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Enhancing Smart City Management with AI: Analyzing Key Criteria and their Interrelationships using DEMATEL under Neutrosophic Numbers and MABAC for Optimal Development

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Abstract: Purpose: This paper explores the transformative role of AI across various domains of smart cities, including urban mobility, energy management, public safety, healthcare, environmental monitoring, economic development, and data management. It aims to develop a novel decision-making framework that integrates AI technologies with a hybrid approach to analyze the interrelationships among smart city components.
Methodology: This paper employs a hybrid decision-making framework that combines the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method with single-valued trapezoidal neutrosophic numbers (STrNN). This approach is used to analyze the complex relationships among criteria and sub-criteria in smart city contexts, addressing uncertainty and incomplete information while providing a structured evaluation of alternatives. Additionally, the study incorporates the Multi-Attributive Border Approximation Area Comparison (MABAC) method to assess and rank alternatives for smart city development. This integration of MABAC complements the insights derived from the STrNN-DEMATEL approach, offering a robust and nuanced evaluation of alternatives. By combining these methodologies for the first time, the research delivers a novel and effective decision-making framework tailored to the complexities of smart city development.
Findings: The key findings of this paper highlight the pivotal role of economic development, Energy Management and Sustainability, and Urban Mobility and Transportation in shaping smart city ecosystems. The paper demonstrates the effectiveness of the proposed framework in identifying and prioritizing key drivers and understanding the causal relationships among various smart city components.
Originality: This paper is pioneering in developing a decision-making framework that integrates AI technologies with a hybrid approach, combining DEMATEL and STrNN for the first time. The framework provides a comprehensive analysis of interrelationships among criteria and sub-criteria in smart city contexts, addressing ethical concerns related to AI and ensuring a balanced approach to technological innovation, and social, environmental, and economic considerations. Incorporating MABAC alongside STrNN-DEMATEL enhances the framework's robustness and effectiveness, offering new insights into smart city development.

Keywords: AI; Smart Cities; DEMATEL; STrNN; MCDM; MABAC.

1. Introduction

The rapid urbanization trend is indeed a significant phenomenon, with more than half of the global population, approximately 55%, currently residing in urban areas. This proportion is expected to increase to 68% by 2050, according to various sources, including the United Nations [1]. To address the challenges posed by urbanization, cities are adopting smart city initiatives, which aim to provide efficient, sustainable, and livable environments for citizens [2]. Artificial intelligence (AI) is a key technology driving the development of smart cities, enabling cities to become more efficient, responsive, and adaptive to the needs of citizens [3]. AI refers to the development of computer systems that can perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making [4]. AI systems can analyze data, recognize patterns, and make predictions or recommendations, often with greater speed and accuracy than humans [5]. AI has the potential to transform many aspects of our lives, from business and healthcare to education and entertainment [4]. Artificial Intelligence (AI) is profoundly transforming smart cities across multiple domains, driving advancements in urban mobility, transportation, energy management, public safety, healthcare, environmental monitoring, economic development, and data management [6]. Figure 1 illustrates the interconnectedness of these domains and how AI is driving innovation across multiple sectors. AI is at the heart of the smart city revolution, fundamentally reshaping how urban environments function, adapt, and respond to the needs of their inhabitants [7]. By integrating AI into various aspects of city management, from transportation to healthcare, smart cities are becoming more efficient, sustainable, and responsive. In urban mobility and transportation, AI plays a pivotal role in optimizing traffic flow through real-time data analysis and intelligent traffic signal systems, reducing congestion and enhancing the efficiency of public transportation networks [8]. Autonomous vehicles powered by AI and predictive maintenance of infrastructure, are gradually becoming integral to urban transportation, offering safer, more reliable alternatives to traditional vehicles [9]. AI-driven public transportation systems can dynamically adjust routes and schedules based on demand, ensuring that resources are used efficiently and that commuters experience minimal delays [10]. In energy management, AI is crucial in optimizing the operation of smart grids, balancing energy supply and demand, integrating renewable energy sources, and enhancing energy efficiency in buildings and public spaces [11]. These advancements not only reduce the environmental impact of urban living by reducing wastage and contributing to a lower carbon footprint but also contribute to significant cost savings for both governments and residents [12].

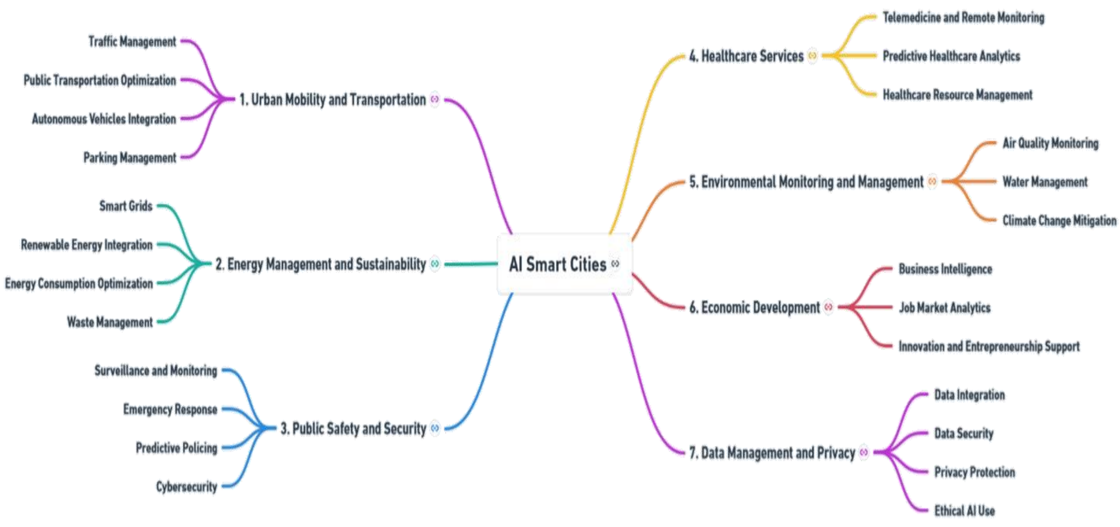

Figure 1. AI smart cities.

AI-driven public safety and security systems, such as predictive policing and intelligent surveillance, enhance the protection of citizens while addressing ethical concerns around privacy [13]. AI's role in public safety and security within smart cities is equally transformative. By analyzing vast amounts of data from surveillance cameras, social media, and other sources, AI can predict and prevent crime, improve emergency response times, and enhance the overall safety of urban areas [14]. However, these benefits come with challenges related to privacy and ethical considerations, as the potential for misuse of AI-powered surveillance and data collection is a significant concern [15]. In the healthcare sector, AI is enabling smart cities to offer more personalized, accessible, and efficient services [16]. Through telemedicine, AI-driven diagnostics, and predictive analytics, healthcare systems can better manage resources, improve patient outcomes, and reduce the burden on healthcare facilities [17]. AI algorithms can analyze vast amounts of health data to predict disease outbreaks and manage public health resources [18]. AI technology plays a vital role in promoting eco-friendly urban development by providing instantaneous insights into air quality, waste management, and resource utilization [19]. By continuously monitoring and tracking environmental metrics, AI enables city authorities to make data-driven decisions that reduce the ecological footprint of urban areas, ultimately contributing to a more sustainable future [20]. This is particularly crucial in the face of climate change, as AI-driven environmental management can help mitigate its devastating impacts on our planet [21]. Moreover, AI is a powerful driver of economic development in smart cities. It enables the creation of new business models, supports innovative startups, and optimizes urban planning to attract investment and foster growth [22]. AI's ability to analyze large datasets helps cities to make strategic decisions that enhance competitiveness and economic resilience [23]. However, the extensive use of AI across these domains generates vast amounts of data, necessitating robust data management strategies to ensure that this data is securely stored, effectively utilized, and protected against breaches [24]. Privacy concerns are paramount, as the integration of AI in smart cities requires a careful balance between leveraging data for the public good and safeguarding the personal information of citizens [25]. As AI continues to evolve, it will be crucial for smart cities to address these challenges, ensuring that AI is deployed in ways that are ethical, transparent, and beneficial to all.

The case studies of Barcelona, Singapore, and Songdo showcase the various ways AI is being utilized in smart cities globally, highlighting both the advantages and challenges of AI integration. These examples provide valuable insights for other cities seeking to adopt similar technologies, enabling urban planners and policymakers to better understand how to harness AI to create more efficient, sustainable, and livable cities [26]. Barcelona's innovative approach to urban planning and environmental management using AI is a great example of how cities can leverage technology to create a more sustainable and livable environment for their citizens [27]. By analyzing vast amounts of data, AI algorithms can identify patterns and trends that inform policy decisions, leading to improved traffic flow, reduced pollution, and increased green spaces [28]. Singapore's innovative use of AI in smart mobility and public safety is another excellent example of how cities can harness the power of AI to improve the lives of their citizens [29]. By leveraging AI in its public transportation system, Singapore has been able to optimize bus routes, reduce wait times, and manage traffic flow, making commuting more efficient and convenient for residents [30]. The city's investment in autonomous vehicles is also noteworthy, as it has the potential to revolutionize the way people move around the city [31]. AI-driven surveillance systems have also been instrumental in maintaining public safety, with facial recognition and behavior analysis enabling law enforcement to respond quickly to potential threats [32]. Songdo, South Korea's purpose-built smart city, is a remarkable example of how urban planning and technology can come together to create a sustainable and efficient living environment [32]. By integrating AI with IoT devices, Songdo has been able to optimize various city functions, including energy consumption, waste management, and transportation [33]. The integration of AI in Songdo's healthcare system is also noteworthy, providing residents with telemedicine services and personalized healthcare plans [31]. This has not only improved the quality of life for residents but also made healthcare more accessible and convenient. Songdo's approach to smart city development serves as a model for other cities, demonstrating the potential of AI and IoT to transform urban living [32]. By leveraging these technologies, cities can become more efficient, sustainable, and livable, providing residents with a high quality of life in a highly connected environment.

Multi-Criteria Decision Making (MCDM) is a critical field in decision science, focusing on evaluating and prioritizing multiple, often conflicting criteria to make informed and rational decisions [9]. MCDM techniques are especially valuable in complex decision-making environments where stakeholders must consider various factors that are quantitative, qualitative, or a combination of both [10]. These methods are widely applied in areas such as urban planning, healthcare, engineering, business, environmental management, and more, enabling decision-makers to systematically compare alternatives and choose the best possible option based on a set of predefined criteria [34]. MCDM in smart cities is an essential approach to addressing the complex and multifaceted challenges that arise in the planning, development, and management of urban environments that are increasingly reliant on technology and data-driven solutions [17]. Smart cities aim to improve the quality of life for their residents by integrating advanced technologies across various domains such as transportation, energy, healthcare, public safety, and environmental management [35]. MCDM techniques provide a structured framework to evaluate and prioritize these diverse and often competing objectives, ensuring that decisions are made in a holistic and balanced manner. One of the key challenges in MCDM is handling uncertainty and imprecision in decision-making, which has led to the integration of advanced mathematical concepts such as Fuzzy Logic and Neutrosophic Sets as Trapezoidal Neutrosophic Sets [36]. These approaches allow for the modeling of vagueness and uncertainty in criteria and decision-makers preferences, providing a more flexible and realistic framework for complex decision-making scenarios [37]. DEMATEL (Decision-Making Trial and Evaluation Laboratory) is a widely used method in the field of MCDM. It is particularly effective for analyzing and modeling complex causal relationships among criteria, making it a powerful tool for decision-makers who need to understand the interdependencies among various factors in a decision-making process [38]. Developed by the Battelle Memorial Institute in the 1970s, DEMATEL helps to visualize the structure of complicated problems and provides insights into the direct and indirect relationships between criteria, which are often difficult to assess using other methods [39]. DEMATEL is designed to identify and quantify the causal relationships between criteria or factors in a decision-making problem. It helps to distinguish between cause-and-effect relationships, providing a clear picture of how different criteria influence each other [40]. One of the strengths of DEMATEL is its ability to represent the relationships between criteria graphically. The results are often visualized as a causal diagram or digraph, which makes it easier to understand the complex interplay between factors [41]. DEMATEL not only identifies the direct influences of one criterion on another but also considers the indirect effects, making it possible to understand the overall impact of one criterion on the system as a whole [42]. The DEMATEL method combined with Trapezoidal Neutrosophic Numbers (TrNN) represents an advanced approach for tackling complex decision-making problems where uncertainty, vagueness, and incomplete information are prevalent. This hybrid method is particularly useful in scenarios where decision-makers must evaluate the interrelationships between multiple criteria that are not only interconnected but also characterized by indeterminacy and fuzziness. Furthermore, DEMATEL can be effectively utilized as a weighting method within MCDM problems to rank alternatives, allowing for a more nuanced assessment of options in the presence of complex interdependencies and uncertain information.

The primary objective of this paper is to investigate and evaluate the role of AI in transforming smart cities, with a focus on how AI technologies are reshaping urban environments across key areas such as urban mobility, energy management, public safety, healthcare, environmental monitoring, economic development, and data management. This study also aims to improve decision-making processes in smart city management by examining the interrelationships among critical criteria and their sub-criteria using the DEMATEL method within the framework of STrNN. By employing DEMATEL as a weighting method, the paper seeks to rank alternatives, thereby enabling more informed and balanced decision-making in the context of smart cities. Additionally, the study highlights the practical implications of combining AI with MCDM techniques to enhance strategic planning and decision-making in urban settings.

