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Leveraging AI and generative AI in urban design and planning: Unveiling advantages and challenges through problem structuring methods

Amali Çipi [a], Neuza C.M.Q.F. Ferreira [b], Fernando A.F. Ferreira [c,d,*], João J.M. Ferreira [e,f], Florentin Smarandache [g]

[a] University of Vlora "Ismail Qemali", Sheshi Pavarësia, 9401, Vlorë, Albania
[b] NECE-UBI, Research Centre for Business Sciences, University of Beira Interior, Estrada do Sineiro, 6200-209, Covilhã, Portugal
[c] ISCTE Business School, BRU-IUL, University Institute of Lisbon, Avenida das Forças Armadas, 1649-026, Lisbon, Portugal
[d] Fogelman College of Business and Economics, University of Memphis, Memphis, TN, 38152-3120, USA
[e] Department of Management and Economics, NECE-UBI, University of Beira Interior, Estrada do Sineiro, 6200-209, Covilhã, Portugal
[f] QUT Australian Centre for Entrepreneurship Research, Australia
[g] Mathematics, Physical and Natural Sciences Division, University of New Mexico, 705 Gurley Avenue, Gallup Campus, NM, 87301, USA

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ABSTRACT

The integration of Artificial Intelligence (AI) in general—and its subfield Generative AI (GenAI) in particular—into urban design and planning is revolutionizing traditional methodologies, providing innovative solutions to complex challenges in city development. Despite their transformative potential, existing research underscores a critical need to better understand the multifaceted advantages and challenges associated with these technologies. This study addresses this gap by investigating the causal relationships between the advantages and challenges of AI and GenAI integration in urban design and planning. Leveraging a novel combination of cognitive mapping and neutrosophic DEcision-MAking Trial and Evaluation Laboratory (DEMATEL), the research identifies and evaluates key factors shaping this integration. The findings reveal that dynamic digital city simulations and scenario modeling emerge as the most significant advantages, underscoring their capacity to drive data-informed innovation in urban development. Conversely, ethical concerns surface as the most critical challenge, exhibiting strong interdependencies with other issues, including the "black box" nature of AI systems and the biases embedded in training data. This study provides a comprehensive framework for understanding the interplay between these factors, offering actionable insights to guide both academic research and practical implementation. By addressing a pressing need in the field, the research paves the way for more responsible and effective applications of AI and GenAI in creating smarter, more sustainable urban environments.

1. Introduction

The integration of Artificial Intelligence (AI) in general—and its subfield Generative AI (GenAI) in particular—in urban design and planning marks a transformative shift in how cities are conceptualized, developed and managed (Sanchez et al., 2024; Ulucan et al., 2025). As urbanization accelerates and societies face mounting challenges, including climate change, congestion and resource management, the potential for AI-driven tools to provide innovative solutions has become a focal point for both researchers and practitioners (Caboz et al., 2025; Son et al., 2023). While these technologies present promising avenues for rapid prototyping, dynamic simulations and stakeholder engagement, their adoption remains in its nascent stages, particularly in practical, real-world contexts (Du et al., 2024; Kashi et al., 2025; Peng et al., 2023).

Integrated urban design and planning has traditionally been a complex, multi-faceted process involving numerous stakeholders and diverse considerations (*e.g.*, Huang et al., 2023; Kempinska and Murcio, 2019; Othengrafen et al., 2025). The advent of AI technologies offers unprecedented opportunities to enhance decision-making, optimize resource allocation and create more responsive urban environments (Du et al., 2024). GenAI models, such as Generative Adversarial Networks (GANs) and some decision-support systems, are already contributing to smart city initiatives by analyzing big data and generating urban design

* Corresponding author. ISCTE Business School, BRU-IUL, University Institute of Lisbon, Avenida das Forças Armadas, 1649-026, Lisbon, Portugal.
E-mail addresses: amali.cipi@univlora.edu.al, amalia.cipi@gmail.com (A. Çipi), neuza.ferreira@ubi.pt (N.C.M.Q.F. Ferreira), fernando.alberto.ferreira@iscte.pt (F.A.F. Ferreira), jjmf@ubi.pt (J.J.M. Ferreira), smarand@unm.edu (F. Smarandache).

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scenarios (*e.g.*, Crumbly et al., 2025; Huang et al., 2024; Phillips and Jiao, 2023). Despite these advancements, existing research predominantly highlights the advantages of these technologies while often overlooking the structured processes needed to manage their challenges effectively (*e.g.*, Furtado et al., 2024; Hajrasouliha, 2024; Huang et al., 2024; Luger, 2024). Moreover, there is limited exploration into the interplay between the advantages and challenges presented by AI integration in urban design and planning (*e.g.*, Jiang et al., 2024; Quan et al., 2019).

Several key gaps have been identified through a comprehensive literature review. First, there is a lack of structured approaches that ensure effective collaboration among stakeholders during problem definition and solution formulation in urban design and planning (*cf.* Asaad et al., 2020; Cozzolino et al., 2020; Rodrigues et al., 2025). Second, research often fails to prioritize the challenges of AI integration (*e.g.*, ethical concerns, data privacy or the "black box" nature) (*cf.* Furtado et al., 2024; Hajrasouliha, 2024; Luger, 2024). Third, there is a need to develop frameworks that not only synthesize existing knowledge but also map causal relationships among advantages and among challenges to create adaptive and inclusive urban planning practices (*cf.* Ali-Toudert et al., 2020; Du et al., 2024). Finally, one of the most critical gaps identified is the lack of studies that address the uncertainties inherent in urban development when applying AI and GenAI (*e.g.*, Quan et al., 2019; Zhou et al., 2023). The complexity of urban systems, with their interdependencies and dynamic interactions, highlights the need for including uncertainty within the causal relationships between the advantages and challenges of AI integration in the planning process (Quan et al., 2019; Zhou et al., 2023). In response to these research gaps, the present study aims to address the following research questions (RQs).

RQ1: What key advantages and challenges are associated with the integration of AI in general—and GenAI in particular—in urban design and planning?
RQ2: What are the causal relationships among the identified advantages and among the challenges related to AI and GenAI integration in urban design and planning?
RQ3: How can stakeholder collaboration and decision-making under uncertainty support the application of AI and GenAI to urban design and planning?

To address these research questions, the present study is underpinned by the Multiple Criteria Decision Analysis (MCDA) approach and employs a combination of Problem Structuring Methods (PSMs). Specifically, cognitive mapping, DEcision MAking Trial and Evaluation Laboratory (DEMATEL) and neutrosophic logic are combined to explore the causal relationships among advantages and among challenges of AI in urban design and planning. This integrated approach facilitates the identification of core issues, driving factors and critical dependencies that influence the effective adoption of AI technologies.

This research contributes to the growing body of knowledge by providing a structured framework for analyzing and addressing the advantages and challenges of AI integration in urban design and planning. By leveraging advanced decision-support methods, it offers actionable insights for both researchers and practitioners aiming to harness the full potential of AI technologies while navigating their associated challenges. The findings serve as a foundation for future studies focused on optimizing AI-driven urban planning practices and fostering human-machine collaboration for smarter, more sustainable cities.

The remainder of this paper is divided into six sections. Section 2 presents a literature review of previous studies on AI and GenAI in urban design and planning, identifying research gaps and opportunities. Section 3 describes the methodology followed to identify and analyze the causal relationships among advantages and among challenges of AI in urban design and planning. Section 4 presents the results obtained. Section 5 provides a discussion integrating theoretical and practical reflections. Finally, Section 6 presents the conclusions, limitations and suggestions for future research.

2. Literature review and research gaps

Urban development refers to the process of planning, expanding and improving cities and urban areas to accommodate population growth and meet residents' socioeconomic needs (Caboz et al., 2025; Cordeiro et al., 2024; Jiang et al., 2024). This process entails the creation of essential infrastructure, including transportation networks, housing, sanitation, energy systems, green spaces and public services. The overarching goal is to design and organize urban areas with a long-term perspective, promoting the rational use of natural resources, integrating technological solutions and ensuring community participation in the planning process (Afzalan et al., 2017; Du et al., 2024). Achieving this goal requires balancing economic and industrial growth with environmental preservation and social cohesion (*i.e.*, principles central to sustainable urban development) (Bafail, 2025; Caboz et al., 2025; Wang et al., 2021).

The concept of urban planning generally refers to the broader strategic process of organizing land use, infrastructure and services to guide the growth and functioning of urban areas (*cf.* Cordeiro et al., 2024). Urban design, in turn, focuses more specifically on the physical form, aesthetic quality and functionality of urban spaces. Its scope spans from individual buildings to neighborhoods, districts, entire cities and regions, addressing how spaces are shaped to better serve people's needs. As Cozzolino et al. (2020, p. 42) note, urban design can be defined as *"a creative and purposeful activity with collective and public concerns that deals with the production and adaptation of the built environment at scales larger than a single plot or building"*. In recent years, urban design has been increasingly linked to sustainability objectives, particularly in minimizing negative environmental impacts (Jiang et al., 2024). In this study, we use urban design and planning as a single term to reflect the intersection of these two perspectives, encompassing both the strategic, policy-oriented dimensions of planning and the physical, place-making dimensions of design. This combined view aligns with the interdisciplinary nature of the challenges addressed.

Because it is complex, multi-dimensional and perceived differently by diverse stakeholders, urban design and planning—as an integrated process—has long been described as a "wicked problem" (Cordeiro et al., 2024; Rittel and Webber, 1973). According to Quan et al. (2019), two main decision-support approaches are commonly employed in this process: (1) planning support systems; and (2) generative design systems. These systems leverage scientific methods, computational tools and optimization algorithms to assist the design and planning processes, especially in sustainable urban contexts. The typical process is iterative and multidisciplinary, involving stakeholders such as local governments, developers, engineers and residents (Jiang et al., 2024). Asaad et al. (2020) identify four main phases in this process: problem formulation, design synthesis, solution evaluation and decision-making. This process relies heavily on specialized expertise, collaborative engagement and effective communication (Jiang et al., 2023; Koenig et al., 2020). In practice, challenges often emerge early in the process, when stakeholders must agree on priorities and specific design elements (Caboz et al., 2025; Afzalan et al., 2017; Cordeiro et al., 2024). Koenig et al. (2020) highlight the value of urban design systems that integrate computational optimization with cognitive heuristics, fostering productive collaboration between human designers and technology. Urban design and planning, therefore, requires reconciling long-term visions with immediate needs, and managing trade-offs among economic, environmental and social objectives. Historically, these processes have relied on expert judgment, iterative negotiation and conventional computational methods.

