"Cities go smart!": A system dynamics-based approach to smart city conceptualization

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ABSTRACT

The world's population has grown rapidly. Thus, new challenges have arisen in terms of people's quality of life, natural resources renewal, and urban environment sustainability. The smart city concept was developed to deal with these challenges by incorporating new technologies in order to find solutions that preserve cities' environment while promoting their residents' wellbeing. However, for cities to be truly "smart", they should be evaluated, and, to that end, determinants that facilitate their creation need to be identified. This study thus sought to combine cognitive mapping and the system dynamics approach to find which factors foster smart city success, as well as the cause-and-effect relationships among these determinants. In two groupwork sessions, a panel of experts identified a wide range of smart city determinants and analyzed the dynamics of their relationships. The results were validated by the panel members and senior representatives of Cascais and Évora City Councils, Portugal, who confirmed that the analysis system developed provides a deeper understanding of this research context. The advantages and limitations of the proposed framework are also discussed.

1. Introduction

Over time, the need to convert urban areas into smart cities has become an increasingly pressing concern for all governments because these cities can have positive impacts on transportation systems, the environment, the economy, and residents. The smart city concept emerged in response to the major problems created when specific regions began to attract a higher number of inhabitants. These migrations resulted in air pollution, difficulties with managing resources, traffic congestion, public health challenges, and infrastructure unable to keep up with cities' permanent state of evolution (Miguel et al., 2019; Correia et al., 2020; Castanho et al., 2021; Ortega-Momtequín et al., 2021).

Smart cities appeared in response to these issues, using information and communication technologies to improve locals' quality of life and promote social and environmental sustainability (Faria et al., 2018; Fernandes et al., 2018; Kumar et al., 2019). In other words, these cities provide greater ease in communicating and exchanging information,

which allows the existing businesses to be more efficient and resilient to market fluctuations. Transportation networks also acquire different characteristics as they offer solutions that allow users to move around their city without battling congestion. These metropolises are further associated with the concepts of smart living and smart people, raising planners' awareness of how the mere existence of means is insufficient. Smart cities require citizens to become involved so that a relationship develops between infrastructure and residents, workers, or visitors (Castanho et al., 2021). These strategies culminate in and translate into a strategic vision of sustainability and environmental protection that pays attention to the limited nature of natural resources increasingly under pressure.

To determine whether cities comply with these guidelines, multiple areas need to be evaluated so that decisions can be consistent with the proposed objectives. However, the studies carried out thus far have had two general limitations. First, previous research has been based only on loosely defined indicators, namely identifying smart city determinants

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in unclear ways. Second, researchers have not carried out analyses of the dynamics between these determinants, thereby failing to develop holistic models that adequately represent the smart city concept (cf. Miguel et al., 2019).

The present study sought to fill this gap to provide decision makers with an analysis system that reflects smart cities as a whole, including accounting for objective and subjective variables related to a broad range of areas. The applied method took a constructivist stance, and it used the strategic options development and analysis (SODA) methodology (Ackermann and Eden, 2001), which is based on cognitive mapping. The latter tool structures complex problems and thus facilitated the identification of smart city determinants based on the values, experience, and knowledge of an expert panel. To complement the initial analysis, system dynamics (SD) (Forrester, 1961) was also applied to analyze the dynamics of the cause-and-effect relationships among the identified smart city determinants. SD enabled simulations based on hypothetical scenarios in which the weights given to one or more determinants were adjusted.

The proposed methodology stands out for its ability to identify causality links between variables over long periods and test various hypotheses by converting the entire process into a system of stocks and flows reflecting the most important relationships. The techniques used simplify and structure an extremely broad, complex topic, thereby helping decision makers make more conscious decisions based on real data. To apply the selected methodology properly, a panel of experts (*i. e.*, decision makers) was recruited from the experienced and knowledgeable professionals who deal with smart cities in order to portray these metropolises' various areas of interest.

Analyzing different smart city determinants and their existing cause-and-effect relationships is a complex but highly important decision problem. The combined used of cognitive mapping and SD facilitates the development of a decision-support mechanism that elucidates the way determinants are interrelated and promotes a strategic vision of and critical thinking about this topic. No prior evidence of this dual-methodology application in this research context was found. Thus, the present results constitute a novel approach within the extant literature on smart cities, strategic planning, and operational research.

The remainder of this paper is structured as follows. The next section presents a review of the literature on smart city, including the methodologies used in previous studies and their main limitations. The review contextualizes the rationale for using cognitive mapping to investigate this topic. Section three discusses the methodology applied. Section four describes the empirical research underlying the development of the cognitive map structure and application of the SD approach. The results and main limitations are also discussed. Section five concludes the paper by highlighting the main contributions to theory and practice and offering suggestions for future research.

2. Related literature

Over 50% of the world's population lives in urban areas and, by 2030, experts estimate that this figure will be around 66% (Camero and Alba, 2019). According to Albino et al. (2015), the latter values are no longer estimates in Europe but facts. That is, about 75% of the population already lived in urban areas at the time of the cited study and, by 2020, the percentage reached 80%. Therefore, thinking up solutions that allow planners to understand and organize their cities has become quite pertinent to making them more habitable.

Traditional cities have begun to develop new ways to organize themselves, giving rise to the concept of smart city (Shi et al., 2017). This term was coined in the United States, specifically in two institutions—International Business Machines and Cisco Systems—which applied the concept, for the first time, to creating the ideal city based on automated processes (Rosati and Conti, 2016). Since then, the topic of smart cities has gained increasing importance.

Bakici et al. (2013) and Ismagilova et al. (2019) define smart cities as metropolises that use cutting-edge technology to connect people, information and urban elements. This model requires carefully considering the available resources and thus providing a greener yet more economically developed city. Chourabi et al. (2012) also see smart cities in terms of housing focused on technological and sustainable resources. Mourshed et al. (2016), in turn, argue that these cities must address concerns about quality of life and become resilient enough to cope with climate change and an aging population. The smart city concept, therefore, includes various players and/or components considered "smart", namely: smart economy; government; people; mobility; environment; and quality of life.

The most attentive governments and citizens are interested in identifying which indicators most contribute to developing more aware, interactive cities. In this context, planners need to understand smart city determinants in order to analyze them. Table 1 presents some fundamental observations presented in prior literature.

Based on Table 1, smart city evolution cannot be restricted to physical aspects such as the construction of buildings and improvement of transportation networks. A more strategic approach to implementing measures is necessary, including appropriate urban assessment and analysis methods and techniques that aim to improve efficiency, equity and residents' quality of life (Miguel et al., 2019). Responding to these multiple criteria in a constantly changing environment is a difficult task given the amount of information accumulated in databases. Analyses of smart cities based on multiple criteria allow decision makers to explore a large amount of complex data since, by definition, these criteria should simplify situations that are challenging to understand into clearer forms of data. Evaluations of smart cities allow planners to understand whether they are moving toward the proposed goals (Carli et al., 2013; Marques et al., 2018; Pires et al., 2018; Reis et al., 2019). Table 2 presents methodological contributions made over the years specifically regarding smart city assessment.

The contents presented in Table 2 indicate that no prior study has developed an integrated decision-support system with a holistic view of smart city determinants. Albino et al.'s (2015) work reinforces how important these systems are given that they can stimulate cities while helping them achieve their goals. Many limitations presented in Table 2 arise from the relatively recent origins of smart city research, which make solid empirical evaluations difficult. In this context, developing an analysis system that can holistically evaluate smart city aspects appears

Table 1
Fundamentals of analyses of smart city determinants.

Authors	Fundamentals
Carli *et al.* (2013)	• To achieve smart cities' objectives, tools are needed to indicate whether these metropolises are moving toward the proposed goals.
Khatoun and Zeadally (2016)	• Indicators must be identified that can measure how much progress is needed to improve residents' quality of life and achieve sustainability.
Mourshed *et al.* (2016)	• Smart city evaluations allow planners to allocate resources efficiently, ensuring cities can constantly evolve.
Ahvenniemi *et al.* (2017)	• Evaluation models can support decision making in urban development since they show how cities can move forward to reach their objectives.
Huovila *et al.* (2019)	• Assessing smart cities using indicators means that the progress of these cities can be analyzed to demonstrate the impacts of implemented solutions.

quite pertinent, and the high complexity of the topic leaves room for new methodologies and approaches that fill the gaps left by previous studies. Two types of general limitations can be deduced from the extant literature on smart cities. The first is the unclear manner in which smart city determinants are identified, while the second is an absence of research that includes dynamic analyses of the interrelationships among these determinants.

Given the limitations of prior studies, cognitive mapping was selected as a technical mechanism that could facilitate the identification of decision/evaluation criteria through an evaluation of smart city determinants. The SD approach, in turn, was chosen to conduct a dynamic analysis of the criteria's cause-and-effect relationships. As mentioned previously, this methodological combination is an innovation in research on this topic.

