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"*QUO VADIS* URBAN AREAS?": (RE)THINKING THE FUTURE OF URBAN AREAS USING INTERPRETIVE STRUCTURAL MODELING

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Abstract. The world's population continues to grow at an unprecedented rate, with urban areas experiencing a more rapid rise in population density than rural regions. This demographic shift compels decision-makers to address pressing urban challenges and rethink future structures of cities. However, a vision for global sustainable urban growth remains elusive, as planners often lack comprehensive, credible and dynamic models to guide decision-making. The main purpose of this study is to propose a process-oriented methodology that integrates cognitive mapping, interpretive structural modeling (ISM) and a *matrice d'impacts croisés multiplication appliquée à un classement* (MICMAC) analysis to evaluate and prioritize key determinants of urban development. Group work sessions involving decision-makers from diverse fields were conducted to identify critical variables influencing urban development. Unlike traditional models, the proposed approach emphasizes participatory decision-making. By combining cognitive mapping and ISM-MICMAC, this study enables the identification of causal relationships among variables and allows decision-makers to anticipate trends and prioritize challenges effectively. The findings were further validated by an external expert to ensure neutrality and reliability. Overall, this study provides a theoretical contribution to decision-making methodologies while offering a practical framework for urban planners to influence cities toward a sustainable future.

Keywords: cognitive mapping, decision making, Interpretive Structural Modeling (ISM), *Matrice d'Impacts Croisés Multiplication Appliquée à un Classement* (MICMAC), population density, urban areas, world population.

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1. Introduction

In recent decades, the world's population has grown at an astonishing rate. Population increases have been accompanied by a notable rural exodus with escalating numbers of people migrating to urban centers (Shen et al., 2012; Lishuang et al., 2013; Cordeiro et al., 2024; Rodrigues et al., 2025).

Multiple factors motivate people to opt for an urban environment. Foremost are social factors where people seek better living conditions and additional opportunities provided by urban areas, where diverse secondary and tertiary sector services provide prospects to earn additional income and a higher standard of living. Environmental factors, including natural disasters in rural regions may prompt populations to reconsider their place of residence and seek alternatives in urban settings. Climate factors, such as a lack of water, may directly affect locals' livelihoods and further boost migration to urban zones. Also, political factors such as a lack of supportive government structures may motivate individuals to search for better economic prospects elsewhere (Pinto et al., 2023; Cordeiro et al., 2024). These combined factors have resulted in an exponential increase in urban residents.

To make population growth sustainable, policy/decision makers must rethink the future of cities and address possibly unexamined problems. Despite numerous studies on urbanization and city planning, most existing methodologies fail to provide a structured and integrated approach to identifying and prioritizing the key factors influencing urban growth (*cf.* Andrade et al., 2022). Many traditional models rely on linear or fragmented analyses, which do not fully capture the complex interdependencies among social, economic, environmental and political variables (cf. Huang et al., 2023). This study addresses this gap by proposing a comprehensive analytical framework that integrates cognitive mapping and interpretive structural modeling (ISM), including a *matrice d'impacts croisés multiplication appliquée à un classment* (MICMAC) analysis. By offering a more holistic perspective, this approach enables a deeper understanding of urban growth dynamics and facilitates the identification of critical determinants shaping the future of urban areas.

Building on this foundation, our study pursues both theoretical and practical objectives. From a theoretical perspective, it advances urban planning methodologies by introducing a structured approach to identifying and analyzing interdependencies among key growth factors. From a practical standpoint, it provides policymakers, urban planners and decision-makers with a systematic, transparent framework to prioritize challenges and develop sustainable urban strategies. We thus seek to address the following questions:

- How can the future of urban areas be anticipated?
- What are the most influential variables in urban growth processes?
- How can decision makers prioritize complex challenges that must be addressed to facilitate urban zones' sustainable evolution?

To facilitate these objectives, our literature review explores important concepts related to urban growth and examines previous studies, including their contributions and limitations.

Following a literature review, two group work sessions were held with a panel of decision/policy makers to tap into their experience and expertise in management, sociology, architecture, geography and urban planning. These meetings allowed the panel members to share knowledge and experiences they had assimilated as professionals and to develop a valid, up-to-date and holistic analytical model. The results of these two group sessions were validated first by the expert panel and then by an external professional who was not a member of the panel, thus remaining external to the decision-making process and ensuring the neutrality of the final evaluation.

While previous studies have explored various aspects of urban planning and growth, few have adopted a structured methodology that combines techniques to identify, prioritize and analyze the interdependencies among key variables shaping urban development. By engaging a multidisciplinary panel of experts, we introduce a novel, constructivist approach that fosters collaboration and ensures a holistic understanding of urban sustainability. Beyond its theoretical contribution, our process-oriented study offers practical relevance, providing a systematic and transparent framework for decision-makers, urban planners and policymakers to identify critical factors influencing urban evolution and prioritize complex challenges.

Although the combination of cognitive mapping and ISM-MICMAC is well-established in the literature (*cf.* Çipi et al., 2023), the novelty of our research lies in its specific application to urban planning. While these methodologies have been used separately–or in conjunction with other techniques–in urban planning domains, our study uniquely integrates them within a participatory framework. This approach allows for an interactive exploration of the interdependencies and causal relationships among urban development variables, improving the understanding of how complex urban systems evolve and enabling more effective prioritization of challenges. Combined with expert validation, this holistic methodology represents a significant innovation in assessing urban growth determinants and how they may be addressed in policy planning.

Our findings provide actionable insights for designing and implementing strategies that address issues such as infrastructure, population density and environmental sustainability. Moreover, by validating the results through both expert consensus and external review, the study confirms the reliability and applicability of its outcomes in real-world scenarios. These contributions not only advance the academic discourse on decision/policy-making but also provide practical tools to support sustainable development of urban areas worldwide.

The following section contains the literature review and theoretical framework development. Section three describes applied methodologies. Section four describes the techniques' application and results, and the last section concludes while also suggesting limitations of this investigation and ideas for future research.

2. Related literature and research gaps

Planners and policy makers regularly distinguish between urban and rural areas within geographical spaces, although classifying these zones correctly is an extremely complex endeavor (Cordeiro et al., 2024). Each urban area encompasses at least one city but may include multiple *"towns, cities, and suburbs"* (National Geographic Society, 2022). These zones are characterized by high population density (Jones & Leather, 2012), and their economies revolve around non-agricultural activities (Gu, 2019; Correia et al., 2024).

Agricultural, industrial and transportation revolutions resulted in profound social transformations (*i.e.*, urban revolution) (Vlahov & Galea, 2002; Godfrey & Julien, 2005). At the broadest level, urbanization is a combination of population migrations from rural to urban areas and their associated diverse ideologies (Cordeiro et al., 2024). Vlahov and Galea (2002) observe that urbanization is a process in which agricultural activities shift to those commonly found in cities, along with corresponding changes in behavioral patterns. Mitchell (1956) and Correia et al. (2024) define urbanization as involving both demographic and sociological features. The former are directly linked to population movements from rural to urban areas, while the latter comprises residents' behavioral changes due to differences between urban and rural lifestyles (Ferreira et al., 2022; Pinto et al., 2023).