The recent integration of AI in general—and its subfield GenAI in particular—represents a paradigm shift, offering transformative possibilities for how cities are conceived, evaluated and adapted (Du et al., 2024; Sanchez et al., 2024). In this study, we adopt a definition of AI that acknowledges both its historical origins and its contemporary scope. The term AI was first coined by McCarthy et al. (1955), referring to the science and engineering of making machines capable of performing tasks that would require intelligence if done by humans. Over time, as noted by modern AI pioneers such as LeCun et al. (2015), the field has evolved to encompass a wide spectrum of computational methods capable of perception, reasoning, learning and decision-making. In this context, AI includes machine learning, simulation, optimization and decision-support systems. GenAI is considered a subfield of AI, encompassing systems that produce novel outputs (*e.g.*, images, designs or scenarios) through deep generative models, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), diffusion models and transformer-based large language models (LLMs) such as ChatGPT (Huang et al., 2024; Rana et al., 2024; Senem et al., 2024). While simulation, optimization and testing are not inherently generative tasks, they increasingly rely on AI-enabled methods in urban planning (*e.g.*, reinforcement learning for traffic management, deep learning for predictive modeling and generative models for scenario creation), making them relevant to the current investigation.

The advantages of AI and GenAI in urban design and planning include rapid prototyping of design alternatives, dynamic city- and neighborhood-scale simulations, enhanced stakeholder engagement through interactive visualization tools and more efficient resource allocation in both the design and implementation phases (Hajrasouliha, 2024; Huang et al., 2024; Phillips and Jiao, 2023; Schlickman and Magana-Leon, 2024; Shen et al., 2020). Nonetheless, real-world applications remain limited (*cf.* Du et al., 2024; Peng et al., 2023; Son et al., 2023). Much of the literature emphasizes technical capabilities, while challenges (*e.g.*, data quality, algorithmic bias, ethical and privacy issues, regulatory gaps or technological dependence) are less explored (Furtado et al., 2024; Hajrasouliha, 2024). Moreover, many studies fail to clearly define the scope of technologies under examination, leading to ambiguity over whether they address generative models, traditional AI optimization or other computational methods (Luger, 2024).

Following this, AI and GenAI in urban design and planning remain emergent in practice, with a need for further research on their integration with participatory approaches (Du et al., 2024; Peng et al., 2023; Son et al., 2023). Although their advantages are widely recognized, significant gaps exist in identifying and prioritizing integration advantages and challenges (Furtado et al., 2024; Hajrasouliha, 2024; Luger, 2024). The absence of causal analyses hampers the development of resilient strategies, risking the transformative potential of AI and GenAI due to unresolved technical, organizational and societal barriers. This study aims to fill these gaps by mapping causal linkages among AI and GenAI advantages and among their challenges to guide responsible implementation. To address this, it combines PSMs (Rosenhead and Mingers, 2001) and MCDA (Belton and Stewart, 2002) to structure stakeholder knowledge, quantify causal relationships and account for uncertainty and indeterminacy. The following section outlines the methodological framework used to capture and analyze stakeholder perspectives.

3. Methods

3.1. MCDA and PSMs

According to Belton and Stewart (2002), the MCDA approach effectively addresses complex decision-making problems involving multiple stakeholders, while accounting for diverse and sometimes conflicting perspectives, values and preferences. Within the field of operational research (OR), problem-structuring methods (PSMs)—also known as "soft OR" (Rosenhead and Mingers, 2001)—emerged to overcome limitations of traditional optimization-based approaches (Marttunen et al., 2017). Unlike classical OR methods focused primarily on solution generation, PSMs emphasize defining and structuring the problem itself (Ackermann, 2012; Marttunen et al., 2017). This problem-structuring phase is continuous, flexible and iterative, integrating both objective and subjective elements, incorporating decision-makers' values and fostering a deeper understanding of the decision problem aligned with constructivist principles (Piaget, 1964).

The integration of PSMs and MCDA has gained significant momentum through Keeney's (1992) value-focused thinking (VFT), which provides a practical framework for exploring problem structuring in real-world contexts (Marttunen et al., 2017). Building on this foundation and supported by the Strategic Options Development and Analysis (SODA) approach (Eden and Ackermann, 2001), the combined methodology adopted in this study follows a structured three-phase process that integrates PSMs and MCDA to comprehensively address the research problem.

Specifically, during the *structuring phase*, cognitive mapping (Eden, 1988) is employed to capture and integrate individual stakeholder perspectives, fostering a shared, collective understanding of the decision problem. This phase structures the decision problem by visualizing key elements and their interrelations, enabling a rich, stakeholder-driven problem representation. Next, during the *evaluation phase*, the structured problem representation informs the application of DEMATEL enhanced with neutrosophic logic, which quantifies and analyzes causal relationships among factors under uncertainty and indeterminacy. This combined approach provides a rigorous evaluation of interdependencies, allowing for nuanced insights that support decision-making. Finally, in the *phase of recommendations* (or *consolidation*), insights gained from the evaluation phase are consolidated and refined through an independent process, ensuring practical relevance and actionable guidance. This integrated methodology combines the qualitative strengths of PSMs with the quantitative rigor of MCDA tools under uncertainty, providing a coherent and systematic framework to address complex decision problems involving multiple stakeholders and ambiguous information (*cf.* Belton and Stewart, 2002).

3.2. Cognitive mapping

Cognitive mapping, originally developed by Tolman (1948) and later adapted for strategic development by Eden (1988), is a qualitative method. Eden (1988) explains that this approach provides a holistic representation of complex decision problems by incorporating the individual perspectives of various decision-makers. Fig. 1 illustrates the iterative process of cognitive mapping, flowing from left to right.

According to Fig. 1, the process of cognitive mapping includes a feedback loop from analysis and refinement back to concept identification, showing that cognitive mapping is an iterative process that can be refined as understanding develops. This process of joint reflection enables participants to reach a consensus by fostering an understanding of the challenges, dilemmas and obstacles inherent in each individual perspective (Eden and Ackermann, 2001). Importantly, cognitive mapping was used in the present study both to identify and cluster concepts into coherent groups and hierarchies and to capture perceived causal linkages between them. This ensured that the subsequent neutrosophic DEMATEL analysis was grounded in a robust conceptual foundation, avoiding premature quantification and ensuring that all participants shared an understanding of the most relevant factors. The final outcome is a cognitive map. The central goal is typically positioned at the top, with related concepts or criteria logically arranged beneath it by arrows that indicate cause-and-effect relationships. The causal relationships between the criteria reflect the understanding of the decision problem based on the perceptions and judgments of a group of decision-makers.

3.3. DEMATEL and neutrosophic logic

Developed by Fontela and Gabus (1972), DEMATEL maps cause-and-effect relationships among criteria and organizes key criteria based on their level of prominence within a complex system (Bastos

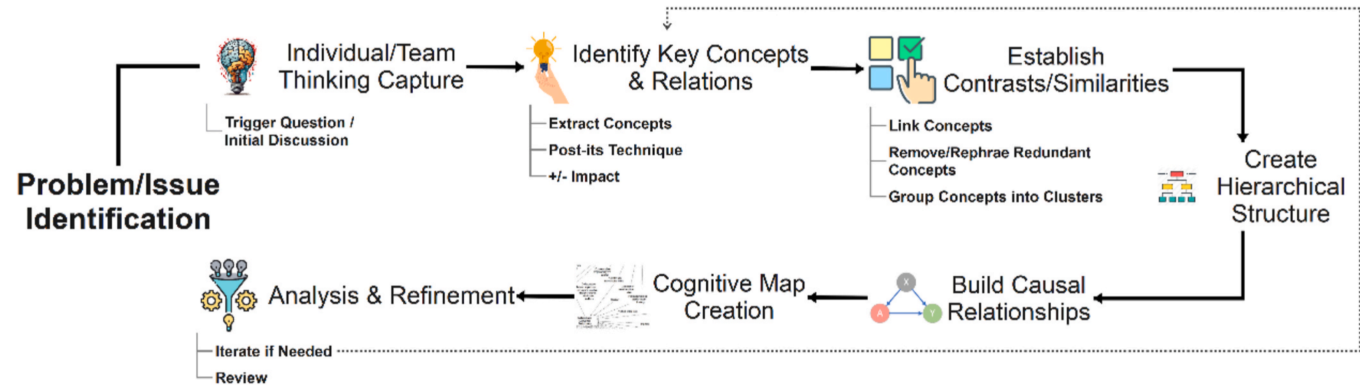

Fig. 1. Iterative process of cognitive mapping.

et al., 2023; Kumar and Dixit, 2018). This method more efficiently uncovers causal relationships compared to traditional methods, offers broad applicability and serves as a valuable tool for decision-making support (*cf.* Fontela and Gabus, 1972). According to Sivakumar et al. (2018), DEMATEL applications usually involve five consecutive steps.

Step 1: Experts conduct pairwise comparisons of criteria to evaluate their mutual influence. These comparisons generate a direct-influence matrix, where the strength of influence is rated using the following scale: 0 = no influence; 1 = low influence; 2 = moderate influence; 3 = strong influence; and 4 = very strong influence. This process results in the formation of a non-negative *n* x *n* matrix, denoted as initial direct-influence matrix $Z = [a_{ij}]\ n \times n$, as illustrated in Equation (1):

$$Z = \begin{array}{c} C_1 \\ C_2 \\ \ddots \\ C_n \end{array} \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ a_{21} & 0 & & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 0 \end{bmatrix}, \tag{1}$$

in which a_{ij} represents the level of intensity assigned by the experts to the relationship between criteria C_i and C_j.

