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Artificial intelligence, society 5.0 and smart city adaptation initiatives for businesses: An integrated approach

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ABSTRACT

The mass migration of human populations to urban areas has resulted in unprecedented challenges for city services. To address and find solutions for these emerging issues, decision-makers must embrace the smart city and Society 5.0 paradigms, which comprehensively tackle various dimensions of the problem and ensure adaptability to evolving citizen needs. Central to the success of these paradigms is technology, particularly artificial intelligence (AI). AI's transformative capabilities enable the expansion of services, automation of tasks, efficient operationalization and processing vast amounts of data to address urban challenges, aligning with several sustainable development goals (SDGs) such as sustainable cities and communities (SDG 11). Municipalities require strategic plans that empower them to adapt to the AI, Society 5.0 and smart city paradigms, involving multiple stakeholders, including businesses. This study presents a multi-criteria analysis system designed to support decision-making in this complex context, considering the subjective nature and inherent complexity of the decision problem. The system development involved input from key decision-makers with relevant expertise, utilizing methodologies such as cognitive mapping and the decision-making trial and evaluation laboratory technique applied in a neutrosophic environment to analyze cause-and-effect relationships between factors affecting adaptation initiatives. Based on a constructivist, process-oriented approach, the developed analysis system can assist decision-makers in navigating uncertainty during evaluations of technology integration. This holistic and comprehensive system promotes informed decision-making within the AI, Society 5.0 and smart city contexts, contributing to the achievement of relevant SDGs.

1. Introduction

Urbanization has become one of the most significant challenges worldwide. Over the decade from 2011 to 2021, there was a noticeable increase in the percentage of urban dwellers. Specifically, the urbanization rate climbed from 52.0% in 2011 to 56.5% in 2021 (cf. United Nations Conference on Trade and Development (UNCTAD), 2022). This indicates a pronounced trend toward urban living during that period. Additionally, the difference in urbanization rates between developed (79.5%) and developing (51.8%) countries during this period is substantial (UNCTAD, 2022). Despite cities only accounting for 2% of the globe's surface (United Nations Environment Program (UNEP), 2011), experts estimate that by 2050 60%–70% of the world's population will live in urban neighborhoods (Singh and Sobti, 2022), and utilize up to

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75% of the natural resources available (UNEP, 2011; Qiu et al., 2023). To address population growth pressures in urban areas and the desertification of rural areas, urban planners need to rethink the way resources are being exploited and consumed.

The issues directly related to this scenario have to be resolved in an efficient, environmentally conscious manner. Researchers have confirmed that the challenges range from ecological impacts to economic and social problems (Caird, 2018; Caboz et al., 2025). This complexity requires technological solutions applicable to not only people's daily lives but also the services that surround residents, thereby enhancing innovation and economic growth that can sustain individuals' well-being (Bartoloni et al., 2022; Bafail, 2025). As a result, the concept of urban quality of life has gained prominence as cities around the world grapple with numerous challenges associated with rapid urbanization (Yadav and Gupta, 2021). Caird (2018), Zeng et al. (2021) and Caboz et al. (2025), among others, have confirmed that the urbanization challenges consist of restoring social, economic and environmental sustainability, and understanding the complex relationships among these domains.

Countries around the world have proposed and implemented various technological solutions to address the challenges associated with rapid urbanization. These solutions aim to improve the quality of life for residents, enhance efficiency in urban services and contribute to innovation and economic growth (Bartoloni et al., 2022; Vaz-Patto et al., 2024). Smart city is a strategic approach to addressing urban challenges and improving the well-being of urban residents. By integrating advanced technologies and data-driven decision-making, smart cities strive to develop more efficient, sustainable and livable urban environments (Zhou et al., 2023). This approach aligns with several sustainable development goals (SDGs), including good health and well-being (SDG 3), decent work and economic growth (SDG 8), industry, innovation and infrastructure (SDG 9), sustainable cities and communities (SDG 11), climate action (SDG 13) and life on land (SDG 15). Key components that constitute smart cities are smart people, governance, economy, mobility, environment and life (Ekin and Sarul, 2022). Gil-Garcia et al. (2015), Boykova et al. (2016) and Çipi et al. (2023) also confirm these components along with many other elements of smart cities.

Society 5.0 is a term associated with Japan's approach to societal development and was illustrated in the Japanese government's *"Growth Strategy 2018"*. Society 5.0 envisions the evolution of society through the integration of information technology (IT) and various services to create a more advanced and human-centric society (Hitachi-UTokyo Laboratory, 2018; Deguchi et al., 2020). Society 5.0 is characterized as an intelligent society that employs standardized processes to assess human demands and fulfill their needs through the utilization of artificial intelligence (AI) technology (Calp and Bütüner, 2022).

Among the existing technologies, those that make the greatest contribution to the new Society 5.0 and smart city paradigms are those that facilitate connectivity and data collection and/or processing (Singh and Sobti, 2022). AI has assumed a leading role in the data analysis supporting city management and decision-support processes (Allam and Dhunny, 2019; Calp and Bütüner, 2022). In the realm of smart city initiatives and technologies, the conventional focus has often been on generating data and acquiring new insights into the complexity and dynamics of urban areas. However, AI propels cities into the next phase by not only generating this data but also harnessing it to actively support and enhance decision-making processes (Diran et al., 2021). AI possesses the capability to analyze intricate recognition patterns, forecast behaviors and precisely execute operations within physical systems. Its objectives include making decisions and addressing exceedingly complex decision problems, contingent upon proper design and execution (Deguchi et al., 2020; Bafail, 2025).

AI adoption barriers in smart cities have been discussed in specialized literature (*e.g.*, Herath and Mittal, 2022; Freire et al., 2023; Barata et al., 2024; Bafail, 2025). Society 5.0 represents the natural progression of smart city initiatives. Among the myriad challenges in the Society 5.0 initiative, a primary obstacle is businesses' initiative to formulate an information integration architecture that adeptly consolidates data and information across diverse services, encompassing transportation, energy and social welfare (Deguchi et al., 2020). In this context, companies play a crucial role in society's development and transformation. Therefore, the present study sought to answer the following interrelated research questions:

- Which initiatives could facilitate companies' adaptation to AI, Society 5.0 and smart city paradigms?
- What elements would accelerate the integration of AI within the Society 5.0 initiative?

A literature review was conducted to develop a deeper understanding of the decision problem and an adequate theoretical framework for the analyses conducted. Next, two group work sessions with experts in relevant areas were organized, during which the problem's structure and the relationships among significant decision criteria were analyzed. The results' main contribution is the methodologies used and processes followed, namely cognitive mapping and the decision-making trial and evaluation laboratory (DEMATEL) technique in a neutrosophic environment. The conceptual framework of this research study, aimed at identifying criteria to facilitate businesses in integrating AI and accelerating the transition to smart cities and Society 5.0 paradigms, is illustrated in Fig. 1.

The methodological approach adopted in this study offers both theoretical and practical implications of significant value. The use of cognitive mapping provides a theoretical lens through which the intricate relationships and interdependencies among various urban decision criteria can be visualized and analyzed, bringing new insights on urbanization and technology integration. Moreover, the application of the DEMATEL technique within a neutrosophic environment contributes to theoretical advancements by addressing the complexities and uncertainties inherent in urban contexts, offering a nuanced understanding that can inform future research in urban studies, technology adoption and societal development.

From a practical perspective, the methodologies employed in this study hold substantial value for urban planners, policymakers and businesses seeking to navigate the challenges and opportunities presented by AI, Society 5.0 and smart city initiatives. The insights derived from the cognitive mapping and DEMATEL analyses can guide strategic decision-making processes, facilitate stakeholder collaboration and inform the development of integrated solutions tailored to the unique needs and complexities of urban environments. By bridging the gap between theory and practice, this study not only enhances our theoretical understanding of urbanization dynamics but also provides actionable insights and methodologies that can contribute to the sustainable and human-centric development of cities in the era of Society 5.0.

This paper is organized into five sections, starting with the present introduction. Section 2 contains the findings of the literature review focused on AI, Society 5.0 and smart cities. Section 3 describes the methodological approach, while Section 4 presents the application and results. To conclude the paper, the study's limitations are discussed and recommendations for future research are offered.