According to the United Nations (UN, 2018), the population residing in urban areas grew annually by an average rate of nearly 50% between 1950 and 2020, rising from 29.6% to 56.2%, and the rate is projected to reach 68.4% by 2050. In Africa, the percentage of inhabitants in urban areas is expected to reach 58.9% of the population by 2050 (UN, 2018). In Asia, the expected total will be 66.2%, while in Europe, the Americas and Oceania, it may reach 83.7%, 89.0% and 72.1%, respectively. Overall, regions with the highest percentage of urban population will be in North America and Europe. The global percentage of city residents in the Asian and Oceanic continents are expected to change little between 2020 and 2050, and Japan and New Zealand/Australia are expected to have the highest percentages of 95% and 91%, respectively (UN, 2018).

Urban areas are closely connected with both economic and social development, which highlights the varied commercial and societal variables that underlie economic growth (Andrade et al., 2022; Huang et al., 2023; Cordeiro et al., 2024).

Common social factors associated with urban zones, including increased demand for education and personal development, contribute to urban citizens' evolution. Another societal variable is the rising number of women in the labor market who must balance family and professional responsibilities while increasingly assuming greater power and authority in decision-making roles. A final social factor is clustering, which leads to specialization, adaptability to a changing job market and high productivity (Bertinelli & Black, 2004; Vieira et al., 2022; Vaz-Patto et al., 2024).

Referencing changing economic variables, Bertinelli and Black (2004) posit that migration from rural to urban areas results in an agglomeration of human capital in cities, which facilitates access to new technologies and knowledge, intensifies economic growth and reduces poverty. These changes in socioeconomic patterns occur due to migrations to urban zones that increase demand for consumer goods in cities, shift the focus of economic activities away from rural areas, boost productivity and, naturally, lead to higher wages and living standards (Martinez-Vazquez et al., 2014). Additionally, Chauvin et al. (2017) notes that incomes rise in larger, denser urban areas, further fostering a diversity of commercial activities, opportunities to create new jobs and easy access to varied facilities in fully developed environments offering a wide range of services and goods (Dociu & Dunarintu, 2012).

Urbanization is increasingly studied by academics and practitioners (*cf.* Vieira et al., 2022; Vaz-Patto et al., 2024), encompassing diverse theoretical perspectives that influence economic, social and environmental factors. Further, urbanization and cutting-edge industry development tend to occur simultaneously, resulting in economic growth (Idowu, 2013). Table 1 summarizes key observations and contributions of recent studies in the field of urbanism.

The limitations listed in Table 1 can be grouped into three basic shortcomings. First, many studies were conducted in only one country, which may result in site-specific findings that may compromise the generalizability of conclusions. Second, some studies failed to provide empirical support for stated findings, making the results less reliable. Lastly, in some studies, relevant determinants of urban development were identified using flawed methodologies, wherein causal relationships between factors were analyzed without empirically robust techniques (*cf.* Ferreira

Table 1. Contributions and limitations of prior research

Authors	Purpose	Results and contributions	Limitations
Limburg et al. (2005)	Clarify the connections between societal initiatives and ecosystems' responses	New policy tool focused on making multi-criteria decision evaluations to help resolve potential conflicts	Empirical support lacking
Martinez-Vazquez et al. (2014)	Identify the effects of urbanization on poverty reduction	Evidence of how the impact of urbanization on poverty reduction varies across regions worldwide	Based on a single case study
Ha et al. (2021)	Determine whether presence of poverty is related to degree of urbanization and what issues should be consider	Poverty significantly reduced with improved human capital, appropriate development policies, and agricultural support	Extremely specific results as only one country studied, which prevents generalization of findings
Ma and Tang (2022)	Improve the quality of tourism development in urbanization contexts and work toward green tourism	Policies need to promote tourism urbanization and rely on development methods aligned with local realities	No empirical support provided
Ran et al. (2022)	Classify areas that are crucial for regional ecological restoration in terms of urban agglomerations	Restoration strategies specifically based on land-use types and spatial distribution patterns to generate ideas for building regional ecological civilization	No empirical support provided and results quite specific as only cover one country, so cannot be generalized
Shaban et al. (2022)	Ascertain if a causal relationship exists between per capita income and urbanization rates	Granger causality method used to show that a one-way causal relationship exists between per capita income and urbanization rates	Based on a single case study

et al., 2022; Vaz-Patto et al., 2024). We address limitations regarding causal relationships between identified determinants by adopting a process-oriented approach based on cognitive mapping to structure a specific decision problem, followed by the application of ISM-MICMAC.

This methodological combination is particularly relevant given ISM's widespread use in decision-making contexts, where it assists in structuring complex decision problems and clarifies interrelationships among factors. Prior studies have applied ISM to urban planning, namely to analyze infrastructure development priorities and the interdependencies among sustainability indicators (e.g., Yadav et al., 2019; Dadashpour et al., 2025). However, these studies often apply ISM in isolation, without fully leveraging complementary methodologies to enhance robustness. Our study builds on these contributions by combining cognitive mapping and ISM-MICMAC, offering a more holistic and interactive approach to identifying critical urban growth determinants. This integration enables a deeper exploration of causal relationships, strengthening strategic decision-making in urban planning.

3. Methodological background

3.1. Group decision making

Decision making comprises three stages: (1) structuring; (2) evaluation; and (3) elaboration of recommendations (Fernandes et al., 2018; Soares et al., 2022). The structuring phase involves analyzing the problem and deciding which criteria to consider when making decisions. The panel of decision makers is also recruited, a trigger question discussed, and the outputs generated by the participants validated (Fernandes et al., 2018).

According to Dong et al. (2018), approximately 80% of the entire decision problem is defined in this first phase. Once the initial phase is completed, the evaluation phase proceeds with the decision makers' assessment of the criteria's interrelationships. In the final phase, other specialists suggest how the constructed model can be improved to strengthen the decision-making processes (Fernandes et al., 2018; Vieira et al., 2022).

These procedures can vary among work groups, but they essentially involve the group members expressing diverse opinions about a set of alternatives in order to choose the most beneficial option (Dong et al., 2018). Decision making is a common activity in human daily life (Zhang et al., 2017), and group work is a way to achieve better results via the contribution of multiple decision-makers (Abdel-Basset et al., 2018). In this process, the group also makes a specific choice based on as many alternatives as possible (Capuano et al., 2018; Soares et al., 2022). Group cohesion can be maintained and a clear understanding of each member's ideas can be reached when constant dialogue is encouraged among individual participants and group decisions rely on more than just intuition.

Group decision-making models focus on two processes: (1) reaching a consensus; and (2) selecting criteria (Li et al., 2018; Soares et al., 2022). In the first process, decision makers may need to adjust or change their opinions to align with the entire group's ideologies to generate the strongest possible consensus among the members. Reaching a consensus is closely tied to dynamism as successful decision making is directly linked to interactions between group members' convictions (Dong et al., 2018; Vieira et al., 2022), which are typically coordinated by a moderator or facilitator (Alonso et al., 2010). In the selection process, the group consensus forms the basis for generating a combination of individual and group convictions (Dong et al., 2018; Vaz et al., 2022).