The contributions of the paper can be highlighted as follows:

i). The paper provides an in-depth analysis of how AI technologies are being integrated into different aspects of smart city development, offering insights into its role in enhancing efficiency, sustainability, and livability in urban areas. Case studies of cities like Barcelona, Singapore, and Songdo are used to illustrate successful implementations and the challenges faced.

ii). The paper introduces the innovative use of the STrNN framework in conjunction with the DEMATEL method. This hybrid approach addresses uncertainty, vagueness, and incomplete information in decision-making, offering a more nuanced analysis of the interrelationships between key criteria and sub-criteria in smart city environments.

iii). Through the application of DEMATEL in two distinct scenarios, the study not only explores the interrelationships between key criteria but also uses DEMATEL as a weighting method to rank alternatives. This dual approach enhances the decision-making process in smart city management, providing a structured framework to prioritize critical factors and assess complex interdependencies across urban domains.

iv). The paper demonstrates the practical benefits of integrating AI with MCDM techniques, offering valuable insights for policymakers, urban planners, and decision-makers. The findings support strategic planning efforts in smart cities, facilitating more effective and data-driven decision-making.

v). The paper applies the hybrid DEMATEL-STrNN framework to real-world smart city scenarios, demonstrating its effectiveness in identifying, analyzing, and prioritizing the interdependencies between various criteria. This application underscores the framework's potential to guide decision-makers in creating more efficient and sustainable urban environments.

vi). The paper also contributes to the ongoing discourse on the ethical implications of AI in smart cities, particularly regarding privacy and data security. By emphasizing the need for ethical, transparent, and beneficial AI deployment, the paper provides a balanced perspective on the integration of AI in urban planning.

This paper is structured as follows: Section 2: Literature Review: Discusses previous studies related to smart cities, AI integration, and the role of MCDM methods and Explores the relevance of DEMATEL and neutrosophic sets in evaluating complex systems like smart cities. Section 3: Methodology: Details the STrNN-DEMATEL methodology. Section 4: Implementation of STrNN-DEMATEL. Section 5: Implement STrNN-DEMATEL in MCDM and apply comparative and sensitivity analysis. Section 6: Results and Discussion: Interrelationship Analysis for Main Criteria and Sub-Criteria. Section 7: Implications for Smart City Planning: Discusses the practical implications of the findings for effective smart city planning and decision-making. Section 8: Future Work and Challenges. Section 9: Conclusion: Summarizes the key findings and their implications for smart city development.

2. Literature Review

The literature highlights the importance of MCDM, DEMATEL, and neutrosophic environments in the development and management of smart cities, emphasizing their role in navigating the complex interplay of technological, social, environmental, and economic factors.

As urban environments become increasingly complex, the development and management of cities leverage technologies like telemedicine, health monitoring wearables, and AI-driven diagnostics smart cities require a balanced approach to decision-making that considers a wide range of factors. MCDM is an indispensable tool in this context, providing decision-makers with the structured methodologies needed to evaluate and prioritize multiple criteria [10]. This ensures that decisions are not only technologically sound but also socially inclusive, environmentally sustainable, and economically resilient [34]. In smart cities, urban mobility and transportation systems are enhanced through technologies like AI, IoT, and big data analytics [17]. MCDM plays a crucial role in optimizing these systems by evaluating multiple criteria such as traffic flow, environmental impact, cost, safety, and user convenience [35]. For instance, when planning a new public transportation system or upgrading existing infrastructure, decision-makers can use MCDM methods like TOPSIS or AHP to compare various options—such as autonomous vehicles, electric buses, or bike-sharing programs—based on how well they meet these criteria [43]. This ensures that the selected solution not only improves mobility but also aligns with broader sustainability and efficiency goals. Smart cities aim to optimize energy use and promote sustainability through smart grids, renewable energy integration, and energy-efficient buildings [44]. MCDM methods are instrumental in these efforts by helping city planners and policymakers evaluate different energy strategies. For example, they might use SWOT combined with VIKOR to rank energy sources based on factors [45]. This approach helps ensure that energy policies in smart cities contribute to sustainability goals while also being economically viable and socially acceptable [11]. Ensuring public safety in smart cities involves deploying technologies like AI-driven surveillance, predictive policing, and emergency response systems [13]. MCDM techniques can be used to assess the effectiveness, cost, ethical implications, and public acceptance of these technologies [46]. For instance, AHP-TOPSIS methods could be employed to prioritize investments in different public safety initiatives, ensuring that resources are allocated to the most effective and socially responsible solutions [15]. This approach helps balance the need for security with concerns about privacy and civil liberties. MCDM methods can assist in evaluating healthcare strategies by considering criteria such as accessibility, cost-effectiveness, patient satisfaction, and technological feasibility [17]. Environmental sustainability is a key objective of smart cities, which use sensors and IoT networks to monitor air and water quality, waste management, and energy consumption in real-time [47]. MCDM can support these efforts by evaluating different environmental strategies based on criteria like effectiveness, cost, public health impact, and ease of implementation [48]. For example, Fuzzy MCDM methods can be used to assess the trade-offs between different waste management technologies, ensuring that the chosen solution minimizes environmental impact while being economically feasible and socially acceptable [46]. Smart cities aim to foster economic growth by attracting investment, supporting innovation, and improving the quality of life for residents [49]. MCDM techniques can be used to evaluate different economic development strategies, considering criteria such as job creation, economic diversification, sustainability, and social equity [50]. The vast amounts of data generated in smart cities present both opportunities and challenges, particularly regarding data management and privacy [52]. MCDM can help city planners and policymakers evaluate different data governance strategies, balancing criteria such as data security, privacy, transparency, and usability [53]. Methods like Fuzzy AHP or Bipolar Neutrosophic Sets can be employed to assess the trade-offs between data accessibility for improving city services and the need to protect citizens' privacy [54]. This ensures that data management practices in smart cities are both effective and ethically sound.

The DEMATEL method is particularly effective in the complex decision-making environment of smart cities, where understanding the interrelationships and causal effects among multiple criteria is crucial [38]. DEMATEL assists decision-makers by identifying and quantifying the direct and indirect influences among various factors, providing a clear picture of how different elements within a smart city ecosystem interact [55]. In the context of urban mobility and transportation, DEMATEL can be employed to analyze the causal relationships between factors such as traffic congestion, public transportation efficiency, and autonomous vehicle integration [56]. This helps city planners identify the most influential factors and make informed decisions to enhance transportation systems [57].

DEMATEL is highly valuable in optimizing energy management strategies in smart cities by analyzing the interdependencies among factors like energy demand, renewable energy integration, grid reliability, and cost [58]. Through DEMATEL, decision-makers can visualize how changes in one area, such as increased renewable energy usage, might impact grid stability or costs [59]. Public safety in smart cities involves multiple interconnected systems, such as surveillance, emergency response, and public awareness [60]. DEMATEL can be used to identify the causal relationships between these systems, allowing city authorities to prioritize areas that will most effectively enhance overall safety [61]. In healthcare, DEMATEL can be applied to understand the relationships between different healthcare initiatives and their impact on patient outcomes, accessibility, and cost-efficiency [62]. In scenarios where uncertainty and imprecision are prevalent, such as in the decision-making processes of smart cities, DEMATEL can be combined with neutrosophic numbers[42, 63]. This hybrid approach allows for better handling of the vagueness and indeterminacy inherent in complex urban environments. When evaluating the impact of a new smart city technology, STrNN can help quantify uncertain data, while DEMATEL can model the interrelationships between the criteria, leading to more robust and informed decision-making. Furthermore, using DEMATEL in MCDM problems allows for the calculation of weights that can be used to rank alternatives through methods like MABAC [64], MOORA [65], COPRAS [66], AHP [67], and TOPSIS [67]. This integration supports a structured approach to evaluating alternatives, ensuring that the most balanced and effective decisions are made in the context of smart city management.

3. Methodology: Integrating DEMATEL with Trapezoidal Neutrosophic Numbers

STrNN is a type of neutrosophic number that extends the concept of fuzzy numbers to handle indeterminacy, inconsistency, and uncertainty in a more comprehensive way [37]. In traditional fuzzy set theory, a fuzzy number is represented by a membership function that assigns a degree of membership to each element in the universe of discourse. However, in neutrosophic set theory, a neutrosophic number is represented by three membership functions: truth membership function (T), indeterminacy membership function (I), and falsity membership function (F) [68].

Definition 3.1. A STrNN $\check{S} = ((a_1, b_1, c_1, d_1); T_s, I_s, F_s)$characterized by three trapezoidal membership functions truth (T), indeterminacy (I), and falsity (F) representing as follows:

$$\text{Truth Membership Function } T_s(x) = f(x) = \begin{cases} \frac{(x - a_1)T_s}{(b_1 - a_1)}, & a_1 \le x \le b_1 \\ T_s, & b_1 \le x \le c_1 \\ \frac{(d_1 - x)T_s}{(d_1 - c_1)}, & c_1 \le x \le d_1 \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Indeterminacy Membership Function } I_s(x) = f(x) = \begin{cases} \frac{(b_1 - x + I_s(x - a_1))}{(b_1 - a_1)}, & a_1 \le x \le b_1 \\ I_s, & b_1 \le x \le c_1 \\ \frac{(x - c_1 + I_s(d_1 - x))}{(d_1 - c_1)}, & c_1 \le x \le d_1 \\ 1, & \text{otherwise} \end{cases}$$

$$\text{Falsity Membership Function } F_s(x) = f(x) = \begin{cases} \frac{(b_1 - x + F_s(x - a_1))}{(b_1 - a_1)}, & a_1 \le x \le b_1 \\ F_s, & b_1 \le x \le c_1 \\ \frac{(x - c_1 + F_s(d_1 - x))}{(d_1 - c_1)}, & c_1 \le x \le d_1 \\ 1, & \text{otherwise} \end{cases}$$

Where $0 \le T_s \le 1$; $0 \le I_s \le 1$; $0 \le F_s \le 1$ and $0 \le T_s + I_s + F_s \le 3$; $a_1, b_1, c_1, d_1 \in R$

DEMATEL method, when combined with STrNN, provides a powerful approach for dealing with uncertainty, vagueness, and indeterminacy in decision-making scenarios, such as smart city planning. The STrNN allows for the incorporation of expert opinions that may not be precise or certain, enhancing the robustness of the DEMATEL analysis. The step-by-step methodology for applying DEMATEL using STrNN:

Table 1. STrNN scale.

Scale Level	Trapezoidal Membership Function $(L_{ij}, M1_{ij}, M2_{ij}, U_{ij})$	Truth-Membership (T_{ij})	Indeterminacy-Membership (I_{ij})	Falsity-Membership (F_{ij})	Score Function
Strongly very low (SVL)	(0, 0.1, 0.2, 0.3)	0.1	0.8	0.9	0.020
Very low (VL)	(0.1,0.2,0.3,0.4)	0.2	0.7	0.8	0.058
Low (L)	(0.2,0.3,0.4,0.5)	0.3	0.7	0.7	0.105
Median low (ML)	(0.3,0.4,0.5,0.6)	0.5	0.4	0.5	0.173
Medium (M)	(0.4,0.5,0.6,0.7)	0.6	0.3	0.4	0.348
Medium high (MH)	(0.5,0.6,0.7,0.8)	0.7	0.3	0.3	0.455
High (H)	(0.6,0.7,0.8,0.9)	0.8	0.1	0.2	0.625
Very high (VH)	(0,7,0.8,0.9,1)	0.9	0.2	0.1	0.737
Strongly very high (SVH)	(0.8,0.9,1,1)	1.0	0.1	0.1	0.863

Step 1: Define the Problem and Identify Criteria: The first step in applying DEMATEL is to define the problem and identify the criteria or factors that need to be evaluated. These criteria should be relevant to the decision-making context and capable of influencing the outcome. Each criterion's influence on others is assessed using linguistic terms (e.g., "low," "medium," "high") that can be represented as STrNN, capturing the uncertainty and indeterminacy inherent in the evaluation using Table 1.

Step 2: Construct the Direct-Relation Matrix: The second step in the STrNN-DEMATEL methodology involves constructing the Direct-Relation Matrix. This matrix captures the direct influence of one criterion on another, as assessed by experts.

Step 2.1: Gather expert opinions using the evaluations to evaluate the direct influence of one criterion on another. Each expert assigns a score to represent the influence using a trapezoidal scale. Each element in the matrix is represented by a STrNN, denoted as $((L_{ij}, M1_{ij}, M2_{ij}, U_{ij}), T_{ij}, I_{ij}, F_{ij})$ where T_{ij}, I_{ij}, F_{ij} are the truth, indeterminacy, and falsity memberships respectively.

Step 2.2: Decision-makers assess the influence of each criterion on every other criterion. This is typically done using an X scale (e.g., 0 = no influence, 1 = low influence, 2 = medium influence, 3 = high influence, 4 = very high influence). The results are compiled into a direct-relation matrix.

Step 2.3: Convert all STrNN to crisp numbers using the score function

$$S\,(\widetilde{A_1}) = (\tfrac{1}{12})(a_1 + a_2 + a_3 + a_4)(2 + T_1 - I_1 - F_1) \tag{1}$$

Step 2.4: By multiplying the score X with the SVTrNNs, the decision-makers can incorporate the importance or weight of each criterion into the direct-relation matrix. The resulting matrix D would contain crisp numbers that reflect the weighted influence of each criterion on every other criterion.

$$A = \begin{array}{cc} C_1 & x_1 \\ C_2 & x_2 \\ \vdots & \vdots \\ C_n & x_n \end{array} \begin{bmatrix} 0 & d_{12} & \dots & d_{1n} \\ d_{21} & 0 & \dots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & 0 \end{bmatrix} \quad (2)$$

$$D = A * X \quad (3)$$

Step 3: Normalize the Direct-Relation Matrix: The direct-relation matrix D is normalized to ensure all values fall within a specific range. This is typically done by dividing each STrNN element by the maximum row or column sum in the matrix.

