(1)}(z)\right)$ And $\breve{U}_e^{(2)} = \left(T_{T_{\tilde{U}1}(2)}(z), T_{I_{\tilde{U}1}(2)}(z), T_{F_{\tilde{U}1}(2)}(z)\right), \left(I_{T_{\tilde{U}1}(2)}(z), I_{I_{\tilde{U}1}(2)}(z), I_{F_{\tilde{U}1}(2)}(z)\right),$

$$\left(F_{T_{\tilde{U}1}(2)}(z), F_{I_{\tilde{U}1}(2)}(z), F_{F_{\tilde{U}1}(2)}(z)\right)$$

T2NN terms from Table 1 will distinguish the experts based on their experiences and expertise.

Step 1.2. Aggregate the reputation of the experts: Using the T2NN weighted aggregation method (T2NNWA), the aggregated reputation Qe is computed:

$$\check{Q}e = T2NNWA\left(\breve{U}_e^{(1)}, \breve{U}_e^{(2)}\right) = \zeta_1 \breve{U}_e^{(1)} \oplus \zeta_2 \breve{U}_e^{(2)} = \oplus_{l=1}^{2}\left(\zeta_l \breve{U}_e^{(l)}\right)$$

$$\Big(\big(1-\prod_{l=1}^{2}(1-T_{T_{\breve{U}_1(1)}}(z))^{\zeta_l}, 1-\prod_{l=1}^{2}(1-T_{I_{\breve{U}_1(1)}}(z))^{\zeta_l}, 1-\prod_{l=1}^{2}(1-T_{F_{\breve{U}_1(1)}}(z))^{\zeta_l}\big),$$
$$\big(\prod_{l=1}^{2} I_{T_{\breve{U}_1(1)}}(z))^{\zeta_l}, \prod_{l=1}^{2} I_{I_{\breve{U}_1(1)}}(z))^{\zeta_l}, \prod_{l=1}^{2} I_{F_{\breve{U}_1(1)}}(z))^{\zeta_l}\big),$$
$$\big(\prod_{l=1}^{2} F_{T_{\breve{U}_1(1)}}(z))^{\zeta_l}, \prod_{l=1}^{2} F_{I_{\breve{U}_1(1)}}(z))^{\zeta_l}, \prod_{l=1}^{2} F_{F_{\breve{U}_1(1)}}(z))^{\zeta_l}\big)\Big) \tag{7}$$

Where ζ_1, ζ_2 are trade-off parameters for expert reputation, such that $\zeta_1, \zeta_2 \in [0,1]$ and $\zeta_1, +\zeta_2 = 1$.

Step 1.3. Then the score function of the aggregated reputation is calculated as follows:

$$S(\widetilde{Qe}) = \frac{1}{12}\Big\langle 8 + \Big(T_{T_{\widetilde{Qe}}}(Z) + 2\Big(T_{I_{\widetilde{Qe}}}(Z)\Big) + T_{F_{\widetilde{Qe}}}(Z)\Big) - \Big(I_{T_{\widetilde{Qe}}}(Z) + 2\Big(I_{I_{\widetilde{Qe}}}(Z)\Big) + I_{F_{\widetilde{Qe}}}(Z)\Big) - \Big(F_{T_{\widetilde{Qe}}}(Z) + 2\Big(F_{I_{\widetilde{Qe}}}(Z)\Big) + F_{F_{\widetilde{Qe}}}(Z)\Big)\Big\rangle \tag{8}$$

Step 1.4. Determine the reputation of the experts

$$\delta_e = \frac{\check{Q}e}{\sum_{l=1}^{k}\check{Q}e} \quad e = 1,\ldots k \tag{9}$$

Phase 2. T2NN-LBWA-EDAS:

Step 2.1: Determining the Most Important Criterion: The decision-maker selectsC_1 from $S = \{C_1, C_2, \ldots, C_n\}$

Step 2.2: Grouping Criteria by Levels of Significance: Group the remaining criteria into subsets $S_1, S_2, \ldots . S_k$ based on their relative significance compared to C_1

Step 2.3: Comparing Criteria within Levels: Assign an integer $I_{is} \in \{0,1,\ldots,r\}$ to each criterion $C_{ip} \in S_i$ Based on their relative significance within their level:

$I_1 = 0$ for the most significant criterion C_1.

$I_p > I_q$ if C_p is more significant than C_q .

If criteria are equivalent in significance, assign the same value for$I_p = I_q$.