Step 2: Normalization of the initial direct-influence matrix *Z*, by applying the coefficient $1/\lambda$, as illustrated by Equations (2) and (3):

$$X = Z^{*}1/\lambda, \tag{2}$$

$$\lambda = max\left(\max_{1\le i\le n}\sum\nolimits_{j=1}^{n} z_{ij}, \max_{1\le j\le n}\sum\nolimits_{i=1}^{n} z_{ij}\right), \tag{3}$$

in which λ is a normalization constant that measures the maximum effect that each criterion exerts on the others (*i.e.*, the sum of row *i* in matrix *Z*). Additionally, this constant calculates the maximum effect that each criterion receives from the others (*i.e.*, the sum of column *j* in matrix *Z*). This results in normalized initial-direct relation matrix *X*, whose values range from 0 to 1.

Step 3: Calculation of total relationships, resulting in the total-relation matrix (*T*). Equation (4) is used to construct matrix *T*:

$$T = \log_{h\to\infty}\left(X^1 + X^2 + \cdots + X^h\right) = X(1-X)^{-1}, \tag{4}$$

where X^h represents the influence exerted by the h^{th} criterion, while *I* denotes the identity matrix. The sum of *X*, X^2, …, X^h represents the overall ratio of the variables. Matrix *T*, therefore, offers insight into the impact each criterion has on another. It combines both direct and indirect effects, quantifying the total degree of influence in the relationship between each pair of criteria.

Step 4: Determining the prominence ($R + C$) and relation ($R - C$) values, by applying Equations (5) and (6):

$$R = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = [r_i]_{n\times 1}, \tag{5}$$

$$C = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n} = [c_j]'_{1\times n}. \tag{6}$$

Set $[r_i]$ represents the driving force of each criterion, while set $[c_j]$ reflects the total effects accumulated by each criterion. When $i = j$ and $i, j \in \{1, 2, \ldots n\}$, the combined value of ($R + C$) represents the overall impact of a criterion, indicating its significance within the analysis model. The difference between *R* and *C* reveals the degree of interrelation of the criterion within the model, showing its role in the decision-support system. Based on this difference, the criteria can be classified into two groups: (1) a positive ($R - C$) value indicates that criterion *i* serves as a cause; and (2) a negative ($R - C$) value suggests that criterion *i* functions as an effect.

Step 5: A threshold value (α) is applied to identify which relationships should be incorporated into the impact-relation map (IRM). The IRM helps decision-makers by simplifying the analysis, categorizing the criteria into four quadrants (Q): *core* (QI), *driving* (QII), *independent* (QIII) and *impact* (QIV). According to Chen et al. (2018), the DEMATEL process produces a visual representation, effectively creating a personalized mind map (*i.e.*, IRM). This map allows decision-makers to structure their actions in alignment with their internal coherence, implicit priorities and goals. As a result, this technique offers researchers a straightforward tool to analyze and understand the structure of complex problems across a range of real-world issues.

Neutrosophic logic is a philosophical approach introduced by Smarandache (1998) that questions the notion of absolute or perfect ideas. It asserts that because the world is inherently indeterminate, a more nuanced form of imprecision is necessary (Smarandache, 2007). This logic can incorporate other ways of thinking included in classical/boolean logic (*i.e.*, true (*T*) and false (*F*)) and fuzzy logic (*i.e.*, something can be partially true and partially false), while also adding the concept of indeterminacy (*I*) for cases where the answer is not known (Smarandache, 1998). This extension allows decision-makers to explicitly acknowledge that the values assigned to *T* and *F* often carry an element of uncertainty (*i.e.*, *I*) (Ashbacher, 2020; Gil et al., 2026).

Specifically, Smarandache (1998) proposes that any variable *x* can be broken down into three components: *T*, *I* and *F*. These components are represented as real-valued subsets within the range [–0, +1]. In practical terms, experts involved in a multicriteria decision-making process can specify the likelihood of a statement being true (*e.g.*, *T* =

0.6), its degree of uncertainty (*e.g.*, $I = 0.2$) and its falseness (*e.g.*, $F = 0.3$). It is important to note that the sum of T, I and F does not necessarily add up to 100%. To complete the process, decision makers must crispify these values, transforming them into a single value. This can be done using the crispification equation outlined by Pramanik et al. (2016) in Equation (7) or Smarandache (2020) in Equation (8):

$$w_k^c = \frac{1 - \sqrt{\left((1 - T_k)^2 + (I_k)^2 + (F_k)^2\right)/3}}{\sum_{k=1}^{r}\left\{1 - \sqrt{\left((1 - T_k)^2 + (I_k)^2 + (F_k)^2\right)/3}\right\}}, \tag{7}$$

in which $w_k^c \geq 0$.

$$s(T, I, F) = \frac{T + (1 - I) + (1 - F)}{3}\Bigg) = \frac{2 + T - I - F}{3}. \tag{8}$$

DEMATEL is an effective method for analyzing and mapping interdependencies within decision-support systems (Mehregan et al., 2014). When combined with neutrosophic logic, it effectively addresses uncertainty by quantifying indeterminacy and integrating diverse stakeholder perspectives (Cordeiro et al., 2024; Ferreira and Meidutė-Kavaliauskienė, 2025; Vaz-Patto et al., 2024). This combination enhances analysis of complex causal relationships, producing realistic insights and supporting informed decision-making.

In urban design and planning, where AI and participatory approaches are still emerging (Du et al., 2024; Son et al., 2023), neutrosophic DEMATEL can address critical gaps related to collaborative problem definition and prioritization (*e.g.*, Quan et al., 2019; Zhou et al., 2023). The present study embeds these methods within PSMs and MCDA to analyze variable dependencies and uncertainties, advancing AI integration in urban design and planning.

4. Application and results

4.1. Structuring phase

The first phase involved selecting a panel of urban planning and AI experts. Following the guidelines of Eden and Ackermann (2001) and Vaz-Patto et al. (2024), decision-maker panels should ideally include 3–10 members to ensure rich discussion while remaining manageable. In this study, the panel comprised eight decision-makers with extensive expertise in AI and urban development. Although based in Portugal, all participants held strategic decision-making roles and had prior involvement in European initiatives, contributing valuable cross-national perspectives. Selection was based on criteria designed to enrich discussion and ensure complementary viewpoints: (1) expertise in the field, defined as at least 10 years of experience in urban planning and AI technologies—*i.e.*, a broad set of AI-related competencies relevant to urban design and planning, including simulation, optimization and generative approaches; (2) diversity in age and gender; (3) diversity in specialization and location; and (4) availability to participate in group meetings. Importantly, representativeness was not a concern—nor did it need to be—since the goal of the chosen methodologies is not to produce generalizations but to maintain a clear emphasis on the process (*cf.* Bell and Morse, 2013; Ormerod, 2020). The first group work session took place in October 2024 and lasted approximately 3 h. Conducted online using *Teams* and *Miro* platforms, the session was divided into three main parts.

1. Identification of the advantages and challenges of AI and GenAI in urban planning: Using the "post-its technique" (Eden and Ackermann, 2001), experts identified advantages and challenges, marking them with positive (+) and negative (−) signs, respectively. Positive signs are frequently omitted to reduce visual complexity.
2. Allocation of criteria by clusters: Similar criteria were grouped by areas of interest, and all repeated criteria were removed until a consensus was reached that the results adequately captured a broad and relevant range of criteria. Five clusters emerged from the collective discussion and were categorized as follows: (1) *Technical and Operational Performance*; (2) *Simulations and Solutions*; (3) *Environmental and Social Impact*; (4) *Engagement and Interactivity*; and (5) *Integration and Adaptability*.
3. Hierarchization of criteria: Within each cluster, the criteria were ranked according to their level of importance—high, medium or low.

After the session, a group cognitive map was created using the *Decision Explorer* software (http://www.banxia.com), which included the organization of all clusters, their respective criteria and cause-and-effect relationships based on the inputs provided by the experts. Finally, the cognitive map was presented and reviewed by the panel members for any necessary adjustments/final changes and final validation. Fig. 2 presents the validated cognitive map created by the group, containing a total of 130 criteria (size restrictions prevent a better visualization, but an editable version of the entire group cognitive map can be obtained from the corresponding author upon request).

Fig. 2 incorporates numerous advantages and challenges already discussed in the literature, while also adding certain elements that have been less thoroughly explored. For instance, some criteria include both recurring (*e.g.*, *high-quality data and training requirements* (25), *biases embedded in training data and algorithms, leading to biased decisions* (57) and *ethical concerns (e.g., transparency, data privacy)* (88)) and emerging challenges (*e.g.*, *lack of specific regulations for technologies applied to urban planning* (62), *power of AI companies in urban planning* (89) and *resistance or rejection of proposed solutions by communities* (90)) in the context of urban planning. The latter, although not as frequently mentioned in the specialized literature, have, according to experts, a substantial impact on the urban planning process and present significant difficulty in being resolved. As such, their analysis not only expands the literature but also helps identify critical points where efforts need to be concentrated to overcome challenges to the adoption of these technologies.

4.2. Evaluation phase

The second work session took place in November 2024, lasting approximately 3 h, and was held on the *Teams* platform. The initial part of the session consisted of selecting the final advantages and challenges to be analyzed for quantifying causal relationships (*cf.* *Table 1*).

In Table 1, A and C stand for "advantages" and "challenges", respectively, with Ai and Ci referring to individual advantages and challenges numbered according to the cognitive mapping process involving stakeholder input. The reduction of the initial set of 130 concepts to 10 advantages and 10 challenges was agreed upon with the panel members due to the process-oriented nature of our study. It was a deliberate methodological choice designed to enhance both focus and analytical feasibility. Applying DEMATEL to the entire list would have been impractical and risked introducing cognitive overload for the experts, potentially diminishing the quality of their judgments (*cf.* Vaz-Patto et al., 2024). Therefore, the panel collectively prioritized the factors they deemed most critical to the research objectives.

To make this selection, the Nominal Group Technique (NGT) (Delbecq et al., 1975) and multi-voting were applied. These structured group decision-making methods ensured that all panel members had an equal opportunity to contribute their perspectives, regardless of seniority or communication style, thereby reducing the risk of dominance by more outspoken participants. The NGT facilitated the generation and clarification of ideas in a systematic manner, enabling participants to articulate and discuss the relevance of each proposed advantage or challenge. Following this, multi-voting was used to prioritize the most critical factors in a transparent and democratic way. Notably, all decisions were taken collectively by the panel members, which allowed for the integration of diverse expertise, fostered mutual understanding and strengthened commitment to the final set of selected

Fig. 2. Group cognitive map.