Normalization Formula:

$$\mathrm{N} = {}^{\mathrm{D}}/_{\mu} \quad (4)$$

$$\mu = \max(\max_{1\le i\le n} \textstyle\sum_{j=1}^{n} \mathrm{D_{ij}}\ , \max_{1\le j\le n} \sum_{i=1}^{n} \mathrm{D_{ij}}) \quad (5)$$

Step 4: Calculate the Total-Relation Matrix T: Calculate the total-relation matrix by summing the direct and indirect influences. This can be done using the formula

$$\mathrm{T} = \lim_{h\to\infty} (\mathrm{N}^1, \mathrm{N}^2, \dots\dots, \mathrm{N}^h) = \mathrm{N}(1-\mathrm{N})^{-1} \quad (6)$$

where N is the normalized direct-relation matrix, and I is the identity matrix.

Step 5: Determine Prominence and Relation: For each criterion, the prominence (overall influence) and relation (net cause or effect) are determined by analyzing the sum of rows and columns in the total-relation matrix.

Prominence: $R = [\sum_{j=1}^{n} t_{ij}]_{nx1} = [r_i]_{nx1}$ (7)

Relation: $C = [\sum_{i=1}^{n} t_{ij}]_{1xn} = [c_j]_{1xn}$ (8)

Step 6: Causal Diagram Representation: Plot the criteria in a diagram based on their prominence and relation values. This visual representation will help identify which criteria are the main causes (influencers) and which are effects (influenced) as Impact Relationship Map (IRM) as in Figure 2 by computing R-C and R+C. The IRM is a visual representation of the relationships between the critical factors and other criteria in the system, and the quartiles help to distinguish between different types of factors. The categorization of factors into quartiles is based on their coordinates, which are determined by relationships in the system as Quartile I: Essential factors, Quartile II: Determinant factors, Quartile III: Independent factors, and Quartile IV: Impact factors [69].

Step 7: Calculating threshold value α: decision-makers can identify the most critical factors in the decision-support system by comparing the truth membership values of each criterion with the threshold value

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[t_{ij}]}{N} \quad (9)$$

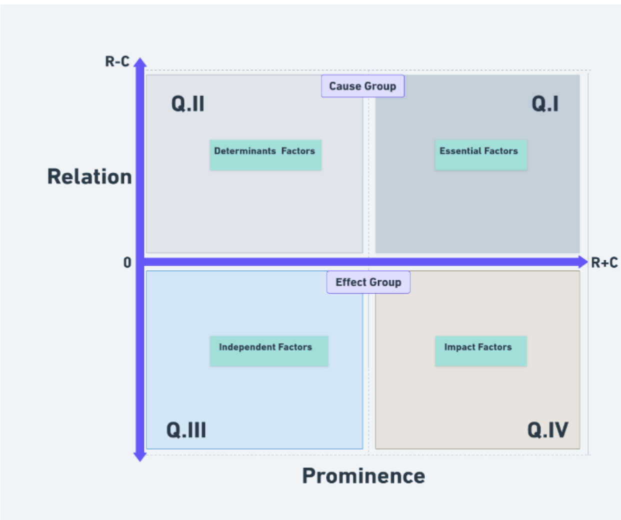

Figure 2. IRM.

Step 8: Calculating Weights for Each Criterion using Prominence and Relation: In this step, we utilize the Prominence (P) and Relation (R) values obtained from Eqs. (7) and (8) to calculate the weights for each criterion. The weights will be used later in MCDM methods to rank alternatives by:

$$\breve{W} = \sqrt{(\mathrm{R} + \mathrm{C})^2 + (\mathrm{R} - \mathrm{C})^2} \tag{10}$$

$$wj = \frac{\breve{W}}{\sum_{i=1}^{n} \breve{W}} \tag{11}$$

4. Implementation of STrNN-DEMATEL

This section details the practical application of the STrNN within the DEMATEL framework to analyze the interrelationships among key criteria in smart city environments. The integration of STrNN with DEMATEL enhances the model's capability to handle the uncertainty, vagueness, and indeterminacy often associated with complex decision-making scenarios.

AI in smart cities is a rapidly growing field that leverages artificial intelligence to enhance the quality of life for citizens, improve operational efficiency, and make cities more sustainable. AI can be applied in various aspects of smart cities, including traffic management, public safety, energy management, waste management, and healthcare. AI has the potential to transform the way cities are designed, built, and managed. However, to fully realize the benefits of AI in smart cities, cities must address the challenges associated with AI adoption. By developing data-driven decision-making processes, ensuring transparency and accountability, addressing the digital divide, and fostering collaboration, cities can create more efficient, sustainable, and livable environments for citizens. The integration of AI in smart cities involves analyzing the complex interrelationships between various criteria and sub-criteria. The STrNN-DEMATEL methodology is suitable for capturing these interdependencies and providing insights into the most influential factors. By capturing these interdependencies, STrNN-DEMATEL can provide valuable insights into the most influential factors driving smart city development and management. This methodology can help cities identify key areas for improvement, optimize resource allocation, and make informed decisions that balance competing demands and priorities. This method is particularly useful when dealing with complex systems, such as smart cities, where there is uncertainty, indeterminacy, and varying degrees of truth, falsity, and indeterminacy. The case study highlights the potential of AI in transforming urban environments and the importance of adopting a holistic approach to smart city development. By leveraging AI and advanced methodologies like STrNN-DEMATEL, cities can create more efficient, sustainable, and livable environments for citizens.

4.1 Steps for Implementing STrNN-DEMATEL for Main Criteria

Step 1: Define the Problem and Criteria:

Problem Statement: The problem involves analyzing the interrelationships among key criteria and their sub-criteria for AI applications in smart cities. These criteria span multiple domains such as urban mobility, energy management, public safety, healthcare, environmental monitoring, economic development, and data management. The goal is to understand how these criteria influence one another and to prioritize them effectively to optimize AI deployment in smart cities.

Identify the Criteria and Sub-Criteria: The criteria should be directly relevant to the successful implementation and operation of AI technologies in smart cities. Below are the criteria and their associated sub-criteria:

C1: Urban Mobility and Transportation:

C11: Traffic Management: Using AI to optimize traffic flow, reduces congestion, and manages traffic signals dynamically.

C12: Public Transportation Optimization: AI-driven schedules, route planning, and real-time tracking to enhance public transport efficiency.

C13: Autonomous Vehicles Integration: Facilitating the integration of self-driving vehicles into the urban transport system.

C14: Parking Management: AI solutions for efficient parking space utilization, reducing search times and congestion

C2: Energy Management and Sustainability:

C21: Smart Grids: AI-enabled smart grids for efficient energy distribution and consumption monitoring.

C22: Renewable Energy Integration: Optimizing the use of renewable energy sources through AI-driven demand forecasting and storage management.

C23: Energy Consumption Optimization: AI systems for reducing energy consumption in buildings, street lighting, and other infrastructure.

C24: Waste Management: Enhancing waste collection, recycling, and disposal processes using AI technologies.

C3: Public Safety and Security:

C31: Surveillance and Monitoring: AI-powered surveillance systems for real-time monitoring and threat detection.

C32: Emergency Response: AI to predict and manage emergencies, optimizing resource allocation and response times.

C33: Predictive Policing: Using AI for crime prediction and resource allocation in law enforcement.

C34: Cybersecurity: Protecting urban infrastructure and citizen data from cyber threats through AI-driven security measures.

C4: Healthcare Services:

C41: Telemedicine and Remote Monitoring: AI applications in remote healthcare services, enabling continuous patient monitoring and consultations.

C42: Predictive Healthcare Analytics: Analyzing healthcare data to predict outbreaks, patient needs, and resource allocation.

C43: Healthcare Resource Management: Optimizing the allocation and use of healthcare resources using AI.

C5: Environmental Monitoring and Management:

C51: Air Quality Monitoring: AI systems for real-time monitoring and analysis of air quality.

C52: Water Management: Optimizing water distribution, consumption, and waste using AI technologies.

C53: Climate Change Mitigation: AI-driven models and simulations to support climate change mitigation efforts.

C6: Economic Development:

C61: Business Intelligence: AI-driven analytics to support business growth and decision-making.

C62: Job Market Analytics: Using AI to analyze job market trends and support workforce development.

C63: Innovation and Entrepreneurship Support: AI as a tool to foster innovation and support entrepreneurship.

C7: Data Management and Privacy:

C71: Data Integration: Efficient integration of data from various sources using AI, enabling holistic insights.

C72: Data Security: Ensuring the security of data through advanced AI-driven encryption and monitoring systems.

C73: Privacy Protection: AI to safeguard citizen privacy while enabling data-driven decision-making.

C74: Ethical AI Use: Ensuring that AI applications adhere to ethical standards, avoiding biases, and ensuring fairness.

Assessing the Influence of main criteria Using Linguistic Terms: Experts will assess the influence of each criterion on the others using linguistic terms in Table 1. These assessments will capture the degree of influence, which is then translated into STrNN to handle the uncertainty and indeterminacy inherent in the evaluation process as represented in Table 2. By establishing these criteria and their linguistic evaluations in terms of STrNN, the DEMATEL method can proceed to analyze the direct and indirect influences among criteria, ultimately helping decision-makers understand the complex interdependencies within the smart city context.

Table 2. Matrix with STrNN for all main criteria.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
C1	-	VL	L	ML	M	MH	VH
C2	VL	-	ML	M	MH	VH	VL
C3	L	ML	-	MH	H	SVH	L
C4	ML	M	MH	-	VH	SVL	VL
C5	M	MH	H	VH	-	VL	ML
C6	MH	H	VH	SVH	SVL	-	L
C7	M	VL	L	ML	M	MH	-

Step 2: Construct the Direct-Relation Matrix: Experts are asked to evaluate the direct influence of one criterion on another using a trapezoidal scale to capture the uncertainty and indeterminacy inherent in the decision-making process so, Table 2 is converted into STrNN values. Each expert evaluates the influence of one criterion on another using a specified scale (e.g., $0 =$ No influence, $1 =$ Low influence, $1.5 =$ Low to medium influence, $2 =$ Medium influence, $2.5 =$ Medium to high influence, $3 =$ High influence, $3.5 =$ High to very high influence, $4 =$ Very high influence). These evaluations are then compiled into the Direct-Relation Matrix as Table 3. Then, Convert STrNN to Crisp Numbers Using Eq. (1) as represented in Table 3. This conversion helps in simplifying the analysis and further computations in the DEMATEL process. After that, the next step is to incorporate the importance or weight of each criterion into the Direct-Relation Matrix. This step ensures that the relative importance of each criterion is factored into the analysis, leading to a more accurate and meaningful evaluation using Eq. (3) to get the direct-influence matrix in Table 4.

Step 3: Normalize the Direct-Relation Matrix: Normalization ensures that all values in the matrix fall within a specific range, typically between 0 and 1, which allows for easier comparison and analysis of the relationships between criteria. To normalize the Direct-Relation Matrix D, each element in the matrix is divided by the maximum row or column sum of the matrix, which was calculated in Table 4. This process is done using Eqs. (4), and (5) to get a normalized matrix in Table 5.

Step 4: Calculate the Total-Relation Matrix T: After normalizing the Direct-Relation Matrix N, this matrix represents the sum of both direct and indirect influences of each criterion on every other criterion using Eq. (6). The Total-Relation Matrix is shown in Table 6.

Step 5: Determine Prominence and Relation: In this step, the prominence (overall influence) and relation (net cause or effect) of each criterion are determined by analyzing the Total-Relation Matrix T using Eqs. (7), and (8) as presented in Table 6. These calculations help in identifying the most influential criteria and understanding the causal relationships within the system, which is vital for informed decision-making in smart cities' AI applications.

Step 6: Causal Diagram Representation: In this step, the IRM is constructed using the prominence (R) and relation (C) values computed in Step 5. To create the Causal Diagram, the $R + C$, and R - C are calculated in table 7. The difference helps distinguish whether a criterion is primarily a cause (influencer) or an effect (influenced). Positive values indicate causes, while negative values indicate effects. The resulting diagram shown in Figure 3 will provide a clear visual of the cause-and-effect relationships within the criteria for AI applications in smart cities. The IRM helps decision-makers prioritize actions by focusing on essential and determinant factors that drive the system's performance.

Step 7: Calculating Threshold Value α, which is used to identify the most critical factors in the decision-support system. This value is calculated by averaging the truth membership values of the elements in the total-relation matrix T by Eq. (9). The threshold helps to distinguish between criteria that have significant influence and those that have less impact.

Table 3. Crisp STrNN values for main criteria.