The maximum value r for the comparison scale is defined as:

$$r = \max\{|S_1|, |S_2|, \ldots\ldots, |S_k|\} \tag{10}$$

Step 2.4: Defining the Elasticity Coefficient r_0: Define the elasticity coefficient $r_0 \in N$ such that $r_0 > r$. This parameter will affect the weighting distribution across levels.

Step 2.5: Calculation of the influence function of the criteria.

$$f(C_{ip}) = \frac{r_0}{i.r_0 + I_{iq}} \tag{11}$$

Step 2.6: Calculation of the optimum values of the weight coefficients of criteria. Compute the weight of the most important criterion C_1

$$w_1 = \frac{1}{1 + f(C_2) + \cdots + f(C_n)} \tag{12}$$

For the remaining criteria $f(C_j)$, the weights are calculated using:

$$w_j = f(C_j).w_1 \tag{13}$$

Where j= 2, 3, …., n and n present the total number of criteria.

Step 2.7: Construct the T2NN Initial Decision Matrix: Experts provide opinions using the linguistic terms presented in Table 2, and a T2NN initial decision matrix is built based on these assessments.

Step 2.8: Aggregate the T2NN Decision Matrix: The T2NN decision matrix is aggregated using the T2NNWA approach from Step 1.2 and the reputation weights of experts calculated in Phase 1.

Step 2.9: Convert T2NN Matrix into Crisp Numbers: The aggregated T2NN matrix is converted into crisp values using the score function. The resulting decision matrix is represented as:

$$\mathcal{M} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array} \tag{14}$$

Step 2.10: Determine the Average Solution: For each attribute C_j, calculate the average solution:

$$AV_j = \frac{\sum_{i=1}^{m} r_{ij}}{m} \quad \text{j=1,….,n} \tag{15}$$

Step 2.11: Calculate Positive and Negative Distances:

For positive attributes:

$$PDA_{ij} = \frac{\max(0,(r_{ij}-AV_j))}{AV_j} \tag{16}$$

$$NDA_{ij} = \frac{\max(0,(AV_j-r_{ij}))}{AV_j} \tag{17}$$

For negative attributes:

$$PDA_{ij} = \frac{\max(0,(AV_j-r_{ij}))}{AV_j} \tag{18}$$

$$NDA_{ij} = \frac{\max(0,(r_{ij}-AV_j))}{AV_j} \tag{19}$$

Step 2.12: Calculate Weighted PDA and NDA: Using the LBA weights from Step 2.6, compute the weighted distances:

$$SP_i = \sum_{j=1}^{n} PDA_{ij}.w_j \tag{20}$$

$$SN_i = \sum_{j=1}^{n} NDA_{ij}.w_j \tag{21}$$

Step 2.13: Normalize the weighted PDA and NDA values:

$$NSP_i = \frac{SP_i}{max_i(SP_i)} \tag{22}$$

$$NSN_i = \frac{SN_i}{max_i(SN_i)} \tag{23}$$

Step 2.14: Compute the Appraisal Score:

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \tag{24}$$

Step 2.15: The final ranking: Rank the alternatives based on their appraisal score AS_i.

4 | Application: Evaluating Smart Cities in Egypt

In the context of Egypt's smart city development, several key criteria have been identified to systematically evaluate and rank the performance of cities transitioning toward smart urban models. The evaluation focuses on six core criteria that reflect Egypt's unique cultural, economic, and environmental contexts.

4.1| Criteria Definition (15)

- **C1: Cultural Interaction:** Egypt's cities hold a rich cultural heritage, and their smart transformation must balance tradition with modernity. Alexandria, Luxor, and Aswan ranked well in this criterion due to their historic significance and efforts to integrate technology into cultural preservation.
- **C2: Economy:** Economic development is a critical component of Egypt's smart city agenda. Factors like job creation, business opportunities, and investment potential were considered. Cities such as Cairo, Alexandria, and the New Administrative Capital scored highly due to their robust economic frameworks.
- **C3: R&D**: Cities were evaluated based on their investments in R&D, innovation hubs, and technological infrastructure. The New Administrative Capital and Smart Village were rated the highest, as they are Egypt's primary hubs for technology and research investments.
- **C4: Livability:** indicators like healthcare, education, housing, and safety were assessed. Cairo's extensive healthcare network and Alexandria's education system contributed to their top scores.
- **C5: Environment:** sustainability is a crucial criterion, especially in managing energy consumption, waste, and pollution. Newer cities like the New Administrative Capital and Smart Village performed better due to their focus on green technologies.
- **C6: Accessibility:** This criterion examined transport networks, connectivity, and infrastructure. Cairo's metro system and accessibility plans for the New Administrative Capital positioned them as the leaders in this category.