3.2. Problem structuring methods (PSMs) and cognitive mapping

PSMs are used to help structure decision problems (Rosenhead & Mingers, 2001). These methods are designed to improve how systems and people function together (Freeman & Yearworth, 2017). Examples of widely disseminated PSMs include: (1) strategic options development and analysis (SODA); (2) soft systems methodology (SSM); (3) strategic choice approach (SCA); (4) robustness analysis; and (5) drama theory (*cf.* Mingers & Rosenhead, 2004). Among these, SODA stands out as a method that employs cognitive mapping. It involves creating cognitive maps (*i.e.*, visual representations of stakeholders' mental models (Ackermann & Eden, 2001; Vaz et al., 2022; Freire et al., 2023)), allowing for a comprehensive understanding of diverse perspectives on a given issue. The linkage between SODA and cognitive mapping is integral to uncovering viewpoints, interconnections and potential solutions within a decision problem.

Cognitive mapping, as facilitated by SODA, provides several benefits in decision-problem structuring. Firstly, it enhances understanding by visually representing complex causal relationships (Ferreira et al., 2022). Secondly, the graphical nature of cognitive maps facilitates effective communication among stakeholders, offering a shared visual language for discussing the intricacies of the problem (Vaz et al., 2022). Additionally, the process aids in identifying various options and potential trade-offs, aligning with SODA's focus on strategic options. Finally, the collaborative nature of cognitive mapping, within the SODA framework, contributes to improved group decision-making, incorporating diverse perspectives and leading to more inclusive and well-informed outcomes (Çipi et al., 2023). In essence, the integration of SODA and cognitive mapping offers a robust approach to decision-problem structuring, promoting comprehensive analysis and collaborative decision-making.

In addition to these widely disseminated PSMs, another notable approach in decision-problem structuring is ISM, which offers a comprehensive framework for visualizing and analyzing complex decision scenarios.

3.3. ISM

ISM was developed alongside PSMs, as a way to transform disorganized systems into coherent, well-defined structures (Attri et al., 2013; Bag & Anand, 2015; Shoar & Chileshe, 2021) by analyzing the relationships between interdependent variables (Talib et al., 2011; Li et al., 2019). This method can be applied to systems with a highly variable number of elements (Tyagi et al., 2022; Santos et al., 2024; Varela et al., 2025).

Created by Warfield (1974), ISM is a computer-assisted technique (Lyer & Sagheer, 2010; Satapathy et al., 2012) that facilitates the generation of enhanced graphical representations (Guo et al., 2012; Attri et al., 2013), and thus better problem perception in decision making (Kim & Watada, 2009). ISM is primarily used to summarize relationships between variables when defining a decision problem (Karadayi-Usta, 2020). This method has six main steps: (1) the structural self-interaction matrix (SSIM); (2) the reachability matrix (RM); (3) levels in the RM; (4) the lower-triangular format of the RM; (5) the ISM digraph; and (6) the ISM model (Sushil, 2012; Digalwar & Giridhar, 2015).

3.3.1. Step one

The first step is to formulate the SSIM, which requires the decision makers to understand that, if one factor influences another, a relationship exists between them. To identify the direction of the link between two factors *i* and *j*, four symbols are used: *V*, *A*, *X*, and *O*:

- *V* designates the relationship moving from factor *i* to *j*, indicating that *i* influences *j*.
- *A* stands for the link moving from factor *j* to *i*, specifying that *i* is influenced by *j*.
- *X* refers to a bi-directional relationship in which factors *i* and *j* influence each other.
- *O* is used when no link exists between factors *i* and *j*, indicating that they are unrelated to each other.

3.3.2. Step two

- The RM is constructed based on the SSIM, after the four symbols used in the first stage are replaced by 1 or 0 as follows:
- When the entry (*i*, *j*) in the SSIM is *V*, that entry becomes 1 in the RM, and the (*j*, *i*) entry becomes 0.
- When the entry (*i*, *j*) in the SSIM is *A*, that entry becomes 0 in the RM, and the (*j*, *i*) entry becomes 1.
- When the entry (*i*, *j*) in the SSIM is *X*, that entry becomes 1 in the RM, and the (*j*, *i*) entry becomes 0.
- When the entry (*i*, *j*) in the SSIM is *O*, that entry becomes 0 in the RM, and the (*j*, *i*) entry also becomes 0.

After the symbols have been changed, the RM is checked for transitivity. If transitivity is present, the SSIM has to be revised and step two repeated.

3.3.3. Step three

The reachability and antecedent sets are defined for each factor. The former set contains each factor itself and other factors on which the first factor may have some impact, while the latter set consists of the same factor itself and any other factor that may affect it. The factors' levels within the decision-support system are derived from the convergence of their own sets, based on the links stipulated between the factors (Oliveira et al., 2024; Çipi et al., 2025). Factors with the same reachability and intersection sets are placed at the top level of the SSIM. These factors are then excluded from further consideration in the subsequent steps. The procedure continues by searching for factors that fit in at the next level, repeating the process until the level of each factor is revealed. This repetition is an important part of developing the digraph and final outcome.

3.3.4. Step four

RM is transformed into a triangular format to identify the highest-level factors and position them in the first rows of the new matrix. Once the highest levels are defined, the process continues by arranging the next levels of factors into a lower-level triangular form. The rows with the most appearances of 0 are related to the highest-level factors, and the rows with the greatest use of 1 are linked to the lower-level factors.

3.3.5. Step five

In the fifth step, the ISM digraph is created to represent the hierarchy of determinants and eliminate transitive relationships. The factor at the highest level is positioned at the top of the digraph, and the factors at lower levels are placed in the digraph until the lowest level appears at the bottom (*i.e.*, the hierarchy of factors). Cycles may appear at some levels (*i.e.*, feedback between the levels and their factors). These cycles and their feedback should be eliminated to minimize the number of edges in the digraph.

3.3.6. Step six

The ISM model depicts the factors and their reachability in relation to those at the top level, which provides a clearer representation of the connections between the factors. According to Attri et al. (2013), this model has some advantages and limitations. The advantages include, first, a more efficient process as, depending on the decision-making context, the use of transitive inference can reduce the number of relational queries needed by 50 to 80 percent. Second, the process is more systematic as the modeling process can consider all possible relationships between pairs within the system. Last, decision makers do not have to have in-depth knowledge–only the necessary information to respond to the questions generated by the software.

The limitations, in turn, include, first, the possibility of numerous variables related to a single decision problem, which can increase the complexity of conducting ISM. Second, the models cannot be statistically validated, and, last, variables with a less significant impact on the problem may not be incorporated into the ISM model developed.