Table 1
Selected advantages and challenges.

Code	Advantages	Code	Challenges
A09	Provide real-time or interactive feedback	C25	High-quality data and training requirements
A29	Enhanced data analysis	C57	Biases embedded in training data and algorithms, leading to biased decisions
A40	Testing alternative building arrangements	C61	Integration of different levels of technological knowledge
A41	Exploring various ideas in a short period of time	C62	Lack of specific regulations for technologies applied to urban planning
A43	Dynamic digital simulations of cities	C64	Creation of false but realistic images
A47	Optimization of traffic lights for real-time traffic management	C88	Ethical concerns (*e.g.*, transparency, data privacy)
A66	Optimization of resource usage (water, energy, etc.)	C89	Power of AI companies in urban planning
A67	Scenario simulation (*e.g.*, traffic flow with narrower/wider streets)	C90	Resistance or rejection of proposed solutions by communities
A84	Reduction of human bias (*e.g.*, subjective human judgment)	C112	Dependence on companies for technology maintenance
A100	Creation and display of urban scenarios as they are designed or modified	C119	"Black box" nature

Note: A = advantage, C = challenge.

elements. This collaborative approach not only enhanced the legitimacy of the results but also ensured that the analysis was grounded in factors considered most relevant and actionable by consensus among experts. As a result, the 10 advantages and 10 challenges retained for further analysis reflected a balanced synthesis of multidisciplinary insights, while keeping the scope manageable for the subsequent causal relationship assessment.

After selecting the criteria, the neutrosophic DEMATEL method was used to quantify the intensity of the cause-and-effect relationships among the criteria within each group (*i.e.*, advantages and challenges). This step complemented the cognitive mapping process, which had previously enabled the systematic capture and structuring of expert knowledge—including the identification of perceived causal relationships—by providing a way to quantify and visualize the strength of those relationships among the most critical factors. Together, these methods offer a complementary and rigorous approach that delivers both a rich qualitative understanding and a robust quantitative assessment, supporting more informed decision-making in the integration of AI and GenAI into urban design and planning. Table 2 displays the initial direct-influence matrix Z, developed for the advantages analysis. This matrix includes neutrosophic values (*i.e.*, T, I, F) that were later refined through the process of crispification (*cf.* *Table 3*) and normalization (*cf.* *Table 4*).

The next step was to construct matrix T. First, the identity matrix I (*cf.* *Table 5*) was created. Then, the elements of the normalized matrix X were subtracted from the corresponding elements of the identity matrix, resulting in the matrix $I-X$. The final intermediate step was to compute $(I-X)^{-1}$, the inverse of the matrix obtained from the subtraction.

Following the intermediate calculations, the total relation matrix T was obtained (*cf.* *Table 6*), which presents the overall relationships between the advantages, including both direct and indirect effects.

Table 6 presents two key metrics. R shows the total impact of each advantage on the others, while C indicates how much each advantage is influenced by the others. The values highlight that A43 is the most influential advantage, while A84 has the least impact. Similarly, A100 is the most influenced by other advantages, and A84 is the least influenced. Table 7 further provides the totals and differences of the vectors R and C.

As shown in Table 7, the $R + C$ values reflect the overall importance

Table 2
Initial matrix Z and neutrosophic values—selected advantages.

	A09	A29	A40	A41	A43	A47	A66	A67	A84	A100
A09	–	4 (0.6, 0.3, 0.1)	4 (0.7, 0.2, 0.1)	3 (0.6, 0.3, 0.1)	3 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	2 (0.5, 0.3, 0.2)	3 (0.6, 0.2, 0.2)	2 (0.4, 0.4, 0.2)	3 (0.7, 0.2, 0.1)
A29	4 (0.8, 0.1, 0.1)	–	3 (0.6, 0.3, 0.1)	2 (0.6, 0.3, 0.1)	2 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.8, 0.1, 0.1)	2 (0.5, 0.3, 0.2)	2 (0.4, 0.4, 0.2)	3 (0.7, 0.2, 0.1)
A40	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	–	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	2 (0.6, 0.3, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.6, 0.2, 0.2)	2 (0.5, 0.3, 0.2)	4 (0.8, 0.1, 0.1)
A41	3 (0.7, 0.2, 0.1)	2 (0.6, 0.3, 0.1)	3 (0.7, 0.2, 0.1)	–	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	2 (0.5, 0.3, 0.2)	3 (0.6, 0.2, 0.2)	2 (0.4, 0.4, 0.2)	4 (0.8, 0.1, 0.1)
A43	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.8, 0.1, 0.1)	4 (0.8, 0.1, 0.1)	–	3 (0.7, 0.2, 0.1)	4 (0.8, 0.1, 0.1)	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	4 (0.8, 0.1, 0.1)
A47	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	2 (0.6, 0.3, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	–	3 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	2 (0.5, 0.3, 0.2)	3 (0.7, 0.2, 0.1)
A66	2 (0.6, 0.3, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	2 (0.6, 0.3, 0.1)	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	–	3 (0.7, 0.2, 0.1)	2 (0.5, 0.3, 0.2)	3 (0.7, 0.2, 0.1)
A67	3 (0.7, 0.2, 0.1)	2 (0.6, 0.3, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	–	3 (0.7, 0.2, 0.1)	4 (0.8, 0.1, 0.1)
A84	2 (0.5, 0.3, 0.2)	2 (0.5, 0.3, 0.2)	2 (0.5, 0.3, 0.2)	2 (0.5, 0.3, 0.2)	3 (0.7, 0.2, 0.1)	2 (0.5, 0.3, 0.2)	2 (0.5, 0.3, 0.2)	2 (0.5, 0.3, 0.2)	–	3 (0.7, 0.2, 0.1)
A100	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	4 (0.8, 0.1, 0.1)	4 (0.8, 0.1, 0.1)	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	3 (0.7, 0.2, 0.1)	4 (0.8, 0.1, 0.1)	3 (0.7, 0.2, 0.1)	–

Note: A = advantage.

Table 3
Neutrosophic crispification—selected advantages.

Pairwise Comparison	DEMATEL Scale (x)	Neutrosophic Values			Neutrosophic Crispification		
		T	I	F	Crispification Equation Numerator	Crisp Weight W	Final Value in Matrix Z
A9-A29	4.0	0.60	0.30	0.10	0.7056	0.0103	2.9333
A9-A40	4.0	0.70	0.20	0.10	0.7840	0.0114	3.2000
A9-A41	3.0	0.60	0.30	0.10	0.7056	0.0103	2.2000
A9-A43	3.0	0.80	0.10	0.10	0.8586	0.0125	2.6000
A9-A47	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A9-A66	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A9-A67	3.0	0.60	0.20	0.20	0.7172	0.0104	2.2000
A9-A84	2.0	0.40	0.40	0.20	0.5680	0.0083	1.2000
A9-A100	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A29-A9	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A29-A40	3.0	0.60	0.30	0.10	0.7056	0.0103	2.2000
A29-A41	2.0	0.60	0.30	0.10	0.7056	0.0103	1.4667
A29-A43	2.0	0.70	0.20	0.10	0.7840	0.0114	1.6000
A29-A47	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A29-A66	3.0	0.80	0.10	0.10	0.8586	0.0125	2.6000
A29-A67	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A29-A84	2.0	0.40	0.40	0.20	0.5680	0.0083	1.2000
A29-A100	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A40-A9	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A40-A29	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A40-A41	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A40-A43	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A40-A47	2.0	0.60	0.30	0.10	0.7056	0.0103	1.4667
A40-A66	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A40-A67	3.0	0.60	0.20	0.20	0.7172	0.0104	2.2000
A40-A84	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A40-A100	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A41-A9	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A41-A29	2.0	0.60	0.30	0.10	0.7056	0.0103	1.4667
A41-A40	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A41-A43	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A41-A47	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A41-A66	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A41-A67	3.0	0.60	0.20	0.20	0.7172	0.0104	2.2000
A41-A84	2.0	0.40	0.40	0.20	0.5680	0.0083	1.2000
A41-A100	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A43-A9	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A43-A29	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A43-A40	3.0	0.80	0.10	0.10	0.8586	0.0125	2.6000
A43-A41	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A43-A47	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A43-A66	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A43-A67	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A43-A84	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A43-A100	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A47-A9	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A47-A29	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A47-A40	2.0	0.60	0.30	0.10	0.7056	0.0103	1.4667
A47-A41	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A47-A43	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A47-A66	3.0	0.80	0.10	0.10	0.8586	0.0125	2.6000
A47-A67	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A47-A84	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A47-A100	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A66-A9	2.0	0.60	0.30	0.10	0.7056	0.0103	1.4667
A66-A29	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A66-A40	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A66-A41	2.0	0.60	0.30	0.10	0.7056	0.0103	1.4667
A66-A43	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A66-A47	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A66-A67	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A66-A84	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A66-A100	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A67-A9	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A67-A29	2.0	0.60	0.30	0.10	0.7056	0.0103	1.4667
A67-A40	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A67-A41	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A67-A43	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A67-A47	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A67-A66	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A67-A84	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A67-A100	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A84-A9	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333

(*continued on next page*)

Table 3 (*continued*)

Pairwise Comparison	DEMATEL Scale (x)	Neutrosophic Values			Neutrosophic Crispification		
		T	I	F	Crispification Equation Numerator	Crisp Weight W	Final Value in Matrix Z
A84-A29	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A84-A40	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A84-A41	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A84-A43	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A84-A47	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A84-A66	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A84-A67	2.0	0.50	0.30	0.20	0.6441	0.0094	1.3333
A84-A100	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A100-A9	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A100-A29	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A100-A40	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A100-A41	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A100-A43	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A100-A47	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A100-A66	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000
A100-A67	4.0	0.80	0.10	0.10	0.8586	0.0125	3.4667
A100-A84	3.0	0.70	0.20	0.10	0.7840	0.0114	2.4000

Table 4
Normalized matrix X—selected advantages.