2. Related literature and research gaps

The concept of the smart city originated from IBM's Smart Earth initiative in 2008 (Qiu et al., 2023). Subsequently, in 2011, the German government introduced the "smart" concept in the manufacturing industry through a set of technology transformation initiatives, known as *Industrie 4.0: Smart Manufacturing for the Future* (Demir et al., 2019). The aim of this action plan was to increase the efficiency and productivity of this industry using technology such as the Internet of things (IoT), robotics and AI. The term "Industry 4.0" was coined at the same time to

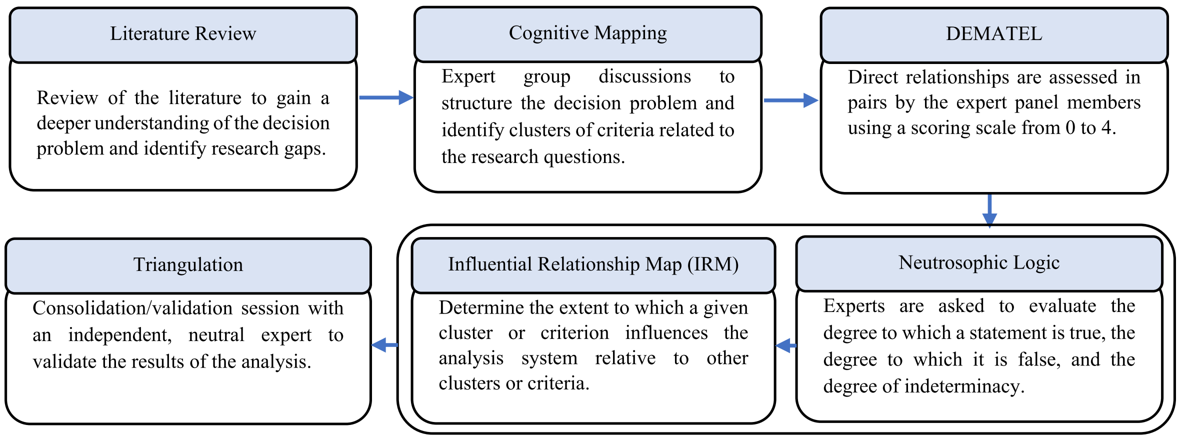

Fig. 1. Schematic diagram of the research.

describe a business model whose principle feature is the convergence of the physical world (*i.e.*, physical spaces or real-world features) with the virtual (*i.e.*, cyberspace). Industry 4.0 as a concept focused solely on describing smart factories' components (*e.g.*, smart mobility and smart grid), but this new approach made the smart concept famous. Soon, the latter was embraced as a wider vision of what cities could be and how they can address problems that have arisen from intense urbanization.

Caragliu et al. (2011, p. 70) describe municipalities as smart *"when investments in human and social capital and traditional (transport) and modern (*[information and communication technology] *ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance"*. Smart cities can be understood as a system of systems (cf. Costa and Oliveira, 2020), so many authors group the dimensions of these municipalities into clusters of systems. For example, Lim et al. (2021) divide the smart city concept into three areas: (1) smart technologies; (2) smart services; and (3) smart policies. The first category focuses on ICT to enable data collection and connectivity, while the second encompasses various resources' usage, such as energy and water resource management and related vehicles. The last area concentrates on citizens' well-being.

In 2016, the smart city concept was expanded by the Japanese government into the idea of Society 5.0, which, instead of having multiple separate systems, seeks to integrate them all into a single system (*i.e.*, cyber-physical space). As a result, Society 5.0 is also referred to as the Super Smart Society (Hitachi-UTokyo Laboratory, 2018). A smart society is characterized by the strategic deployment of digital technology by various entities, aiming to enhance three overarching outcomes: (1) the welfare of people; (2) the robustness of the economy; and (3) the success of organizations. In addition, this new paradigm can be broadened to cover all regions as opposed to only focusing on cities. Thus, rather than listing solutions to problems associated with services in a single city, the primary goal is to address issues by establishing relationships across multiple cities and/or societies (Hitachi-UTokyo Laboratory, 2020). According to the Japanese government (Hitachi-UTokyo Laboratory, 2020, p. 11), "[Society 5.0] *must, through the high degree of merging between cyberspace and physical space, be able to balance economic advancement with the resolution of social problems by providing goods and services that granularly address manifold latent needs regardless of locale, age, sex, or language to ensure that all citizens can lead high-quality lives full of comfort and vitality"*.

Using technology, smart cities—and thus Society 5.0—can collect vast amounts of data from objects and stakeholders on a multitude of aspects of urban life (Allam and Dhunny, 2019; Ekin and Sarul, 2022; Bafail, 2025). Faced with the complexity of transforming data into useful information, an advanced technique emerged (*i.e.*, AI) that facilitates the development of near-reality models, with the ultimate goal of emulating reality perfectly. In other words, AI is present when machines can replicate cognitive functions associated with the human mind (*e.g.*, the ability to learn and to resolve problems) (Ongsulee, 2017; Huang et al., 2023). Society 5.0 thus represents an evolution toward a society where technology, particularly AI, plays a pivotal role in enhancing human life. This vision is characterized by machines and technologies that are situationally aware and environmentally conscious, capable of autonomous decision-making to benefit humanity. Central to this transformation is the integration of AI into urban planning (Çipi et al., 2023; Caboz et al., 2025).

One significant dimension is ICT, which forms the backbone of smart cities. High-speed Internet and connectivity are crucial for efficient data communication. The application of ICT in urban settings aids in enhancing the quality of life, improving urban operations and promoting sustainable practices. Emerging technologies like 5G are poised to revolutionize various sectors, from healthcare to transportation (Rodrigues et al., 2023). Moreover, AI's role in ICT is expanding, with applications ranging from smart home management to predicting and managing 5G network traffic (Winden and Buuse, 2017; Ekin and Sarul, 2022; Qiu et al., 2023).

Another critical facet is smart infrastructure, encompassing smart buildings, grids and water systems (Santos et al., 2024). These infrastructures leverage advanced technologies to create adaptive environments that prioritize user comfort, safety and efficiency. For instance, AI is integrated into Building Information Modeling (BIM) and smart grid operations, enhancing structural safety and grid management. Furthermore, AI-driven urban planning tools are empowering city planners to make informed decisions, optimize resource allocation and envision future urban configurations (Ekin and Sarul, 2022). Additionally, AI's application in governance extends to risk management, data protection and personalized service delivery, ensuring a holistic approach to smart governance in Society 5.0 (Çipi et al., 2023; Bafail, 2025).

Overall, Society 5.0 and smart city initiatives represent a transformative journey toward a technologically integrated and sustainable society. The integration of AI across various dimensions, from infrastructure to governance, underscores the potential for innovation, efficiency and improved quality of life in the urban landscape (Qiu et al., 2023; Ekin and Sarul, 2022; Vaz-Patto et al., 2024).

Despite the challenges the Society 5.0 paradigm presents, it can be seen as an ideal space for creating business opportunities. According to Hitachi-UTokyo Laboratory (2020, p. 169), "[A] *shift* [takes place] *from data monopolies to open data, which will generate new business opportunities. Traditionally, companies have made profits by monopolising their customer and marketing data. From now on, companies will create new business opportunities by releasing their data sets as open data (after ensuring human security) and sharing them with others in cyberspace. While paying* *due attention to the protection of personal information, companies will publicly release data that they could not fully analysze themselves"*. Thus, by finding gaps and/or synergies, Society 5.0 can offer not only better services but also foster new business opportunities (Çipi et al., 2023). Previous studies have demonstrated technologies' applicability in multiple industries, with the end goal of making societies increasingly smart. Table 1 summarizes some of this research, highlighting its contributions and limitations.

The studies conducted to date have multiple limitations, but the greatest shortcoming is the inability to analyze multiple social and technological criteria simultaneously. Winden and Buuse (2017, p. 68) point out that: *"most smart city technology projects are not only technical, but involve social, cultural, political, institutional, and behavioural changes that are very context sensitive. In this respect, there are reasons to be doubtful about the effectiveness of dissemination and replication activities"*. The diverse variables involved are an intrinsic part of smart cities' implementation, as well as applications of the Society 5.0 model.

The consequences of this limitation include an inability, first, to define cause-and-effect relationships between criteria and, second, to analyze subjective criteria that reflect social patterns and that are inherent to society (cf. Çipi et al., 2023; Santos et al., 2024). The latter restriction is due to the preference of prior research for methodologies emphasizing mathematical optimization. Third, the existing studies have included few scenarios that offer a holistic, realistic vision of the decision problem (cf. Çipi et al., 2023; Santos et al., 2024). Last, the literature shows a scarcity of dynamic analyses of the identified issues. Given the limitations identified in the extant literature, the present research resorted to a combined use of cognitive mapping and DEMATEL with neutrosophic logic to develop a multi-criteria analysis system that overcomes some of these shortcomings.

3. Methodological background

The purpose of the present study is to identify the factors that would accelerate the adoption of AI in smart city and Society 5.0 initiatives. In this process, the research also aims to elucidate any interrelationships among these elements in an organized and efficient manner. To address this objective and pinpoint the factors facilitating AI adoption, cognitive mapping is employed alongside DEMATEL within a neuromorphic environment. The choice to apply both cognitive mapping and DEMATEL techniques was largely made because both are well-established sociotechnical methods known for being simple to apply and facilitating decision making in varied organizational contexts (cf. Rodrigues et al., 2022). DEMATEL's key strength is its ability to include qualitative and quantitative criteria and visualize the cause-and-effect relationships between criteria, which allows decision makers to analyze and prioritize factors according to their degree of influence and importance (Si et al., 2018; Rodrigues et al., 2022).

3.1. Cognitive mapping

Every decision-making process needs to begin with structuring the decision problem since all subsequent steps are strongly affected by the structuring phase (Marttunen et al., 2017). The process's success depends on first determining the type of problem involved (Rosenhead, 2006). Rittel and Webber (1973), for example, categorize decision problems according to whether they can be resolved using traditional methods. *"Tame"* problems have precise, non-problematic formulations, whereas *"wicked"* ones do not lend themselves to a unified representation and thus require decision makers to apply *"an alternative paradigm for problem-solving"* (Smith and Shaw, 2019, p. 403). To address these complexities, problem-structuring methods emerged in the 1970s known collectively as soft operational research. These techniques *"are a broad group of model-based problem handling approaches whose purpose is to assist in the structuring of problems rather than directly to derive a solution"* (Rosenhead, 2013, p. 1162). In addition, these methods *"help*

Table 1
Previous studies.