4. Application and results

4.1. Basic cognitive structure

The structuring phase of the present study relies on a panel of experts with knowledge about management, urbanism, architecture, geography and sociology, who applied the selected methodologies during two group work sessions. The selection of the expert panel was carefully aligned with established recommendations in the literature. According to Ackermann and Eden (2001), cognitive mapping is most effective when the facilitator works directly with a small group of participants–typically between three and ten individuals. In line with this guideline, our panel consisted of five decision-makers with recognized expertise in the topic under study. Efforts were made to ensure diversity in terms of gender, age and professional background. Although the participants were all based in Portugal, they had prior experience in European projects, offering broader perspectives. Their voluntary participation fostered a high level of engagement and ownership in the process. Because the study adopts a process-oriented approach, it is worth noting that the literature emphasizes that a detailed characterization of individual panel members is not always necessary (*cf.* Bell & Morse, 2013; Ormerod, 2013). The emphasis lies in the quality of the collective dialogue and the richness of the insights generated, rather than in the individual profiles *per se*.

The sessions were conducted online using the *Teams* platform. The panel members also made use of the *Miro* platform (see https://miro.com/), which offers suitable resources for applying the "post-its technique" (Ackermann & Eden, 2001). This platform facilitates simultaneous interactions among multiple users, thereby providing an environment conducive to collaborative work and efficient organization of the identified criteria.

The first session lasted approximately four hours and began with the introduction of each panel member, followed by a brief explanation of the *Miro* platform. The three procedures to be followed were then outlined: (1) identifying decision criteria of relevance to the model; (2) grouping the criteria into clusters; and (3) prioritizing the criteria within each cluster. The following trigger question was posed to obtain the criteria: *"Based on your knowledge and professional experience*, *what initiatives and/or actions do you think would improve urban areas in the future?"*. The decision makers used the "post-its technique" (Ackermann & Eden, 2001) to structure the model, writing each criterion considered important on a single virtual post-it note. The participants were also asked to identify each factor's causal relationship by adding a plus (+) or minus (–) sign, depending on the type of link with the decision problem. This procedure was completed when a sufficient number of criteria were identified.

In the second part of the first session, the criteria were grouped into five clusters labeled as follows: *Urban Design*, *Planning*, *and Public Spaces* (C1); *Quality of Life* (C2); *Sustainability* (C3); *Mobility* (C4); and *Technology* (C5). In the last procedure, the criteria within each cluster were prioritized by importance. The most significant factors were placed at the top of their cluster, the least important at the bottom, and the intermediate ones in between. A group map of 107 evaluation criteria was generated based on the information gathered from the exchange of the panel members' ideas during the first group work session, in this case using the *Decision Explorer* software (see http://www.banxia.com). In the second session, the map was analyzed by the participants, who agreed that no changes needed to be made, thus validating the cognitive map presented in Figure 1.

To further clarify, the clustering process follows an iterative and participatory procedure, consistent with established problem-structuring methods (*cf.* Ackermann & Eden, 2001). During the first facilitated session, the expert panel collectively organized the criteria into clusters based on their perceived conceptual proximity and mutual influence, rather than on rigid definitions. The final five clusters reflect a consensual understanding among the experts, derived through discussion and negotiation, aiming to balance thematic coherence with practical relevance. We acknowledge that some criteria may relate to multiple thematic areas, such as sustainability, which is inherently a cross-cutting concept. In such cases, and in line with the constructivist nature of the methodology, criteria could be simultaneously allocated to more than one cluster if the panel reached an agreement on their relevance in different contexts. This methodological decision aligns with the process-oriented nature of our study, which values the co-construction of meaning by stakeholders over externally imposed classifications (*cf.* Ackermann & Eden, 2001).

4.2. Evaluation phase: ISM and *Matrice d'Impacts Croisés Multiplication Appliquée à un Classment* (MICMAC)

After completing the structuring phase, the evaluation phase proceeded with the application of the ISM method. The second group work session lasted approximately two hours. The second primary technique of the present research was presented to and applied by the decision makers, starting with the panel's refinement of the list of the most important criteria within each cluster (*i.e.*, selected criteria (SC)) via multi-voting (*cf.* Table 2).

The next objective was to identify causal relationships between the clusters (*i.e.*, inter-cluster analysis) and between the criteria within each cluster (*i.e.*, intra-cluster analysis). As mentioned previously (see subsection 3.3), a direct relationship was assigned a *V*. An inverse relationship was given an *A*. No relationship was designated by an *O*, and a bidirectional relationship was given a *X*. An example of the procedure followed for all five clusters is given in Table 3, which presents the SSIM for C1.

Next, the RM was generated for each cluster (see Table 4 for C1's RM). First, the coordinates with the same criteria (*i.e.*, along the diagonal) were given a 1. Above the diagonal, the *V* and *X* links were then changed to 1, while the *A* and *O* connections were replaced by 0. Below the diagonal, the *A* and *X* relationships were changed to 1, while the remaining entries were replaced by 0.

In the next step, the cells with a 0 were shaded in yellow, which facilitated an analysis of possible transitivities (see Table 5). This procedure generated a final RM (FRM) for each cluster.