Relation-ships analyzed	X scale	L	M1	M2	U	T	I	F	Score	Matrix D
C1-C2	1	0.1	0.2	0.3	0.4	0.2	0.7	0.8	0.058333	0.058333
C1-C3	1.5	0.2	0.3	0.4	0.5	0.3	0.7	0.7	0.105	0.1575
C1-C4	2	0.3	0.4	0	0.6	0.5	0.4	0.5	0.173333	0.346667
C1-C5	3	0.4	0.5	0.6	0.7	0.6	0.3	0.4	0.348333	1.045
C1-C6	3.5	0.5	0.6	0.7	0.8	0.7	0.3	0.3	0.455	1.5925
C1-C7	4	0.7	0.8	0.9	1	0.9	0.2	0.1	0.736667	2.946667
C2-C1	1	0.1	0.2	0.3	0.4	0.2	0.7	0.8	0.058333	0.058333
C2-C3	2	0.3	0.4	0	0.6	0.5	0.4	0.5	0.173333	0.346667
C2-C4	3	0.4	0.5	0.6	0.7	0.6	0.3	0.4	0.348333	1.045
C2-C5	3.5	0.5	0.6	0.7	0.8	0.7	0.3	0.3	0.455	1.5925
C2-C6	4	0.7	0.8	0.9	1	0.9	0.2	0.1	0.736667	2.946667
C2-C7	1	0.1	0.2	0.3	0.4	0.2	0.7	0.8	0.058333	0.058333
C3-C1	1.5	0.2	0.3	0.4	0.5	0.3	0.7	0.7	0.105	0.1575
C3-C2	2	0.3	0.4	0	0.6	0.5	0.4	0.5	0.173333	0.346667
C3-C4	3.5	0.5	0.6	0.7	0.8	0.7	0.3	0.3	0.455	1.5925
C3-C5	3.5	0.6	0.7	0.8	0.9	0.8	0.1	0.2	0.625	2.1875
C3-C6	4	0.8	0.9	1	1	1	0.1	0.1	0.863333	3.453333
C3-C7	1.5	0.2	0.3	0.4	0.5	0.3	0.7	0.7	0.105	0.1575
C4-C1	2	0.3	0.4	0	0.6	0.5	0.4	0.5	0.173333	0.346667
C4-C2	3	0.4	0.5	0.6	0.7	0.6	0.3	0.4	0.348333	1.045
C4-C3	3.5	0.5	0.6	0.7	0.8	0.7	0.3	0.3	0.455	1.5925
C4-C5	4	0.7	0.8	0.9	1	0.9	0.2	0.1	0.736667	2.946667
C4-C6	1	0	0.1	0.2	0.3	0.1	0.8	0.9	0.02	0.02
C4-C7	1	0.1	0.2	0.3	0.4	0.2	0.7	0.8	0.058333	0.058333
C5-C1	3	0.4	0.5	0.6	0.7	0.6	0.3	0.4	0.348333	1.045
C5-C2	3.5	0.5	0.6	0.7	0.8	0.7	0.3	0.3	0.455	1.5925

C5-C3	3.5	0.6	0.7	0.8	0.9	0.8	0.1	0.2	0.625	2.1875
C5-C4	4	0.7	0.8	0.9	1	0.9	0.2	0.1	0.736667	2.946667
C5-C6	1	0.1	0.2	0.3	0.4	0.2	0.7	0.8	0.058333	0.058333
C5-C7	2	0.3	0.4	0	0.6	0.5	0.4	0.5	0.173333	0.346667
C6-C1	3.5	0.5	0.6	0.7	0.8	0.7	0.3	0.3	0.455	1.5925
C6-C2	3.5	0.6	0.7	0.8	0.9	0.8	0.1	0.2	0.625	2.1875
C6-C3	4	0.7	0.8	0.9	1	0.9	0.2	0.1	0.736667	2.946667
C6-C4	4	0.8	0.9	1	1	1	0.1	0.1	0.863333	3.453333
C6-C5	1	0	0.1	0.2	0.3	0.1	0.8	0.9	0.02	0.02
C6-C7	1.5	0.2	0.3	0.4	0.5	0.3	0.7	0.7	0.105	0.1575
C7-C1	3	0.4	0.5	0.6	0.7	0.6	0.3	0.4	0.348333	1.045
C7-C2	1	0.1	0.2	0.3	0.4	0.2	0.7	0.8	0.058333	0.058333
C7-C3	1.5	0.2	0.3	0.4	0.5	0.3	0.7	0.7	0.105	0.1575
C7-C4	2	0.3	0.4	0	0.6	0.5	0.4	0.5	0.173333	0.346667
C7-C5	3	0.4	0.5	0.6	0.7	0.6	0.3	0.4	0.348333	1.045
C7-C6	3.5	0.5	0.6	0.7	0.8	0.7	0.3	0.3	0.455	1.5925

Table 4. Direct-Influence matrix D.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**Total**
C1	0	0.058333	0.1575	0.346667	1.045	1.5925	2.946667	6.146667
C2	0.058333	0	0.346667	1.045	1.5925	2.946667	0.058333	6.0475
C3	0.1575	0.346667	0	1.5925	2.1875	3.453333	0.1575	7.895
C4	0.346667	1.045	1.5925	0	2.946667	0.02	0.058333	6.009167
C5	1.045	1.5925	2.1875	2.946667	0	0.058333	0.346667	8.176667
C6	1.5925	2.1875	2.946667	3.453333	0.02	0	0.1575	10.3575
C7	1.045	0.058333	0.1575	0.346667	1.045	1.5925	0	4.245
Total	4.245	5.288333	7.388333	9.730833	8.836667	9.663333	3.725	10.3575

Table 2. Normalized matrix.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
C1	0	0.029752	0.040166	0.044204	0.155456	0.145043	0.281798
C2	0.011157	0	0.088407	0.044416	0.145043	0.281798	0.029752
C3	0.040166	0.044204	0	0.116034	0.119541	0.27521	0.053554
C4	0.066305	0.133248	0.20306	0	0.093933	0.003825	0.014876
C5	0.177664	0.232069	0.239082	0.187865	0	0.014876	0.022102
C6	0.087026	0.239082	0.375731	0.220168	0.010201	0	0.033471
C7	0.133248	0.018595	0.053554	0.033153	0.088832	0.058017	0

Table 6. Total relational matrix.

	C1	C2	C3	C4	C5	C6	C7	R
C1	0.138532	0.174684	0.248257	0.317721	0.320231	0.363245	0.346698	1.909366
C2	0.157734	0.234241	0.353013	0.477534	0.425338	0.508992	0.08186	2.238711
C3	0.206307	0.327297	0.404361	0.623311	0.557699	0.614852	0.113419	2.847246
C4	0.154336	0.286516	0.405116	0.337218	0.534291	0.258363	0.081025	2.056865
C5	0.235018	0.36574	0.50197	0.631052	0.3794	0.33674	0.131398	2.581319
C6	0.321972	0.479155	0.651538	0.778242	0.482708	0.429798	0.146487	3.289899
C7	0.197277	0.149715	0.212771	0.272306	0.274458	0.311324	0.075657	1.493508
C	1.411176	2.017347	2.777025	3.437384	2.974124	2.823312	0.976543	α =0.335039

Table 7. R+C and R-C

	R	C	$R+C$	$R-C$	Identify
C1	1.909366	1.411176	3.320542	0.49819	Cause
C2	2.238711	2.017347	4.256059	0.221364	Cause
C3	2.847246	2.777025	5.624271	0.07022	Cause
C4	2.056865	3.437384	5.494249	-1.38052	Effect
C5	2.581319	2.974124	5.555443	-0.39281	Effect
C6	3.289899	2.823312	6.113211	0.466586	Cause
C7	1.493508	0.976543	2.470051	0.516965	Cause

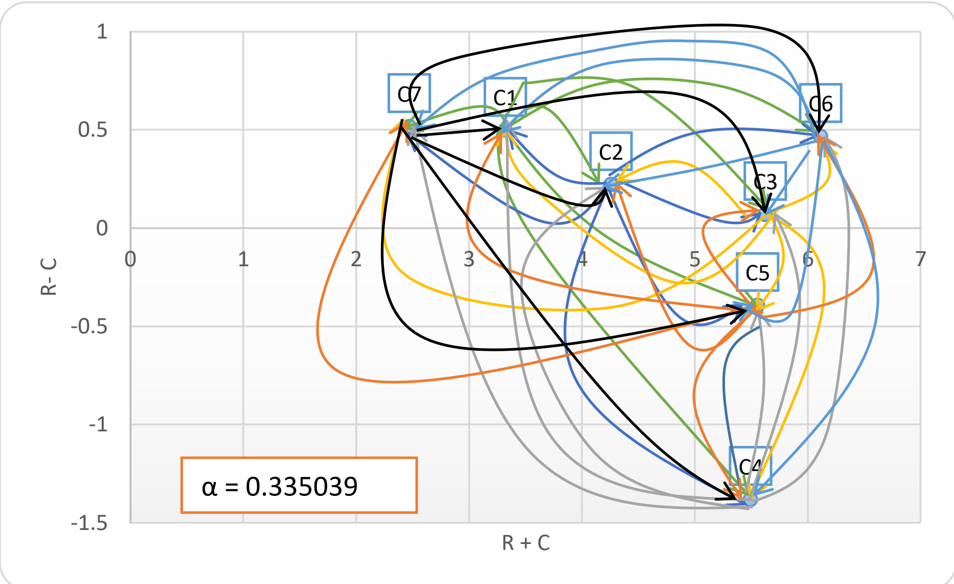

Figure 3. IRM for main criteria.

4.2 Steps for Implementing STrNN-DEMATEL for Sub-Criteria

To analyze the interrelationships among sub-criteria for each main criterion using the STrNN-DEMATEL method, a similar process as for the main criteria is applied:

Step 1: Direct-Relation Matrix: For each main criterion, refer to Tables 8 to 14 to understand the influence each sub-criterion has on the others. Each table provides the STrNN values converted to crisp numbers, reflecting direct influences.

Step 2: Total-Relation Matrix: Tables 15 to 21 contain the total-relation matrices for the sub-criteria of each main criterion. These matrices incorporate both direct and indirect influences, providing a comprehensive view of how each sub-criterion impacts others.

Step 3: IRM: Figures 4 to 10 visually represent the relationships between sub-criteria based on their prominence and relation values.

Table 8. Direct-relation matrix for C1.

	C11	C12	C13	C14	Total
C11	0	0.058333	0.1575	0.346667	0.5625
C12	1.045	0	1.5925	0.1575	2.795
C13	0.346667	1.045	0	1.5925	2.984167
C14	0.346667	1.045	1.5925	0	2.984167
Total	1.738333	2.148333	3.3425	2.096667	3.3425

Table 9. Direct-relation matrix for C2.

	C21	C22	C23	C24	Total
C21	0	1.045	1.5925	2.5	5.1375
C22	2.946667	0	3.453333	1.5925	7.9925
C23	2.5	2.946667	0	3.453333	8.9
C24	0.02	2.5	2.946667	0	5.466667
Total	5.466667	6.491667	7.9925	7.545833	8.9

Table 10. Direct-relation matrix for C3.

	C31	C32	C33	C34	Total
C31	0	2.946667	3.453333	0.02	6.42
C32	0.058333	0	0.1575	0.346667	0.5625
C33	1.045	1.5925	0	2.5	5.1375
C34	0.02	0.058333	0.346667	0	0.425
Total	1.123333	4.5975	3.9575	2.866667	6.42

Table 11. Direct-relation matrix for C4.

	C41	C42	C43	Total
C41	0	0.26	0.870833	1.130833
C42	1.365	0	2.1875	3.5525
C43	2.946667	1.045	0	3.991667
Total	4.311667	1.305	3.058333	4.311667

Table 12. Direct-relation matrix for C5.

	C51	C52	C53	Total
C51	0	1.365	2.1875	3.5525
C52	2.946667	0	3.453333	6.4
C53	0.02	2.1875	0	2.2075
Total	2.966667	3.5525	5.640833	6.4

Table 13. Direct-relation matrix for C6.

	C61	C62	C63	Total
C61	0	2.946667	3.453333	6.4
C62	0.02	0	0.058333	0.078333
C63	0.1575	0.02	0	0.1775
Total	0.1775	2.966667	3.511667	6.4

Table 14. Direct-relation matrix for C7.

	C71	C72	C73	C74	Total
C71	0	0.058333	0.105	0.26	0.423333
C72	0.696667	0	1.1375	0.058333	1.8925
C73	0.105	0.26	0	0.696667	1.061667
C74	0.058333	0.105	0.26	0	0.423333
Total	0.86	0.423333	1.5025	1.015	1.8925

Table 15. Total-relation matrix for C1.

	C11	C12	C13	C14	R
C11	0.104984	0.17285	0.249548	0.241643	0.769024
C12	0.669323	0.559543	1.0901	0.662272	2.981237
C13	0.618573	0.965511	0.994032	1.059687	3.637803
C14	0.618573	0.965511	1.316727	0.736992	3.637803
C	2.011453	2.663414	3.650407	2.700593	α = 0.689117

Table 16. Total-relation matrix for C2.

	C21	C22	C23	C24	R
C21	0.445025	0.66599	0.792649	0.832633	2.736297
C22	0.950357	0.819418	1.230224	1.069853	4.069852
C23	0.947064	1.134029	1.024869	1.254623	4.360585
C24	0.583761	0.88803	1.017756	0.71778	3.207327
C	2.926207	3.507466	4.065499	3.874889	α = 0.898379

Table 17. Total-relation matrix for C3.

	C31	C32	C33	C34	R
C31	0.109235	0.667574	0.628384	0.284201	1.689393
C32	0.015482	0.01692	0.037022	0.069376	0.1388
C33	0.189784	0.373167	0.136253	0.463207	1.162412
C34	0.013844	0.03147	0.063649	0.026528	0.135491
C	0.328346	1.089131	0.865307	0.843313	α = 0.19538

Table 18. Total-relation matrix for C4.