3. Methodology

The existing studies identified in the previous section sought to analyze smart city determinants. However, their results present methodological limitations that compromise the clarity of the findings and leave room for new research focused on overcoming these limitations.

3.1. Human cognition and cognitive mapping

Understanding the complexity of human cognition is quite important because, during individuals' daily life, they face numerous problems that require them to make decisions (Ferreira et al., 2011). Whenever these decisions take place, human values and cultural factors are part of finding the best solutions (Keeney, 1992). This process relies on mechanisms that support decision making.

The idea of cognitive maps originated with Tolman (1948), who,

during a learning trial, placed a rat in a labyrinth to analyze the rodent's behavior. To navigate the labyrinth, the animal developed a cognitive process in response to the environment, which guided the rat's movements and overall mobility (Cossette and Audet, 2003). Transposing this study to research on human cognition, Wong (2010) found that cognitive mapping consists of a series of psychological transformations whose purpose is to shape the way information about environment-specific characteristics is treated.

Eden and Ackermann (2004) assert that cognitive maps are models in the form of a diagram that are translated into representations of preferences, convictions, beliefs and goals. These maps reflect how specific individuals' experience create perceptions of problematic situations. Filipe et al. (2015), Simões et al. (2020) and Silva et al. 's (2021) studies reinforced this reasoning, highlighting the importance of cognitive maps in negotiations and the assistance provided to those responsible for interpreting and structuring decision problems. According to Wong (2010: 288), *"cognitive mapping encompasses the terms of causal mapping, semantic mapping and concept mapping, which usually also refers to mental models, mental maps, cognitive maps, scripts, schemata, and frames of reference. Cognitive mapping techniques are usually used to identify subjective beliefs and to portray these beliefs externally"*.

Cognitive maps resemble influence diagrams in which individuals' concepts are visualized (Mackenzie et al., 2006) and the relationships between concepts are represented by arrows (Montibeller et al., 2008). Cognitive mapping thus minimizes the possibility that criteria will be omitted and strengthens decision makers' understanding of the cause-and-effect relationships between factors (Jalali et al., 2016; Azevedo and Ferreira, 2019; Ferreira et al., 2021). Fig. 1 provides an example of a cognitive map.

Cognitive mapping usually starts with oral or written interactions within or between decision makers, which allow them to ascertain

Table 2
Synthesis of related studies.

Authors	Methods	Contributions	Main Limitations
Lombardi et al. (2012)	Triple-helix model and analytic network process	• Support for the formulation of guidelines for identifying smart city determinants. • Intuitive system focused on performance indicators.	• A practical application was not conducted. • The system only indicates current performance rather than finding long-term patterns in determinants.
Dall'O et al. (2017)	Organization for International Standardization (ISO) 37120	• Applicability to specific contexts. • Focus on developing smart policies based on environmental concerns.	• The ISO standard was only applied in Italy, and the results cannot be generalized without first being empirically validated. • The standard constantly needs to be updated to take into account technological developments.
Romão et al. (2017)	Latent growth curve modeling	• Ability to define standards for indicators of what attracts residents and tourists. • Acknowledgement of the importance of finding ways to balance these two population segments.	• This study divided the research population into residents and tourists without considering the determinants that appeal to each type of residents (*e.g.*, researchers, government, and workers). • The model was applied to extremely diversified areas. Thus, the results fail to identify specific determinants.
Borsekova et al. (2018)	Decision tree modeling	• Identification of indicators according to the size of the city in question. • Evidence that cities considered smart are more environmentally conscious.	• The method was only applied to European cities. • The number of indicators is reduced, and their cause-and-effect relationships are imprecisely defined.
Lim et al. (2018)	Case analysis and action research	• Basis for urban planning and policy development to accommodate the digital economy. • Development of knowledge about and guidelines for technology use in cities.	• The relationships identified are not deep enough to be useful when evaluating smart city indicators and determinants. • No single system was developed to integrate the variables.
Yigitcanlar et al. (2018)	Systematic literature review	• Ability to aggregate subthemes of city factors and relate these to city planning objectives. • Development of a new smart city multidimensional structure.	• The research provided "loose" indicators that were not integrated into a single system. • The study only used a theoretical approach without any experimental methods. • The characteristics presented are generalized. Thus, they cannot be adapted to match each city's realities.
Huovila et al. (2019)	Definition of indicators using smart city standards	• Guidelines to help leaders identify the standards that best suit their cities' needs. • Possible characteristics of indicators.	• The guidelines are simplified. Thus, they do not indicate in advance what the determinants are. • The results do not include a system that can generate smart and sustainable cities at the same time.
Sharif (2019)	Case analysis	• Indicators' weaknesses that must be discussed in the future. • Tools that make positive contributions to city evolution.	• The methodology was recently developed. Thus, it still lacks empirical research to confirm how useful the approach is.

relevant concepts that are then used to build cognitive maps. The discussion facilitators need to pay attention to the way the information shared by the decision makers is interpreted because the purpose of cognitive mapping is to clearly represent the decision makers' thinking about the problems under discussion (Cossette and Audet, 2003; Village et al., 2013). This technique identifies decision criteria, reduces errors and fosters the finding of appropriate solutions for specific situations through an intensive examination of both quantitative and qualitative data (Jalali et al., 2016; Barão et al., 2021). These maps can be especially useful in smart city contexts.

3.2. SD approach

The SD approach was first developed by Forrester in 1958 (cf. Forrester (1961)). According to Mansilha et al. (2019), this methodology is based on the concepts of systemic thinking and systemic method. The associated models facilitate analyses of variables as dynamic systems, treating these as a single unit. The SD approach seeks to explain decision effects on complex and dynamic systems by highlighting internal structures and visualizing the causal relationships between concepts. This methodology also generates models that are suitable for depicting driving forces in socioeconomics and simulations of complex systems and that are able to facilitate decision making in constantly changing environments that may involve different scenarios (Han et al., 2009). Castellacci (2018: 273) defines SD as *"a modeling methodology that studies the dynamic interactions and feedback effects among a set of variables that compose a system"*. The variables are treated as stocks with inputs and outputs that determine their value. In this way, information also flows throughout and connects the entire system.

According to Thaller et al. (2017), Fonseca et al. (2020) and Paes de Faria et al. (2020), the need to make informed decisions highlights a gap in the search for models that consider and explain patterns of functional behavior and correlations between subsystems. The SD approach is thus a useful modeling technique that creates a transparent, detailed structure allowing decision makers to identify the relationships between multiple variables, as well as the impacts of changes in any of these variables. Jokar and Mokhtar (2018), Pereira et al. (2020) and Paiva et al. (2021) highlight four phases in the methodology applied in the present study. The first is identifying the problem and the associated needs and the desired results of its resolution, as well as stipulating the variables in question and the system durability. The second phase is developing a model by identifying the cause-and-effect relationships between variables and constructing diagrams. The third phase is validating the model, which facilitates an assessment of whether the results obtained are in theory consistent with reality. The last phase is providing guidelines based on the evaluation and analyzing which processes to follow to improve the situation in question.

Zomorodian et al. (2018) and Rodrigues et al. (2020) state that, after identifying the problem, the SD approach allows decision makers to

develop causal loop diagrams (CLDs) to visualize the cause-and-effect relationships between multiple concepts. At a later stage, these CLDs are transformed into stock and flow diagrams (SFDs) so that the CLD logic can be expressed mathematically. In CLDs, the dynamics between variables oscillate between positive and negative loops. In positive ($+$) loops, ideas are reinforced, which, in turn, contribute to variables' augmentation. In negative ($-$) loops, the effect is inversely proportional, so decision makers need to take corrective measures (Walters et al., 2016). CLDs also consist of multiple nodes and edges. Castellacci (2018: 273) explains that *"nodes are the variables composing the system, and edges are arrows representing the causal relationships among these variables"*. In contrast, SFDs are represented by integral equations that refer to the analysis system quantification (Castellacci, 2018). The introduction of new elements into the visualization, namely stocks and flows, also needs to be highlighted. These relationships can be represented by Equation (1) (Drews et al., 2016; Cai et al., 2019):

$$Stock_t = Stock_{ts} + \int_{ts}^{t} (Inflow_s - Outflows_s)\, ds \qquad (1)$$

The stocks are the system's current reality and the result of past activities, which can be changed by adding flows that represent the rate of change associated with stocks (Drews et al., 2016; Ahmadi and Zarghamib, 2019). In addition, inflows and outflows appear as auxiliary variables (*i.e.*, converters) that act through stock oscillations at time *s*. The initial time is represented by *ts* and the present time by *t*, both of which influence decision-making processes (Drews et al., 2016; Cai et al., 2019). Thaller et al. (2017: 1077) add that *"the specific feature of SD is its non-linear feedback structures and functions"*, in which flows are formalized in differential equations and auxiliary mechanisms related to algebraic functions. Finally, the connectors link all the above elements via arrows.