Author	Approach/Method	Contribution	Limitation
Pramanik et al. (2017)	Smart healthcare	- Confirmation of big data (BD) and advanced technologies' applicability (*e.g.*, machine learning) to enable improved healthcare quality and efficiency.	- Health systems need to be updated for various stakeholders. - Technical, social, financial, ethical and organizational challenges are identified, but analyses need to be done in future research.
Mtshali and Khubisa (2019)	Smart homes for disabled people	- Identification of solutions that make smart homes' accessible to individuals with some level of disability through the use of control systems controlled by digital assistants (*e.g.*, Google Assistant, Apple's Siri and Amazon's Alexa).	- The model created relies on the use of voice commands, so people with speech impairments are automatically excluded from using this system.
Ullah et al. (2020)	AI, machine learning, and deep learning applications in smart cities	- Identification of studies and technological trends focused on AI, machine learning and deep learning, as well as a clarification of the challenges of and future options for how to optimize these techniques' performance in smart cities.	- The narrow approach to technology excludes listing the social, economic, and sustainable dimensions of constructing smart cities.
Mishra et al. (2020)	AI system to detect pneumonia caused by coronavirus disease-19	- Confirmation of AI's applicability in the interpretation of X-ray images as a way to assist clinicians and radiologists.	- Researchers have limited access to information on different types of pneumonia needed to enrich the model developed.
Iqbal et al. (2020)	BD—computational intelligence (CI) in smart cities	- Identification of the tangible benefits of analyzing BD using CI in smart cities: (1) reducing costs; (2) supporting decision makers in real time; and (3) encouraging the development of new products and services.	- The methodology presented needs to be applied and developed further in other areas of smart cities to create commercial and academic value.
Fathi et al. (2023)	Sensor location model for security protection in Society 5.0	- Location sensors as a service used to increase security around valuable infrastructure	- Implementation presents challenges due to long waiting times in the screening process, which can

(*continued on next page*)

Table 1 (*continued*)

Author	Approach/Method	Contribution	Limitation
		and through queue tracking (*i.e.*, applicable to people and goods) and to implement a bi-level model for estimating sensors' impact.	lead to congestion when people or goods enter the system. • The number of test scenarios was limited.

people who might initially have different perspectives on an issue to clarify and develop their understandings" (Cronin et al., 2014, p. 145). In other words, structuring a problem relies on the individuals involved sharing their knowledge and participating in open communication. This approach is based on the premise that interactions between decision makers is a crucial element of any problem-structuring process and, consequently, of decision making. The procedures followed need to reflect how *"human beings understand reality and* […] *manage and control reality by accessing and associating various elements of each individual's memory"* (Lousada et al., 2021, p. 4). Cognitive mapping was selected as a methodology that could incorporate these basic assumptions into the present study.

Cognitive mapping techniques are based on personal construct theory (Kelly, 1955), which proposes that people seek to make sense of the world around them as a way to manage and control it. Cognitive mapping thus seeks to clarify how an individual or group of individuals understands a given decision problem by encouraging discussions and the sharing of knowledge during the decision-making process (Castanho et al., 2021). The practical result is a cognitive map containing a network of nodes (*i.e.*, concepts, ideas and criteria) connected by arrows that define the causal relationships between the nodes (Fonseca et al., 2018).

Developing this kind of map while structuring complex decision-making problems has three advantages. The first is the promotion of discussion between stakeholders (*i.e.*, decision-makers) in order to identify more accurately opportunities and action points. The second advantage is the smaller number of criteria omitted during the decision-making process, while the last benefit is a better understanding of the causal relationships between the criteria under analysis (Brito et al., 2019).

3.2. Neutrosophic logic and DEMATEL

Decision-makers frequently struggle to quantify and analyze uncertain or incomplete information, as traditional mathematical methods often fall short in capturing the complexity and ambiguity of real-world situations. To overcome this limitation, Smarandache (1999) introduced the concept of neutrosophic logic, which expands on conventional many-valued logics by proposing that *"every idea has not only a certain degree of truth, as is generally assumed in many-valued logic contexts, but also a* [degree of] *falsity* […] *and* […] *indeterminacy* […] *that have to be considered independently from each other"* (Rivieccio, 2008, p. 1860). This logic is operationalized by representing each variable (*i.e.*, criterion) as a neutrosophic set composed of three components: the degree of truth (T), the degree of indeterminacy (I) and the degree of falsity (F) (Smarandache, 2007). Such a structure is particularly valuable in complex socio-technical environments—like those associated with AI, Society 5.0 and smart city transitions—where ambiguity and incomplete knowledge are pervasive (Santos et al., 2024).

Unlike traditional decision-making approaches, which typically require well-defined inputs and clear-cut preferences, neutrosophic logic offers a more flexible framework for capturing the nuanced and sometimes hesitant judgments of experts. By allowing T, I and F to be expressed independently, it accommodates the uncertainty and plurality of views often encountered in group-based strategic processes (cf. Smarandache, 1999, 2007; Vaz-Patto et al., 2024). In the present study, this feature proved particularly beneficial. When combined with the DEMATEL method, neutrosophic logic enhanced the overall robustness of the analysis by enabling experts to articulate ambiguity more explicitly, thereby improving both the transparency and the quality of the decision-making process.

To integrate neutrosophic logic into the DEMATEL framework, the three components—T, I and F—were aggregated into a single representative value. Each expert assessment, expressed as $w_k = (T_k, I_k, F_k)$, was thus converted into a neutrosophic number. The corresponding crisp weight was then calculated using Equation (1), as proposed by Pramanik et al. (2017):

$$w_k = \frac{1 - \sqrt{\left((1-\mathrm{T}_k)^2 + (\mathrm{I}_k)^2 + (\mathrm{F}_k)^2\right)/3}}{\sum_{k=1}^{r}\left\{1 - \sqrt{\left((1-\mathrm{T}_k)^2 + (\mathrm{I}_k)^2 + (\mathrm{F}_k)^2\right)/3}\right\}} \tag{1}$$

in which r represents the decision makers' total number of evaluations. The above crispification formula must comply with two conditions: (1) $w_k \geq 0$; and (2) the total of all evaluations' crisp neutrosophic weight w $= 1$ (*i.e.*, $\sum_{k=1}^{r} w_k = 1$).

The present study is *"not only technical, but involve*[s] *social, cultural, political, institutional, and behavioral changes that are very context sensitive"* (Winden and Buuse, 2017, p. 48), so considering multiple variables was crucial to the development of an empirically robust analytical framework. This research thus applied a multiple-criteria decision analysis (MCDA) approach, namely the DEMATEL technique. MCDA specifically values the incorporation and discussion of decision makers' diverse values and preferences (Bana e Costa et al., 1997).

Developed by Gabus and Fontela (1972), DEMATEL is *"a useful approach to the structure of complex causal relationships with direct relationship matrices or digraphs (e.g., cause and effect diagram interaction map* [s]*) that describe* […] *contextual relationship between different elements of the system"* (Song and Cao, 2017, p. 354). This technique produces a correlation matrix based on experts' opinions about cause-and-effect relationships between criteria. The links between these variables are quantified on a scale from 0 to 4, in which 0 represents "no influence", 1 "little influence", 2 "medium influence", 3 "strong influence" and 4 "very strong influence" (Gabus and Fontela, 1972; Bastos et al., 2023; Freire et al., 2023). This method usually involves six steps.

3.2.1. Step one: calculate group direct influence matrix Z

This step requires recruiting a group of m experts to evaluate and solve a complex problem involving n factors or criteria. To establish the direct influence that factor F_i has on factor F_j, the experts begin by making comparisons between the two factors using the aforementioned scale from 0 to 4. This procedure generates an individual influence matrix $Z = \left[z_{ij}^{k}\right]_{n\times n}$ for each expert, whose diagonal is made up of elements equal to zero and in which z_{ij}^{k} corresponds to each expert's judgment and k indicates the number of participants ($1 \leq k \leq m$). To aggregate all the matrices created by m experts, the average matrix is calculated based on Equation (2) (Ferreira et al., 2021; Rodrigues et al., 2022):

$$Z_{ij} = \frac{1}{m}\sum_{k=1}^{m} x_{ij}^{k}, \text{with } i,j = 1,2,\ldots,n \tag{2}$$

3.2.2. Step two: construct normalized direct-influence matrix X

Matrix X is developed by applying Equation (3) (Lin et al., 2010; Rodrigues et al., 2022):

$$X = \frac{Z}{s} \tag{3}$$

in which s represents the normalized constant calculated using Equation (4) (Ferreira et al., 2021):

$$s = \max\left[\max_{1\le i\le n}\sum_{j=1}^{n}|z_{ij}|, \max_{1\le i\le n}\sum_{i=1}^{n}|z_{ij}|\right], \tag{4}$$

in which $i,j = 1,2,\dots,n$.

3.2.3. Step three: create total-influence matrix T

This matrix reflects both the direct and indirect effects that factor F_i exerts on factor F_j. Matrix T is produced by applying Equation (5) (Chen et al., 2019; Freire et al., 2023):

$$T = X + X^2 + X^3 + \dots + X^h = X(I - X)^{-1} \tag{5}$$

in which I correspond to identity matrix $n \times n$ when $\lim_{h\to\infty} X^h = [0]_{n\times n}$.