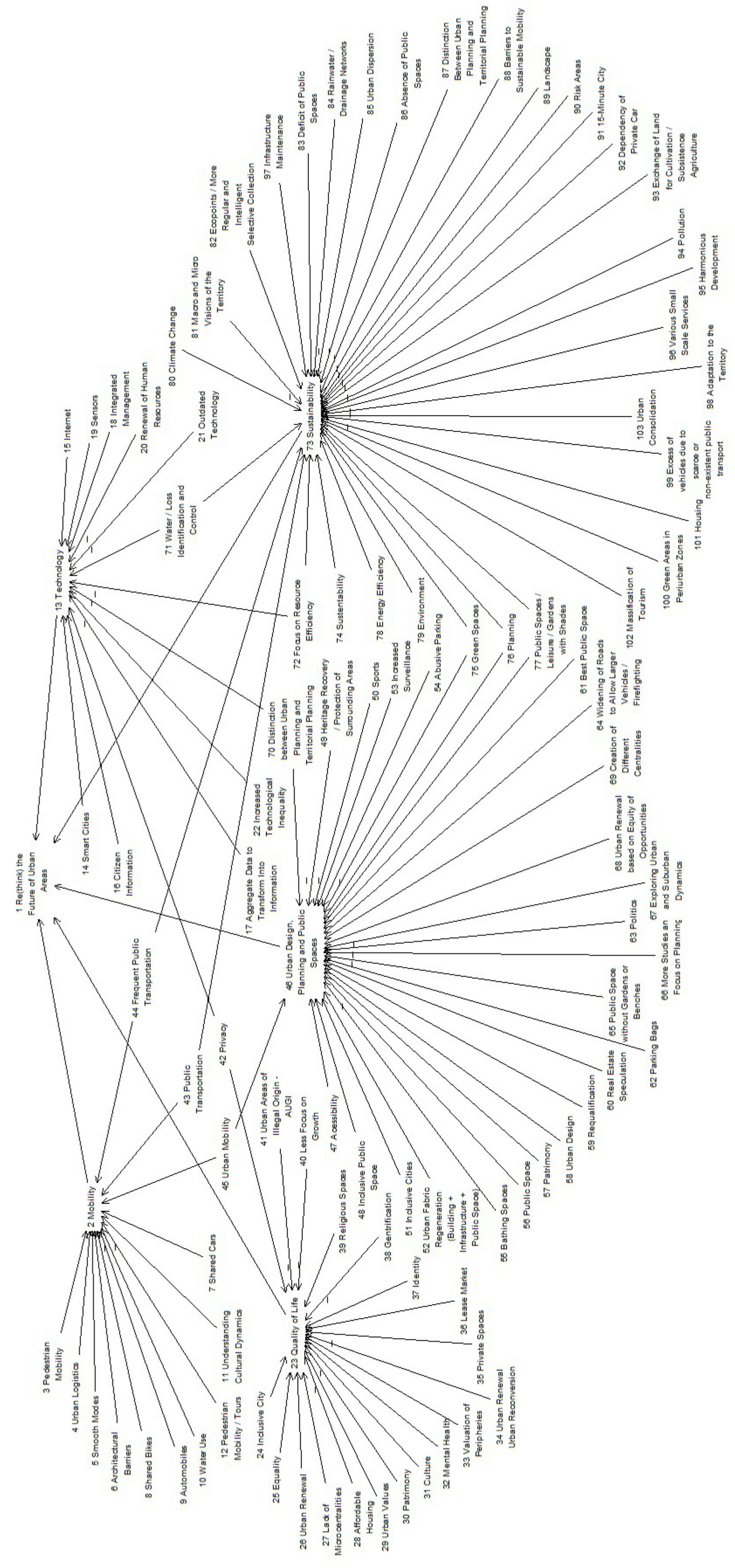


Figure 1. Group cognitive map

Table 2. Selected criteria by cluster

Cluster	#	Criteria
Urban design, planning, and public spaces (C1)	SC49	Heritage recovery / protection of surrounding areas (–)
	SC50	Sports
	SC56	Public space
	SC58	Urban design
	SC63	Politics (–)
	SC69	Creation of different centralities
	SC76	Planning
Quality of life (C2)	SC24	Inclusive city
	SC28	Affordable housing (–)
	SC29	Urban values
	SC30	Patrimony
	SC31	Culture
	SC33	Valuation of peripheries (–)
	SC34	Urban renewal / urban reconversion
Sustainability (C3)	SC43	Public transportation
	SC81	Macro and micro visions of the territory
	SC83	Deficit of public spaces
	SC89	Landscape
	SC90	Risk areas
	SC98	Adaptation to the territory
	SC100	Green areas in peri-urban zones
Mobility (C4)	SC03	Pedestrian mobility
	SC04	Urban logistics
	SC05	Smooth modes
	SC09	Automobiles (–)
	SC11	Understanding cultural dynamics
Technology (C5)	SC14	Smart cities
	SC15	Internet
	SC17	Aggregate data to transform into information
	SC18	Integrated management
	SC20	Renewal of human resources (–)

Note: SC – selected criterion.

Warshall's (1962) algorithm was applied to deal with possible transitivities in which as many steps were taken as the number of criteria defined in each cluster. First, all the criteria with a 1 were identified in the first column, and all criteria with a 1 were selected in the first row. Then, pairs of coordinates with criteria from the columns and rows with a 1 were identified.

Similarly, all criteria with a 1 were identified in the second column, and, in the second row, all criteria with a 1 were found. Again, pairs of coordinates with criteria from the columns and rows with a 1 were identified. The next step was to find intersections between a particular criterion in a column and a particular criterion in a row that contained a cell with a 0, which were then changed to 1* and displayed in red. The procedures remained similar for the remaining steps in each cluster, which produced their respective FRMs. Table 6 shows the results for C1, while Table 7 contains the final matrix.

Then levels for the SCs in each cluster were identified (*i.e.*, multi-level partitioning). The first to be analyzed was C1, in which SCs were placed in Level 1 when the first column of Table 8 (*i.e.*, the reachability set) was exactly the same as the third column (*i.e.*, the antecedent set). The first column showed how many times 1 or 1* was present in the FRM rows, while the second column referred to the times a 1 or 1* appeared in the same FRM columns. The third column represented the intersection between the first and second columns. When the first column was different from the third, the SC in question automatically moved to the next level (*i.e.*, Level 2). The same procedure was applied to each level, except that the SCs already assigned a level were not included when counting the times a 1 or 1* appeared in both columns and rows.

The MICMAC technique was applied to establish independencies among distinct variables. The first step was

Table 3. Structural self-interaction matrix for C1

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49		*A*	*V*	*O*	*X*	*A*	*V*
SC76			*V*	*V*	*X*	*A*	*V*
SC56				*V*	*X*	*A*	*V*
SC50					*A*	*A*	*V*
SC58						*A*	*V*
SC63							*V*
SC69							

Note: SC – selected criterion; *A* – inverse relationship; *V* – direct relationship; *O* – no relationship; *X* – bidirectional relationship.

Table 4. Reachability matrix for C1

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	0	1	0	1	0	1
SC76	1	1	1	1	1	0	1
SC56	0	0	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Note: SC – selected criterion.

to add up the 1 and 1* values for each column and row (see Figure 2). Then, these totals were allocated to each SC, bearing in mind that dependence power *x* is related to the columns and driving power *y* is linked to the rows. The coordinates (*x*, *y*) of each SC were used to construct a frame of reference to determine whether that SC fell into Quadrant I, II, III, or IV, as shown in Figure 2. In other words, each urban area determinant was classified as *independent*, *autonomous*, *linkage* or *dependent*.

Finally, the previously determined levels within each cluster were translated into a diagram, as shown in the C1 example in Figure 3. When horizontal connections were detected between the SCs, arrows were placed both to the right and left. When different levels appeared, an arrow

Table 5. Analysis of possible transitivities in C1

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	0	1	0	1	0	1
SC76	1	1	1	1	1	0	1
SC56	0	0	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Note: SC – selected criterion.

Table 6. Steps in Warshall's (1962) algorithm application for C1

Step 1

C1 = {SC49, SC76, SC58, SC63}

L1 = {SC49, SC56, SC58, SC69}

C1 × L1 = {(SC49, SC49), (SC49, SC56), (SC49, SC58), (SC49, SC69), (SC76, SC49), (SC76, SC56), (SC76, SC58), (SC76, SC69), (SC58, SC49), (SC58, SC56), (SC58, SC58), (SC58, SC69), (SC63, SC49), (SC63, SC56), (SC63, SC58), (SC63, SC69)}

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	0	1	0	1	0	1
SC76	1	1	1	1	1	0	1
SC56	0	0	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Step 2

C2 = {SC76, SC58, SC63}

L2 = {SC49, SC76, SC56, SC50, SC58, SC69}

C2 × L2 = {(SC76, SC49), (SC76, SC76), (SC76, SC56), (SC76, SC50), (SC76, SC58), (SC76, SC69), (SC58, SC49), (SC58, SC76), (SC58, SC56), (SC58, SC50), (SC58, SC58), (SC58, SC69), (SC63, SC49), (SC63, SC76), (SC63, SC56),(SC63, SC50), (SC63, SC58), (SC63, SC69)}