The SD methodology thus facilitates placing assumptions within systems and running tests on these assumptions, thereby elucidating the cause-and-effect relationships between the variables related to the decision problem in question. Combining SD with cognitive mapping has great potential in the context of smart cities.

4. Methodological application and analysis of results

Analyzing smart city determinants in order to develop improvement initiatives presents a highly complex decision problem because countless, constantly changing variables need to be considered. For this reason, the present study used the SODA methodology (Eden and Ackermann, 2001)—based on cognitive maps—and the SD approach. These methods together enabled a holistic representation of the problem, which reflected a wide range of perspectives and included objective and subjective elements.

To apply the selected methodologies correctly, a panel of specialists (*i.e.*, decision makers) was recruited from among the professionals with
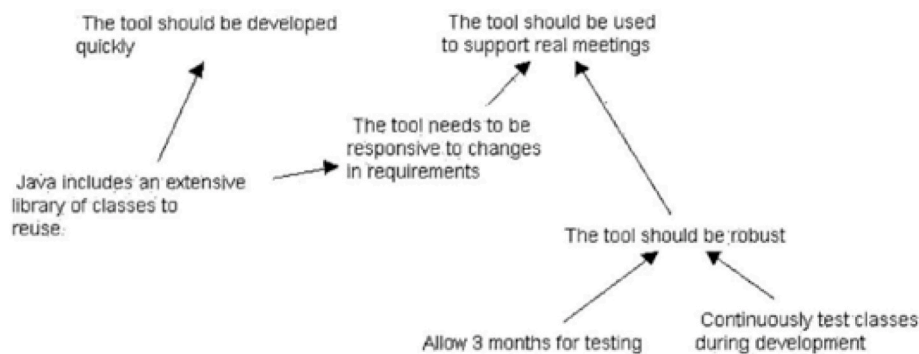

Fig. 1. Basic example of cognitive map.
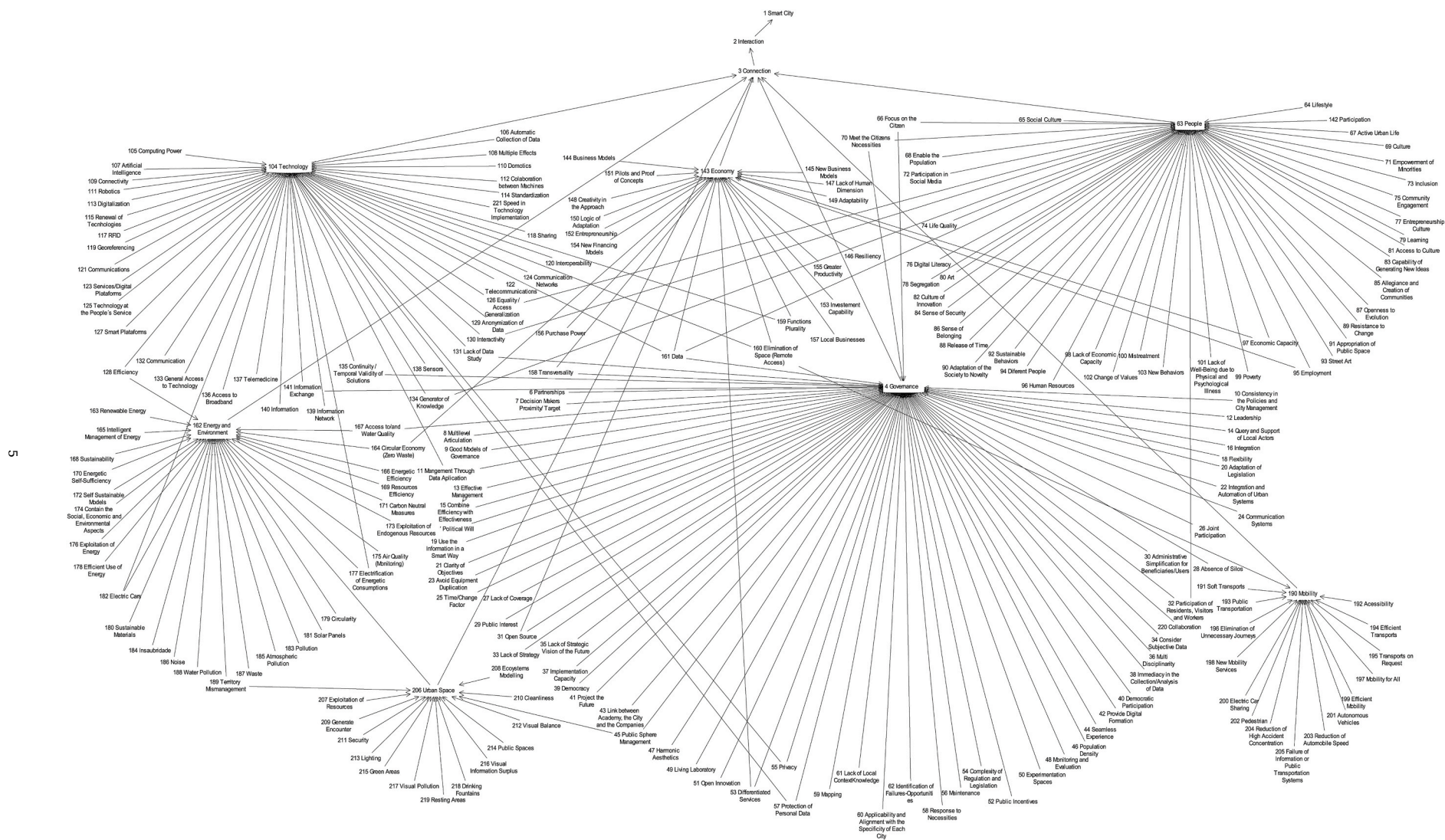Source: Mackenzie et al. (2006: 160)

Fig. 2. Group cognitive map.
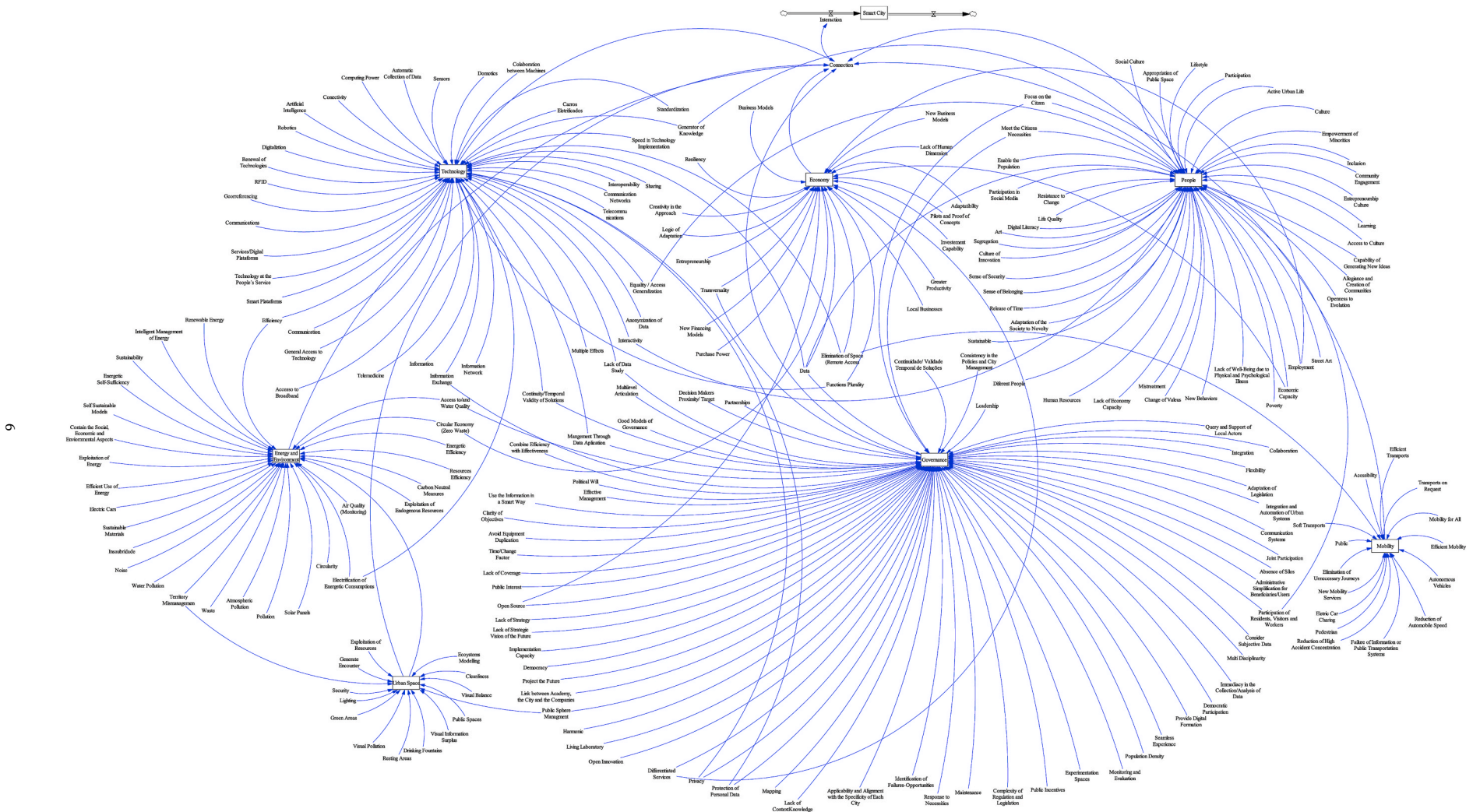Source: Vaz et al. (2021).