3.2.4. Step four: calculate vectors R and C

The rows and columns of total-influence matrix T are added up to obtain vectors R and C, respectively, according to Equations (6) and (7) (Lin et al., 2010):

$$R = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = [r_i]_{n\times 1} = (r_1, \dots, r_i, \dots, r_n) \tag{6}$$

$$C = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n} = [c_j]'_{1\times n} = (c_1, \dots, c_j, \dots, c_n) \tag{7}$$

in which $[c_j]'$ is the transpose matrix. R_i corresponds to the total of matrix T's row i, so this vector reflects the direct or indirect influence the factor in question exerts on the other criteria in the analysis system. Concurrently, C_j is the total influence that each factor j receives from the other variables. When $i = j$, $(R_i + C_i)$ represents a criterion's degree of importance in the system and $(R_i - C_i)$ that factor's degree of influence. Thus, when $(R_i - C_i) > 0$, factor F_i has a net effect on the other criteria. Conversely, when $(R_i - C_i) < 0$, factor F_i is overall more influenced by the other variables (Chen et al., 2019).

3.2.5. Step five: determine threshold (α) value

The average value of the total matrix T is calculated considering the N elements present in the matrix. This average corresponds to the α value, which is obtained through Equation (8):

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[t_{ij}]}{N} \tag{8}$$

Based on the α value, factors with a lesser effect and significance can be eliminated from matrix T (Sumrit and Anuntavoranich, 2013). Only criteria with higher values within the matrix are included in the influential relations map (IRM) generated next in order to facilitate interpretations of the connections between factors (Si et al., 2018).

3.2.6. Step six: create IRM

The map representing the cause-and-effect relationships between factors has $(R - C)$ as its vertical axis and $(R + C)$ as its horizontal axis. This diagram reveals not only the most important factors but also their influence on the other criteria analyzed, which allows decision makers to draw conclusions and make recommendations or change their strategies. In Fig. 2, quarter (Q) I contains the core factors (*i.e.*, cause criteria perceived as valuable), QII encompasses the driving factors (*i.e.*, cause criteria seen as sources of risk), and QIII has the independent factors (*i.e.*, effect criteria perceived as risks). Finally, QIV includes the impact factors (*i.e.*, effect criteria perceived as benefits) (Si et al., 2018).

Overall, DEMATEL assumes that the relationships among criteria can be meaningfully evaluated by experts using pairwise comparisons, and

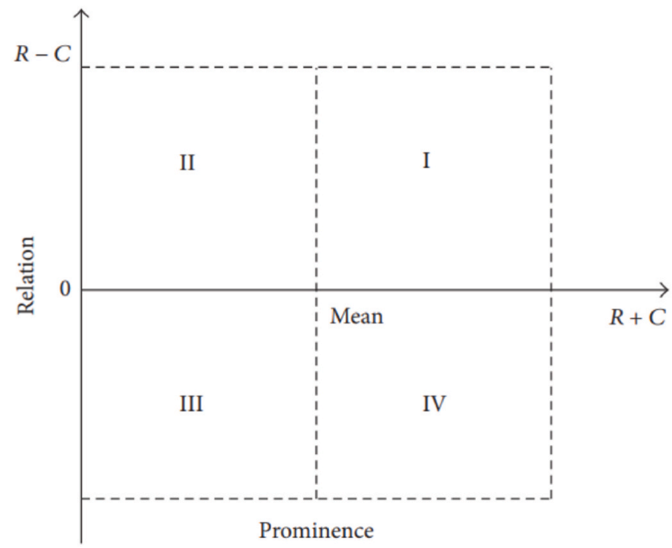

Fig. 2. Four quadrant influential relations Map.
Source: Si et al. (2018).

that these judgments can be aggregated into a direct influence matrix reflecting the strength and direction of causal relationships. It also assumes a certain level of consistency and coherence in expert evaluations, which is essential for producing a reliable influence structure. One of the method's key strengths lies in its ability to handle complex systems with interdependent criteria and to generate a visual representation that supports a more intuitive understanding of cause-and-effect dynamics (cf. Gabus and Fontela, 1972; Song and Cao, 2017).

However, DEMATEL is not without limitations. First, its effectiveness depends heavily on the quality of expert input, and subjective biases may influence the pairwise assessments. Second, the method does not account for trade-offs or preferences in the way that other MCDA methods (*e.g.*, utility-based models) might. Third, while DEMATEL can identify influential factors, it does not rank alternatives or suggest optimal courses of action, which may be necessary in certain decision-making contexts (cf. Freire et al., 2023). In the present study, these limitations were addressed in part by combining DEMATEL with cognitive mapping (to support initial structuring and interpretation) and neutrosophic logic (to better accommodate uncertainty, hesitation and imprecision in expert judgments).

While DEMATEL is one of several available MCDA techniques—such as the Analytic Hierarchy Process (AHP), Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) or Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)—it was selected primarily for its ability to model complex interrelationships among evaluation criteria by identifying and visualizing cause-and-effect structures. Unlike these other methods, which are more suitable for ranking alternatives or prioritizing criteria in linear or hierarchical models, DEMATEL is particularly well-suited to analyzing feedback-rich systems with intertwined and interdependent factors (cf. Gabus and Fontela, 1972; Song and Cao, 2017)—precisely the type of complexity present in the current study. Moreover, when combined with cognitive mapping, DEMATEL facilitates a smooth transition from qualitative problem structuring to quantitative analysis of interdependencies (cf. Freire et al., 2023). The integration of neutrosophic reasoning further enhances this approach by allowing truth and falsity to be treated independently and by introducing a third dimension—*i.e.*, indeterminacy—which is especially valuable in contexts characterized by ambiguity, incomplete information or expert hesitation (cf. Smarandache, 2007). In the present study, this enabled experts to provide more nuanced evaluations, particularly in areas involving uncertainty or partial consensus. The triadic structure of neutrosophic logic thus improved both the transparency and the robustness of the analysis by explicitly capturing the epistemic uncertainty that often characterizes complex strategic decision-making processes. While each of these methods has been applied individually in previous studies, their specific integration within the context of AI, Society 5.0 and smart city adaptation represents a meaningful contribution to the state of the art in the field of MCDA.

4. Application and results

The above theoretical and methodological framework supported all subsequent procedures. The following section describes the empirical research carried out and analyses of the results.

4.1. Structuring phase

According to Carayannis et al. (2018) and Braga et al. (2021), decision-maker panels should have 5–12 members. The techniques selected for the present study were applied by a group of six professionals specializing in areas directly connected to the decision problem. The participants included a marketing specialist with experience in the banking sector but currently working in the real estate sector, a mergers-and-acquisitions analyst specializing in the renewable energy sector, and a smart city business development manager working for a construction company. The fourth panel member was another smart city business development manager involved in a European-level pilot project focused on leveraging high-risk, high-impact technologies. The remaining two experts were an information technology (IT) consultant and software developer with experience in innovative technologies (*e.g.*, AI, blockchain and big data) and an IT consultant specializing in security.

This multidisciplinary composition was deliberately designed to ensure relevant expertise and diverse perspectives on the complex, cross-sectoral challenges under analysis. Each expert held a strategic decision-making position and had more than ten years of relevant professional experience. Caution was taken to ensure diversity in gender, age and professional background. Although based in Portugal, all participants had prior involvement in European initiatives, providing them with broader, cross-national perspectives. Overall, experts were selected based on their practical involvement and recognized domain knowledge, rather than for statistical representativeness. In line with the process-oriented, constructivist nature of the present study (Bell and Morse, 2013; Ormerod, 2013), this means that the selection process was purposeful, aiming to assemble a knowledgeable and diverse group of practitioners capable of engaging meaningfully with the complexity of the decision problem. Our objective was not to achieve statistical generalizability, but to ensure depth, relevance and contextual richness in the analysis. Their voluntary participation further ensured a high level of commitment and engagement throughout the process. We also acknowledge the possibility that the panel's national and professional backgrounds may have influenced the prioritization of certain issues (*e.g.*, regulatory complexity and social resistance to change). However, this context specificity was intentionally preserved, as the goal was to reflect the situated knowledge and judgments of informed stakeholders within a clearly defined decision environment.

Due to coronavirus disease-19 restrictions, the group work sessions were held remotely using the *Teams* platform. The first session began with a brief introduction of each panel member, followed by a brief explanation of the procedures given by the facilitator (*i.e.*, one of the authors of this paper). The latter was included to foster a consensus among the specialists during the decision-making process (Ferreira, 2011). In this way, the experts understood from the beginning the *modus operandi* of the session, which contributed to ensuring the group work ran as smoothly as possible. Fig. 3 shows the sequence of steps followed in the two group work sessions involving the expert panel.

After this brief introduction, the first discussion was started with a trigger question to generate discussion and knowledge sharing among the experts (*i.e.*, *"Based on your professional experience, what initiatives can facilitate companies' adaptation to AI, Society 5.0, and smart city paradigms?"*). The "post-its technique" (Eden and Ackermann, 2004) was used to help each decision maker write down the criteria, ideas or initiatives they deemed relevant (*i.e.*, one response per post-it note). A negative sign (−) was added to the appropriate post-it notes to indicate the negative causal relationship between the criterion and the goal of the initiatives. A minus sign (−) thus signaled the factor is an obstacle to businesses' adapting to the three models, while the sign's omission suggested that factor reinforces companies' ability to adapt to these paradigms as needed.

The decision makers were informed in advance that the group cognitive map should include over 100 nodes (*i.e.*, criteria) (Eden and Ackermann, 2004). Ultimately, the process yielded 111 criteria, which were grouped into four clusters labeled as follows: *Legislation and Public Policies* (C1); *Technology* (C2); *Performance* (C3); and *People* (C4). In the final step of the first session, each cluster was internally organized based on the perceived importance of its criteria, with the most critical positioned at the top and the least significant at the bottom.

