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RANKING RESIDENTIAL NEIGHBORHOODS BASED ON THEIR SUSTAINABILITY: A CM-BWM APPROACH

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Abstract. Population growth and rapid urbanization have consequences that are reflected in the economic, environmental, and social stability of city-residential neighborhoods. These impacts directly affect not only residents but also real estate markets and local governments. The professionals working in the latter entities have become increasingly concerned about urban sustainability and its strategic integration into their plans. Strategies have been implemented that focus on both addressing negative aspects of residential neighborhoods and enhancing positive features that can contribute to the continuous improvement of locals' living conditions. This study applies the multiple-criteria decision analysis approach and a combination of cognitive mapping and the best-worst method (BWM) to identify the most relevant criteria and use these to rank residential neighborhoods according to their sustainability. To apply the selected techniques, two group meetings were held with a panel of decision makers. The results were validated by the panel members and the Funchal City Council councilor for urbanism, who concurred that the proposed ranking system facilitates the identification of the most sustainable residential neighborhoods. The contributions and limitations of the methodological approach are also discussed.

Keywords: best-worst method (BWM), cognitive mapping, multiple criteria decision analysis (MCDA), real estate market, residential neighborhood, sustainability.

Introduction

Cities and their residential neighborhoods currently encompass the majority of most populations' economic activities and wealth. Thus, these areas have the greatest potential for boosting economic growth, employment rates, companies' competitiveness, and innovation (Correia et al., 2020). However, urban neighborhoods are also characterized by complex environmental, social exclusion, and polarization issues, which have severe consequences for residents' quality of life and for community cohesion (Barão et al., 2021; Costa et al., 2021). In recent decades, expanding urban populations have resulted in serious problems with efficiency and sustainability, which currently constitute some of urban policymakers' main challenges. Given globalization and the dynamics of global economy, government organizations and decision makers must adopt strategies that support sustainable development, thereby encouraging a balance between the economic, social, and environmental aspects of residential neighborhoods and the surrounding cities (Lousada et al., 2021; Pinto et al., 2021).

Sustainability plays an increasingly important role in people's choice of where to live. Residential areas need to include buildings that meet environmental requirements, have multifunctional facilities, allow ease of mobility, and provide opportunities to engage in professional activities. All these qualities will naturally make neighborhoods more attractive to live in than other areas that fail to meet these requirements (Ferreira et al., 2022).

An efficient system for ranking residential neighborhoods based on their sustainability could thus help urban planners make strategic decisions and understand which areas need interventions more urgently or which should only be considered an investment opportunity. The present study uses cognitive mapping and the best-worst method (BWM) (Rezaei, 2015) to address this decision problem as

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the existing literature reports that these techniques have a high potential in terms of solving complex decision problems and resolving decision makers' conflicting positions (Silva et al., 2022). These two methodologies were chosen to facilitate the identification of a set of criteria that directly or indirectly influence the classification of residential areas with regard to sustainability, as well as clarifying the cause-and-effect relationships between criteria.

A literature review was first conducted to gain a deeper understanding of the decision problem in question and prior research on the advances already made toward determining urban-neighborhood sustainability. The findings include the contributions and limitations of previous studies, providing a conceptual framework for an empirically robust, transparent, and realistic analysis model to enhance and support the relevant stakeholders' decision making about city-residential areas. This research also sought to achieve four other objectives. The first was to integrate objective and subjective elements into the process of classifying residential areas, while the second goal was to base the decision-support system on a group of experts' professional experience with–and opinion about–this topic. The third was to test the applicability of the classification model in a real-life context. The last objective was to expand the existing knowledge about ranking urban residential neighborhoods according to their sustainability.

The decision problem under analysis is quite complex. Thus, the methodologies selected are based on constructivist principles to allow objective and subjective elements to be combined in the decision-support system. In this way, the analysis model developed can be used to conduct wide-ranging, realistic assessments of residential-neighborhood sustainability.

The rest of this paper is organized as follows. The next section presents the literature review focused on sustainable residential areas. The ensuing section discusses important concepts related to the methodologies used. Next, results are analyzed, including a sustainability ranking of actual residential neighborhoods. The final section offers the main conclusions and limitations of this study, and provides suggestions for future research.

1. Literature review and research gap

Krivo et al. (2015, p. 3) define residential neighborhoods as *"small socially meaningful areas where people live and carry out many regular activities"*. The delineations of these neighborhoods are closely related to real estate prices. Droj and Droj (2015, p. 827) note that "[R]*eal estate market values may differ* [… to] *a large extent depending on the type of fiscal and functional areas, reputation and popularity of the quarter, position of the plot in relation to the functions within the town/village, the existence within the area of utilities* [...], *access to additional services [...], and crime rate in the region or possible ecological issues*".