Fig. 3. SFD of smart city determinants.

experience in and extensive knowledge about smart cities in order to incorporate the topic varied areas. After the panel was formed, two groupwork sessions were held. The first one focused on identifying smart city determinants so that the *Decision Explorer* software (www.banxia.com) could be used to generate a group cognitive map. The second session involved validating the cognitive map and assigning degrees of intensity to the cause-and-effect relationships between determinants.

After the sessions, the cognitive map was rebuilt using to the *Vensim* software (https://vensim.com/), which ran simulations based on future scenarios to identify specific decision consequences. These simulations were determined by oscillations induced in the determinants' intensities, thereby enabling quantitative and graphical visualizations of decision impacts. A formal analysis of the results produced a greater awareness of the benefits of specific improvement initiatives, making the proposed methodology an extremely useful tool in decision-making processes in smart city evaluations.

4.1. Definition of decision problem and initial cognitive structure

To create the necessary cognitive structure, two meetings were conducted with the expert panel. According to Eden and Ackermann (2001), the panel needs to include from 3 to 10 decision makers to ensure the coherence and validity of results. The panel comprised seven members in order to follow the guidelines provided. In addition to different levels of knowledge about and years of experience with smart cities, various other criteria guided the selection process. First, the participants needed to have expertise in and experience with energy and environmental issues. Second, the decision makers had to been responsible for technology-related operations. Third, the experts needed to work in areas dealing with mobility and transportation. Fourth, the specialists had to have developed an architectural and urban vision. Last, the panel members' functions needed to combine economic development with innovation.

The two sessions lasted approximately 4 h each, and they were attended by 2 facilitators (*i.e.*, researchers) whose function was to guide and record the data obtained. The first group meeting was divided into three phases: (1) identifying smart city determinants; (2) grouping them into clusters; and (3) forming a hierarchy of concepts within the clusters. After the research project was introduced, the decision makers were asked the following trigger question: *"Based on your values and professional experience, what factors and characteristics foster the best smart cities?"*. The smart city concept had been previously clarified fully, and any doubts regarding the related issues had been addressed.

At this point, the "post-its technique" was applied (Ackermann and Eden, 2001) so that the decision makers could write on each post-it note the criteria that the experts felt best answered the trigger question. Each note could only contain one criterion. The panel members were also asked to put a negative sign (−) in the upper righthand corner of the respective post-it note whenever a specific concept had a negative influence on smart city development (*i.e.*, a negative cause-and-effect relationship) (Eden and Ackermann, 2001). The post-it notes were then placed on a vertical whiteboard so that all the participants could see the results (Eden and Ackermann, 2001; Ferreira and Jalali, 2015).

In the next phase, the panel members were tasked with grouping the concepts into clusters (*i.e.*, areas of interest or concern). The process of organizing the criteria into clusters started with the identification of possible clusters. All the concepts were then allocated to an existing cluster, with some determinants associated with several clusters. This procedure continued until all the criteria were placed into at least one cluster. During the process, various determinants with the same meaning (*i.e.*, redundant criteria) were eliminated with the decision makers' consent. The panel members were also given the opportunity to change the determinants' name and/or cluster whenever they found this necessary. The results included six main clusters and one subcluster: (1) technology; (2) mobility; (3) people; (4) energy and the environment plus urban spaces; (5) governance; and (6) economy.

In the last phase of the first session, the decision makers reordered the determinants hierarchically within each cluster. The most important determinants were placed at the top of the respective cluster and the least relevant criteria at the bottom (*i.e.*, base). Fig. 2 displays the resulting group cognitive map after it was validated by the panel members based on intensive collective analysis and discussion (as size restrictions prevent a better visualization, an editable version of the group cognitive map is available upon request).

The cognitive map presented in Fig. 2 brings together all the concepts and clusters identified by the panel members (*i.e.*, a total of 220 criteria), which reflect their knowledge about and experience with the subject under discussion. The second session started with a collective analysis of the map generated during the first meeting. After it was validated, the decision makers were asked to focus their attention on the cause-and-effect relationships between the variables in order to establish the intensity degrees of these links based on the interval [–1, 1]. Whenever the criteria in question had a negative relationship, the range was [–1, 0 [. The interval]0, 1] was used whenever a connection was positive (Barroso et al., 2019; Miguel et al., 2019). The SD approach could then be applied to the criteria's relationships.

4.2. Dynamic analysis of results

The SD approach allows decision makers to examine the dynamics of variable interactions, cause-and-effect relationships, and feedback links between indicators (Assunção et al., 2020). Thus, SD facilitates a deeper understanding of the analysis system over time and the implications of each concept within that same overall structure. In complex and dynamic contexts such as smart cities, technological advances result in a constant restructuring of society. Thus, the SD approach provides significant support for decision making.

Based on the information gathered during the two group meetings (*i.e.*, the group cognitive map and the intensity degrees of the cause-and-effect relationship), an SFD was created that allowed scenarios and simulations to be run. Fig. 3 shows the SFD developed for the present study (an editable version is available upon request).

Based on Fig. 3, the main stock comprises the dominant concept in the current research—the smart city dynamics variable. This variable is linked with an inflow that can change over time that is termed "interactions". The inflow is influenced by another inflow—connections—that, in turn, is affected by seven stocks (*i.e.*, the variable clusters identified in the first session by the expert panel). These clusters consist of agglomerations of concepts or constant variables.

When the concepts were aggregated, the formulae used for each cluster had to be similar and coherent with each other, thereby following a logic of centrality to match the practical realities of the analysis system. The function that brings together the technology, mobility, people, energy and the environment plus urban spaces, governance, and economy clusters produces the sum of the intensity degrees of these concepts. In mathematical terms, this integral function aggregates all the variables with which each cluster has a cause-and-effect relationship, which is then divided by 100 to avoid an exponential increase in the scale (*i.e.*, oversizing). The aggregation equations applied are shown in Table 3.

The constant variables do not involve aggregation formulas since these criteria were assigned cause-and-effect degrees of intensity by the expert panel during the second group session. In the technology cluster equation, *Technology(t)* represents the value of the technology dynamic variable at time *t*. Thus, $T(t_0)$ corresponds to the value of the technology cluster at time t_0 (*i.e.*, the initial moment). *Indicators T* total refers to all the degrees of intensity of the technology cluster indicators that have an associated cause-and-effect relationship. The remaining cluster aggregation equations followed the same logic.

The analysis using Equation (9) included verifying that a logarithmic function was used in the cluster agglomeration to ensure its stability. *Connections(t)*, therefore, represents the values of the connections at time *t*, while *T(t)* stands for the technology cluster value at time *t*. In

addition, $M(t)$ is the value of the mobility dynamic variable at time t, $P(t)$ represents the people cluster value at time t, and $EA(t)$ shows the value of the energy and the environment cluster at time t. $EU(t)$ further translates the value of the urban spaces subcluster at time t, $G(t)$ represents the value of the governance cluster at time t, and $E(t)$ stands for the value of the economy cluster at time t. In Equation (10) in Table 3, *Interactions(t)* is the value of the interactions inflow at time t using the connections' logarithmic function. Finally, the same logic was followed with Equation (11), which guided the process that revealed the main stock. In this equation, *Smart City (t)* stands for the value of smart cities at time t, *Smart City*(t_0) corresponds to the value of the smart city stock at time t_0, and *Interaction(t)* indicates the value of the interactions inflow at time t. Once again, the integrals' value had to be divided by 100 to avoid oversizing the scale. After the SFD was constructed, a horizon of 100 months was defined for the three simulations: intra-cluster, inter-cluster, and multi-cluster.

4.2.1. Intra-cluster analysis

The simulations started with the intra-cluster analysis, which consisted of measuring the effect on a specific cluster of changing the intensity degree of its cause-and-effect relationships. The technology cluster was subjected to a negative scenario in which a social deficit occurs in the formation and/or acquisition of human capital skills

related to technological knowledge, namely programming. This scenario was applied in *Simulation 1*.