These clusters were not derived from existing frameworks in the literature; rather, they emerged inductively from the expert elicitation process conducted using Strategic Options Development and Analysis (SODA) and cognitive mapping (Eden and Ackermann, 2004). This constructivist approach enabled participants to collaboratively structure the problem, drawing on their professional expertise and real-world experience. During the facilitated group session, experts identified and discussed a wide array of criteria, which were refined and grouped into clusters through iterative dialogue, negotiation and consensus. As such,

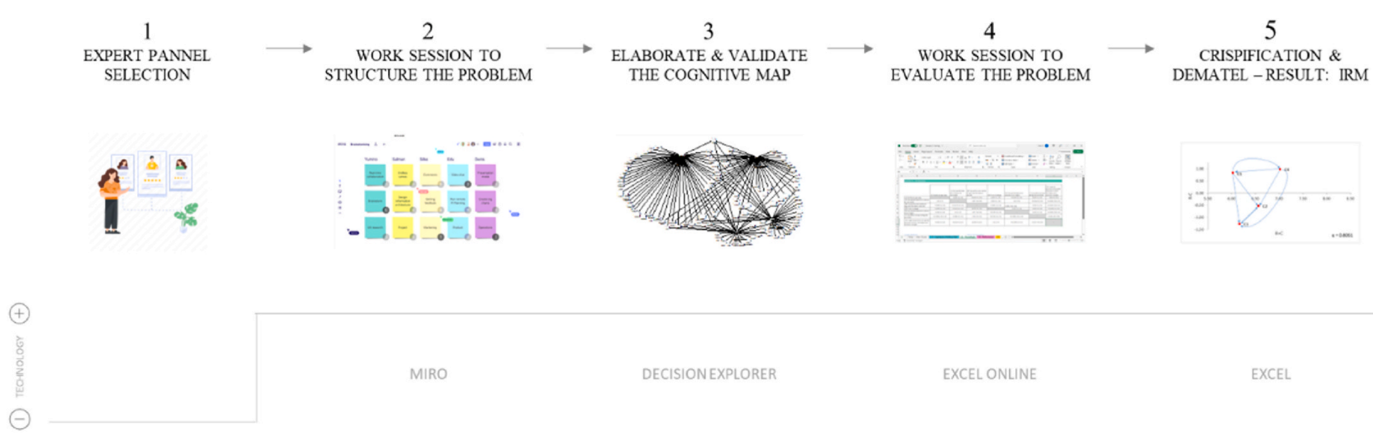

Fig. 3. Decision-making process followed.

the resulting categories reflect a shared cognitive model shaped by decision-makers actively involved in the domains of AI, Society 5.0 and smart city development.

While the cluster labels may appear to align conceptually with themes from prior studies, their specific composition and the interrelationships among criteria reflect a unique, context-sensitive understanding of the factors influencing corporate adaptation to smart urban environments. The mapping process facilitated the integration of diverse perspectives and supported the construction of a holistic framework through which causal relationships among variables could be collaboratively identified and interpreted. For example, elements such as *short-term political horizon* (SC28) and *rivalry among entities* (SC92)—often underrepresented in technocratic or quantitative models—were highlighted as critical real-world constraints. Cognitive mapping played a central role in this process by encouraging the exchange of ideas and experiences, deepening understanding of the decision context and enabling the identification of causal linkages among criteria. This allowed participants to explore underlying questions such as "why does this happen?"—a key advantage of this approach. As noted in the literature (cf. Eden and Ackermann, 2004; Marttunen et al., 2017), the interactive and discursive nature of cognitive mapping helps decision-makers engage with aspects of the problem that are often inaccessible through traditional or data-driven methods.

By directly drawing on expert input, the method supports a more context-sensitive and realistic representation of the problem. This approach revealed insights not typically captured through statistical or optimization-based techniques and offered a flexible framework that can be adapted to different contexts and stakeholder perspectives (cf. Freire et al., 2023), supporting future applications and refinements. The cognitive map presented in Fig. 4 was developed using this information (space constraints limit the clarity of the visual presentation but an editable version of the complete group cognitive map can be requested directly from the corresponding author).

4.2. Evaluation phase

After the group cognitive map was generated, a second group work session was held—still remotely—with the same expert panel. First, the members were asked to choose the most significant criteria (SC) within each cluster using the nominal group technique (NGT) and multi-voting method. These techniques were selected because they foster a meaningful discussion and avoid any ties by ensuring only the criteria receiving the most votes (*i.e.*, highest priority) are retained. Table 2 lists the selected factors.

The decision makers were then asked to construct five matrices (*i.e.*, one inter-cluster and four intra-cluster) with the values obtained by applying the DEMATEL method in a neutrosophic environment (*i.e.*, quantifying factors' weight as $x(T, I, F)$). DEMATEL thus included subjecting the decision makers' T, I and F values to crispification in order to generate single-valued neutrosophic numbers. The second session ended when all the matrices had been completed. Importantly, all information used in the study was directly provided and validated by the panel members during the group sessions, ensuring that all viewpoints were considered, debated and reconciled prior to analysis. This emphasis on group dynamics is a core strength of the methodology, as it enables participants to confront differing perspectives, clarify assumptions and work collaboratively toward more consensual and robust solutions. Such interaction not only enhances the quality and legitimacy of the resulting model but also fosters shared ownership of the outcomes—an essential factor in real-world strategic decision-making (cf. Vaz-Patto et al., 2024).

The first matrix created during the session was the inter-cluster matrix, which represents the inter-relationships between clusters (see Table 3). The six DEMATEL steps began with the creation of the initial matrix shown in Table 4 and the crispification computations in Table 5. Equations (3) and (4) (see subsection 3.2.2) were applied (see Table 6) to obtain the normalized direct-influence matrix presented in Table 7. Three iterations were needed to apply Equation (5) (see subsection 3.2.3) and produce matrix T. The supporting calculations and this matrix are shown in Table 8.

Table 9 lists the R and C values, as well as the results obtained by adding and subtracting them. These values were then used to generate the DEMATEL IRM.

As discussed in Section 3, $(R - C)$ indicates the degree of influence that a given factor or cluster has on the analysis system in relation to the other criteria or clusters. The factors or clusters can then be categorized into a causes group in which $(R - C) > 0$ and an effects group in which $(R - C) < 0$. $(R + C)$, in turn, reveals each factor or cluster's importance in the system, quantifying the total effects given and received by each criterion or cluster.

As can be seen by the $(R + C)$ axis in Fig. 5, C4 is the most important cluster, and C1 the least important in the analysis system. The clusters can be ranked by order of importance as follows: C4 > C2 > C3 > C1. In addition, the $(R - C)$ axis places C1 and C4 in the causes group as they exert direct influence on the other clusters. C2 and C3 belong to the effects group, so they are passive clusters that do not affect other clusters significantly. A further analysis of Fig. 5 reveals that C4 contains core factors as it is in QI, C1 has driving criteria in QII, C3 comprises independent factors in QIII, and C2 encompasses impact criteria in QIV.

The intra-cluster analyses first focused on C1, in which SC6 has the strongest impact on the other clusters (*i.e.*, $R = 3.4924$) (see Table 10). In contrast, SC36 is the most influenced by the other initiatives as its C score is 3.1546. The SCs' importance was then assessed based on the $(R + C)$ values. SC33 is the most prominent, whereas SC27 is the least significant. The SCs were next ranked by order of importance: SC33 > SC36 > SC6 > SC22 > SC18 > SC16 > SC27. According to the $(R - C)$ scores, SC6, SC16 and SC33 belong to the causes group, and the remainder comprise the effects group.

Fig. 6 presents the classification of the C1 criteria according to type of factor. That is, SC6 and SC33 are core factors (QI), and SC16 is a driving criterion (QII). SC18, SC22 and SC27 are independent factors (QIII), while SC36 is an impact criterion (QIV).

In C2, the initiative that exerts the greatest influence on the other factors is SC76 (see Table 11), with an R value of 4.277. SC56 receives the most effects, with a C score of 4.0901. The most important SC is SC12, while SC71 is the least prominent. The C2 initiatives can be ordered by importance as follows: SC12 > SC56 > SC14 > SC48 > SC76 > SC59 > SC71. In addition, SC48 and SC76 make up the causes group, and the remaining SCs belong to the effects group.

Fig. 7 shows that SC48 and SC76 can be classified as driving factors. SC59 and SC71 are independent criteria, and SC12, SC14 and SC56 are impact factors.

In C3, the most influential SC is SC81 ($R = 3.3120$) (see Table 12). SC84 in turn receives the strongest impacts ($C = 3.1111$). The results also reveal that SC81 is the most important initiative, while SC89 is the least prominent. The SCs were ranked by order of importance as follows: SC81 > SC84 > SC8 > SC86 > SC89. SC86 and SC89 comprise the effects group, while the remaining factors make up the causes group.

Fig. 8 organizes the C3 initiatives by their function within the cluster. The core factors are SC81 and SC84, and the driving, independent and impact factors are SC8, SC89 and SC86, respectively.

Finally, the C4 SC with the greatest influence on the other factors is SC32 ($R = 10.0122$) (see Table 13). SC39 receives the most effects ($C = 10.1675$). In addition, the most important SC also has the most influence in this cluster on the analysis system (*i.e.*, SC32). The least prominent is SC108. The initiatives were ranked by order of importance as follows: SC32 > SC42 > SC39 > SC109 > SC108. The results also show that SC39 and SC42 are the effects group and the remaining SCs are the causes group.