4.2| Implementation and Evaluation

Phase 1: T2NN Expert Reputation Rating: In this phase, the reputation of experts is assessed using T2NN, which considers their experience and expertise in the decision-making process as Table 1

Step 1.1: Construct the T2NN Expert Reputation Matrix: construct the T2NN expert reputation matrices for experiences and expertise. Table 3 provides T2NN values for the experiences and expertise of four experts. Based on the values from Table 3, the T2NN reputation matrices for experiences and expertise will be structured as Table 4.

Step 1.2: Aggregate the reputation matrices using T2NNWA Eq. (7) Using the parameters $\zeta 1= 0.50$ and $\zeta 2= 0.50$ the T2NNWA will be at Table 5.

Step 1.3: Calculate the score function Eq. (8) in Table 5

Step 1.4: determine the reputation of each expert using the aggregated reputation as Eq. (9) as Table 5.

Table 3. Experts profile.

Experts	Experiences	Expertise	Occupation
DM1	6	Medium	Industry
DM2	17	Good	urabn management
DM3	9	very good	Industry
DM4	26	Medium P	Industry

Table 4. T2NN expert reputation matrices.

Expetrs	**Experience**									**Expertise**								
	Tt	Ti	Tf	It	Ii	If	Ft	Fi	Ff	Tt	Ti	Tf	It	Ii	If	Ft	Fi	Ff
DM1	0.20	0.30	0.20	0.60	0.70	0.80	0.45	0.75	0.75	0.65	0.55	0.55	0.40	0.45	0.55	0.30	0.40	0.35
DM2	0.65	0.55	0.55	0.40	0.45	0.55	0.30	0.40	0.35	0.80	0.75	0.70	0.20	0.15	0.30	0.15	0.10	0.20
DM3	0.40	0.30	0.25	0.45	0.55	0.40	0.45	0.60	0.55	0.90	0.85	0.95	0.10	0.15	0.10	0.05	0.05	0.10
DM4	0.90	0.85	0.95	0.10	0.15	0.10	0.05	0.05	0.10	0.40	0.30	0.25	0.45	0.55	0.40	0.45	0.60	0.55

Table 5. Aggregated Reputation and Score Functions

	Tt	**Ti**	**Tf**	**It**	**Ii**	**If**	**Ft**	**Fi**	**Ff**	**Score**	**Reputation**
DM1	0.47	0.44	0.40	0.49	0.56	0.66	0.37	0.55	0.51	0.46	0.17
DM2	0.74	0.66	0.63	0.28	0.26	0.41	0.21	0.20	0.26	0.72	0.26
DM3	0.76	0.68	0.81	0.21	0.29	0.20	0.15	0.17	0.23	0.77	0.28
DM4	0.76	0.68	0.81	0.21	0.29	0.20	0.15	0.17	0.23	0.77	0.28

Phase 2. T2NN-LBWA-EDAS:

Step 2.1: The decision-maker selects: C_2 from $S = \{C_1, C_2, C_3, C_4, C_5, C_6\}$ as the most important criterion.

Step 2.2: Compare the remaining criteria C_1, C_3, C_4, C_5, C_6 against C_2 to group them by their significance. The decision-maker evaluates the criteria and finds the following relative significance

$S_1 = \{C_2, C_5, C_1, C_3\}$ (more significant group)

$S_2 = \{C_4, C_6\}$ (less significant group)

Step 2.3: Assign integers based on relative significance Thus, the integer values assigned are:

$$I_1 = 4, I_2 = 0, I_3 = 5, I_4 = 2, I_5 = 2, I_6 = 1$$

Maximum Value of r = 4

Step 2.4: Define r_0 such that r_0 > r so, r_0 = 5

Step 2.5: Use Eq.(11) to get the Influence Function of the Criteria.

Step 2.6: Calculation of the Optimum Values of the Weight Coefficients

Weight of the Most Important Criterion by Eq. (12) $C_2 = 0.274645794$. Weights for Remaining Criteria by Eq. (13) at Table 6.

Table 6. Final weights.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
W	0.152581	0.274646	0.137323	0.114436	0.196176	0.124839

Step 2.7: Experts provide their evaluations for each alternative Ai against each criterion Cj using linguistic terms. These linguistic terms are associated with T2NN as described in Table 2. Based on these assessments, we construct a T2NN decision matrix as Table 7.