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	0	1	1*	1	0	1
SC76	1	1	1	1	1	0	1
SC56	0	0	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Step 3

C3 = {SC49, SC76, SC56, SC58, SC63}

L3 ={SC56, SC50, SC58, SC69}

C3 × L3 = {(SC49, SC56), (SC49, SC50), (SC49, SC58), (SC49, SC69), (SC76, SC56), (SC76, SC50),(SC76, SC58), (SC76, SC69), (SC56, SC56), (SC56, SC50), (SC56, SC58), (SC56, SC69), (SC58, SC56), (SC58, SC50), (SC58, SC58), (SC58, SC69), (SC63, SC56), (SC63, SC50), (SC63, SC58), (SC63, SC69)}

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	0	1	1*	1	0	1
SC76	1	1	1	1	1	0	1
SC56	0	0	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Step 4

C4 = {SC49, SC76, SC56, SC50, SC58, SC63}

L4 = {SC50, SC69}

C4 × L4 = {(SC76, SC50), (SC76, SC69), (SC56, SC50), (SC56, SC69), (SC50, SC50), (SC50, SC69), (SC58, SC50), (SC58, SC69), (SC63, SC50), (SC63, SC69)}

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	0	1	1*	1	0	1
SC76	1	1	1	1	1	0	1
SC56	0	0	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Step 5

C5 = {SC49, SC76, SC56, SC58, SC63}

L5 = {SC49, SC76, SC56, SC50, SC58, SC69}

C5 × L5 = {(SC49, SC49), (SC49, SC76), (SC49, SC56), (SC49, SC50), (SC49, SC58), (SC49, SC69), (SC76, SC49), (SC76, SC76), (SC76, SC56), (SC76, SC50), (SC76, SC58), (SC76, SC69), (SC56, SC49), (SC56, SC76), (SC56, SC56), (SC56, SC50), (SC56, SC58), (SC56, SC69), (SC58, SC49), (SC58, SC76), (SC58, SC56), (SC58, SC50), (SC58, SC58), (SC58, SC69), (SC63, SC49), (SC63, SC76), (SC63, SC56), (SC63, SC50), (SC63, SC58), (SC63, SC69)}

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	1*	1	1*	1	0	1
SC76	1	1	1	1	1	0	1
SC56	1*	1*	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Step 6

C6 = {SC63}

L6 = {SC49, SC76, SC56, SC50, SC58, SC63, SC69}

C6 × L6 = {(SC63, SC49), (SC63, SC76), (SC63, SC56), (SC63, SC50), (SC63, SC58), (SC63, SC63), (SC63, SC69)}

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	1*	1	1*	1	0	1
SC76	1	1	1	1	1	0	1
SC56	1*	1*	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Step 7

C7 = {SC49, SC76, SC56, SC50, SC58, SC63, SC69}

L7 = {SC69}

C7 × L7 = {(SC49, SC69), (SC76, SC69), (SC56, SC69), (SC50, SC69), (SC58, SC69), (SC63, SC69), (SC69, SC69)}

	SC49	SC76	SC56	SC50	SC58	SC63	SC69
SC49	1	1*	1	1*	1	0	1
SC76	1	1	1	1	1	0	1
SC56	1*	1*	1	1	1	0	1
SC50	0	0	0	1	0	0	1
SC58	1	1	1	1	1	0	1
SC63	1	1	1	1	1	1	1
SC69	0	0	0	0	0	0	1

Note: C – column; L – line; SC – selected criterion.

Table 7. Final reachability matrix for C1

	SC49	SC76	SC56	SC50	SC58	SC63	SC69	Dr Pw
SC49	1	1*	1	1*	1	0	1	6
SC76	1	1	1	1	1	0	1	6
SC56	1*	1*	1	1	1	0	1	6
SC50	0	0	0	1	0	0	1	2
SC58	1	1	1	1	1	0	1	6
SC63	1	1	1	1	1	1	1	7
SC69	0	0	0	0	0	0	1	1
Dp Pw	5	5	5	6	5	1	7	

Note: SC – selected criterion; Dr Pw – driving power; Dp Pw – dependence power.

Table 8. Multi-level partitioning for C1

	Reachability set	Antecedent set	Intersection set	Level
SC49	SC49-SC76-SC56-SC50-SC58-SC69	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC76	SC49-SC76-SC56-SC50-SC58-SC69	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC56	SC49-SC76-SC56-SC50-SC58-SC69	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC50	SC50-SC69	SC49-SC76-SC56-SC50-SC58-SC63	SC50	–
SC58	SC49-SC76-SC56-SC50-SC58-SC69	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC63	SC49-SC76-SC56-SC50-SC58-SC63-SC69	SC63	SC63	–
SC69	SC69	SC49-SC76-SC56-SC50-SC58-SC63-SC69	SC69	1
	Reachability set	Antecedent set	Intersection set	Level
SC49	SC49-SC76-SC56-SC50-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC76	SC49-SC76-SC56-SC50-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC56	SC49-SC76-SC56-SC50-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC50	SC50	SC49-SC76-SC56-SC50-SC58-SC63	SC50	2
SC58	SC49-SC76-SC56-SC50-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	–
SC63	SC49-SC76-SC56-SC50-SC58-SC63	SC63	SC63	–
	Reachability set	Antecedent set	Intersection set	Level
SC49	SC49-SC76-SC56-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	3
SC76	SC49-SC76-SC56-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	3
SC56	SC49-SC76-SC56-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	3
SC58	SC49-SC76-SC56-SC58	SC49-SC76-SC56-SC58-SC63	SC49-SC76-SC56-SC58	3
SC63	SC49-SC76-SC56-SC58-SC63	SC63	SC63	–
	Reachability set	Antecedent set	Intersection set	Level
SC63	SC63	SC63	SC63	4

Note: SC – selected criterion.

	Dp Pw *x*	Dr Pw *y*	Type	Quadrant
SC49	5	6	Linkage	III
SC76	5	6	Linkage	III
SC56	5	6	Linkage	III
SC50	6	2	Dependent	II
SC58	5	6	Linkage	III
SC63	1	7	Independent	IV
SC69	7	1	Dependent	II

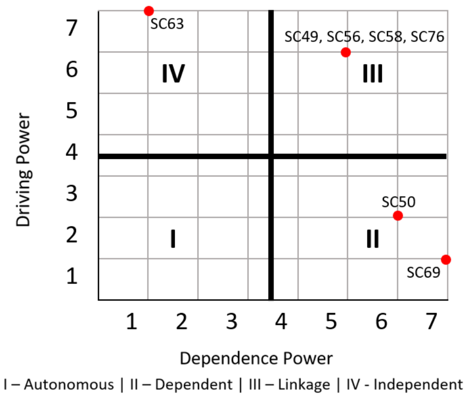
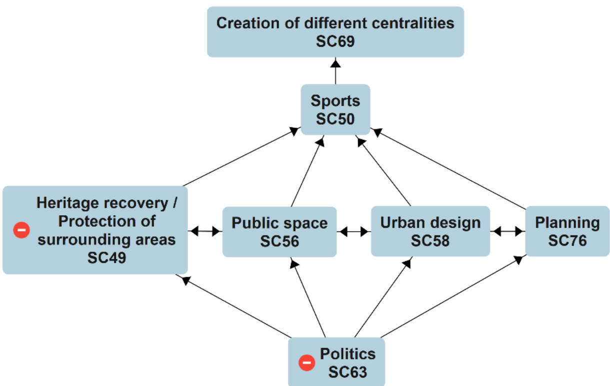


Figure 2. MICMAC of C1 variables



Note: SC – selected criterion; ⊖ – negative impact on the future of urban areas.