	A09	A29	A40	A41	A43	A47	A66	A67	A84	A100
A09	0.0000	0.1081	0.1179	0.0811	0.0958	0.0885	0.0491	0.0811	0.0442	0.0885
A29	0.1278	0.0000	0.0811	0.0541	0.0590	0.0885	0.0958	0.0491	0.0442	0.0885
A40	0.1278	0.0885	0.0000	0.0885	0.0885	0.0541	0.0885	0.0811	0.0491	0.1278
A41	0.0885	0.0541	0.0885	0.0000	0.1278	0.0885	0.0491	0.0811	0.0442	0.1278
A43	0.1278	0.0885	0.0958	0.1278	0.0000	0.0885	0.1278	0.1278	0.0885	0.1278
A47	0.0885	0.0885	0.0541	0.0885	0.0885	0.0000	0.0958	0.0885	0.0491	0.0885
A66	0.0541	0.0885	0.0885	0.0541	0.1278	0.0885	0.0000	0.0885	0.0491	0.0885
A67	0.0885	0.0541	0.0885	0.0885	0.1278	0.0885	0.0885	0.0000	0.0885	0.1278
A84	0.0491	0.0491	0.0491	0.0491	0.0885	0.0491	0.0491	0.0491	0.0000	0.0885
A100	0.0885	0.0885	0.1278	0.1278	0.1278	0.0885	0.0885	0.1278	0.0885	0.0000

Note: A = advantage.

of each advantage, while $R-C$ distinguishes the advantages as either causes (*i.e.*, positive values) or effects (*i.e.*, negative values) within the context of AI in urban design and planning. According to the results obtained, A43 (*i.e.*, dynamic digital simulations of cities), with a value of 9.0380, is the most significant advantage. The ten advantages are ranked by importance as follows: dynamic digital simulations of cities (A43) > creation and display of urban scenarios as they are designed or modified (A100) > scenario simulation (*e.g.*, traffic flow with narrower/wider streets) (A67) > testing alternative building arrangements (A40) > provide real-time or interactive feedback (A09) > exploring various ideas in a short period of time (A41) > optimization of resource usage (water, energy, etc.) (A66) > optimization of traffic lights for real-time traffic management (A47) > enhanced data analysis (A29) > reduction of human bias (*e.g.*, subjective human judgment (A84).

In the next step, an α threshold of 0.3720—*i.e.*, average of the values in matrix T—was applied to identify the most critical effects in the decision-support system and to filter out less significant interactions. Interactions above the threshold represent elements with greater relevance in the model, while values below the threshold are considered less significant and are therefore excluded from the IRM (*cf.* *Fig. 3*). The IRM was generated based on matrix T, illustrating the cause-and-effect relationships among the ten advantages and providing a visual representation of their interdependencies.

In Fig. 3, A43 (*i.e.*, dynamic digital simulations of cities) emerges as the most prominent advantage, positioned at the far right of the horizontal axis, while A84 (*i.e.*, reduction of human bias (*e.g.*, subjective human judgment)) is the least significant, located at the opposite end. Advantages A43, A47 (*i.e.*, optimization of traffic lights for real-time traffic management), A66 (*i.e.*, optimization of resource usage (water, energy, etc.)), A67 (*i.e.*, scenario simulation (*e.g.*, traffic flow with narrower/wider streets)) and A100 (*i.e.*, creation and display of urban scenarios as they are designed or modified) are categorized as part of the cause group, whereas A09 (*i.e.*, provide real-time or interactive feedback), A29 (*i.e.*, enhanced data analysis), A40 (*i.e.*, testing alternative building arrangements) and A84 belong to the effect group. Based on their coordinates, A43, A67 and A100 are identified as core advantages (*i.e.*, QI), A47 and A66 as driving advantages (*i.e.*, QII) and A09, A40 and A41 as impact advantages (*i.e.*, QIV). Notably, A29 and A84 are positioned as independent (*i.e.*, QIII), indicating that they have minimal influence on other advantages and are also less affected by them.

Subsequently, the same analysis steps were applied to the challenges of AI in urban design and planning presented in Table 1. The causal relationships among them were examined, resulting in the creation of the initial direct-influence matrix Z (*cf.* *Table 8*) and the total relation matrix T with the corresponding R and C values (*cf.* *Table 9*).

The positive $R-C$ values presented in Table 8 indicate that the cause challenges are: high-quality data and training requirements (C25), integration of different levels of technological knowledge (C61), lack of specific regulations for technologies applied to urban planning (C62), ethical concerns (*e.g.*, transparency, data privacy) (C88), resistance or rejection of proposed solutions by communities (C90), dependence on companies for technology maintenance (C112) and "black box" nature (C119), while the effect challenges are: biases embedded in training data and algorithms, leading to biased decisions (C57), creation of false but realistic images (C64) and power of AI companies in urban planning (C89). Fig. 4 illustrates the IRM diagram for the challenges, highlighting the positioning of each one.

According to Fig. 4, the $R+C$ values indicate that the most pivotal challenge is C88 (*i.e.*, 5.9489), positioned at the far right. The least prominent challenge, C62, appears at the extreme left due to its lowest $R+C$ value (*i.e.*, 2.9355). The ten challenges are ranked by importance as follows: C88 > C57 > C89 > C119 > C25 > C112 > C64 > C90 > C61 >

Table 5
Intermediate steps for matrix *T*—Selected Advantages.

Matrix *I*

	A09	A29	A40	A41	A43	A47	A66	A67	A84	A100
A09	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A29	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A40	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A41	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A43	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A47	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
A66	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000
A67	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
A84	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
A100	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

I-X

	A09	A29	A40	A41	A43	A47	A66	A67	A84	A100
A09	1.0000	−0.1081	−0.1179	−0.0811	−0.0958	−0.0885	−0.0491	−0.0811	−0.0442	−0.0885
A29	−0.1278	1.0000	−0.0811	−0.0541	−0.0590	−0.0885	−0.0958	−0.0491	−0.0442	−0.0885
A40	−0.1278	−0.0885	1.0000	−0.0885	−0.0885	−0.0541	−0.0885	−0.0811	−0.0491	−0.1278
A41	−0.0885	−0.0541	−0.0885	1.0000	−0.1278	−0.0885	−0.0491	−0.0811	−0.0442	−0.1278
A43	−0.1278	−0.0885	−0.0958	−0.1278	1.0000	−0.0885	−0.1278	−0.1278	−0.0885	−0.1278
A47	−0.0885	−0.0885	−0.0541	−0.0885	−0.0885	1.0000	−0.0958	−0.0885	−0.0491	−0.0885
A66	−0.0541	−0.0885	−0.0885	−0.0541	−0.1278	−0.0885	1.0000	−0.0885	−0.0491	−0.0885
A67	−0.0885	−0.0541	−0.0885	−0.0885	−0.1278	−0.0885	−0.0885	1.0000	−0.0885	−0.1278
A84	−0.0491	−0.0491	−0.0491	−0.0491	−0.0885	−0.0491	−0.0491	−0.0491	1.0000	−0.0885
A100	−0.0885	−0.0885	−0.1278	−0.1278	−0.1278	−0.0885	−0.0885	−0.1278	−0.0885	1.0000

(I-X) $^{-1}$

	A09	A29	A40	A41	A43	A47	A66	A67	A84	A100
A09	1.3187	0.3673	0.4074	0.3671	0.4290	0.3539	0.3263	0.3705	0.2532	0.4328
A29	0.4006	1.2464	0.3492	0.3152	0.3671	0.3293	0.3384	0.3158	0.2323	0.3974
A40	0.4466	0.3650	1.3196	0.3886	0.4433	0.3398	0.3721	0.3872	0.2691	0.4829
A41	0.4029	0.3251	0.3884	1.2999	0.4637	0.3586	0.3307	0.3787	0.2589	0.4716
A43	0.5176	0.4260	0.4754	0.4885	1.4441	0.4327	0.4694	0.4949	0.3526	0.5653
A47	0.3854	0.3408	0.3431	0.3624	0.4138	1.2648	0.3558	0.3674	0.2509	0.4197
A66	0.3613	0.3436	0.3743	0.3374	0.4487	0.3476	1.2738	0.3713	0.2542	0.4239
A67	0.4299	0.3495	0.4154	0.4065	0.4965	0.3835	0.3893	1.3304	0.3170	0.5038
A84	0.27156	0.23811	0.26177	0.25609	0.32590	0.24122	0.24545	0.25927	1.15167	0.33092
A100	0.47173	0.41159	0.48555	0.47499	0.53934	0.41791	0.42416	0.48003	0.34248	1.43587

Table 6
Matrix *T*—selected advantages.

	A09	A29	A40	A41	A43	A47	A66	A67	A84	A100	*R*
A09	0.3187	0.3673	0.4074	0.3671	0.4290	0.3539	0.3263	0.3705	0.2532	0.4328	3.6260
A29	0.4006	0.2464	0.3492	0.3152	0.3671	0.3293	0.3384	0.3158	0.2323	0.3974	3.2917
A40	0.4466	0.3650	0.3196	0.3886	0.4433	0.3398	0.3721	0.3872	0.2691	0.4829	3.8142
A41	0.4029	0.3251	0.3884	0.2999	0.4637	0.3586	0.3307	0.3787	0.2589	0.4716	3.6785
A43	0.5176	0.4260	0.4754	0.4885	0.4441	0.4327	0.4694	0.4949	0.3526	0.5653	4.6667
A47	0.3854	0.3408	0.3431	0.3624	0.4138	0.2648	0.3558	0.3674	0.2509	0.4197	3.5040
A66	0.3613	0.3436	0.3743	0.3374	0.4487	0.3476	0.2738	0.3713	0.2542	0.4239	3.5360
A67	0.4299	0.3495	0.4154	0.4065	0.4965	0.3835	0.3893	0.3304	0.3170	0.5038	4.0219
A84	0.2716	0.2381	0.2618	0.2561	0.3259	0.2412	0.2454	0.2593	0.1517	0.3309	2.5820
A100	0.4717	0.4116	0.4856	0.4750	0.5393	0.4179	0.4242	0.4800	0.3425	0.4359	4.4837
C	4.0062	3.4135	3.8200	3.6967	4.3713	3.4694	3.5255	3.7554	2.6822	4.4642	

Note: A = advantage; *C* = cumulative value of columns; *R* = cumulative value of rows.