	C41	C42	C43	R
C41	0.283136	0.15984	0.340251	0.783227
C42	0.970447	0.261091	0.83581	2.067348
C43	1.11212	0.414883	0.435105	1.962107
C	2.365702	0.835814	1.611165	α = 0.534742

Table 19. Total-relation matrix for C5.

	C51	C52	C53	R
C51	0.231688	0.498531	0.689986	1.420206
C52	0.697874	0.508601	1.052547	2.259022
C53	0.24238	0.517193	0.361913	1.121487
C	1.171943	1.524325	2.104447	α = 0.533413

Table 20. Total-relation matrix for C6.

	C61	C62	C63	R
C61	0.01505	0.469071	0.551979	1.0361
C62	0.0034	0.0016	0.010964	0.015963
C63	0.02499	0.014674	0.013618	0.053282
C	0.04344	0.485344	0.576561	α = 0.122816

Table 21. Total-relation matrix for C7.

	C71	C72	C73	C74	R
C71	0.033878	0.058513	0.118275	0.187382	0.398047
C72	0.474135	0.140815	0.764441	0.381709	1.7611
C73	0.151581	0.193739	0.188654	0.464364	0.998338
C74	0.078999	0.091715	0.209361	0.09075	0.470825
C	0.738593	0.484782	1.280732	1.124204	α = 0.226769

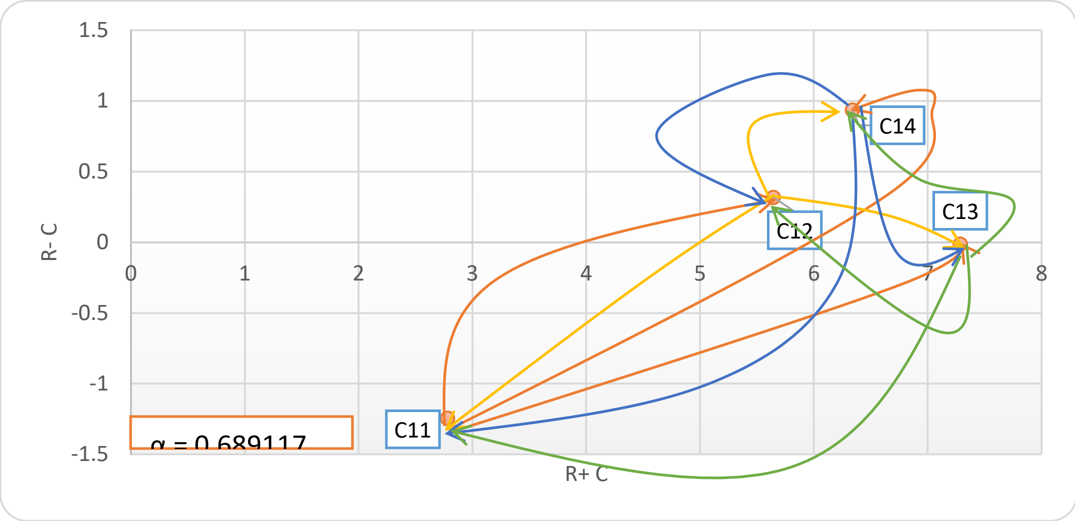

Figure 4. C1 IRM.

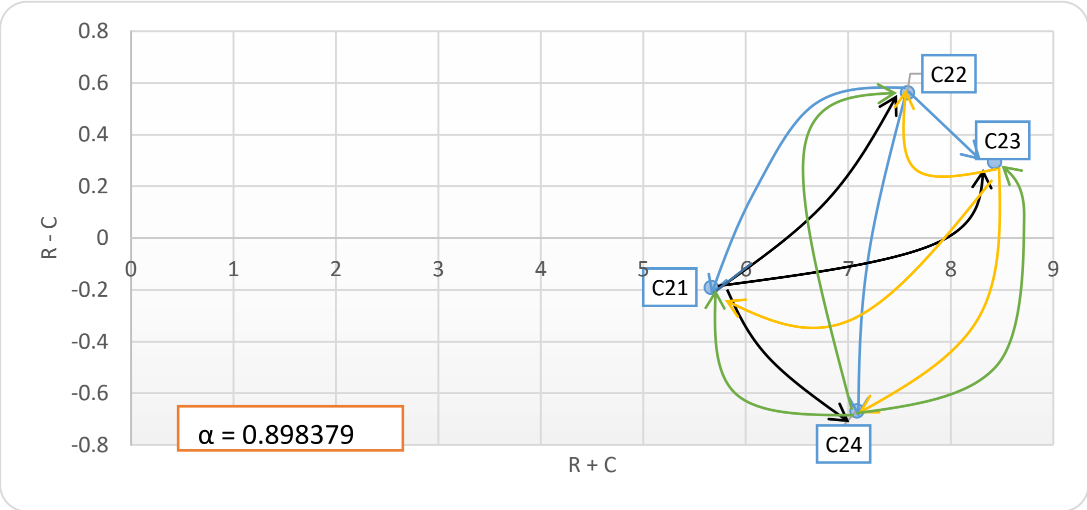

Figure 5. C2 IRM.

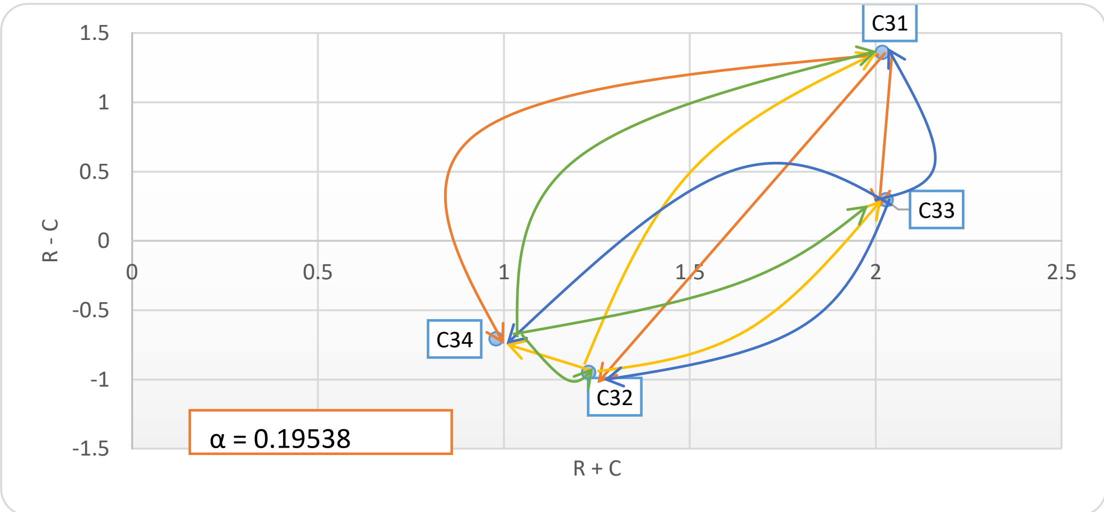

Figure 6. C3 IRM.

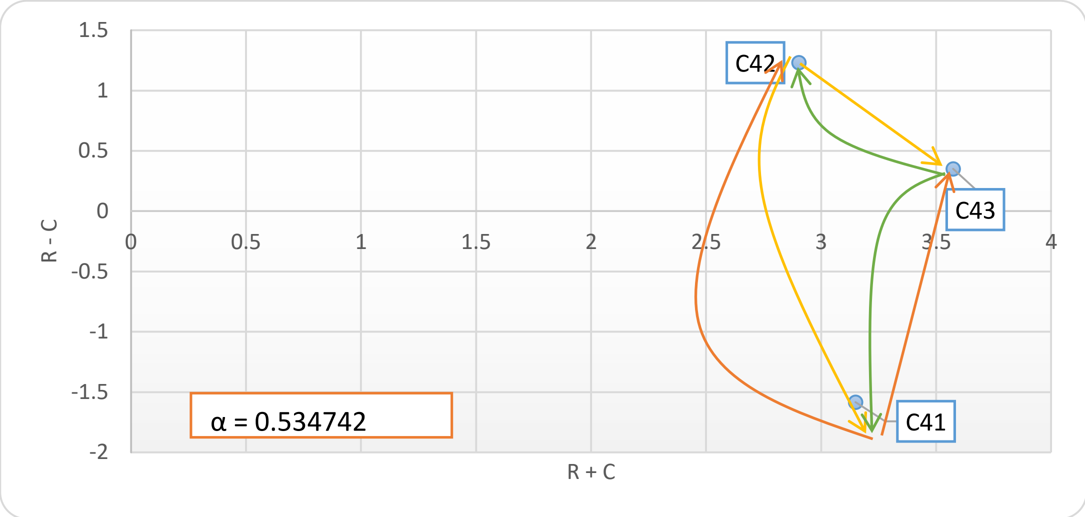

Figure 7. C4 IRM.

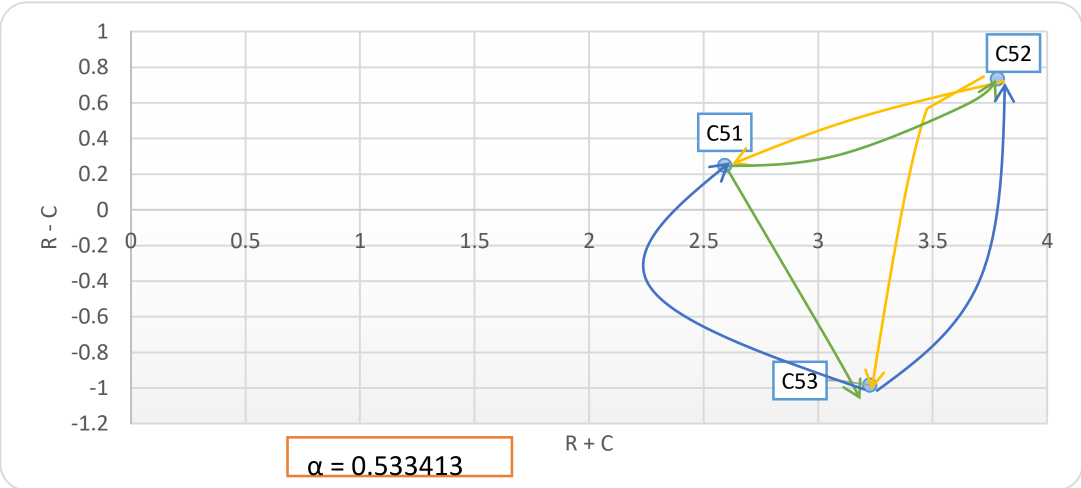

Figure 8. C5 IRM.

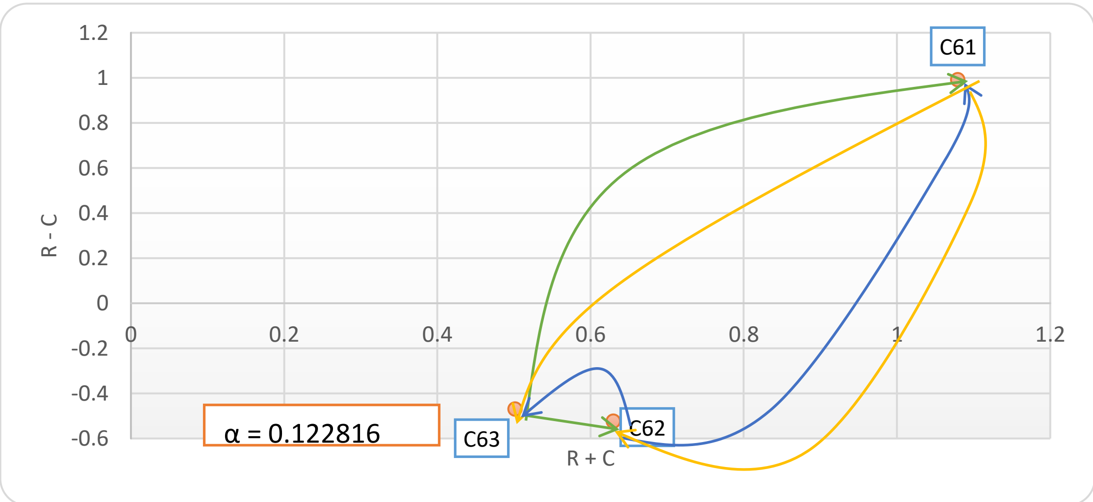

Figure 9. C6 IRM.

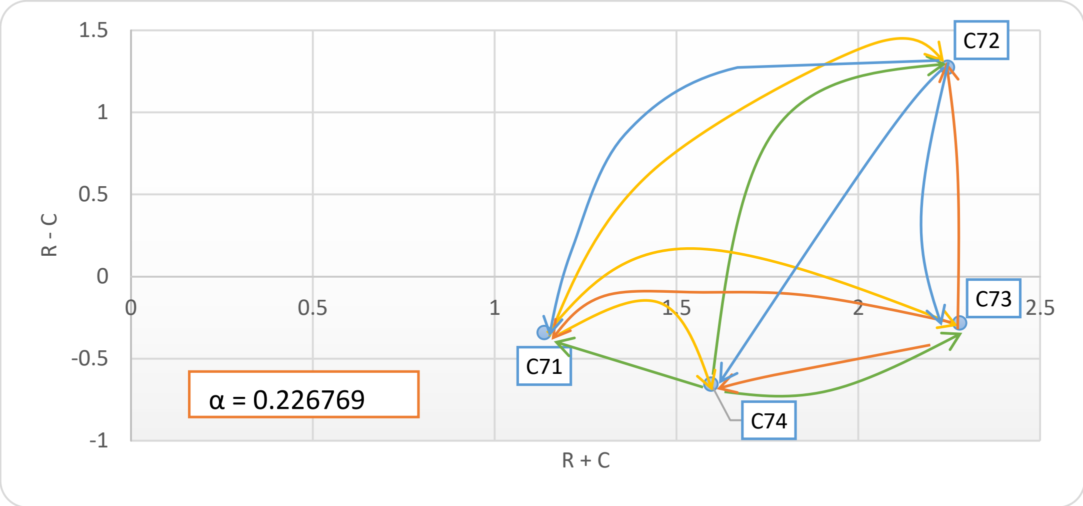

Figure 10. C7 IRM.