Figure 3. Final model digraph for C1

was drawn from the lower level determinants to the next level above. A minus (–) sign was added if an SC was considered to have an overall negative impact on the future of urban areas, during the criteria's definition in the first group work session.

Figure 3 shows that politics (SC63) is the basis for the entire hierarchy, as SC63 influences heritage recovery and/or protection of surrounding areas (SC49), public space (SC56), urban design (SC58), and planning (SC76), which all have the same level of importance. These SCs then encourage sports (SC50), which in turn influences the creation of different centralities (SC69). The procedure followed for this cluster was the same as for the others, after which a final ISM model could be created by combining the digraphs of the five clusters (see Figure 4).

Although certain SCs (*e.g.*, SC49 and SC63) are typically associated with positive contributions to sustainable urban development, they received a minus (–) sign because, within the scope of our analysis–particularly in the context of scenario planning and long-term urban evolution–the expert panel identified potential negative implications under certain circumstances. For example, while heritage recovery and protection helps preserve cultural identity and urban character, it may also restrict urban transformation, limit new construction and/or increase regulatory and financial burdens, especially in areas under pressure for densification or infrastructure renewal. Similarly, affordable housing (SC28)–despite its vital role in promoting inclusivity–can sometimes lead to the concentration of low-income populations in peripheral or underserved zones, potentially reinforcing patterns of social segregation or placing strain on local services and transport systems (Vaz-Patto et al., 2024). In line with the constructivist nature of the study, such assessments reflect the subjective perspectives of the expert panel and the trade-offs they considered when analyzing how each criterion might impact the future of urban areas under different conditions.

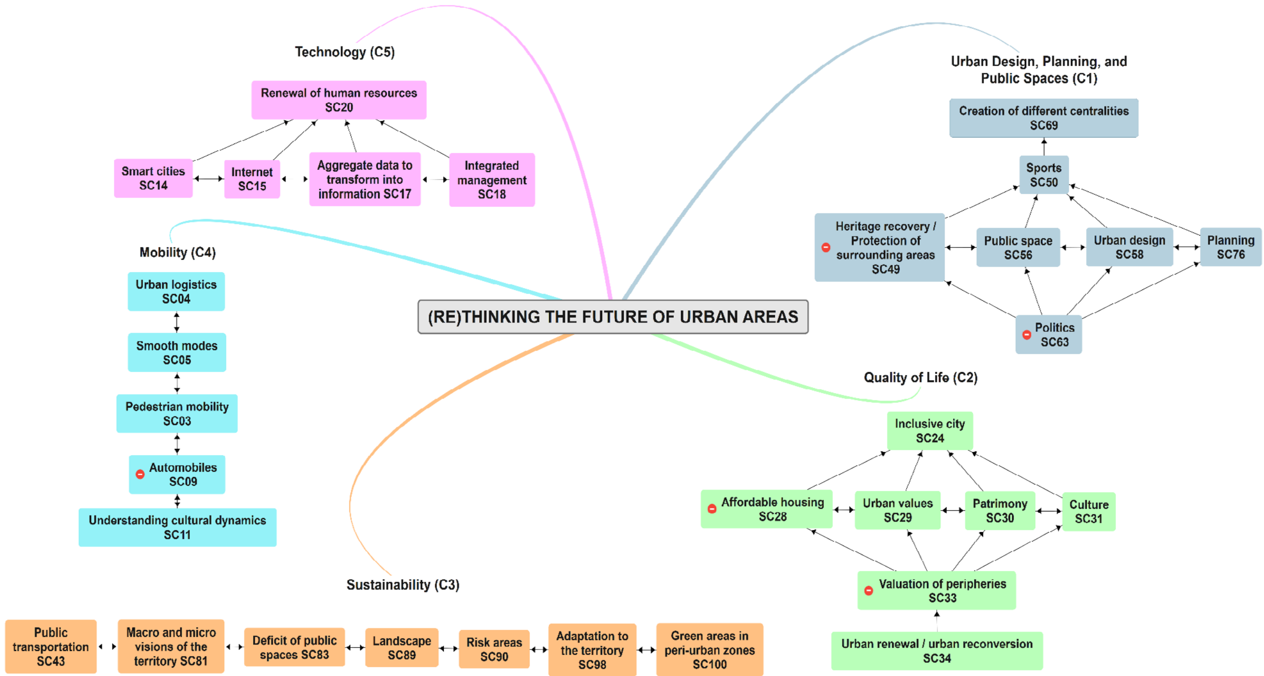
4.3. Consolidation, discussion and formulation of recommendations

A final consolidation session was held to analyze the practical applicability of the proposed evaluation system. An invitation was extended to a co-founder of the Ilha Atelier Association, as this person possesses professional knowledge of and experience in the future of urban areas. This specialist was not involved in the first two group work sessions, so he did not participate in the model development process. This neutral expert was invited to share his opinions about the expert panel's work. The session lasted approximately 45 minutes and was held online again.

Four objectives were defined for the consolidation session. The first was to clarify how the decision-support system was developed in the first two sessions using the applied methods. The second objective was to analyze the results and the advantages and disadvantages of the selected methodological approach. The third was to assess the applicability of the proposed model in specific situations and real-world contexts. The last objective was to suggest ways to improve the analysis system shown in Figure 4.

The interviewee was introduced to the session's objectives, after which the methodology applied to develop the evaluation system was explained. Next, the specialist was shown the cognitive map created with the decision-maker panel's input and asked to assess the map briefly. The results of the ISM-MICMAC application were also presented and evaluated.

After analyzing the panel's findings, the expert expressed agreement with the identified and structured



Note: SC – selected criterion; C – cluster; ⊖ – negative effect on the future of urban areas.

Figure 4. Final graph of the models for each cluster

criteria. He observed that the methodology *"involves general data collection, followed by categorization of the data and the relationships between them, thereby facilitating the creation of a cognitive map"* (in his words). The interviewee found the methods to be *"extremely valid"* (also in his words). One advantage identified by the expert was that the model generates a mental image highlighting the points of greatest interest while planning city development projects. This professional affirmed that the *"analysis allows for a quick and expedited understanding of what should be the primary focus of attention"* (again in his words). He also considered the hierarchy generated by the methods important.