Step 2.8: Use the T2NNWA Eq. (5) to aggregate expert opinions as the reputation weights of experts from Phase 1 for the aggregation process.

Step 2.9: Convert the aggregated T2NN decision matrix into crisp values using a score function in Eq. (8) to get the decision matrix as Table 8.

Step 2.10: For each criterion Cj , calculate the average solution as shown in Table 8.

Step 2.11: For each alternative Ai under each criterion Cj, calculate the (PDA) and (NDA). For Positive Attributes (C1,C2,C3,C5) using Eqs. (16,17) and for Negative Attributes (C4,C6) using Eqs.(18,19)

Step 2.12: Using the weights wj obtained from Table 6, calculate the weighted PDA and weighted NDA for each alternative by Eqs. (20,21)

Step 2.13: To ensure comparability across alternatives, normalize the weighted PDA and NDA values by Eqs.(22,23) as Table 9.

Step 2.14: For each alternative, calculate the Appraisal Score by Eq.(24) to determine the overall performance of each alternative as shown in Table 9.

Step 2.15: Rank the alternatives based on their Appraisal Score ASi. The alternative with the highest appraisal score is considered the best, followed by others in descending order.

Table 7. Decision makers' opinions.

	Experts	C1	C2	C3	C4	C5	C6
Alt1	DM1	VB	M	MB	MB	B	VG
	DM2	B	B	B	G	VB	G
	DM3	B	MG	VB	MG	M	M
	DM4	VG	M	MB	G	B	B
Alt2	DM1	VB	M	M	M	B	MB
	DM2	MG	MG	G	MB	MG	B
	DM3	G	MB	M	B	G	MG
	DM4	M	B	M	MB	M	G
Alt3	DM1	MG	MG	M	MG	MG	VG
	DM2	M	MB	MB	M	MB	B
	DM3	G	G	M	M	MG	M
	DM4	G	M	MG	MB	M	VB
Alt4	DM1	MB	MG	MG	MG	MG	VG
	DM2	G	VB	M	MG	MB	MB
	DM3	B	G	B	VG	M	M
	DM4	MB	MG	B	G	VB	VB

Table 8. Decision matrix.

	C1 +	C2+	C3+	C4 -	C5+	C6-
Alt1	0.64	0.56	0.41	0.75	0.37	0.70
Alt2	0.65	0.55	0.61	0.50	0.64	0.61
Alt3	0.74	0.67	0.60	0.57	0.63	0.57
Alt4	0.59	0.67	0.47	0.83	0.51	0.61
Avj	0.65	0.61	0.52	0.66	0.54	0.63

Table 9. Final rank.

SPI	SNI	NSPi	NSNi	ASI	Rank
0.00	0.15	0	0	0	4
0.18	0.03	0.842479	0.8199	0.831189	2
0.21	0.00	1	1	1	1
0.13	0.07	0.604698	0.554277	0.579488	3

5 | Discussion

5.1| Results

In the discussion based on the Appraisal Scores using T2NN-LBWA-EDAS methods. Best Alternative: Alternative 3, this alternative scored the highest, which suggests it has the most favorable evaluation across all criteria when considering the uncertainty and linguistic preferences modeled by T2NN and LBWA. The EDAS method likely determined that Alternative 3 has the smallest distance from the "average solution," indicating strong performance across multiple evaluation dimensions. Second Best Alternative: Alternative 2, although not ranked as high as Alternative 3, Alternative 2 still performs well, making it a competitive option in this decision-making scenario. It has a favorable score when accounting for the decision-makers' preferences and the handling of indeterminacy in the data through T2NN. Third Best Alternative: Alternative 4, is ranked slightly lower, indicating that while it has decent performance, it is not as strong as Alternatives 3 and 2 in addressing the criteria. Least Preferred Alternative: Alternative 1, with the lowest appraisal score, Alternative 1 performs the worst among the alternatives evaluated, suggesting it may not meet the desired outcomes or decision criteria as effectively as the others.

5.2| Sensitivity Analysis

For the sensitivity analysis, we will vary the values of $\zeta 1$ and $\zeta 2$ (which were initially set as 0.50 each) and observe how changes affect the final reputation scores of the experts. Table 10 shows the final rank of EDAS in sensitivity analysis. Based on the variations in $\zeta 1$, the rankings of the alternatives remain constant, with the same rankings being observed for A1, A2, A3, and A4 regardless of changes to $\zeta 1$ (and, implicitly, $\zeta 2=1-\zeta 1$). The rankings for A1, A2, A3, and A4 are invariant to changes in $\zeta 1$ across the range from 0 to 1. This suggests that the rankings are stable and not sensitive to the relative weight given to experience ($\zeta 1$) versus expertise ($\zeta 2$) as shown in Figure 1.