4.3 Comparative Analysis Using STrNN-DEMATEL in Different Environments

To perform a comprehensive comparative analysis using the STrNN-DEMATEL method and assess the robustness and stability of results under different conditions, we will compare two approaches:

Crisp-DEMATEL [41]: Table 22 defines the crisp values assigned to each linguistic term. Convert the linguistic variables from Table 2 into a crisp decision matrix using the defined crisp values to get Direct-Relation Matrix in Table 23. Apply DEMATEL Steps to get the Prominence and Relation for each criterion as in Table 24 to create graphical representations as in Figure 11.

Neutrosophic-DEMATEL [42]: Table 22 defines the neutrosophic values assigned to each linguistic term as single neutrosophic numbers. Convert the linguistic variables from Table 2 into a neutrosophic decision matrix using single neutrosophic values. Apply these values to construct the direct-relation matrix in neutrosophic terms, as shown in Table 25. Apply DEMATEL Steps to calculate Prominence and Relation for each criterion as in Table 26 to create graphical representations as in Figure 12.

Table 22. Scale.

Scale	**Neutrosophic**			**Crisp**
	T	I	F	
SVL	0.1	0.8	0.9	1
VL	0.3	0.7	0.8	2
L	0.4	0.6	0.7	3
ML	0.5	0.4	0.5	4
M	0.6	0.4	0.5	5
MH	0.7	0.3	0.4	6
H	0.8	0.2	0.3	7
VH	0.9	0.1	0.1	8
SVH	1	0.1	0.1	9

Table 23. Direct-relation matrix for crisp.

	C1	C2	C3	C4	C5	C6	C7
C1	0	2	3	4	5	6	8
C2	2	0	4	5	6	8	2
C3	3	4	0	6	7	9	3
C4	4	5	6	0	8	1	2
C5	5	6	7	8	0	2	4
C6	6	7	8	9	1	0	3
C7	5	2	3	4	5	6	0

Table 24. Total-relation matrix for crisp.

	C1	C2	C3	C4	C5	C6	C7	R
C1	0.440547	0.518114	0.619205	0.710892	0.66216	0.661343	0.568685	4.180946
C2	0.48918	0.476484	0.652419	0.74222	0.683744	0.701473	0.420764	4.166284
C3	0.582276	0.650175	0.638747	0.860941	0.791624	0.803244	0.504803	4.83181
C4	0.505975	0.565227	0.65869	0.580668	0.715377	0.526577	0.409914	3.962428
C5	0.601698	0.663597	0.769888	0.866292	0.625972	0.64077	0.516923	4.685139
C6	0.651491	0.717902	0.828367	0.928555	0.694654	0.625918	0.517953	4.96484
C7	0.524146	0.482788	0.576986	0.662422	0.617013	0.616252	0.348093	3.827699
C	3.795314	4.074287	4.744301	5.351988	4.790543	4.575577	3.287135	α = 0.624880541

Table 25. Direct-relation matrix for neutrosophic.

Relationships analyzed	X scale	T	I	F	Score	Matrix D
C1-C2	2	0.3	0.7	0.8	0.265153	0.530306
C1-C3	2.5	0.4	0.6	0.7	0.364915	0.912287
C1-C4	3	0.5	0.4	0.5	0.530958	1.592875
C1-C5	3.5	0.6	0.4	0.5	0.56411	1.974385
C1-C6	3.5	0.7	0.3	0.4	0.66335	2.321724
C1-C7	4	0.9	0.1	0.1	0.9	3.6
C2-C1	2	0.3	0.7	0.8	0.265153	0.530306
C2-C3	3	0.5	0.4	0.5	0.530958	1.592875
C2-C4	3.5	0.6	0.4	0.5	0.56411	1.974385
C2-C5	3.5	0.7	0.3	0.4	0.66335	2.321724
C2-C6	4	0.9	0.1	0.1	0.9	3.6
C2-C7	2	0.3	0.7	0.8	0.265153	0.530306
C3-C1	2.5	0.4	0.6	0.7	0.364915	0.912287
C3-C2	3	0.5	0.4	0.5	0.530958	1.592875
C3-C4	3.5	0.6	0.4	0.5	0.56411	1.974385

C3-C5	4	0.8	0.2	0.3	0.761952	3.04781
C3-C6	1	1	0.1	0.1	0.91835	0.91835
C3-C7	2.5	0.4	0.6	0.7	0.364915	0.912287
C4-C1	3	0.5	0.4	0.5	0.530958	1.592875
C4-C2	3.5	0.6	0.4	0.5	0.56411	1.974385
C4-C3	3.5	0.7	0.3	0.4	0.66335	2.321724
C4-C5	4	0.9	0.1	0.1	0.9	3.6
C4-C6	1	0.1	0.8	0.9	0.132052	0.132052
C4-C7	2	0.3	0.7	0.8	0.265153	0.530306
C5-C1	3.5	0.6	0.4	0.5	0.56411	1.974385
C5-C2	3.5	0.7	0.3	0.4	0.66335	2.321724
C5-C3	4	0.8	0.2	0.3	0.761952	3.04781
C5-C4	4	0.9	0.1	0.1	0.9	3.6
C5-C6	2	0.3	0.7	0.8	0.265153	0.530306
C5-C7	3.5	0.5	0.4	0.5	0.530958	1.858354
C6-C1	3.5	0.7	0.3	0.4	0.66335	2.321724
C6-C2	4	0.8	0.2	0.3	0.761952	3.04781
C6-C3	4	0.9	0.1	0.1	0.9	3.6
C6-C4	1	1	0.1	0.1	0.91835	0.91835
C6-C5	1	0.1	0.8	0.9	0.132052	0.132052
C6-C7	2.5	0.4	0.6	0.7	0.364915	0.912287
C7-C1	3	0.6	0.4	0.5	0.56411	1.69233
C7-C2	1.5	0.3	0.7	0.8	0.265153	0.39773
C7-C3	2.5	0.4	0.6	0.7	0.364915	0.912287
C7-C4	3	0.5	0.4	0.5	0.530958	1.592875
C7-C5	3.5	0.6	0.4	0.5	0.56411	1.974385
C7-C6	3.5	0.7	0.3	0.4	0.66335	2.321724

Table 26. Total-relation matrix for neutrosophic.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	$\boldsymbol{R}$
C1	0.418158	0.494965	0.62222	0.636892	0.705957	0.563638	0.607486	3.130174
C2	0.453085	0.480766	0.686922	0.66234	0.726159	0.630965	0.398975	5.652861
C3	0.433954	0.52921	0.513623	0.630145	0.735857	0.427659	0.398688	5.253887
C4	0.500737	0.58144	0.699426	0.547699	0.817977	0.411622	0.409931	4.855199
C5	0.609961	0.69434	0.85339	0.872966	0.730607	0.527965	0.562778	4.445268
C6	0.540223	0.643775	0.768123	0.586034	0.603583	0.42533	0.429002	3.88249
C7	0.467445	0.427607	0.54674	0.559952	0.620736	0.495197	0.323314	3.453487
$\boldsymbol{C}$	3.423564	3.852104	4.690445	4.496027	4.940876	3.482377	3.130174	$\alpha = 0.571746$

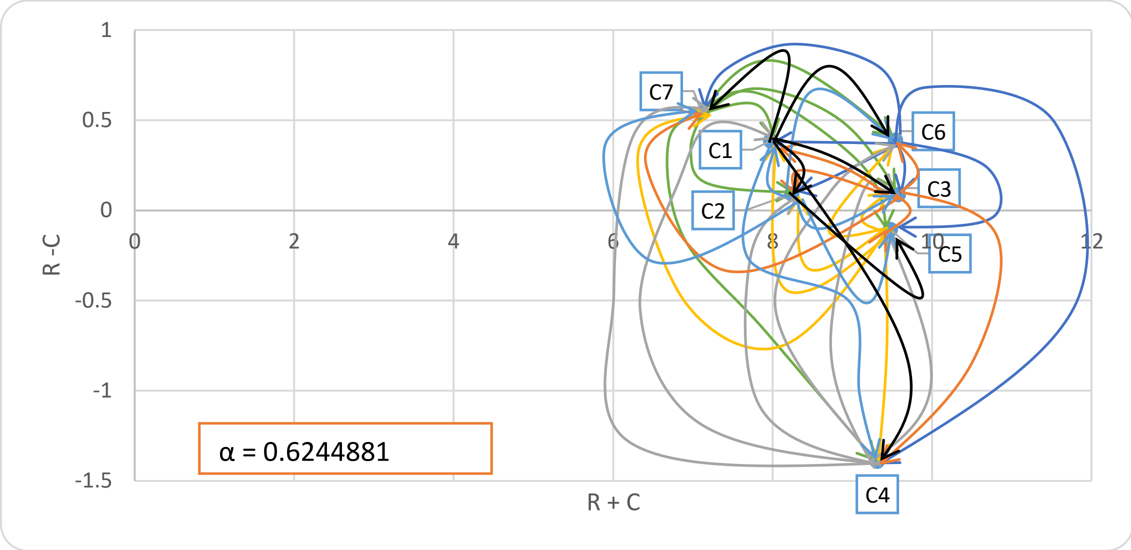

Figure 11. Crisp-DEMATEL IRM.

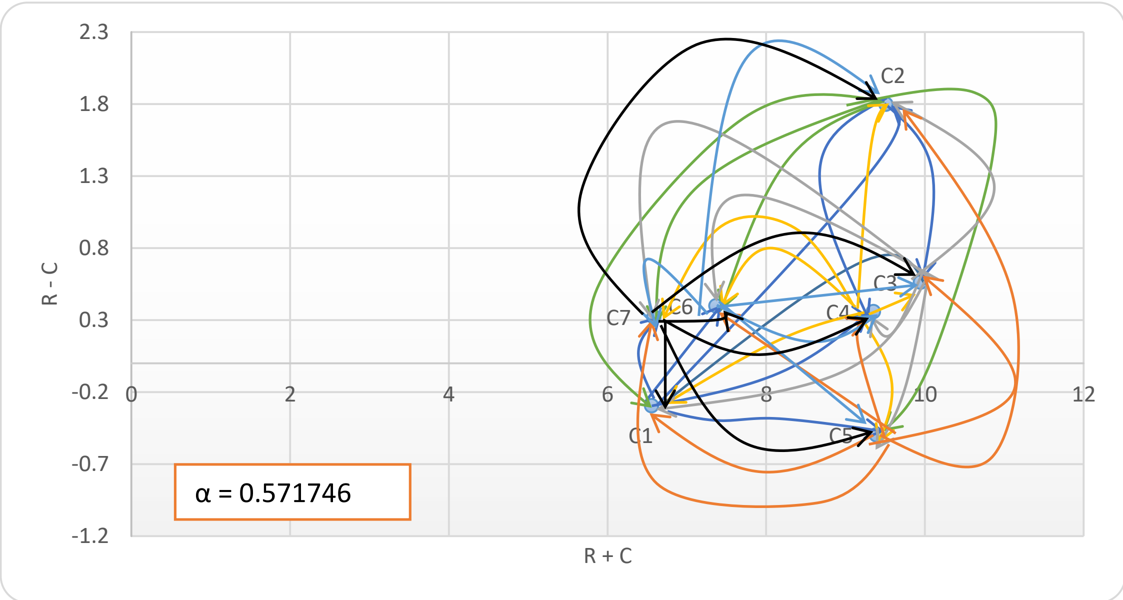

Figure 12. Neutrosophic- DEMATEL IRM.

From Figures 11 and 12: Crisp-DEMATEL Analysis: Causes: C1 (Urban Mobility and Transportation), C2 (Energy Management and Sustainability), C3 (Public Safety and Security), C6 (Economic Development), and C7 (Data Management and Privacy) are identified as driving factors, indicating they are influential in shaping other criteria. Effects: C4 (Healthcare Services) and C5 (Environmental Monitoring and Management) are categorized as effects. This suggests they are more influenced by other criteria than they influence. Neutrosophic-DEMATEL Analysis: Major Driving Force: C2 (Energy Management and Sustainability) stands out with the highest total influence, marking it as a key driver in the smart city system. C4 (Healthcare Services), C3 (Public Safety and Security), C6 (Economic Development), and C7 (Data Management and Privacy) are also influential, both in terms of their impact and susceptibility to other criteria. Effects: C1 (Urban Mobility and Transportation) and C5 (Environmental Monitoring and Management) are categorized as effects, meaning they are influenced more by other criteria. This comparative analysis not only reinforces the importance of understanding the roles and interactions of different criteria but also helps in crafting strategies that leverage driving factors to support and enhance dependent factors in the smart city ecosystem.

5. DEMATEL as a Weighting Method for Alternative Ranking

In this section, the DEMATEL method is applied to derive weights for various criteria, which are then utilized in different MCDM methods to rank alternatives effectively such as MABAC, MOORA, COPRAS, and TOPSIS.