Fig. 9 classifies the C4 SCs into four types of factors. SC32 is a core factor, SC108 and SC109 driving factors, SC39 an independent factor, and SC42 an impact factor.

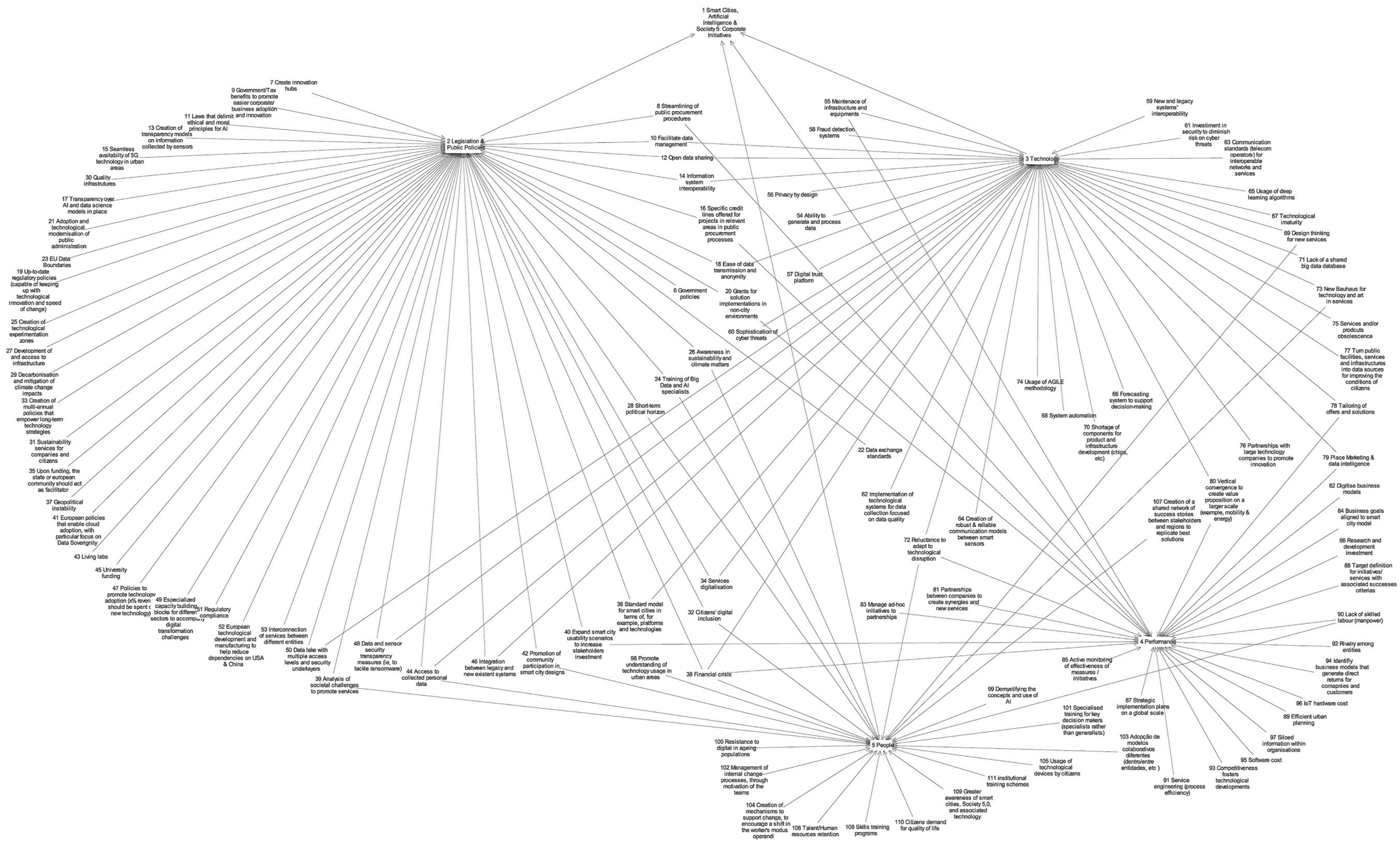

Fig. 4. Group cognitive map.

Table 2
Most significant criteria for significant criteria for each cluster.ach cluster.

Cluster	Most Significant Criteria	Supporting Literature
C1 Legislation and Public Policies	SC6. Government policies	Thilagavathy (2023)
	SC16. Specific credit lines offered for projects in relevant areas in public procurement processes	World Economic Forum (2020); U4SSC (2023)
	SC18. Ease of data transmission and anonymity	Gumzej and Rosi (2023); Glerean (2025)
	SC22. Data exchange standards	Romeo and Lacko (2025)
	SC27. Development of and access to infrastructure	Folorunso et al. (2024)
	SC33. Creation of multi-annual policies that empower long-term technology strategies	United Nations (2021)
	SC36. Standard model for smart cities in terms of, for example, platforms and technologies	Salkuti (2021); UN-Habitat (2025)
C2 Technology	SC12. Open data sharing	Publications Office of the European Union (2024)
	SC14. Information system interoperability	Gonzalez-Torres and Ali-Vehmas (2025)
	SC48. Data and sensor security transparency measures (*i.e.*, to tackle ransomware)	Akinsuli (2021); Visave (2025)
	SC56. Privacy by design	Malmio (2024)
	SC59. New and legacy systems' interoperability	Kapoor (2024); Singh (2025)
	SC71. Lack of a shared big data database	Zhuang et al. (2024)
	SC76. Partnerships with large technology companies to promote innovation	Kong et al. (2025)
C3 Performance	SC8. Streamlining of public procurement procedures	U4SSC (2023)
	SC81. Partnerships between companies to create synergies and new services	Vrabie (2020)
	SC84. Business goals aligned to smart city model	Eggers and Skowron (2018)
	SC86. Research and development investment	Neirotti et al. (2014)
	SC89. Efficient urban planning	Rathore et al. (2016); Jacques et al. (2024)
C4 People	SC32. Citizens' digital inclusion	Eggers and Skowron (2018); Wolniak and Stecuła (2024)
	SC39. Analysis of societal challenges to promote services	Shayan and Kim (2023); Szczepańska et al. (2023)
	SC42. Promotion of community participation in smart city designs	Anthony (2024)
	SC108. Skills training programs	U4SSC (2023)
	SC109. Greater awareness of smart cities, Society 5.0, and associated technology	Al-Saidi and Zaidan (2024)

Table 3
Inter-cluster matrix with neutrosophic values constructed in second group work session.

	C1	C2	C3	C4
C1	–	2 (0.95, 0.4, 0.1)	3 (0.8, 0.2, 0.15)	3.5 (0.95, 0.1, 0.1)
C2	1.5 (0.9, 0.45, 0.1)	–	3 (0.9, 0.1, 0.1)	3 (0.85, 0.2, 0.1)
C3	1 (0.75, 0.4, 0.1)	4 (0.9, 0.1, 0.1)	–	1.5 (0.6, 0.5, 0.45)
C4	4 (0.95, 0.1, 0.1)	3 (0.95, 0.3, 0.3)	3.5 (0.85, 0.15, 0.15)	–

Table 4
Direct-influence matrix: Inter-cluster analysis.

	C1	C2	C3	C4	TOTAL
C1	0.0	1.5	2.4	3.2	7.2
C2	1.1	0.0	2.7	2.5	6.3
C3	0.7	3.6	0.0	0.8	5.1
C4	3.7	2.3	3.0	0.0	8.9
TOTAL	5.5	7.4	8.1	6.6	

4.3. Discussion and consolidation of results

To finalize the study, a consolidation/validation session was held with an independent, neutral expert who coordinates the Portuguese government's digitalization process at Portugal Digital—an agency in charge of accelerating digital transformation in Portugal. This four-part meeting lasted approximately one hour. First, the interviewer explained the research's main goal and methodologies and then presented the results. The interviewee was next asked to give feedback on the methods applied with reference to the decision problem. In the last part of the session, this expert evaluated the practical applicability of the proposed analysis system.

The specialist expressed surprise about how close a number of the proposed initiatives were to the realities detected by a study of over 50 Portuguese town and county councils. That research had also found that factors similar to SC8 from C3 and SC108 and SC109 from C4 are extremely important and that they should be classified as pivotal criteria in companies' adaptation of the AI, Society 5.0 and smart city paradigms. However, the interviewee pointed out that the present study might not mirror the actual challenges faced by every sector since the expert panel did not encompass all industries and regions. This decision maker, nonetheless, acknowledged that the current research was constructivist, process-oriented nature, so the objective was not to find optimum solutions and the evaluation system can be adjusted to fit other contexts at any time. At the conclusion of the meeting, the expert underscored the significance of the analysis system as a decision-support tool, noting that managerial indecision often obstructs the implementation of suggested measures and solutions. This closing session therefore emerged as a pivotal moment to solidify the findings and enhance their empirical validity through increased transparency in the interpretation of the proposed system. Ultimately, the insights provided by this external, impartial specialist served to validate the decision-support system within a practical context, adding substantial value.