Table 10. Sensitivity analysis.

	$\zeta 1=0.1$	$\zeta 1=0.2$	$\zeta 1=0.3$	$\zeta 1=0.4$	$\zeta 1=0.5$	$\zeta 1=0.6$	$\zeta 1=0.7$	$\zeta 1=0.8$	$\zeta 1=0.9$	$\zeta 1=1$	$\zeta 1=0$
A1	4	4	4	4	4	4	4	4	4	4	4
A2	2	2	2	2	2	2	2	2	2	2	2
A3	1	1	1	1	1	1	1	1	1	1	1
A4	3	3	3	3	3	3	3	3	3	3	3

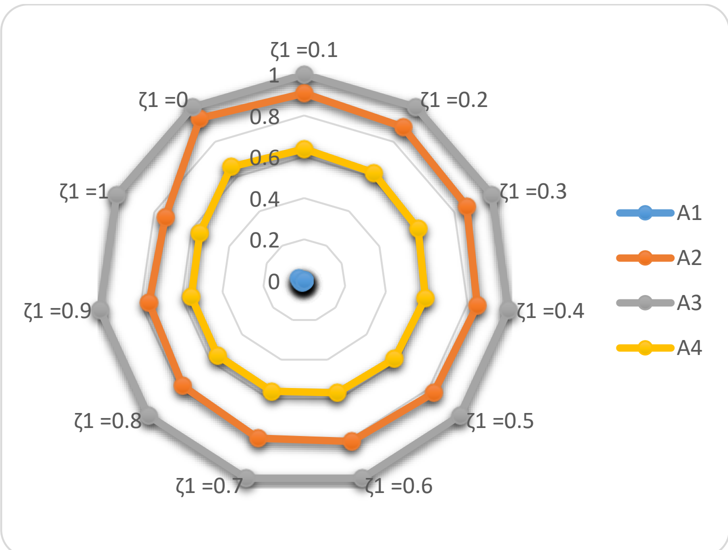

Figure 1. Sensitivity analysis.

5.3| Comparative Analysis

While the rankings are the same, it's worth noting the different ways these methods approach decision-making:

- **EDAS** (28): evaluates alternatives based on positive and negative distances from the average solution.
- **TOPSIS** (42): ranks alternatives based on their relative closeness to the ideal and negative-ideal solutions.
- **MABAC** (44): focuses on distance from the border approximation area for ranking alternatives.
- **CODAS** (43): ranks alternatives based on Euclidean and Taxicab distances from the negative-ideal solution.
- **WASPAS** (45): combines both additive and multiplicative utility functions for ranking.

Table 11 and Figure 2 show that EDAS, TOPSIS, MABAC, CODAS, and WASPAS methods all produce identical rankings for the alternatives (A1, A2, A3, A4). A3 is ranked 1st across all methods. A2 is ranked 2nd across all methods. The same rankings for all five methods indicate high consistency in the evaluation criteria and robustness of the alternatives. Regardless of the different approaches these methods use, the outcome remains the same. The identical rankings suggest that, for the given data and alternatives, all these methods converge on the same solution. This suggests the problem formulation and criteria used are well-structured, leaving little room for variation among methods.

Table 11. Comparative analysis.