5.1 Derivation of Criterion Weights Using DEMATEL

The DEMATEL method is employed to calculate the weights for each criterion. These weights are derived from the prominence (RI + CI) and relation (RI - CI) values obtained from the DEMATEL analysis by using Eqs. (10), and (11). The weights calculated for the criteria are shown in Table 27:

Table 27. Criteria weights.

Criteria	w
C1	0.10134
C2	0.128627
C3	0.169761
C4	0.170978
C5	0.168089
C6	0.185041
C7	0.076165

5.2 Application of Weights in MCDM Methods

Once the weights for each criterion are derived using the DEMATEL method, these weights are applied to rank various alternatives or scenarios using different MCDM methods. In this analysis, we focus on three smart cities—Barcelona, Singapore, and Songdo—and evaluate them based on a set of seven criteria. The decision matrix incorporates the performance of each city across the seven criteria, with the linguistic variables converted into STrNN and then into crisp numbers using Eq. (1). The decision matrix is shown in Tables 23, and 24 taking into account that C1, C2, C4, and C5 are beneficial criteria where C3, C5, and C7 are non- beneficial ones. The weights derived from the DEMATEL method are applied in MABAC MCDM methods: The MABAC method evaluates alternatives based on the weighted criteria, focusing on both the performance and border approximation areas to identify the most favorable options [64]. The MABAC method involves the following steps:

i). Normalize the decision matrix for each criterion in Table 28.
ii). Calculate the weighted decision matrix by multiplying the decision matrix with the weights obtained from the DEMATEL method exist in Table 27 the weighted normalized matrix is in Table 29.
iii). Calculate the border approximation area for each alternative found in the last row in Table 30
iv). Calculate the Distance from the Border Approximation Area.
v). Calculate the performance of each alternative based on the Distance.
vi). Rank alternatives based on their performance and border approximation as Table 30. The alternative with the highest performance score is ranked first, followed by the others in descending order.

Table 28. Decision matrix with linguistic variables.

	C1	C2	C3	C4	C5	C6	C7
A1	VL	VL	L	ML	M	MH	VH
A2	ML	M	MH	VH	VH	VH	VL
A3	MH	H	VH	SVH	SVL	SVL	L

Table 29. Decision matrix with crisp values.

	C1	C2	C3	C4	C5	C6	C7
A1	0.0583333	0.0583333	0.105	0.1733333	0.348333	0.455	0.736667
A2	0.1733333	0.3483333	0.455	0.7366667	0.736667	0.7366667	0.058333
A3	0.455	0.625	0.7366667	0.8633333	0.02	0.02	0.105

Table 30. Steps of MABAC method.

	C1	C2	C3	C4	C5	C6	C7	Rank
A1	0.122726	0.145715	0.364589	0.127774	0.191689	0.256355	0.084555	3
A2	0.1583063	0.252246	0.263581	0.232092	0.277746	0.184028	0.164587	2
A3	0.2454521	0.353879	0.182294	0.255548	0.118929	0.368056	0.159081	1
$\boldsymbol{g_i}$	0.1683193	0.235177	0.259715	0.196423	0.185002	0.258948	0.130332	

5.3 Comparative and Sensitivity Analysis

To ensure the robustness and reliability of the rankings derived from the MABAC method, a comparative analysis using other MCDM methods (MOORA, COPRAS, and TOPSIS) is conducted. This comparison allows for the validation of the results by examining whether different methodologies produce consistent rankings. Additionally, sensitivity analysis is performed to assess the stability of the rankings when criteria weights are varied.

5.3.1 Comparative Analysis

The following MCDM methods are utilized alongside MABAC to validate the rankings:

- MOORA [65]: uses the weighted criteria to optimize multiple objectives simultaneously, providing a ranking of alternatives based on their overall performance.
- COPRAS [66]: ranks alternatives by considering the criteria's importance and their corresponding weights, allowing for the comparison of multiple options.

TOPSIS [67]: evaluates alternatives based on their distance from an ideal solution and an anti-ideal solution, ranking them according to their relative closeness to the ideal solution.

Table 31 presents the final rankings obtained from the MABAC, MOORA, COPRAS, and TOPSIS methods. Figure 13 graphically illustrates these rankings, showing that MABAC, MOORA, and COPRAS produce identical rankings for the alternatives. However, TOPSIS yields a different ranking for alternatives A2 and A3, indicating a slight variation in results. The Spearman's rank correlation coefficient [70] is calculated to measure the agreement between the rankings produced by these methods. The coefficient is found to be 1 between MABAC, MOORA, and COPRAS, indicating perfect agreement. However, the correlation with TOPSIS is 0.5, reflecting a moderate difference in the ranking of A2 and A3.

Table 31. Comparative analysis.

Rank	MABAC	MOORA	COPRAS	TOPSIS
A1	3	3	3	3
A2	2	2	2	1
A3	1	1	1	2

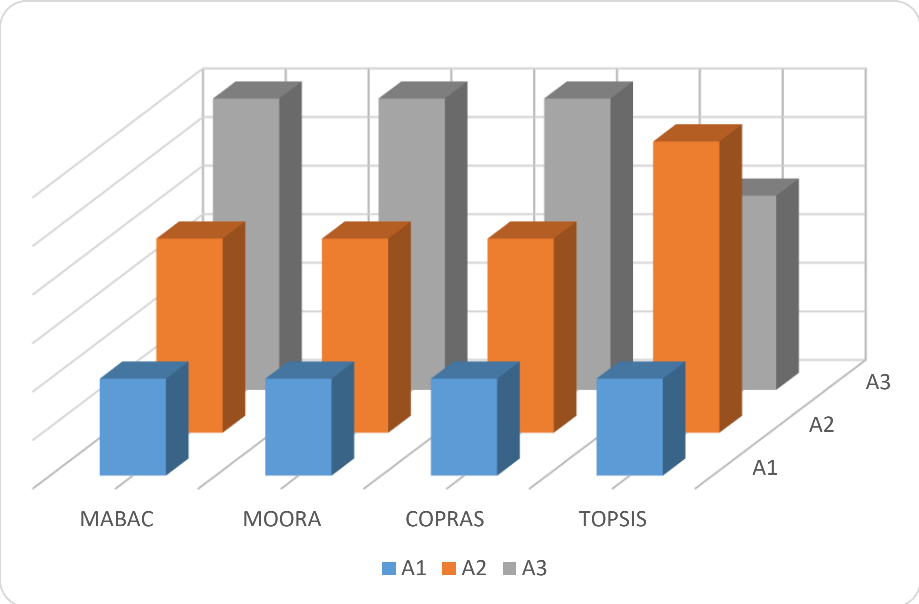

Figure 13. MCDM rank.

5.3.2 Sensitivity Analysis

The sensitivity analysis aims to examine how changes in the weights of the criteria affect the rankings of the alternatives. By altering the weights across different scenarios, the analysis identifies which criteria exert the most influence on the final rankings. This process is crucial for understanding the robustness of the decision-making model. Five scenarios are considered:

- Scenario 1: Equal Weights: All criteria are assigned equal weights: 0.142857143.
- Scenario 2: Increase the weight of C1 by 0.05, and decrease the weight of C7 by 0.05: Weights: C1 = 0.172726, C2 = 0.145715, C3 = 0.1822944, C4 = 0.1277739, C5 = 0.152908, C6 = 0.1840279, C7 = 0.0345546.
- Scenario 3: Increase the weight of C2 by 0.03, and decrease the weight of C5 by 0.03: Weights: C1 = 0.122726, C2 = 0.175715, C3 = 0.1822944, C4 = 0.1277739, C5 = 0.122908, C6 = 0.1840279, C7 = 0.0845546.
- Scenario 4: Increase the weight of C4 by 0.04, and decrease the weight of C6 by 0.04: Weights: C1= 0. 122726, C2=0. 145715, C3= 0. 1822944, C4= 0. 1677739, C5=0. 152908, C6= 0. 1440279, C7= 0. 0845546
- Scenario 5: Swap the weights of C1 and C6. Weights: C1= 0. 1840279, C2=0. 145715, C3= 0. 1822944, C4= 0. 1277739, C5=0. 152908, C6= 0. 122726, C7= 0. 0845546

Table 32 presents the results of the sensitivity analysis for each scenario, showing that the rankings of the alternatives remain consistent across all cases. Figure 14 visually represents these results, confirming that the rankings are robust and unaffected by the changes in criteria weights. The consistency of the rankings across all scenarios indicates that the decision-making model is stable and resilient to variations in the criteria weights. This stability enhances confidence in the robustness and reliability of the analysis, ensuring that the chosen alternatives remain optimal under different weight configurations.

Table 32. Sensitivity analysis.

Rank	Base Case	Case 1	Case 2	Case 3	Case 4	Case 5
A1	3	3	3	3	3	3
A2	2	2	2	2	2	2
A3	1	1	1	1	1	1

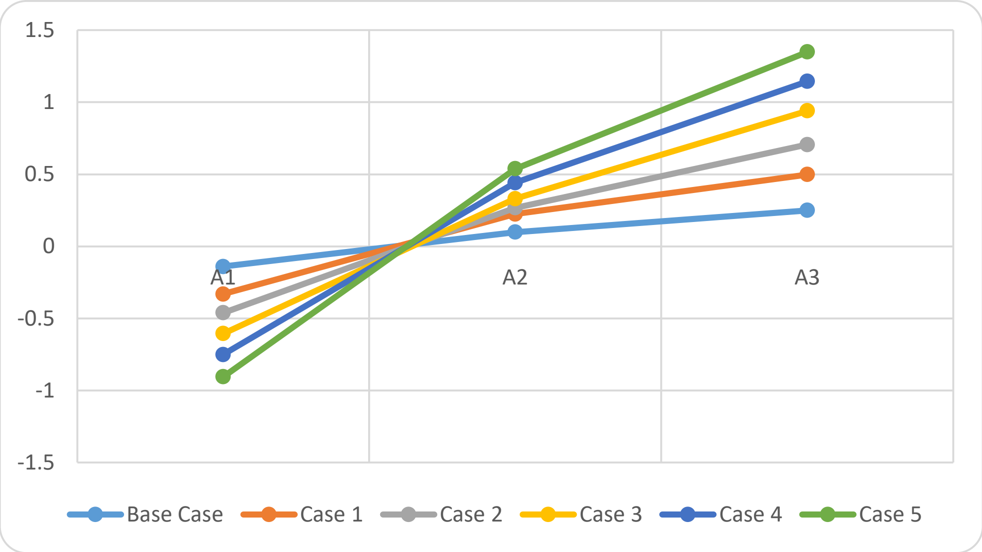

Figure 14. Sensitivity analysis.

6. Results and Discussion

The implementation of the STrNN-DEMATEL methodology has provided a comprehensive view of the interrelationships among the main criteria and their sub-criteria for AI applications in smart cities. This section discusses the findings from the STrNN-DEMATEL analysis and the MABAC method, supported by comparative and sensitivity analyses.

6.1 Interrelationship Analysis for Main Criteria

Economic Development (C6): With the highest Relative Influence (RI), economic development plays a pivotal role in the smart city ecosystem. Investments in this area can drive significant improvements across various sectors, fostering overall progress and innovation. Public Safety and Security (C3): With high Causal Influence, Public Safety and Security are significantly impacted by advancements in other criteria. Enhancements in technology and other smart city components largely drive improvements in public safety. Urban Mobility and Transportation (C1): With a higher Relative Influence compared to its Causal Influence, Urban Mobility and Transportation acts as a key driver. Enhancements in this area can lead to improvements in related fields such as energy management and public safety. Data Management and Privacy (C7): While its values are lower, Data Management and Privacy still hold significant importance. Maintaining data integrity and privacy is crucial, though it may not be a primary driver of change. Energy Management and Sustainability (C2): This criterion is more influenced by other factors than it influences them. Effective energy management depends on advancements in other areas, including economic development and environmental policies. Environmental Monitoring and Management (C5): As an effect criterion, Environmental Monitoring and Management is primarily influenced by changes in other areas. Effective environmental management relies on progress in sectors like economic development and energy management. Healthcare Services (C4): As another effect criterion, Healthcare Services are notably impacted by advancements in other areas. Improvements in healthcare depend on advancements in data management, predictive analytics, and other relevant fields.

6.2 Interrelationship Analysis of Sub-Criteria

The analysis of the sub-criteria using the STrNN-DEMATEL methodology provides insights into how each sub-criterion influences and is influenced by others within the main criteria for AI applications in smart cities. Parking Management (C14) stands out as a key driver. Its high Relative Influence suggests it plays a major role in shaping changes and advancements in the field. Public Transportation Optimization (C12) also has a high Influence. Autonomous Vehicles Integration (C13) and Traffic Management (C11) are impacted. They are influenced by broader trends and developments in Urban Mobility rather than driving them. These sub-criteria should be managed with consideration of their dependence on broader changes. Renewable Energy Integration (C22) and Energy Consumption Optimization (C23) are key essentials. They have a high Relative Influence, indicating their significant role in advancing energy management and sustainability practices. Emphasis on these areas can drive substantial progress in energy efficiency and sustainability. Smart Grids (C21) and Waste Management (C24) are impacted. They are influenced by broader trends and developments in energy management and sustainability rather than driving them. Strategies for these sub-criteria should be designed to adapt to changes and improvements in the energy management landscape.