The values of the determinants were changed by -0.5 to mirror the negative impacts associated with the first scenario. The factors involved were computing capacity, digitization, domotics, knowledge generator, artificial intelligence, interoperability, smart platforms, automatic data collection, information network, renewal of technologies, robotics, and telemedicine. The changes made in the technology cluster are represented in Fig. 4 by the values projected along the blue line, under the caption "Intra-cluster (1)".

Fig. 4 confirmed that the absence of qualified human capital in technological areas has a negative impact on the performance of the technology cluster, reducing its centrality by six points over time. The value of the knowledge generator determinant changed with the first scenario and included cause-and-effect relationships with the technology and people clusters, which thus caused more than one variation in the model. This phenomenon is visualized in Fig. 5, which shows a negative effect of -0.5 on the performance of the people cluster.

Simulation 2 was conducted with the mobility cluster so that the second scenario consisted of intensive social interventions to make the transportation network more dynamic. The interventions created more sophisticated means of transportation and considerably increased the mobility of smart city residents. The variables affected were:

Table 3
Aggregation equations.

Variables	Aggregation Equations	
Technology		
	$Technology(t) = T(t_0) + \int_{t_0}^{t} \left(\frac{\sum Indicators\ T}{100} \right)$	(2)
Mobility		
	$Mobility(t) = M(t_0) + \int_{t_0}^{t} \left(\frac{\sum Indicators\ M}{100} \right)$	(3)
People		
	$People(t) = P(t_0) + \int_{t_0}^{t} \left(\frac{\sum Indicators\ P}{100} \right)$	(4)
Energy and the Environment		
	$Energy\ and\ Environment(t) = EA(t_0) + \int_{t_0}^{t} \left(\frac{\sum Indicators\ EA}{100} \right)$	(5)
Urban Spaces		
	$Urban\ Space(t) = EU(t_0) + \int_{t_0}^{t} \left(\frac{\sum Indicators\ EU}{100} \right)$	(6)
Governance		
	$Governance(t) = G(t_0) + \int_{t_0}^{t} \left(\frac{\sum Indicators\ G}{100} \right)$	(7)
Economy		
	$Economy(t) = E(t_0) + \int_{t_0}^{t} \left(\frac{\sum Indicators\ E}{100} \right)$	(8)
Connections		
	$Connections(t) = LN\ (T(t) + M(t) + P(t) + EA(t) + EU(t) + G(t) + E(t))$	(9)
Interactions		
	$Interactions(t) = LN\ (Connection\ (t))$	(10)
Smart Cities		
	$Smart\ City(t) = Smart\ City(t_0) + \int_{t_0}^{t} \left(\frac{Interaction(t)}{100} \right)$	(11)

information system or public transportation failures; efficient mobility; new mobility services; transportation orders; efficient transportation; and public transportation. Fig. 6 depicts the changes made, which are represented by the blue line with the caption "Intra-cluster (2)". The simulation verified the positive impact that the determinants' variations had on the mobility cluster as compared to the base values since its performance had increased by 1.4 by the end of the 100-month time horizon. Thus, the model's usefulness was confirmed because changing the variables' values allows for real-time visualizations of the future impacts of a given decision and/or initiative.

A scenario was set for the people cluster in which the population's involvement was reduced. This situation had a negative impact because smart cities are strongly linked to their users (*i.e.*, smart citizens) given that these metropolises always seek to improve the quality of life of those who live in, work in, or visit these cities. The scenario was used in intra-cluster *Simulation 3*. The determinants of the people cluster were reduced by −0.5 compared to their initial value. The factors affected were: society's adaptation to novelty; social culture; community involvement; lifestyle; participation; participation in social networks; citizens, visitors, and workers' participation; membership in and creation of communities; sense of belonging; and, finally, active urban lifestyle. The visualization of this simulation and the impacts on the model's performance during the 100-month period are shown in Fig. 7 by the blue line, under the caption "Intra-cluster (3)".

The oscillations presented in Fig. 7 for *Simulation 3* reveal that, when the population's involvement is reduced, the overall performance of the people cluster drops from 30 to 25. Notably, the model also shows strong interactions between indicators, and various cause-and-effect relationships affect more than one cluster at different levels of intensity. In this scenario, the citizens, visitors, and workers' participation determinant has two different cause-and-effect relationships involving the people and governance clusters. When *Simulation 3* was run, the centrality value of the governance cluster decreased by −0.5—from 45.8 to 45.3—as depicted in Fig. 8.

Simulation 4 focused on the energy and the environment cluster, including the urban spaces subcluster, and the proposed scenario consisted of delays in the transition from non-renewable to renewable energy consumption. In this simulation, potential energy sources were not maximized, producing a negative impact on determinants directly related to energy consumption in the cluster and subcluster. The factors were: energy exploitation; endogenous resources exploitation; electric cars; electrification of energy consumption; carbon neutral measures; solar panels; and atmospheric pollution—determinants in the energy and environment cluster—and lighting in the urban spaces subcluster. The oscillations caused by *Simulation 4* reduced the weighting of the indicators by −0.5. These changes are visualized in Figs. 9 and *10*, referring to the energy and the environment cluster and the urban spaces subcluster, respectively.
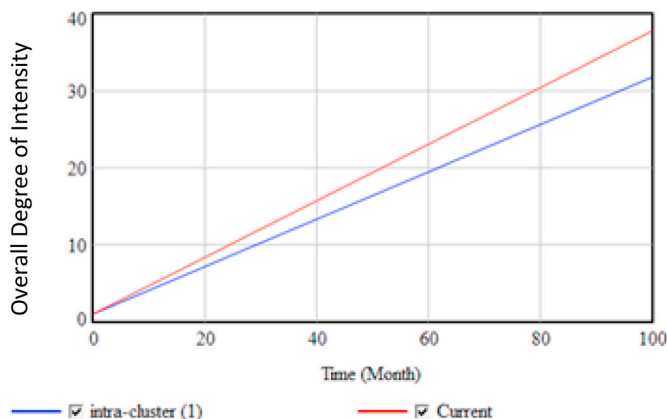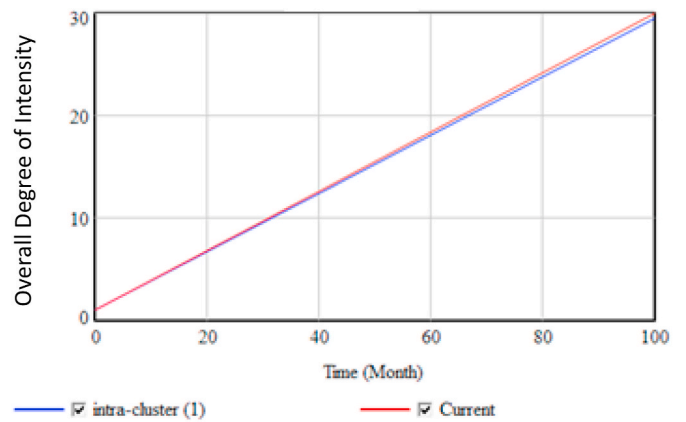
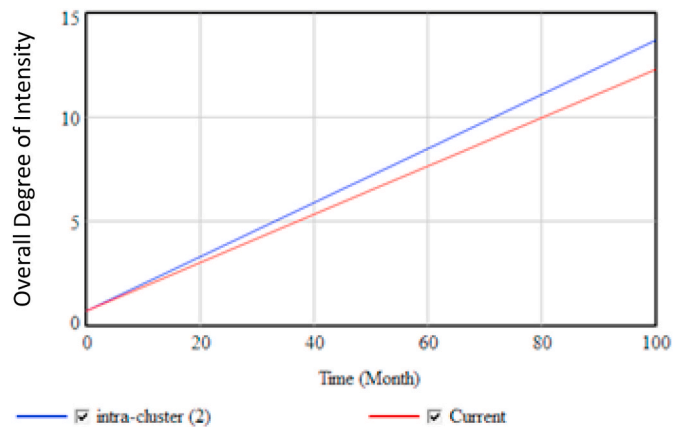**Fig. 5.** First intra-cluster simulation: People.

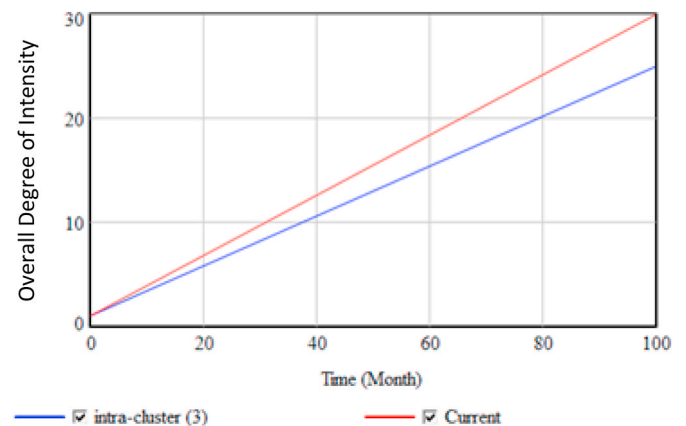**Fig. 6.** Second intra-cluster simulation: Mobility.