However, the methodology relies on input from a single expert panel (*i.e.*, subjective opinions rather than factual data), which may be considered a disadvantage. The specialist was reminded that the decision-support system is necessarily process-oriented, so it should be seen as a learning mechanism rather than an end in itself or a tool for finding optimal solutions. The interviewee subsequently asserted that the proposed techniques should be adopted by local authorities and that the results would be especially interesting if various departments within local authorities started addressing the defined issues. He suggested that *"the different divisions should be combined, and their managers should identify which divisions should be talking to each other at specific moments as they work to solve certain problems. It* [this process] *could allow those involved to create a map of the relationships between organisms"* (in his words).

These findings reinforce the practical applicability of the proposed decision-support system, particularly in urban development contexts where interdisciplinary collaboration is crucial (*cf.* Fernandes et al., 2018; Pinto et al., 2023). By hierarchically structuring decision criteria, local authorities and planners may use this model to facilitate more integrated and efficient decision-making processes. The results align with previous studies that highlight the increasing importance of cognitive mapping and multiple criteria decision analysis (MCDA) in urban planning (*e.g.*, Andrade et al., 2022; Cordeiro et al., 2024; Correia et al., 2024). Additionally, while previous research has demonstrated the effectiveness of cognitive mapping and MCDA in structuring urban decision-making (*cf.* Vaz-Patto et al., 2024), this study advances the discussion by demonstrating how the integration of cognitive mapping and ISM-MICMAC can enhance the systematic analysis of interdependencies between decision criteria in urban planning contexts. The involvement of the external expert further contributed to assessing the coherence and practical feasibility of the proposed approach, reinforcing its relevance for urban development applications.

Finally, the guest expert agreed with the data gathered but thought that their applicability could be increased *"exponentially, as the digraphs could depict interrelationships between groups* [of SCs], *almost like a Venn diagram that shows areas that will interconnect"* (in his words). Thus, he felt important insights could be provided by expanding the present study to *"combine groups"* of SCs (his expression). This suggests an avenue for potential future research–*i.e.*, exploring how interconnections between SCs could further enhance decision-making effectiveness in urban projects. By extending the model to incorporate cross-sectoral linkages, future studies could provide deeper insights into systemic urban challenges and possible solutions. The session concluded with the interviewee providing additional positive and relevant feedback regarding possible future initiatives.

5. Conclusions

In recent years, the world's population has been growing at an unprecedented rate, making the future structure and livability of urban areas a critical and widely debated topic. Therefore, rethinking what urban planners and policymakers should prioritize in these dynamic and complex environments has never been more urgent. Addressing this multifaceted challenge requires a robust, up-to-date and holistic analytical framework.

This study proposes an innovative decision-support model that integrates cognitive mapping and ISM-MICMAC to identify, prioritize, and analyze the determinants of urban areas' sustainable evolution. This model not only provides a structured way to approach urban planning but also represents a significant contribution to the theoretical advancement of decision-making methodologies by combining participatory and constructivist approaches.

The proposed framework was designed to address three fundamental research questions: (1) How can the future of urban areas be anticipated?; (2) What are the most influential variables in urban processes?; and (3) How can decision-makers prioritize which complex challenges should be met to facilitate urban zones' sustainable evolution? Specifically, the combined application of cognitive mapping and ISM-MICMAC helps to identify and analyze a broad range of urban development variables and examines how they interact over time. This enables the anticipation of future challenges and opportunities in urban areas, offering valuable insights into potential urban growth scenarios. In this way, the study effectively addresses the first research question. To address the second question, the study facilitates the systematic identification of key variables and the assessment of their influence and dependence within the urban system. This facilitates distinguishing between driving forces, dependent variables and linkage factors, thereby clarifying their roles and significance in shaping urban development. Regarding the third question, the participatory and process-oriented nature of the framework supports the prioritization of complex challenges through consensus-building among experts. By structuring the decision-making process and visualizing interdependencies among variables, the framework empowers stakeholders to focus on the most impactful issues, enabling more strategic, transparent and sustainable urban planning decisions.

The study's findings provide robust answers to these questions, highlighting the importance of a decision-support model that integrates stakeholder input through cognitive mapping and applies ISM to structure and evaluate relationships between critical variables. This approach allows decision-makers to adopt a more informed, systematic and holistic strategy for addressing urban complexity, which is crucial for promoting sustainable urban development. Overall, this study presents a novel framework that integrates cognitive mapping and ISM-MICMAC to tackle urban planning challenges. It advances both theoretical and practical knowledge while providing clear, systematic answers to the three core research questions. The societal relevance of the study underscores its potential to foster sustainable urban development.

From a theoretical perspective, we contribute to the field of decision analysis by enhancing the integration of cognitive mapping and ISM within urban planning contexts. This integration facilitates the exploration of both qualitative insights and quantitative relationships, resulting in a more balanced and reflective decision-making process. By incorporating MICMAC analysis into the framework, the study improves the identification of influential variables and key leverage points within urban systems. These theoretical advancements deepen the academic discourse on PSMs and lay the foundation for future applications in similar complex decision-making domains.

The proposed model offers significant practical implications for urban planning and policy-making, identifying a straightforward yet powerful tool for understanding and addressing the complexities of urban systems. The participatory nature of the process fosters stakeholder engagement and collaboration, ensuring that decisions are informed by real-world expertise and perspectives. Urban planners, policymakers and other stakeholders can use this model to design strategies that are both actionable and well-informed, thereby improving the quality of urban development initiatives. By providing a deeper understanding of the factors driving urban sustainability, the model helps decision-makers prioritize investments, policies and interventions, ultimately creating cities that are resilient, inclusive and future-ready.

The societal implications of this study are equally significant. Rapid urbanization demands solutions that not only address infrastructure and resource challenges but also promote social equity and environmental sustainability. The proposed model, with its emphasis on inclusivity and collective learning, offers a pathway to achieve these goals. By fostering discussions among diverse stakeholders and integrating their perspectives, the model supports more equitable and sustainable urban development. Furthermore, aligning urban planning with broader societal goals–such as the United Nations Sustainable Development Goals (SDGs)–ensures that cities evolve in ways that promote well-being, economic opportunities, and environmental stewardship.

Despite its substantial contributions, this study has some limitations. The scheduling challenges and time constraints faced by panel members highlight the practical difficulties of participatory methods. Additionally, the model's reliance on expert judgment and subjective inputs may introduce biases or limit its generalizability. Future research should address these limitations by involving multiple panels across diverse contexts, enabling cross-panel comparisons to validate and enrich results. Such comparisons could reveal how cultural, geographic and socioeconomic factors influence urban planning decisions.

Looking ahead, emerging technologies such as artificial intelligence (AI), big data and Geographic Information Systems (GIS) offer promising opportunities to further refine ISM-based urban planning. AI and big data analytics could improve predictive accuracy, leading to more informed decision-making, while GIS technologies may enhance spatial analysis, enabling more precise mapping and evaluation of urban systems. Future research should and most likely will explore how these technologies can strengthen and expand existing frameworks, leading to more adaptive and responsive urban planning strategies. Ongoing investigations will further enhance the model's utility, ensuring that cities are better equipped to meet the challenges posed by growing populations while promoting long-term sustainability and resilience.

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