Table 7
Advantages' total influences.

	R	C	R + C	R–C
A09	3.6260	4.0062	7.6322	−0.3803
A29	3.2917	3.4135	6.7052	−0.1218
A40	3.8142	3.8200	7.6342	−0.0058
A41	3.6785	3.6967	7.3752	−0.0182
A43	4.6667	4.3713	9.0380	0.2954
A47	3.5040	3.4694	6.9734	0.0345
A66	3.5360	3.5255	7.0615	0.0105
A67	4.0219	3.7554	7.7772	0.2665
A84	2.5820	2.6822	5.2642	−0.1003
A100	4.4837	4.4642	8.9479	0.0194

Note: A = advantage; *C* = cumulative value of columns; *R* = cumulative value of rows.

C62.

The challenges' coordinates identify C88 and C119 as core challenges (*i.e.*, QI), being highly influential and significantly influenced by others, making them central to the system. QII is composed by C25, C61, C62, C90 and C112 as key drivers of the system, indicating that they strongly influence others. Furthermore, C64 is positioned in the independent quadrant (*i.e.*, QIII), suggesting a minimal interaction with the rest of the system. In contrast, C57 and C89 fall within the impact quadrant (*i.e.*, QIV), indicating they are significantly influenced by other challenges but have a limited ability to influence others.

4.3. *Consolidation phase*

The analysis of the results was further enriched by integrating

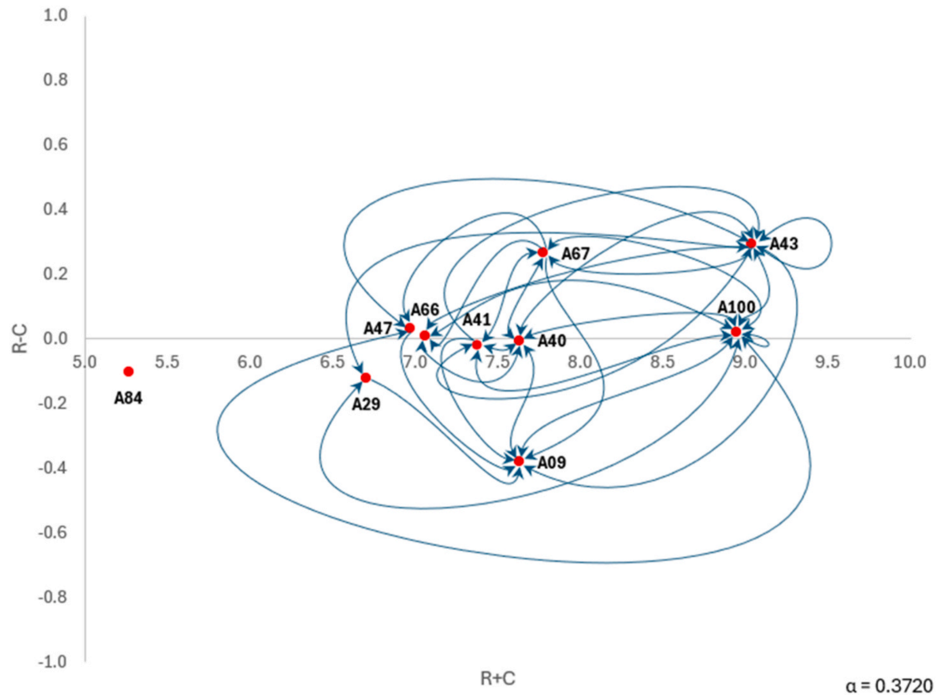

Fig. 3. IRM for AI advantages in urban design and planning.

insights from the existing literature and complementing them with the consolidation phase (*i.e.*, the last phase in the MCDA process), offering deeper insights into the dynamic interactions among AI's advantages and among its challenges in urban design and planning. To gain an independent perspective, an interview was conducted with the Information Systems Coordinator at Portugal's *Agência Nacional de Inovação* (ANI) (*i.e.*, National Innovation Agency) who had not participated in previous sessions. The interview was structured in three parts: (1) an introduction to the research topic and methodological framework; (2) a presentation and discussion of the findings; and (3) an evaluation of their practical applicability by the expert.

The expert agreed with the results, highlighting their role in identifying strategic factors related to dynamic digital simulations of cities and addressing ethical considerations, both of which are essential for the success of urban projects. The analysis conducted thus supports informed decision-making, enabling urban planners and policymakers to implement strategic, impactful initiatives that can augment AI's advantages while addressing its challenges. These results are also critical for constructing a *"correct and assertive decision tree"* (according to the expert) and for *"understanding the social trends and logics underlying the evaluation of specific criteria"* (in his words). However, the expert emphasized that such evaluations will inevitably rely *"on the judgments of the participants involved and their expertise as professionals in this context"* (also in his words). In this regard, it is worth noting that *"subjectivity is an integral part of managerial decision-making and cannot be ignored or assumed to be eliminated by the pursuit of an intersubjective ideal"* (Ormerod, 2013, p. 486). Thus, underpinned by Keeney's (1992) VFT, the methodological approach followed in this study incorporates both objective and subjective elements, including the decision-makers' value judgements (Bana e Costa et al., 1997; Ferreira and Ferreira, 2025).

The results reveal important insights into the role of each AI advantage in urban planning. In the QI, advantages A43 (*i.e.*, dynamic digital simulations of cities), A100 (*i.e.*, creation and display of urban scenarios as they are designed or modified) and A67 (*i.e.*, scenario simulation (*e.g.*, traffic flow with narrower/wider streets)) stand out as the most prominent advantages, highlighting their central and influential role in the system. This reflects their importance in structuring AI-based urban planning models, particularly in the context of complex urban simulations and interactive visualizations. These results reinforce the significance of these mentioned advantages in previous studies (*e.g.*, Batty and Yang, 2022; Sanchez et al., 2024; Shen et al., 2020) and the concept of complementary tools that facilitate the urban planning process (Furtado et al., 2024). However, this study not only confirms previous ideas but also advances the literature in urban planning by revealing the degree of dependence and mutual influence among these advantages, illustrating their relationships with other advantages through a causality matrix.

As causal advantages, both core (*i.e.*, those present in the QI) and driving advantages (*i.e.*, those present in the QII) should establish synergies between them to enable concrete actions in urban planning. For instance, the integration of real-time optimized traffic data (A47) is essential for dynamic simulations (A43) and for creating more realistic urban scenarios (A100). These synergies can help create more accurate models to predict city behavior and the impact of interventions on traffic. However, according to the members of the panel, these synergies are still limited, suggesting that urban planning is not currently leveraging the full potential of these driving advantages to "feed" dynamic urban scenario simulation models effectively. The advantages positioned in the QIV, such as providing real-time or interactive feedback (A09), testing alternative building arrangements (A40) and exploring various ideas in a short period of time (A41), are classified as effects. This means that they heavily depend on the core and driving advantages. In the expert's words, for urban design and planning to be truly iterative and responsive, *"a smooth flow of data and integration between different technologies is essential"*. In QIII, the advantages A29 (*i.e.*, enhanced data analysis) and A84 (*i.e.*, reduction of human bias) are independent, occurring with minimal interaction. For instance, enhanced data analysis primarily impacts real-time feedback (A09), dynamic simulations (A43) and the creation of realistic urban scenarios (A100), indicating that it is not being widely leveraged in other areas within urban planning. According to the expert, A29 proves particularly beneficial in the context of decision-making frameworks, especially within the *"logic of structures and decision trees"* (in his own words). This is because it minimizes errors and enhances the robustness of urban planning strategies, ultimately supporting a more data-driven and efficient decision-making process. In the case of reducing human bias

Table 8
Initial matrix *Z* and neutrosophic values—selected challenges.

	C25	C57	C61	C62	C64	C88	C89	C90	C112	C119
C25	–	4 (0.9, 0.1, 0.1)	3 (0.7, 0.2, 0.2)	0 (0.1, 0.6, 0.8)	4 (0.6, 0.3, 0.3)	3 (0.8, 0.2, 0.2)	2 (0.7, 0.3, 0.2)	1 (0.5, 0.4, 0.4)	1 (0.5, 0.3, 0.4)	1 (0.5, 0.4, 0.4)
C57	4 (0.9, 0.1, 0.1)	–	2 (0.7, 0.3, 0.3)	1 (0.5, 0.4, 0.4)	3 (0.8, 0.2, 0.2)	4 (0.9, 0.1, 0.1)	3 (0.8, 0.2, 0.2)	1 (0.5, 0.4, 0.4)	2 (0.6, 0.3, 0.3)	2 (0.6, 0.3, 0.3)
C61	3 (0.7, 0.2, 0.2)	3 (0.8, 0.2, 0.2)	–	2 (0.6, 0.3, 0.3)	1 (0.5, 0.4, 0.4)	2 (0.7, 0.2, 0.3)	2 (0.7, 0.3, 0.3)	1 (0.4, 0.5, 0.4)	1 (0.5, 0.4, 0.4)	1 (0.5, 0.4, 0.4)
C62	0 (0.1, 0.6, 0.8)	1 (0.5, 0.4, 0.4)	2 (0.6, 0.3, 0.3)	–	1 (0.5, 0.4, 0.4)	3 (0.8, 0.2, 0.3)	2 (0.7, 0.3, 0.3)	2 (0.6, 0.3, 0.3)	2 (0.6, 0.3, 0.3)	2 (0.6, 0.3, 0.3)
C64	2 (0.6, 0.3, 0.3)	3 (0.8, 0.2, 0.2)	1 (0.5, 0.4, 0.4)	1 (0.5, 0.4, 0.4)	–	2 (0.6, 0.3, 0.3)	2 (0.7, 0.3, 0.2)	2 (0.6, 0.3, 0.3)	1 (0.5, 0.4, 0.4)	1 (0.5, 0.4, 0.4)
C88	3 (0.8, 0.2, 0.2)	4 (0.9, 0.1, 0.1)	2 (0.7, 0.2, 0.3)	3 (0.8, 0.2, 0.3)	2 (0.6, 0.3, 0.3)	–	3 (0.8, 0.2, 0.2)	3 (0.8, 0.2, 0.2)	3 (0.8, 0.2, 0.2)	4 (0.9, 0.1, 0.1)
C89	2 (0.7, 0.3, 0.2)	3 (0.8, 0.2, 0.2)	2 (0.7, 0.3, 0.3)	2 (0.7, 0.3, 0.3)	2 (0.6, 0.3, 0.3)	3 (0.8, 0.2, 0.2)	–	2 (0.6, 0.3, 0.3)	3 (0.8, 0.2, 0.2)	3 (0.8, 0.2, 0.2)
C90	1 (0.5, 0.4, 0.4)	1 (0.5, 0.4, 0.4)	1 (0.4, 0.5, 0.4)	2 (0.6, 0.3, 0.3)	2 (0.6, 0.3, 0.3)	3 (0.8, 0.2, 0.2)	2 (0.6, 0.3, 0.3)	–	2 (0.6, 0.3, 0.3)	2 (0.6, 0.3, 0.3)
C112	1 (0.5, 0.3, 0.4)	2 (0.6, 0.3, 0.3)	1 (0.5, 0.4, 0.4)	2 (0.6, 0.3, 0.3)	1 (0.5, 0.4, 0.4)	3 (0.8, 0.2, 0.2)	3 (0.8, 0.2, 0.2)	2 (0.6, 0.3, 0.3)	–	3 (0.8, 0.2, 0.2)
C119	1 (0.5, 0.4, 0.4)	2 (0.6, 0.3, 0.3)	1 (0.5, 0.4, 0.4)	2 (0.6, 0.3, 0.3)	4 (0.5, 0.4, 0.4)	4 (0.9, 0.1, 0.1)	3 (0.8, 0.2, 0.2)	2 (0.6, 0.3, 0.3)	3 (0.8, 0.2, 0.2)	–