Fig. 7. Third intra-cluster simulation: People.

According to Figs. 9 and *10*, the search for fossil energy has a negative effect, more specifically in the absence of renewable energies in energy consumption behaviors. Fig. 10 shows how the variation in the lighting indicator affects the urban spaces subcluster, namely a reduction of its overall value by −0.4. This scenario also influences the oscillations observed in the energy and the environment cluster. Fig. 9 reveals how the energy and the environment cluster was weakened in this scenario, presenting decreased performance over the 100-month period.

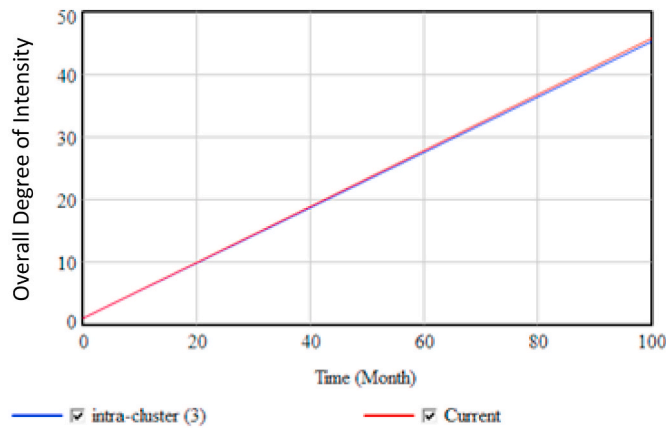The weaker performance of the governance cluster can be triggered

Fig. 4. First intra-cluster simulation: Technology.

Fig. 8. Impact of the third simulation on governance cluster.

Fig. 10. Impact of the fourth simulation on urban spaces subcluster.

by a political crisis, reducing the influence of the determinants associated with governmental instability by −0.5. These factors include, for example, good governance models, implementation capacity, consistency in city policies and management, absence of strategy, no strategic vision of the future, time and/or change, effective management, leadership, future projects, and political will. The weighting of the absence of strategy and no strategic vision of the future determinants became the minimum possible since their degrees of intensity fell to extremely low values due to the negative impact of this scenario on the cluster's overall performance. The blue line in Fig. 11 represents the behavior of the governance cluster over the 100-month time horizon.

As Fig. 11 shows, the negative effects of *Simulation 5* reflected the potential impacts of a political crisis. Over time, the cluster's performance was reduced by −4.2.

The last intra-cluster simulation involved the economy cluster. As mentioned previously, a smart economy is considered one of the most important dimensions of smart cities since it facilitates communication and sustained economic growth through entrepreneurship. A smart economy has a prominent role as it fosters economic development based on new job creation and fulfillment of pre-existing needs. Thus, *Simulation 6* consisted of a decrease in the entrepreneurship variable of −0.5, which may be caused by, for example, community divestment for cultural reasons arising from an increasingly conservative society or, more simply, financial shortages. The blue line in Fig. 12 corresponds to the quantitative change made, resulting in reductions in economic performance over time.

Fig. 12 depicts the impact caused by a variation in only one variable in the cluster, demonstrating the potential of the proposed system and contributing to more conscious decision-making processes. In *Simulation*
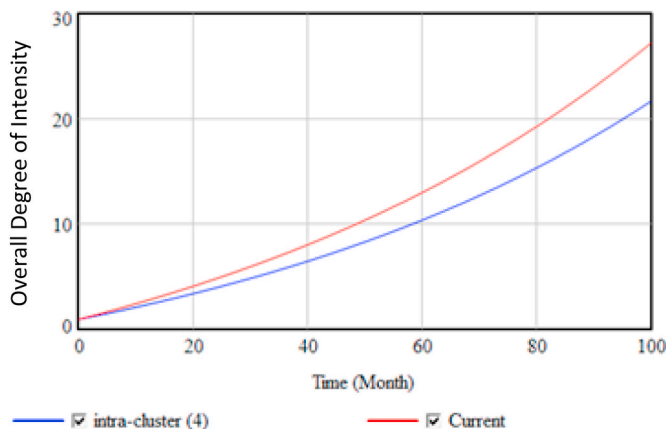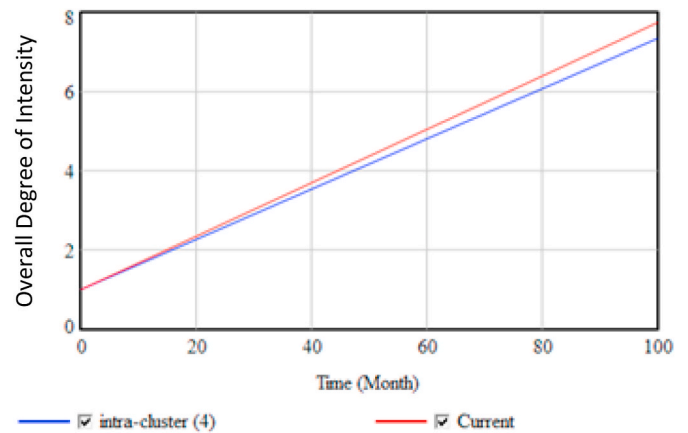
6 scenario, the performance of the economy cluster was reduced by −0.5. After all the intra-cluster simulations were run, the results confirmed the importance of this type of analysis. The SD approach makes the impacts of the clusters clearer based on the different degrees of intensity of their determinants in response to internal variations or the external environment volatility.

4.2.2. Inter-cluster analysis

The following analyses were carried out on an inter-cluster level in which variations were introduced at the cluster level to highlight the impacts on the most prominent determinants and, consequently, on the main stock. The scenario in question consisted of a pandemic that could have various long-term consequences for all aspects of smart cities. *Simulation 7* corresponded to the effect of the first measures implemented in response to the pandemic, with the restrictions lasting for 100 months. In contrast, *Simulation 8* was a more drastic situation in which the 100 months involved more stringent coercive measures.

Simulations 7 and *8* produced changes in the clusters' intensity that negatively affected smart city performance. The variation of the energy and the environment cluster resulted in the smallest reduction largely because the determinants that constitute this cluster, such as pollution, were altered in positive ways by the pandemic scenario. However, in general, the clusters did not benefit from the variations in both simulations. Fig. 13, 14 and 15 present the results.

An analysis of Fig. 13 verified the effects of *Simulations 7* and *8*. The base values are represented by the green line, the red line is the oscillations caused by the first negative scenario (*i.e.*, *Simulation 7*), and the more radical scenario of 100 months under extremely strict restrictions appears as a blue line (*i.e.*, *Simulation 8*). The model stabilization over
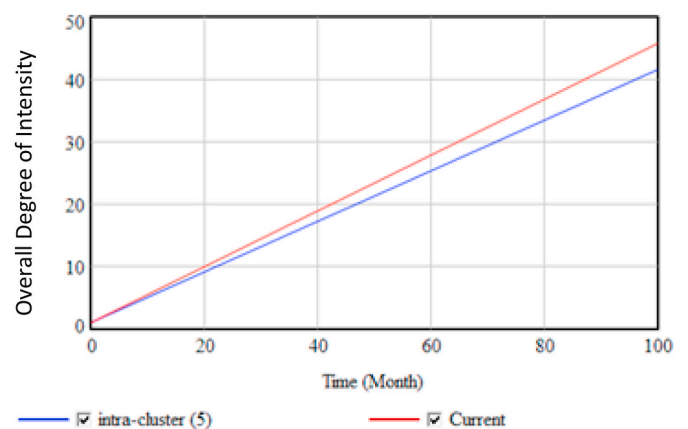

Fig. 9. Impact of the fourth simulation on energy and the environment cluster.

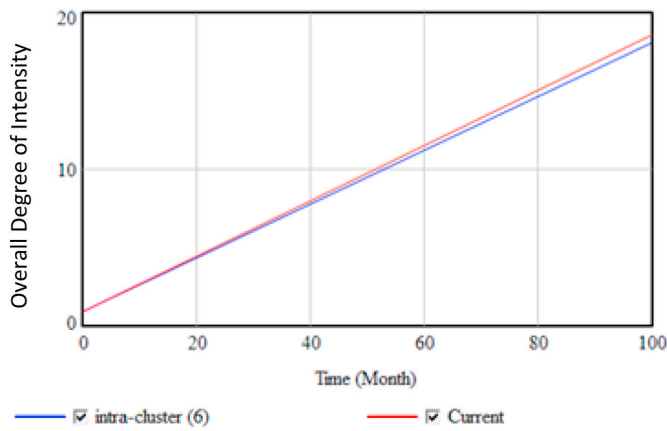**Fig. 11.** Impact of the fifth simulation on governance cluster.