Overall, the results of our constructivist and process-oriented framework illuminate a nuanced understanding of the intricate relationships among AI, Society 5.0 and smart city paradigms, particularly concerning businesses' adaptation and integration. Through the multicriteria analysis system developed in this study, key initiatives were identified that can facilitate businesses in navigating and harnessing the transformative power of AI within the context of Society 5.0 and smart cities. In fact, the insights derived from cognitive mapping and DEMATEL, when applied in a neutrosophic environment, provided a structured understanding of the interdependencies and priorities among various decision criteria.

The results seem to be aligned with prior literature (cf. Çipi et al., 2023; Santos et al., 2024). However, the methodologies employed in this study offer a novel theoretical lens for understanding the dynamics of AI, Society 5.0 and smart city integration. By visualizing complex relationships and uncertainties inherent this context, the study advances theoretical discourse on technology adoption, urban studies and societal development. It paves the way for future research endeavors to delve deeper into the intricate dynamics of AI, Society 5.0 and smart city integration, fostering a more holistic and integrated approach to business planning and development.

From a practical standpoint, the findings provide actionable insights for urban planners, policymakers and businesses to formulate informed

Table 5
Crispification of neutrosophic values: Inter-cluster analysis.

	Relationship under Analysis	DEMATEL Scale (x)	Neutrosophic Values (T, I, F)			Neutrosophic Crispification		
			T	I	F	Crispification Formula Numerator	Neutrosophic Weight w Crispified	Final Value in DEMATEL Matrix
Inter-Cluster Analysis	C1–C2	2.0	0.95	0.40	0.10	0.7602	0.0788	1.52
	C1–C3	3.0	0.80	0.20	0.15	0.8152	0.0845	2.44
	C1–C4	3.5	0.95	0.10	0.10	0.9134	0.0947	3.20
	C2–C1	1.5	0.90	0.45	0.10	0.7277	0.0754	1.09
	C2–C3	3.0	0.90	0.10	0.10	0.9000	0.0933	2.70
	C2–C4	3.0	0.85	0.20	0.10	0.8445	0.0875	2.53
	C3–C1	1.0	0.75	0.40	0.10	0.7216	0.0748	0.72
	C3–C2	4.0	0.90	0.10	0.10	0.9000	0.0933	3.60
	C3–C4	1.5	0.60	0.50	0.45	0.5482	0.0568	0.82
	C4–C1	4.0	0.95	0.10	0.10	0.9134	0.0947	3.65
	C4–C2	3.0	0.95	0.30	0.30	0.7534	0.0781	2.26
	C4–C3	3.5	0.85	0.15	0.15	0.8500	0.0881	2.98
If $S = 1$, the conditions of the relevant equation are respected.					Crispification formula denominator	**9.6475**	**1**	

Note. DEMATEL = decision-making trial and evaluation laboratory; C = cluster.

Table 6
Auxiliary calculations.

Max	8.1	8.9
1/Max	0.1231	0.1125
1/s	0.1125	

Table 7
Normalized direct-influence Matrix X: Inter-cluster analysis.

	C1	C2	C3	C4
C1	0.0000	0.1711	0.2751	0.3597
C2	0.1228	0.0000	0.3038	0.2850
C3	0.0812	0.4050	0.0000	0.0925
C4	0.4110	0.2543	0.3347	0.0000

Table 8
Matrix T with auxiliary calculations: Inter-cluster analysis.

I

	C1	C2	C3	C4
C1	1.0000	0.0000	0.0000	0.0000
C2	0.0000	1.0000	0.0000	0.0000
C3	0.0000	0.0000	1.0000	0.0000
C4	0.0000	0.0000	0.0000	1.0000

I – X

	C1	C2	C3	C4
C1	1.0000	−0.1711	−0.2751	−0.3597
C2	−0.1228	1.0000	−0.3038	−0.2850
C3	−0.0812	−0.4050	1.0000	−0.0925
C4	−0.4110	−0.2543	−0.3347	1.0000

(I – X)^–1

	C1	C2	C3	C4
C1	1.5744	0.9170	1.0203	0.9220
C2	0.6060	1.6845	0.9412	0.7852
C3	0.4617	0.8577	1.5737	0.5561
C4	0.9557	1.0923	1.1854	1.7647

Matrix T

	C1	C2	C3	C4	R
C1	0.5744	0.9170	1.0203	0.9220	3.4337
C2	0.6060	0.6845	0.9412	0.7852	3.0168
C3	0.4617	0.8577	0.5737	0.5561	2.4491
C4	0.9557	1.0923	1.1854	0.7647	3.9982
C	2.5978	3.5514	3.7205	3.0280	

Table 9
Inter-cluster interactions.

	R	C	R + C	R – C
C1	3.4337	2.5978	6.0314	0.8359
C2	3.0168	3.5514	6.5683	−0.5346
C3	2.4491	3.7205	6.1697	−1.2714
C4	3.9982	3.0280	7.0261	0.9702

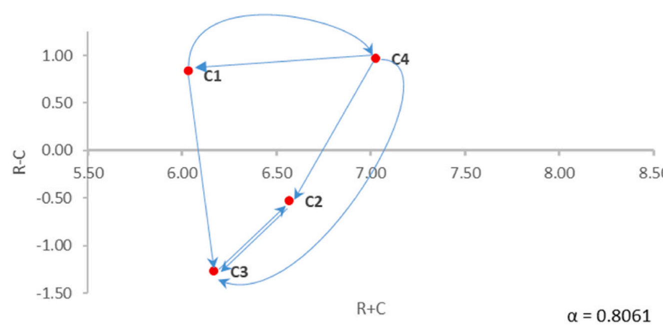

Fig. 5. Influential relations map: Inter-cluster analysis.

strategies and collaborative initiatives. The study's emphasis on stakeholder collaboration and the development of integrated solutions tailored to urban complexities are aligned with the literature (Bartoloni et al., 2022; Rodrigues et al., 2023), and can guide decision-making processes and policy formulations, fostering sustainable and human-centric urban development. Societally, the study underscores the imperative of harnessing AI and technological advancements to address the multifaceted challenges of rapid urbanization, ensuring that cities of the future are not only technologically advanced but also inclusive, resilient and conducive to enhancing the overall quality of life for their residents.

Table 10
Interactions between initiatives in cluster one.

	R	C	R + C	R – C
SC6	3.4924	2.1786	5.6710	1.3138
SC16	2.9155	1.7395	4.6550	1.1760
SC18	1.5733	3.0875	4.6609	−1.5142
SC22	2.0400	2.7347	4.7748	−0.6947
SC27	1.9685	2.6326	4.6011	−0.6641
SC33	3.4332	2.6149	6.0481	0.8183
SC36	2.7194	3.1546	5.8740	−0.4352

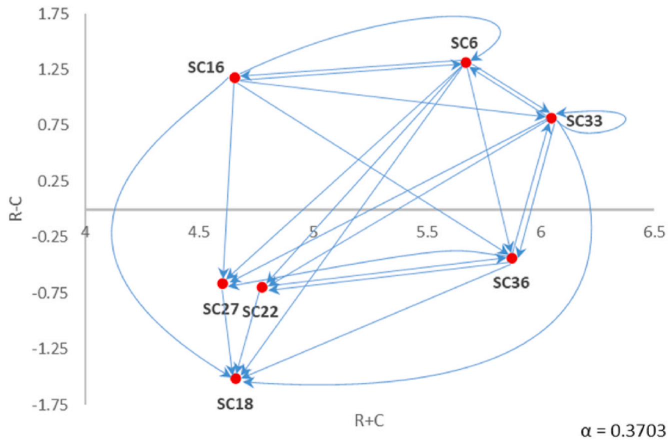

Fig. 6. Influential relations map for cluster one.

Table 11
Interactions between initiatives in cluster two.

	R	C	R + C	R – C
SC12	3.6455	3.9553	7.6007	−0.3098
SC14	3.5798	3.6941	7.2739	−0.1143
SC48	3.5261	3.0747	6.6008	0.4514
SC56	3.3795	4.0901	7.4696	−0.7106
SC59	2.9774	3.1134	6.0908	−0.1360
SC71	1.8879	3.1616	5.0495	−1.2738
SC76	4.2770	2.1840	6.4610	2.0930

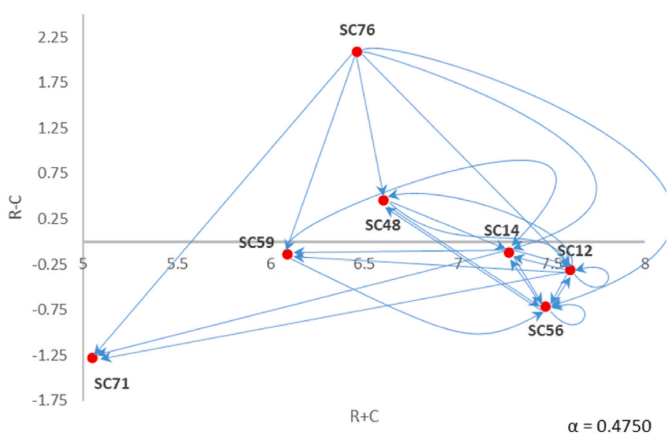

Fig. 7. Influential relations map for cluster two.

While these contributions are significant, the implementation of the methodology was not without practical challenges. In particular, the structure of four interrelated clusters and respective 111 criteria placed substantial demands on the evaluation process. These challenges included increased time requirements, cognitive fatigue and difficulty in making fine-grained distinctions across the matrices of interdependencies. To address these issues, we applied the NGT and multi-voting to help the panel converge on the most influential criteria within each cluster before proceeding to pairwise evaluations. Although this approach proved effective in our case, we acknowledge that scalability remains an important consideration when applying the methodology in other contexts with varying levels of technological readiness, institutional capacity or stakeholder diversity. While the framework is designed to be flexible and adaptable, successful replication would likely require tailored facilitation, targeted capacity building and, where necessary, a streamlined set of evaluation criteria.