Note: C = challenge.

(A84), despite its theoretical relevance for more impartial decision-making in urban planning (*cf.* Schlickman and Magana-Leon, 2024) and in interdisciplinary collaboration among stakeholders (Furtado et al., 2024), AI may be used to reduce human bias in isolation, without coordination with other tools and technological solutions, suggesting an underutilized potential. The analysis reinforces the idea that the effectiveness of AI in urban design and planning depends on the integration and balance between advantages, enabling synergies that maximize the impact of these technologies.

Regarding the challenges analyzed, the results show that ethical concerns (*e.g.*, transparency, data privacy) (C88) is the most prominent and relevant challenge within the system. Positioned in QI, it is a central and interactive challenge, meaning it is both highly influential and significantly influenced by others. For instance, it is strongly interdependent on the "black box" nature of AI (C119). This latter challenge is recognized as important, but most attention has focused on its limitations from technical and user-system interaction perspectives (*e.g.*, Hughes et al., 2021; Kempinska and Murcio, 2019; Wang et al., 2021). Therefore, resolving this issue should be given high priority, as it directly impacts trust and the adoption of AI solutions, which are crucial for the development and acceptance of AI in urban planning. As Batty and Yang (2022) suggest, adopting open-source software and languages could reduce opacity, enabling developers, urban planners and communities to audit and understand the systems.

Ethical concerns are identified in the literature (*e.g.*, Hajrasouliha, 2024; Sanchez et al., 2024; Son et al., 2023) as essential for promoting transparency, equity and accountability. The results obtained in this study provide a quantitative and systemic approach, revealing interdependencies that have not been thoroughly explored. For example, ethical issues affect the biases embedded in training data and algorithms (C57). In other words, as ethical concerns are addressed, AI developers must implement more careful, transparent and fair data training practices to prevent bias from negatively influencing the automated decisions made by AI tools that support urban planners' decision-making. Addressing these challenges will help increase the reliability of AI-based decisions. Ye et al. (2023, p. 7) state that *"every community has its own unique set of needs, values, and characteristics"*. According to the results, ethical concerns (C88) impact the resistance or rejection of AI-based solutions by communities (C90). There is a risk that local communities may distrust AI solutions, fearing they could alter their routines or shape the urban space in ways that do not align with their needs. This distrust, amplified by the perception of insufficient involvement in decision-making processes, can significantly influence urban planners' choices, who must balance technological innovation and social consensus. This finding is related to the fear and lack of trust in machines, issues addressed in Du et al. (2024), Sanchez et al. (2024) and Ulucan et al. (2025), but in the present study, it is directly linked to the resistance from communities.

Technological dependency is an aspect mentioned in some studies and is directly associated, on the one hand, with the lack of transparency, as pointed out by Sanchez et al. (2024). This lack of transparency largely stems from the fact that AI algorithms are proprietary, meaning that the tools and methodologies used are treated as trade secrets by the companies that develop them. On the other hand, dependency is associated with excessive and blind trust (Du et al., 2024). Our results provide a new perspective on technological dependency: urban planners may become overly reliant on companies for technological maintenance (C112), which, in turn, amplifies the power of AI companies in urban planning (C89). This type of dependency has received little attention and is especially critical because it can undermine the autonomy of urban planning, restricting the capacity for democratic decision-making and increasing corporate influence in urban choices (Du et al., 2024).

From the perspective of implementing these technologies, *"it is likely to be dominated by a small number of large companies. The development, maintenance and operation of these technologies rely on the efforts of those*

Table 9
Matrix T and total influences—selected challenges.

	C25	C57	C61	C62	C64	C88	C89	C90	C112	C119	R	C	$R+C$	$R–C$
C25	0.1529	0.3399	0.2043	0.1020	0.2474	0.3056	0.2281	0.1316	0.1545	0.1680	2.0342	1.8987	3.9329	0.1356
C57	0.3195	0.2367	0.1976	0.1489	0.2654	0.3960	0.3000	0.1592	0.2163	0.2354	2.4749	2.5703	5.0452	−0.0953
C61	0.2106	0.2491	0.0882	0.1346	0.1338	0.2277	0.1918	0.1056	0.1247	0.1357	1.6017	1.4769	3.0786	0.1249
C62	0.0972	0.1546	0.1299	0.0807	0.1162	0.2456	0.1803	0.1402	0.1577	0.1697	1.4721	1.4633	2.9355	0.0088
C64	0.1615	0.2342	0.1035	0.0981	0.0994	0.2100	0.1822	0.1350	0.1210	0.1312	1.4760	1.8629	3.3389	−0.3869
C88	0.2950	0.4060	0.2143	0.2455	0.2537	0.3121	0.3426	0.2580	0.2957	0.3601	2.9829	2.9660	5.9489	0.0168
C89	0.2168	0.3055	0.1776	0.1789	0.2079	0.3400	0.1910	0.1827	0.2533	0.2698	2.3236	2.3399	4.6635	−0.0163
C90	0.1244	0.1633	0.1028	0.1399	0.1546	0.2572	0.1837	0.0876	0.1618	0.1744	1.5496	1.5472	3.0967	0.0024
C112	0.1491	0.2227	0.1207	0.1581	0.1479	0.2966	0.2556	0.1628	0.1310	0.2443	1.8887	1.8685	3.7572	0.0202
C119	0.1718	0.2582	0.1380	0.1768	0.2366	0.3752	0.2847	0.1846	0.2525	0.1720	2.2503	2.0604	4.3107	0.1899

Note: C = challenge; C = cumulative value of columns; R = cumulative value of rows.

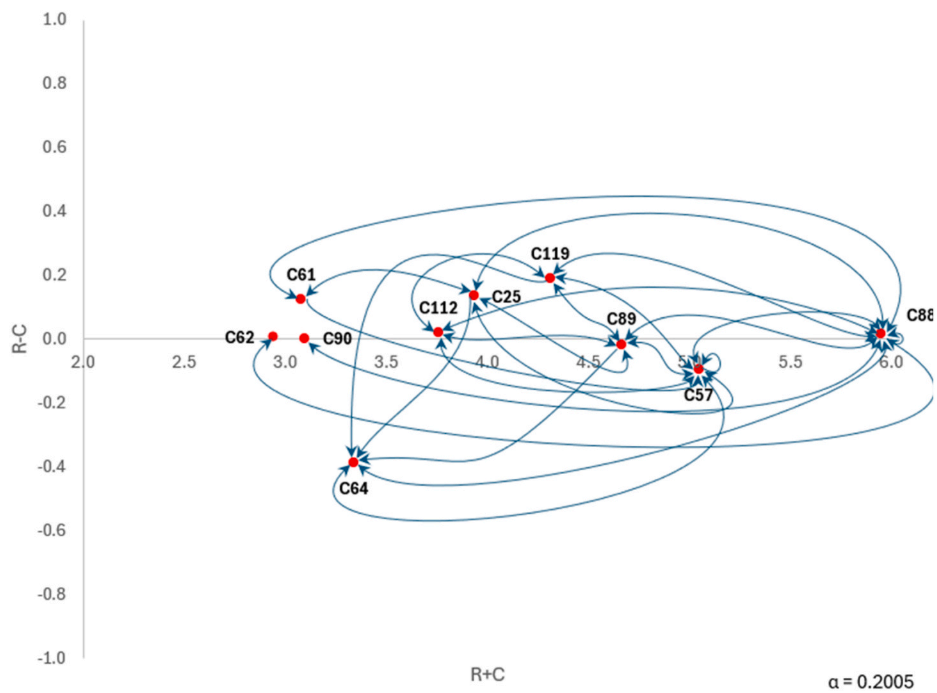

Fig. 4. Irm for AI challenges in urban design and planning.

working behind the scenes. Additionally, the resources required to sustain these systems—whether water for cooling, electricity for powering machines or processing capacity—play a critical role in their ongoing operation" (in the expert's words). Additionally, the expert argued that, *"on the one hand, assuming that urban planning can be improved by AI companies, it could be beneficial to have entities that are less biased in their evaluations and decisions. These entities could act as more transparent stakeholders, aligned with best practices and capable of identifying and suggesting improvements in urban planning. On the other hand, excessive power concentrated in AI companies and an over-reliance on AI-driven planning could stifle creativity and undermine the logic of urban development and planning"* (in his words).