Fig. 12. Impact of the sixth simulation on economy cluster.

time was achieved by applying the logarithmic function. The decreased performance of the connections determinant naturally had a negative impact on the interactions inflow. Fig. 14 represents the logarithmic function of the interactions inflow over time, verifying again the negative effects of the simulations. In addition, Fig. 14 depicts the initial values in green, the *Simulation 7* values in red, and the *Simulation 8* values in blue. The reduced performance of the determinants is influenced by the connections concept. However, the negative changes started with the reduction of the clusters' aggregate values.

The simulations conducted have implications for the entire model, which reflects a performance reduction in the main stock. This decrease can be seen in Fig. 15, which reflects the impact of a pandemic scenario on the main stock (*i.e.*, smart cities) when the clusters' values are changed. *Simulations 7* and *8* facilitated a comparison of the variations generated when the surrounding's stimuli become more permanent but the measures implemented diverge, revealing the consequences of new long-term guidelines.

In summary, the inter-cluster analyses identified the effect on the main stock when the clusters' intensity was varied. The proposed approach is thus important to smart city research as this methodology enables sustained and objective analyses of risks that can make decision-making processes more effective.

4.2.3. Multi-cluster analysis

The final, multi-cluster analyses applied scenarios that influenced determinants of more than one cluster simultaneously. The changes to which the indicators were subjected affected the inflows and, consequently, the smart city stock. *Simulation 9* was run to clarify the impacts
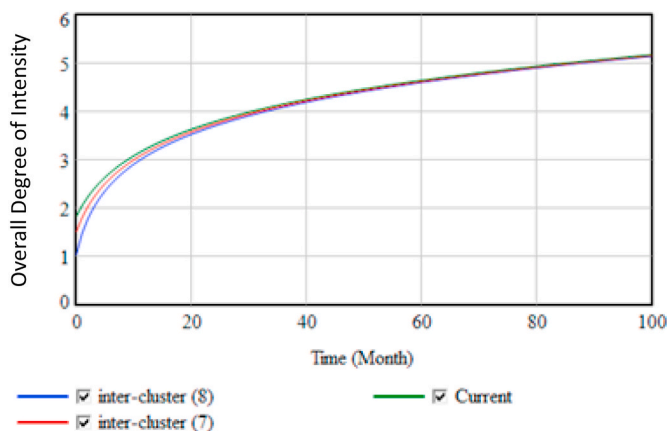

Fig. 13. Impact of the seventh and eighth simulations on connections determinant.
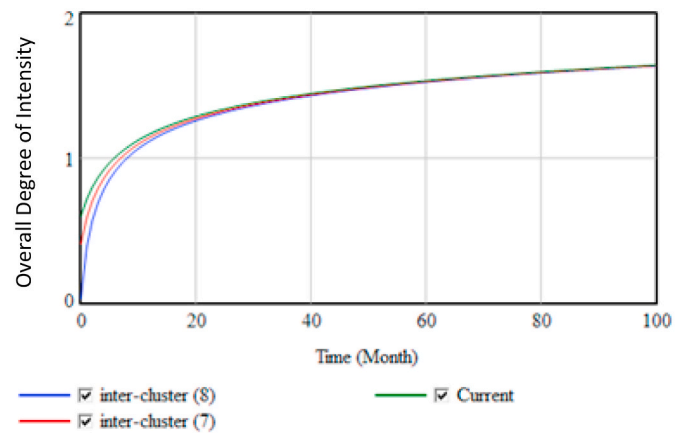

Fig. 14. Impact of the seventh and eighth simulations on interactions determinant.
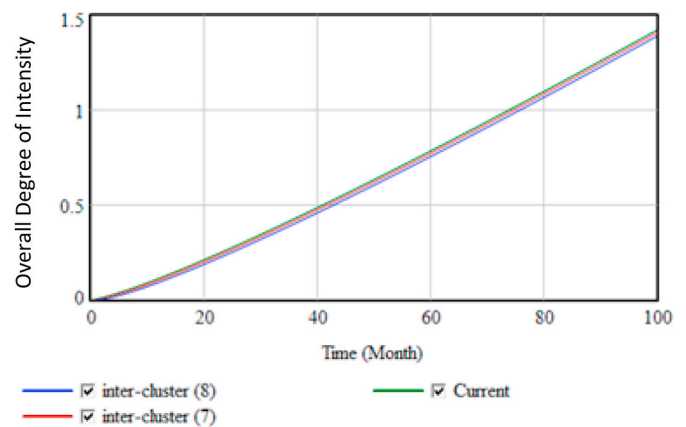

Fig. 15. Impact of the seventh and eighth simulations on smart city stock.

of a negative scenario in which the age structure of a specific region showed a marked aging demographic. This trend resulted in residents' limited technological knowledge since no readjustments had been made to the relevant mechanisms to accommodate the growing population segment with low digital literacy.

The scenario consisted of a reduction of −0.5 in the intensity degrees, which affected the technology, people, governance, and economy clusters. More specifically, the changed variables were: adaptation of society to novelty; applicability to and alignment with each city's specificities; computing capacity; population's empowerment; response to citizens' needs; digitization; and inadequate knowledge about the local context. Other factors affected were: absence of strategy; no strategic vision of the future; focus on residents; digital literacy; adaptation logic; participation; participation in social networks; future projects; and provision of digital training. Other criteria that changed were: resistance to change; responses to needs; digital services and/or platforms; and administrative process simplification for users. *Simulation 9* affected a greater number of indicators due to the scenario's importance and the impacts it could have on society. The changes made had consequences for the model's performance in terms of input variables and the main stock. These results are shown in Fig. 16, 17 and 18.

Fig. 16 reveals that, over a 100-month time horizon, the performance of the connections determinant decreases. *Simulation 9* is represented by the blue line, and the base values are in red. In numerical terms, the reduced performance is reflected in values decreased by −0.15. The variable interactions include the influence of the connections indicators on the interactions inflow, which resulted in a decrease of −0.11 in the performance of the latter indicator. Fig. 17 depicts this situation, with

the *Simulation 9* modifications shown in blue.

Fig. 18 reveals that, based on the 100-month time span, the scenario in question converged on a reduction of the model's performance by −0.1. The blue line shows the negative impacts of *Simulation 9* scenario. This simulation warns city planners that they need to allocate resources to older age groups, especially when the population segments in question do not have the capacity to adapt to novelty. Given that communication is permanent in smart cities, scenarios that involve various clusters end up becoming recurrent. Thus, the pertinence of the multi-cluster analyses is quite self-evident since they help decision makers perceive more clearly the effects on the proposed model when changes are made to determinants present in various clusters.

4.3. Validation, implications, and recommendations

The empirical component of the present study was based on the creation of a cognitive map, measurement of the degrees of intensity of existing cause-and-effect relationships between smart city determinants, and analyses of their dynamics through simulations. Additional experts were subsequently asked to validate the proposed model. Because they had not been present during the model construction, these external specialists were considered neutral in terms of the study previous structuring and evaluation process.

Two validation sessions were carried out with experts from two different entities. The first to be contacted was the Évora City Council in Portugal. This entity was selected because of its previous smart city projects, which made this city council a pioneer in new forms of energy management. The session began with a presentation of the research topic and techniques used, including an explanation of the entire process of collecting information from the expert panel. Next, the interviewee (*i. e.*, an Évora City Council member) was asked to comment on the techniques' results, strengths and weaknesses, as well as what would be necessary to integrate the model into practice.

This expert's feedback was quite positive regarding the techniques used, including that the *"multicriteria analysis facilitated the integration of a large number of quantitative and qualitative components"* (in his words). This process was seen as an added value in terms of *"systems subject to permanent renovation"* (also in his words). The interviewee also emphasized that the methodology applied becomes more useful as the number of variables in question increases. Overall, this specialist was satisfied with the methods used. The results were also welcomed because the determinants identified, in general, accurately reflect smart city varied dimensions. The clusters were considered essential pillars underpinning efforts to make smart cities more dynamic. Finally, the council member considered the simulations to be *"pertinent"* (citing the interviewee).