Finally, in line with Bell and Morse (2013), it is important to emphasize that this study—given its constructivist and process-oriented nature—should be viewed as a learning mechanism rather than a pursuit of optimal solutions. This perspective underscores the critical importance of cohesive information integration architectures and collaborative efforts among stakeholders, highlighting the indispensable role that businesses play in the broader societal shift toward smarter and more sustainable urban environments. The complementary nature of our contribution is also noteworthy. The intent is not to replace existing frameworks, but rather to enrich and extend them. Because our approach allows for the integration of new information at any stage, the proposed model is not only robust but also highly adaptable. As a result, the methodology adopted in this study has led to the development of a novel yet complementary analytical system that blends both objective

Table 12
Interactions between initiatives in cluster three.

	R	C	R + C	R – C
SC8	2.6601	1.4734	4.1335	1.1867
SC81	3.3120	2.5489	5.8609	0.7632
SC84	3.1388	3.1111	6.2498	0.0277
SC86	2.3302	2.8200	5.1502	−0.4898
SC89	0.7832	2.2710	3.0542	−1.4877

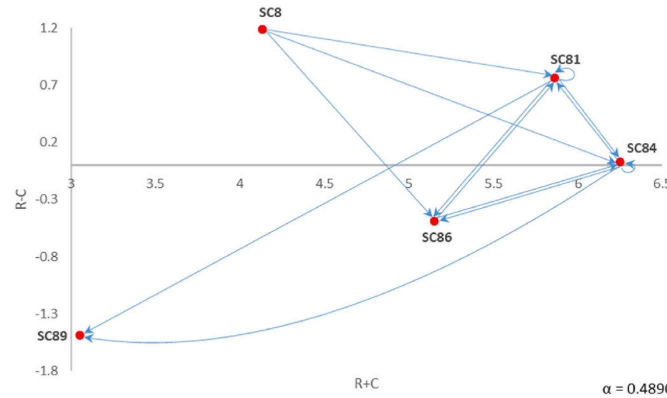

Fig. 8. Influential relations map for cluster three.

Table 13
Interactions between initiatives in cluster four.

	R	C	R + C	R – C
SC32	10.0122	9.5478	19.5599	0.4644
SC39	8.4051	10.1675	18.5725	−1.7624
SC42	8.9470	10.1086	19.0556	−1.1616
SC108	9.4302	8.2942	17.7244	1.1359
SC109	9.8102	8.4865	18.2967	1.3237

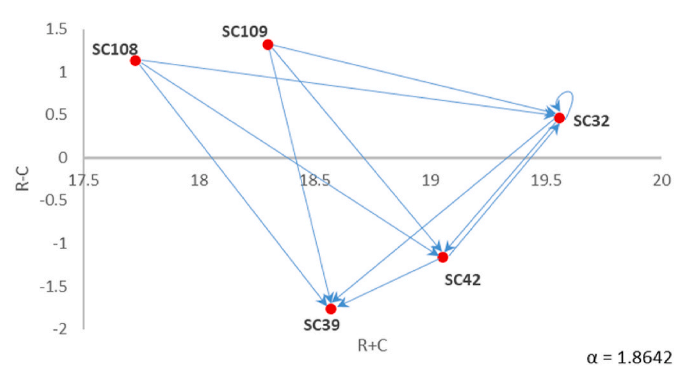

Fig. 9. Influential relations map for cluster four.

and subjective elements to produce a transparent and well-informed decision support tool. The system is inherently open to evolution and can readily accommodate the incorporation of new clusters as different contexts, decision-makers or priorities emerge.

5. Conclusion

The present study sought to create a framework based on dynamic analyses of businesses' adaptation to the AI, Society 5.0 and smart city paradigms, using cognitive mapping and DEMATEL in a neutrosophic environment. Both objective and subjective variables were included in the system-development process due to the combination of DEMATEL and neutrosophic logic, which facilitated evaluations of the subjectivity and uncertainty associated with each factor. The methodologies were applied with the help of a panel of experts who identified four clusters of criteria—*Legislation and Public Policies* (C1), *Technology* (C2), *Performance* (C3) and *People* (C4). Within each cluster, the panel members isolated the most significant initiatives and the cause-and-effect relationships between them. The most important cluster is C4, with SC32 as the most prominent criterion, followed by C2, with SC12 standing out as the most significant; C3, with SC81 being the most relevant; and C1, with SC33 considered the most important. This approach enabled us to address the two initial research questions (*i.e.*, Which initiatives could facilitate companies' adaptation to AI, Society 5.0 and smart city paradigms? What elements would accelerate the integration of AI within the Society 5.0 initiative?).

By combining cognitive mapping, DEMATEL and neutrosophic logic, the findings contribute not only to the refinement of methodological practice, but also to the advancement of theoretical understanding in several fields. Specifically, our study informs conceptual debates on AI integration by highlighting that its success is not merely a function of technical feasibility but is deeply shaped by organizational, institutional and societal contexts. The bottom-up identification of barriers and enablers through cognitive mapping challenges linear, deterministic models of AI diffusion. Instead, it supports a sociotechnical framing—in which AI is treated as a socially embedded process subject to negotiation, resistance and path dependencies. This contributes to emerging discussions on responsible AI adoption, by showing that effective integration demands alignment with local realities, including policy frameworks, user capacities and institutional constraints.

In relation to urban innovation ecosystems, our results offer a more systemic view of transformation processes. The identification of clusters and their internal dynamics—especially the cause-and-effect relationships between people, technology, performance and public policy—suggests that urban innovation is best understood not as the deployment of isolated technologies, but as a co-evolutionary process shaped by interactions between multiple actors and domains. This resonates with and extends existing literature on urban governance, adaptive capacity and policy alignment, providing an operational model for identifying leverage points and bottlenecks in complex urban systems. The findings thus offer a conceptual lens for theorizing innovation ecosystems as networked environments shaped by both soft (*e.g.*, trust and knowledge exchange) and hard (*e.g.*, infrastructure and regulation) enablers.

The study also contributes to the literature on decision-making under uncertainty. By applying neutrosophic logic—an extension of fuzzy and intuitionistic logics—we show how epistemic uncertainty, partial consensus and ambiguity can be explicitly modeled rather than ignored or forced into artificial precision. In contrast to probabilistic or crisp models, our approach accommodates indeterminacy as a first-class construct, making it particularly useful in strategic decisions involving future-oriented planning, limited data or contested knowledge. This aligns with and enhances the growing body of work on constructivist decision theory, and further illustrates how group-based participatory methods can be used to formalize qualitative judgments without reducing them to false objectivity.

From a practical standpoint, the framework developed provides actionable insights for urban planners, policymakers and business leaders. It offers a structured, transparent basis for prioritizing initiatives, allocating resources and designing multi-stakeholder strategies aligned with the complexities of AI, Society 5.0 and smart city transitions. The feedback received from the Portugal Digital specialist reinforces the applicability of the model for informing strategic planning and mapping adaptation initiatives.

The study also has significant societal implications, contributing directly to several SDGs. It supports SDG 11 (sustainable cities and communities) through its focus on inclusive and adaptive urban development; SDG 9 (industry, innovation and infrastructure) by encouraging resilient digital and physical infrastructure; SDG 3 (good health and well-being) and SDG 8 (decent work and economic growth) by exploring the benefits of AI deployment in public services and the labor market; SDG 13 (climate action) by improving environmental decision-making; and SDG 15 (life on land) through the promotion of responsible land use. The study's holistic approach to technological integration reinforces the idea that digital transitions must be embedded in broader sustainability frameworks, advancing both equity and resilience.

Naturally, the study has limitations. The expert sessions were held online, which occasionally impacted the fluidity of interaction due to connectivity issues. Scheduling sessions after working hours may also have affected the depth of participant engagement. Moreover, the expert panel was context-specific, and while it provided rich insight into the Portuguese and European innovation landscape, the results should not be generalized to other sectors or geographies without appropriate adaptation. Nevertheless, the feedback from the Portugal Digital specialist suggests that the model can serve as a valuable starting point for broader applications.

These limitations point to several avenues for future research. Expanding the expert panel to include participants from diverse geographic, institutional and sectoral backgrounds would enhance the framework's generalizability. Future studies could also test the model in real-world implementation settings, documenting its impact on strategic planning and adaptation over time. Additionally, methodological developments could explore the integration of neutrosophic logic with other MCDA tools, opening new paths for hybrid approaches. As AI, Society 5.0 and smart cities continue to evolve, so too must our conceptual and methodological frameworks—ensuring they remain sensitive to uncertainty, embedded in real-world dynamics and capable of supporting inclusive and forward-looking decision-making.

CRediT authorship contribution statement

Inês A.M. Gil: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Fernando A.F. Ferreira:** Writing – review & editing, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Neuza C.M.Q.F. Ferreira:** Writing – review & editing, Visualization, Validation, Funding acquisition, Formal analysis, Data curation. **Florentin Smarandache:** Writing – review & editing, Validation, Methodology, Conceptualization. **Momtaj Khanam:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Tugrul Daim:** Writing – review & editing, Formal analysis, Conceptualization.

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Data availability

Data will be made available on request.

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