The integration of different levels of technological knowledge (C61) is a major challenge in urban planning literature (*e.g.*, Asaad et al., 2020; Cozzolino et al., 2020; Quan et al., 2019; Wang et al., 2021). This challenge is linked to the technical barriers of cross-disciplinary collaboration, highlighting that urban planners and AI professionals often struggle to communicate effectively due to differences in knowledge, language and priorities. According to the expert, *"the integration of distinct and diverse datasets from various cities at the highest level, aimed at extracting their full value through the logic of knowledge absorption, provides access to a significantly broader pool of knowledge. This includes a wide range of information, such as geographic and geological data, water networks, traffic systems, and more"* (again in his words).

While ethical considerations in AI typically call for greater transparency, accountability and fairness in algorithms, they do not necessarily explore how interdisciplinary collaboration can prevent or reduce these issues. Thus, the current study extends this understanding by proposing that addressing C61 is not just about overcoming communication and knowledge barriers for better collaboration, but also about ensuring that ethical concerns (*e.g.*, transparency and data privacy) (C88) are integrated into the design of AI tools and solutions from the outset. Building on the expert's observations regarding the integration of technological knowledge, ethical considerations and the balance of AI's advantages and challenges, the following section discusses the broader implications of these findings for theory, practice and policy in urban planning.

5. Discussion

5.1. Contributions to theory, practice and society

Although the methodological components employed—cognitive mapping, neutrosophic logic and DEMATEL—are well-established in the literature, the novelty of our work lies in the innovative integration and application of these methods to a contemporary and underexplored decision problem (*i.e.*, the causal interplay among advantages and among challenges of integrating AI and GenAI into urban design and planning). To our knowledge, this is the first study to systematically capture and quantify expert knowledge in this domain using a structured combination of problem structuring and causal analysis techniques, thereby revealing interdependencies not previously mapped.

Theoretically, the present study makes three significant contributions to the integration of AI and GenAI in urban design and planning, addressing key gaps identified in the existing literature (*cf.* Du et al., 2024; Peng et al., 2023; Son et al., 2023). First, it presents a comprehensive framework that enables the understanding of complex causal interactions among advantages and among challenges of these technologies, thus responding to the call for more in-depth analyses of the causal relationships among AI's advantages and among its challenges (*cf.* Furtado et al., 2024; Hajrasouliha, 2024; Tekouabou et al., 2023), thereby answering RQ1 and RQ2. Second, by emphasizing the importance of approaches that consider uncertainties and causal dependencies, the study directly contributes to bridging the gap in literature concerning the need for studies focused on urban design and planning problems with multiple, interacting components (*e.g.*, Ali-Toudert et al., 2020; Batty and Yang, 2022). Finally, the study addresses the lack of a structured approach in previous research by combining cognitive mapping, DEMATEL and neutrosophic logic—methods not previously integrated in the context of AI and urban design and planning. This methodological integration allowed to answer RQ3, provide a more precise evaluation of AI's role in urban design and planning and offer a pathway for future research and practices that can optimize the use of these technologies in developing smarter, more inclusive and sustainable cities.

From a practical perspective, our study highlights the importance of structured decision-making processes grounded in a constructivist approach, enhancing the understanding of causal relationships and uncertainties in urban design and planning. By integrating cognitive mapping and neutrosophic DEMATEL, the study proposes a dynamic and collaborative process that engages diverse stakeholders—including urban planners, engineers and local communities—in identifying causal links among AI's advantages and among its challenges. This inclusive approach ensures that varied perspectives shape the structuring of urban problems and the formulation of solutions. The approach explicitly addresses uncertainties associated with AI integration, acknowledging that decision-making often occurs under incomplete or uncertain data. The methods' ability to model complexity and unpredictability supports a flexible and precise option analysis, which is essential in the rapidly evolving technological environment. Aligned with principles of the soft OR community (Ackermann, 2012; Midgley et al., 2018), the process-based framework organizes decision-making and enables stakeholders to identify critical dependencies among technical, ethical, social and environmental factors. This facilitates the creation of balanced public policies and urban projects that reflect the multifaceted challenges cities face. Finally, the combined use of PSMs—as suggested by Mingers and Rosenhead (2004)—not only improves the planning process but also offers a customizable and transferable approach adaptable to the specific socioeconomic, cultural and environmental contexts of diverse cities or regions. This adaptability ensures the practical relevance of our framework for real-world urban planning challenges.

An additional strength of this study is its process-oriented nature. The methodological pathway—beginning with the structured elicitation of expert knowledge, followed by consensus-building, prioritization and causal analysis—is designed to be fully transferable to other contexts (*cf.* Bell and Morse, 2013; Ormerod, 2013). Because it is based on facilitated expert participation, the process can be adapted to reflect the specific realities, constraints and priorities of different application domains, thereby producing results that are both realistic and tailored to the decision-making environment in question. This adaptability makes the framework particularly valuable for addressing emerging challenges in diverse policy and planning contexts, where ready-made, one-size-fits-all solutions are unlikely to be effective.

5.2. Recommendations

Given the inherently process-oriented nature of this study, caution is advised when considering the generalizability of its findings. The research is deeply embedded in a context-specific framework that reflects the perspectives, judgments and interactions of particular experts and stakeholders involved in the cognitive mapping and decision structuring processes. Unlike purely quantitative studies that aim to produce universally generalizable results, this study prioritizes rich, contextualized insights and structured knowledge elicitation that capture the complexity and nuance of real-world decision-making in urban design and planning (*cf.* Bell and Morse, 2013; Ormerod, 2020). Consequently, the findings should not be interpreted as definitive or broadly applicable conclusions but rather as a detailed exploration of the dynamics at play within the studied context.

Instead, this work is best understood as a learning mechanism that complements and enriches the broader field of AI and GenAI integration in urban design and planning. By systematically structuring expert knowledge and revealing causal interdependencies among advantages and among challenges, the study offers valuable heuristics and conceptual frameworks that can inform subsequent empirical research, policy development and practical applications. This approach encourages iterative learning and adaptation, fostering a deeper understanding of complex, multi-stakeholder problems where uncertainty and subjectivity are unavoidable. In this way, the research contributes to cumulative knowledge-building rather than attempting to prescribe one-size-fits-all solutions.

One of the key advantages of adopting a process-oriented and constructivist methodology lies in its flexibility and adaptability. The participatory and transparent nature of the methods employed enables diverse stakeholders to engage meaningfully, ensuring that multiple perspectives and value systems are incorporated into the decision-making process (*cf.* Vaz-Patto et al., 2024). This inclusiveness enhances the relevance and legitimacy of the findings within the specific context and supports tailored decision support rather than rigid prescriptions. Moreover, by explicitly acknowledging and modeling uncertainty and interdependencies, the approach facilitates a nuanced understanding of urban planning challenges that traditional deterministic methods often overlook (*cf.* Correia et al., 2024). As such, the study provides a robust foundation for ongoing dialogue, reflection and refinement of AI applications in urban design and planning, ultimately contributing to more resilient, inclusive and context-sensitive planning practices.

6. Conclusion

The integration of AI into urban design and planning represents a significant transformation in how cities are conceived, developed and managed. Both the reviewed literature and the empirical results demonstrate the vast potential of these technologies to optimize decision-making processes, enhance collaboration among stakeholders and foster innovative solutions to complex urban challenges. However, the study also identified critical gaps, particularly in managing uncertainties and understanding the intricate causal relationships among advantages and among challenges of AI integration. Addressing these gaps requires structured, participatory approaches capable of analyzing causal dependencies and handling uncertainty.

This research addressed three guiding questions. Regarding RQ1 ("What key advantages and challenges are associated with the integration of AI in general—and GenAI in particular—in urban design and planning?"), the study identified core advantages such as dynamic digital simulations, real-time scenario modeling and adaptive traffic flow analysis. Ethical concerns and technological dependency emerged as the most significant challenges, underscoring areas requiring focused attention. In response to RQ2 ("What are the causal relationships among the identified advantages and among the challenges related to AI and GenAI integration in urban design and planning?"), the neutrosophic DEMATEL analysis revealed complex interdependencies among these factors, illustrating how driving advantages reinforce each other and how challenges interact with technological dependencies. For RQ3 ("How can stakeholder collaboration and decision-making under uncertainty support the application of AI and GenAI to urban design and planning?"), the use of PSMs enabled collaborative engagement and systematic exploration of uncertainties inherent to urban contexts.

The novelty of this study lies not in proposing new methods but in the innovative integration of established techniques within an MCDA framework applied to a contemporary and underexplored problem (*i.e.*, the causal interplay among advantages and among challenges of AI and GenAI in urban design and planning). To the best of our knowledge, this is the first study to systematically capture, quantify and model expert knowledge in this field, revealing the causal structures underpinning these complex dynamics. The results move beyond descriptive listings of pros and cons, offering actionable insights to inform strategic planning and policymaking.

In terms of contributions, the study offers empirical insights into the dynamic relationships among AI's advantages and among its challenges, highlights critical synergies and bottlenecks and proposes a replicable, process-oriented methodological framework that supports collaborative decision-making under uncertainty. This framework is adaptable to diverse urban contexts, providing a valuable tool for both researchers and practitioners aiming to optimize the integration of AI technologies in urban design and planning.

Despite these advances, some limitations should be noted. The study's findings are grounded in expert input and future applications across cities with different socio-economic and technological conditions are needed to generalize and refine the framework. Additionally, while digital tools facilitated collaboration, the process remained resource intensive. Integrating such approaches with AI-enhanced platforms capable of real-time feedback and dynamic simulation could streamline participation, improve inclusivity and accelerate decision-making. These advancements would further promote the responsible and sustainable integration of AI and GenAI into urban development.

CRediT authorship contribution statement

Amali Çipi: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Neuza C.M.Q.F. Ferreira:** Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Fernando A.F. Ferreira:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization. **João J.M. Ferreira:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Data curation, Conceptualization. **Florentin Smarandache:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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Data availability

Data will be made available on request.

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