	EDAS	TOPSIS	MABAC	CODAS	WASPAS
A1	4	4	4	4	4
A2	2	2	2	2	2
A3	1	1	1	1	1
A4	3	3	3	3	3

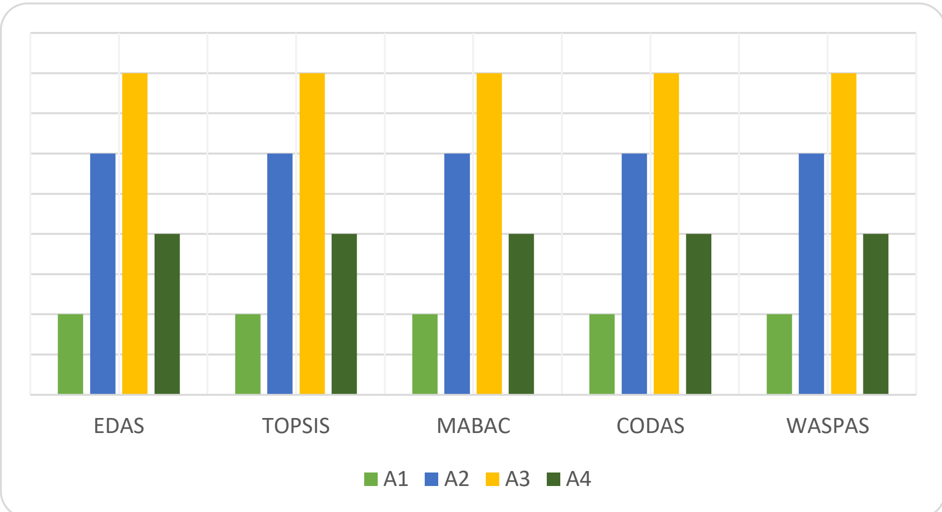

Figure 2. Comparative analysis.

6 | Implication and Future work

The findings from this study have significant implications for the evaluation and management of smart cities. The integration of T2NN, LBWA, and EDAS provides a robust framework for decision-makers to assess smart city alternatives systematically. This approach allows for a nuanced understanding of uncertainty and ambiguity, which is often present in urban planning and management contexts. By employing advanced decision-making methods, city planners and policymakers can make more informed choices regarding resource allocation. This ensures that investments are directed toward initiatives that have the most substantial impact on improving citizen welfare and urban sustainability. The comprehensive evaluation framework facilitates strategic planning by enabling stakeholders to prioritize initiatives based on their effectiveness and alignment with the city's long-term goals. This is particularly crucial for addressing the challenges of rapid urbanization and environmental sustainability.

Future studies could explore the application of T2NN in other domains beyond smart cities, such as healthcare, transportation, and energy management. Investigating its effectiveness in different contexts will help refine its applicability and enhance its robustness. Further research can conduct comparative analyses between T2NN, LBWA, and other MCDM methods, such as the Analytic Hierarchy Process (AHP) or Fuzzy Logic, to identify strengths, weaknesses, and optimal use cases for each method. Future studies could focus on integrating real-time data analytics into the evaluation framework. By leveraging IoT and big data, decision-makers can enhance the timeliness and relevance of their assessments, allowing for dynamic adjustments to urban policies and strategies. A more comprehensive sensitivity analysis of the criteria weights could be performed to understand how variations in parameters affect decision outcomes. This can help identify the most critical factors influencing smart city evaluations and enhance the robustness of the decision-making process. Integrating T2NN, LBWA, and EDAS with other emerging technologies such as machine learning and artificial intelligence could enhance the decision-making framework's predictive capabilities and improve the evaluation of complex scenarios.

7 | Conclusion

This study presented a comprehensive evaluation framework for assessing smart cities in Egypt using advanced MCDM methods. By employing T2NN, LBWA, and EDAS methods, we addressed the complexities and uncertainties inherent in smart city evaluation. The integration of these methodologies enabled a more robust and systematic assessment, effectively capturing decision-makers preferences and handling the indeterminacy present in the data. Six key criteria—Cultural Interaction, Economy, Research & Development (R&D), Livability, Environment, and Accessibility—were identified as essential for evaluating the performance of smart cities in Egypt. These criteria reflect Egypt's strategic vision, particularly its Vision 2030 initiative, which promotes sustainable, inclusive, and technologically advanced urban development. The evaluation revealed that Alternative 3 emerged as the top performer, excelling in areas such as economic development, technological innovation, and environmental sustainability, thus positioning it as a model for smart city development in Egypt. The use of T2NN allowed for a more nuanced representation of uncertainty, vagueness, and ambiguity in decision-maker judgments. This approach significantly improved the evaluation's ability to manage uncertainty while ensuring reliable decision-making. Furthermore, the convergence of rankings across several MCDM methods, including EDAS, TOPSIS, MABAC, CODAS, and WASPAS, highlighted the consistency and robustness of the proposed decision-making framework. This consistency provides confidence in the evaluation results, ensuring that stakeholders can use these findings to inform strategic decisions about smart city investments and initiatives. This approach proved particularly valuable in the complex, multi-dimensional evaluation of smart city performance, where qualitative and quantitative uncertainties often complicate decision-making processes. The proposed framework offers a reliable method for prioritizing urban development projects and supports Egypt's broader objectives of sustainable and technologically advanced urban growth.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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