Surveillance and Monitoring (C31) and Predictive Policing (C33) are key essentials. They have a high relative Influence, indicating their significant role in advancing public safety and security measures. Emphasizing these areas can lead to more proactive and effective safety strategies. Emergency Response (C32) and Cybersecurity (C34) are more reactive. They are influenced by advancements in surveillance, monitoring, and predictive policing, rather than driving changes themselves. Strategies for these sub-criteria should focus on adapting to and integrating with evolving safety and security technologies. Predictive Healthcare Analytics (C42) is a major essential, with high Relative Influence indicating its pivotal role in advancing healthcare services. Investing in predictive analytics can lead to significant improvements in healthcare delivery and efficiency and Healthcare Resource Management (C43) also causes criteria. Telemedicine and Remote Monitoring (C41) is effect, influenced by advancements in predictive analytics and other healthcare innovations. Strategies should focus on integrating these sub-criteria with emerging technologies and optimizing resource management based on new insights. Water Management (C52) and Air Quality Monitoring (C51) are determinate keys, significantly influencing other aspects of environmental management. Prioritizing air quality monitoring can lead to broader environmental benefits and improvements in other areas. Climate Change Mitigation (C53) is more influenced by other criteria. Strategies should focus on integrating these sub-criteria with advancements in air quality monitoring and other environmental initiatives to enhance overall effectiveness.

Data Integration (C61) is a major driver with a significant impact on other aspects of data management and privacy. Enhancing data integration can lead to improvements in data security and privacy protection. Data Security (C62) and Privacy Protection (C63) are more influenced by other sub-criteria. Efforts to improve data security and privacy protection should focus on the effectiveness of data integration strategies and overall data management practices. Waste Management (C72) is a key driver with significant influence on other aspects of environmental monitoring and management. Improvements in these areas can lead to positive changes in air quality monitoring and climate change mitigation. Water Management (C73), Air Quality Monitoring (C71), and Climate Change

Mitigation (C74) are more influenced by other sub-criteria. Their effectiveness largely depends on the advancements made in waste and water management. The analysis highlights the complex interdependencies among criteria and sub-criteria in smart cities. By understanding these relationships, stakeholders can develop more effective strategies that leverage key drivers, address reactive areas, and ensure a balanced approach to implementing AI applications in smart cities. This holistic view facilitates targeted improvements and fosters a more integrated and efficient urban environment.

6.3 Discussion on Analysis and MABAC Method

The STrNN-DEMATEL results align with the Crisp-DEMATEL results in the identification of causes and effects, showing a similar pattern of criteria as drivers and influencing factors. However, it presents some differences compared to Neutrosophic-DEMATEL, particularly in the roles of C5 and C2. STrNN-DEMATEL provides a perspective that incorporates the impacts of criteria in a nuanced manner, and combining insights from different methods helps in forming a more comprehensive understanding of the smart city ecosystem. C1 (Urban Mobility and Transportation): Identified as a cause in Crisp-DEMATEL, Neutrosophic-DEMATEL, and STrNN-DEMATEL. C6 (Economic Development): Consistently identified as a cause in all three methods. C7 (Data Management and Privacy): Identified as a cause in all methods. C2 (Energy Management and Sustainability): Identified as an effect in both STrNN-DEMATEL and Neutrosophic-DEMATEL. C3 (Public Safety and Security): Identified as an effect in both STrNN-DEMATEL and Neutrosophic-DEMATEL. C4 (Healthcare Services): Identified as an effect in STrNN-DEMATEL, Crisp-DEMATEL, and Neutrosophic-DEMATEL.

The MABAC method was applied to rank the alternatives based on the selected criteria. The results, as depicted in Table 31, show the final rankings of the alternatives. Alternative A3 emerged as the top choice, indicating that it performs the best across all criteria. Alternative A2 was ranked second, reflecting its strong performance but slightly lower than A3. Alternative A1 was ranked third, indicating that it is the least preferable alternative among the three. These rankings reflect the effectiveness of the MABAC method in integrating various criteria to provide a comprehensive evaluation of the alternatives. To validate the robustness of the MABAC method, a comparative analysis was conducted using three additional MCDM methods: MOORA, COPRAS, and TOPSIS. MOORA and COPRAS produced rankings identical to those obtained with MABAC, further affirming the robustness and reliability of the MABAC method in evaluating the alternatives. TOPSIS, however, showed a slight variation in the rankings of alternatives A2 and A3, with these two alternatives swapping positions compared to the rankings from MABAC, MOORA, and COPRA. Spearman's rank correlation coefficients were calculated to assess the consistency between the rankings produced by different methods. The correlation between MABAC, MOORA, and COPRAS was found to be 1, indicating perfect agreement. The correlation between TOPSIS and the other methods was 0.5, indicating moderate agreement but suggesting some sensitivity to the criteria's influence. These findings demonstrate that while MABAC, MOORA, and COPRAS provide consistent rankings, TOPSIS may be more sensitive to certain criteria, which could lead to variations in the final rankings. The sensitivity analysis was conducted by altering the weights of the criteria under five different scenarios to test the stability of the rankings. The results across all scenarios consistently showed the same rankings, with A3 ranked first, A2 ranked second, and A1 ranked third. This consistency highlights the robustness of the decision-making process, indicating that the rankings are not significantly affected by changes in the weights of the criteria.

7. Implications for Smart City Planning

This study presents several crucial managerial implications for those involved in the planning, development, and management of smart cities. Integrating MCDM methods with the STrNN-

DEMATEL approach offers a well-structured and comprehensive framework that can significantly improve decision-making processes in complex urban settings. The STrNN-DEMATEL framework allows city managers to systematically assess and prioritize various, often conflicting, criteria. By understanding the interrelationships among different factors, managers can make more informed decisions that align with both immediate objectives and long-term sustainability goals. This approach minimizes the risk of suboptimal decisions that might result from a narrow focus on individual criteria without considering their broader impacts. The ability to identify and quantify the causal relationships among various smart city criteria empowers managers to allocate resources more effectively. For instance, by recognizing which factors, such as economic development or energy management, exert the greatest influence on others, managers can prioritize investments in areas that will yield the most substantial overall benefits for the city. This strategic approach to resource allocation can lead to a more efficient use of financial and human resources. As smart cities increasingly adopt advanced technologies like AI, IoT, and big data analytics, it becomes essential to balance technological innovation with social, environmental, and economic considerations. The MCDM-based analysis ensures that decisions are not only technologically sound but also socially inclusive, environmentally sustainable, and economically viable. This holistic approach helps managers avoid potential pitfalls associated with focusing solely on technological solutions without addressing their broader impacts. In the realm of public safety, applying the STrNN-DEMATEL method enables a deeper understanding of how different safety measures interact. By prioritizing initiatives that have the most significant impact on overall safety, such as predictive policing or AI-driven surveillance, managers can enhance public safety strategies while addressing ethical concerns related to privacy and civil liberties. The structured nature of MCDM methods fosters better communication and collaboration among diverse stakeholders, including government agencies, private sector partners, and the public. By providing a clear and transparent decision-making process, city managers can engage stakeholders more effectively, building consensus and ensuring that decisions reflect the needs and priorities of all relevant parties. The insights gained from the interrelationship analysis can guide the development of policies that address the most critical areas of smart city development. For example, understanding the strong influence of economic development on other criteria can lead to policies that prioritize innovation and entrepreneurship as key drivers of smart city growth. Finally, the emphasis on sustainability within the MCDM framework aligns with the global push toward environmentally responsible urban development. Managers can leverage the findings from this study to implement energy management strategies, waste reduction initiatives, and other sustainability measures that contribute to the overall well-being of the urban environment and its inhabitants. By adopting the STrNN-DEMATEL approach, smart city managers can better navigate the complexities of urban development, leading to more informed, balanced, and sustainable decisions that drive the successful evolution of smart cities.

8. Challenges and Future Work

8.1 Challenges and Considerations

Smart cities generate vast amounts of data from diverse sources such as IoT devices, sensors, public services, and social media. Integrating these heterogeneous data types into a unified analytical framework presents significant challenges, particularly regarding data quality, standardization, and real-time processing. The smart city landscape is continually changing due to technological advancements, policy shifts, and societal needs. This dynamism complicates the maintenance of a stable decision-making model, necessitating ongoing updates and adjustments to the STrNN-DEMATEL framework. While technological innovation is crucial for smart city development, it must be balanced with social concerns such as privacy, equity, and inclusiveness. Ensuring that technological advancements do not exacerbate inequalities or create new ethical dilemmas is a key challenge. Implementing smart city initiatives often requires substantial financial and human resources. Resource constraints can lead to delays or compromises in project quality, making it challenging for managers to prioritize initiatives based on their impact and available resources. Ensuring the protection of personal data in AI-driven environments is critical. Robust cybersecurity measures are essential to protect city infrastructure from potential cyber threats. AI systems must be developed and deployed in ways that are fair, transparent, and free from bias, especially in sensitive areas like law enforcement and social services. Ensuring that AI-driven decision-making processes are equitable and transparent is vital to avoid biases and ensure fair outcomes. Integrating AI systems with existing city infrastructure involves overcoming technical challenges related to interoperability and scalability. Developing standardized frameworks for AI implementation is necessary to ensure seamless integration across various domains. Building trust in AI systems among citizens requires clear communication, transparent decision-making processes, and accountability in AI-driven initiatives.

8.2 Future Work

Future papers could explore the integration of advanced AI and machine learning techniques with the STrNN-DEMATEL framework. These technologies could enhance the model's ability to process large datasets, identify patterns, and make predictive assessments, thereby improving decision-making in smart cities. While this study focuses on specific smart city criteria, future work could expand the application of the STrNN-DEMATEL approach to emerging domains such as smart healthcare, autonomous transportation, and sustainable urban agriculture. Each of these areas presents unique challenges and opportunities for smart city development. Conducting longitudinal studies to assess the long-term impact of decisions made using the STrNN-DEMATEL framework would provide valuable insights into its effectiveness. Additionally, real-world implementations of this approach in different smart city contexts could help refine the model and demonstrate its practical utility. Future papers could explore ways to incorporate real-time stakeholder feedback into the STrNN-DEMATEL decision-making process. This could involve developing interactive platforms where stakeholders can input their preferences and concerns, allowing for a more participatory approach to smart city planning. Further exploration of hybrid MCDM methods that combine the strengths of STrNN-DEMATEL with other decision-making frameworks, such as AHP or TOPSIS could yield more robust decision-support tools for complex smart city environments. Smart city initiatives vary significantly across different cultural and geographical contexts. Future work could investigate how the STrNN-DEMATEL framework can be adapted to reflect these differences, ensuring that the model is globally applicable while remaining sensitive to local conditions and cultural values. By addressing these challenges and pursuing these avenues for future papers, the STrNN-DEMATEL framework can be further refined and expanded, ultimately contributing to the successful and sustainable development of smart cities worldwide.

9. Conclusion

This paper underscores the transformative potential of Artificial Intelligence (AI) in shaping the future of smart cities. By integrating AI technologies into urban management, cities can address critical challenges related to mobility, energy, safety, healthcare, environmental sustainability, economic growth, and data management. The paper highlights that AI not only enhances operational efficiency but also drives innovation and sustainability in urban environments. Through the application of the STrNN-DEMATEL methodology, this study provides a comprehensive framework for analyzing the complex interrelationships among key criteria and sub-criteria in smart cities. The findings reveal that economic development and environmental management are pivotal in influencing and driving other smart city components. This highlights the necessity for a holistic approach that balances technological advancements with socio-economic and environmental considerations. The insights gained from this paper offer valuable guidance for urban planners and policymakers. By understanding the causal relationships and relative influences among different smart city criteria, stakeholders can make informed decisions that optimize resource allocation, improve urban services, and enhance the overall quality of life for residents. Additionally, the study addresses the ethical dimensions of AI, emphasizing the importance of privacy, data security, and responsible AI use to build trust and ensure equitable outcomes. Looking ahead, this paper opens avenues for further exploration of smart city development. Future work could extend the STrNN-DEMATEL model to incorporate additional MCDM methods and uncertainty theories, as well as apply the framework to other domains such as healthcare and finance. Addressing these areas will contribute to the ongoing evolution of smart cities, fostering environments that are not only technologically advanced but also sustainable, inclusive, and resilient. In conclusion, the integration of AI in smart cities represents a significant step towards creating intelligent, adaptive urban spaces. By leveraging advanced decision-making frameworks and addressing the multifaceted challenges of urbanization, cities can pave the way for a more sustainable and prosperous future.

The MABAC method, in conjunction with the STrNN-DEMATEL approach, highlighted the significant influence of key criteria on the overall evaluation. The findings underscored the importance of factors such as economic development, environmental management, and urban mobility, which play pivotal roles in shaping the effectiveness of smart city alternatives. This insight enables decision-makers to prioritize and allocate resources more strategically based on the critical drivers identified. The sensitivity analysis conducted within the MABAC framework demonstrated the stability of the rankings across different scenarios. The consistent outcomes reinforce the robustness of the decision-making process and indicate that the rankings are resilient to changes in the weights of the criteria. This robustness is crucial for ensuring that decisions made based on the MABAC analysis are both reliable and actionable. The integration of MABAC with the STrNN-DEMATEL approach provides a comprehensive framework for evaluating smart city alternatives. By combining these methods, the study offers a nuanced understanding of the complex interrelationships among criteria and their impact on the overall effectiveness of smart city initiatives. The conclusions drawn from this analysis can guide city planners and managers in making informed decisions that align with both immediate needs and long-term strategic goals.

Declarations

Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

Consent for Publication

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

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare no competing interests in the research.

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Author Contribution

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