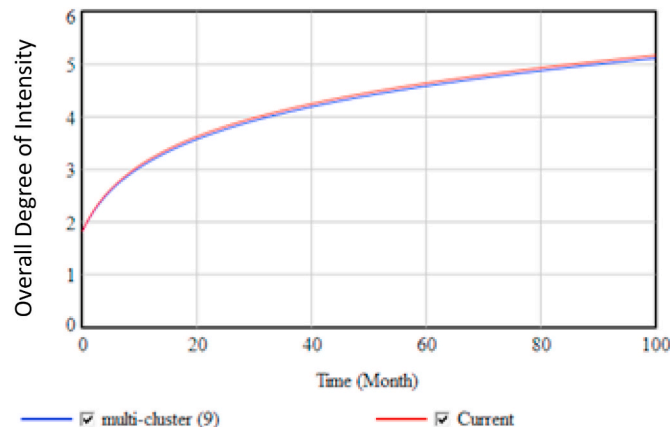When asked to analyze the strengths and weaknesses of the proposed
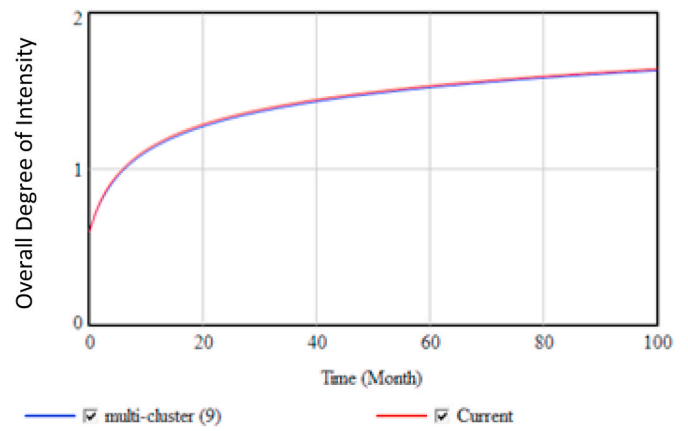
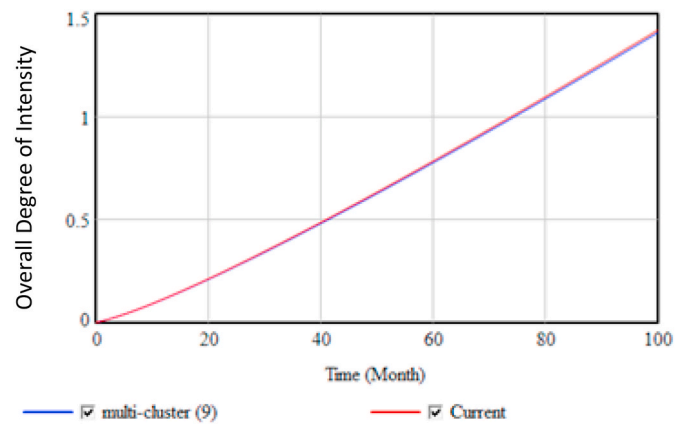**Fig. 17.** Impact of the ninth simulation on interactions determinant.

Fig. 18. Impact of the ninth simulation on smart city stock.

methodology, the interviewee said that one of the greatest advantages of the combined approach is its ability to encourage group discussion and the exchange of ideas associated with theoretical and practical knowledge. This expert suggested that, since *"what [information] is given to us is not always logical, the results can become more reliable"* (again in his words). The substantial number of subjective determinants was also considered to be important. The expert felt that, as a constructivist methodology, the methodology seeks to improve decision making about existing resources by complementing the positivist approach based on optimum mathematical solutions, which may not always take important factors into account in decision-making processes. Regarding the limitations of the analysis system, the interviewee underlined the subjectivity associated with the intensity of the causal relationships and recommended that user opinions be integrated as well. This Évora council member showed interest in a practical application of the model. However, he asserted that, *"first, a test should be carried out of how applicable the model is to the present realities of the city of Évora. After analyzing the results, this approach could be implemented"* (in his words).

The second entity contacted was the Cascais City Council, also in Portugal, which quickly forwarded the request for a meeting to two senior experts in the Information and Smart Cities Division of the Innovation and Communication Department. The structure of the second validation session followed the same format as the first meeting. The interviewees said that techniques used are extremely intuitive since *"they make it possible to visualize the city as a whole"* (citing their words), with the entire city interconnected. However, decision makers still need to *"pay attention to the generalizability of results to all cities"* (also in their words). Regarding the results, the experts considered *"the model quite useful"* (in their words), highlighting that the clusters identified are

Fig. 16. Impact of the ninth simulation on connections determinant.

essential to smart city development because *"they involve several components commonly found in any smart city"* (again in their words). The interviewees also said that the main utility of the proposed model is that it allows planners to focus their attention appropriately. That is, the methodology facilitates visualizations through simulations of where resources can be allocated sustainably. The experts asserted that, *"sometimes, we may be investing in an area that is not a suitable way to solve the existing problems"* (citing them).

According to the interviewees, the strong points of the analyses carried out are that the SD approach allows decision makers to visualize and demonstrate quantitatively the effects of changing a variable. *"Acknowledging the interconnections of causes and effects introduces a realism into the model that is essential to decision making"* (according to the interviewees). Even small variable oscillations have implications for the entire model. A less positive point brought up was the *"subjectivity inherent to the technicians' involvement in the process of defining the degrees of intensity"* (in their words).

To implement the model, the two specialists suggested that *"an adaptation to specific ecosystems would be necessary because the perception of each smart city varies for each municipality"* (again in their words). The interviewees also mentioned that formulating guidelines would be important to facilitate the introduction of the map elements (*i.e.*, determinants, clusters, intensities, and simulations) to practitioners. The experts concluded that the model could substantially assist smart city decision-making processes as it helps planners to gain a more holistic understanding of the cause-and-effect relationships between these municipalities' various areas.

The two final meetings with experts were considered a validation of the results based on the specialists' high level of satisfaction. The methodology applied allows for a greater clarification of decision problems because the group dialogue and discussion stimulate synergies that could otherwise be overlooked. However, no methodologies are exempt from limitations, which in this case were associated with the constructivist approach and process orientation of the present study. The results' dependence on the specific ecosystem in question introduced idiosyncratic tendencies since the conclusions could have been different with: (1) other facilitators; (2) different expert panel members; or (3) a session structure based on a different script.

Despite the above limitations, this research verified that the smart city determinants identified, as well as the cause-and-effect relationships analyzed, resulted in a better explanation of smart city dynamics. In addition, the SD approach complemented this understanding by developing hypothetical scenarios through simulations and thus constructing an extremely useful model that can assist decision makers.

5. Conclusion

Keeping up with smart ecosystem rapid rate of mutation requires a robust, comprehensive, and yet objective analysis model. For cities to be truly smart, they need to be evaluated to ensure greater harmony between defined objectives and actual practices. The main limitations found in previous studies on this topic were: (1) the unclear way in which smart city determinants have been identified; and (2) no research that has conducted analyses of the dynamics between determinants. Therefore, the present study proposed a decision-support model based on cognitive mapping techniques, which facilitated the aggregation of determinants from the most varied areas of smart cities. The methodology also included applying the SD approach to clarify the cause-and-effect relationships existing between the determinants and to run simulations in order to verify the impacts of the measures taken. The selected methodology resulted in a holistic representation of smart city conceptualization that has greater relevance due to the model's breadth and importance. The development of a dynamic model based on a constructivist stance proved to be critical to obtaining these results.

The analysis system developed is not free from limitations. Although the predefined objectives were achieved, the findings are strongly dependent on the expert panel's knowledge and experience. In other words, the proposed model is contingent on the context in which it was built so that, if any variations had occurred in the research context/ environment, the results could have differed, thereby restricting any generalizations. However, the constructivist and process-oriented nature of the model makes it a tool that allows adjustments to be made to ensure a better use of the relevant smart city determinants in practice. The present results are thus based on the expert panel's inputs and are supported by their empirical knowledge about smart cities, including their beliefs, experiences, and know-how. This approach contributed to a much richer process and deeper clarification of the topic. The proposed methodology linked smart city theoretical components to their practical mechanisms, allowing planners to make decisions based on more realistic perceptions. This process could help smart cities move in increasingly smart directions.

Given that no methodology is without limitations—including this study approach—any research will always leave room for further investigations. Since one of the study limitations was that the results are context dependent, a pertinent future direction could be to adapt the proposed model to specific city realities to facilitate its application. In addition, the methodologies used here can be applied with an international panel of decision makers to understand what brings the smart city concept in different countries closer or further apart. Researchers may also get interesting results by using other positivist or constructivist methodologies in order to compare the results and evaluate the robustness of the present study outputs. In conclusion, this research should stimulate further studies on smart city determinants, which may have varied practical applications after appropriate adjustments are made to match the relevant ecosystems.

CRediT authorship contribution statement

Simão A.S. Nunes: Writing – original draft, Investigation, Writing – review & editing. **Fernando A.F. Ferreira:** Writing – original draft, Conceptualization, Writing – review & editing, Funding acquisition. **Kannan Govindan:** Methodology, Writing – original draft, Formal analysis, Writing – review & editing. **Leandro F. Pereira:** Formal analysis, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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