Regarding sustainability, Gagnon (2012) and Soares et al. (2022) point out that the key challenge is to apply three principles: economic, social, and environmental standards. The consequences of unsustainability have led the international community to commit to finding alternatives to conventional growth patterns, namely sustainable development. According to Eurostat (2021, p. 30): *"sustainable development* [...] *aims to renew and plan cities and other human settlements in a way that offers opportunities for all, with access to basic services, energy, housing, transportation and green public spaces, while reducing resource use and* [its] *environmental impact"*. Efforts have thus been made to transpose the concept of sustainable development to the built environment and to ensure that environmental protection goals are reflected in regulations of urban communities' required level of environmental performance (Laboratório Nacional de Engenharia Civil, 2010; Freire et al., 2021; Soares et al., 2022).

Multiple variables influence individuals' decision to purchase a property, such as socioeconomic variables, urban strategies, or even the buyers' health needs (Haybatollahi et al., 2015; Lousada et al., 2021). A preference for a particular locality depends on each person's disposition, tastes, needs, and way of life (Komeily & Srinivasan, 2016; Pinto et al., 2022). In this context, buyers' search for a better quality of life have motivated individuals, municipalities, and real estate markets to join together in efforts to classify residential areas. The resulting rankings can guide people's choices and decisions and present solutions that are more appropriate to societies' evolving needs and the ongoing development of residential neighborhoods (Ciampalini et al., 2016; Nunes et al., 2021; Soares et al., 2022).

Urban areas can be seen as real-life operating systems in which each resident can find the necessary infrastructure to support their lifestyle, as well as services, associations, and/or other individuals with whom social relationships can be formed. Studies and evaluations of city neighborhoods serve as a starting point for dealing with more subjective, difficult-to-understand issues (*e.g.*, quality of life and personal choices). However, individuals spend much time in their residential area. Thus, better than anyone else, they can define the qualities and defects of that neighborhood and compare it to other areas. Residents' degree of satisfaction is an important starting point for classifications of neighborhoods, serving as feedback to local authorities and real estate agents who are concerned about increasing the quality of life within the residential areas for which they are responsible (Abdullah et al., 2012; Ferreira, 2016).

In practice, classifying residential neighborhoods is a complex, time-consuming process as rankings can be based on multiple variables. In addition, the boundaries of residential zones are difficult to define and map, which increases the importance of creating models that can reflect the relationships between different variables within well-defined geographical spaces, and thus facilitate strategic planning decisions (Steenberg et al., 2015). Municipalities and the competent authorities are naturally concerned about maintaining residents' quality of life and feeling of security in their neighborhoods. Thus, these professionals often use classifications of residential areas to define intervention priorities (Ferreira et al., 2018). Analysis models that assess and rank residential neighborhoods are an important tool for gaining a fuller understanding of local environments so that improvements can be made to control crime through both strategic planning and solutions that maintain residents' quality of life (Marvi & Behzadfar, 2015; Marques et al., 2018). Ranking residential urban neighborhoods also benefits real estate markets because property location is one of the most important factors in buyers' decisions to invest in specific areas (Marques et al., 2018). Analysis models that rank city-residential areas are thus necessary as they help local authorities and the housing market in general make decisions, thereby fostering fairer and/or up-to-date real estate evaluations. A better grasp of the available classification models is important to build on their contributions and overcome any limitations. Table 1 presents some examples of previous studies of this topic.

Table 1. Contributions and limitations of models for classifying residential neighborhoods

Authors	Methods	Results and contributions	Limitations
Delmelle (2015)	Census tracts	– Identified commonalities and differences between socioeconomic trajectories of different neighborhoods. – Analyzed 12 variables based on demographic, socioeconomic, and urban conditions factors with reference to five clusters: (1) suburban zones; (2) neighborhood stability; (3) blue-collar areas; (4) struggling neighborhoods; and (5) new starts.	– Study applied to a small sample of cities. – Failure to evaluate drivers at a macro level to develop a general understanding of changing neighborhoods. – Analysis limited by segmentation of areas according to poverty rates, so no analysis of areas' potential combination of attributes. – More analytical methodologies needed to expand the study's applicability to other areas.
Jones Lang LaSalle (2015)	Real estate market division	– Divided real estate market operations into four markets: (1) office; (2) retail; (3) investment; and (4) residential.	– Vision focused only on widespread real estate markets without great strategic importance.
Steenberg et al. (2015)	Urban forest ecosystem classification	– Developed viable alternative for ranking residential areas through their representative ecosystem. – Defined 12 real estate clusters: (1) industrial parkland; (2) mixed residential neighborhood; (3) mixed residential neighborhood on steep terrain; (4) typical residential neighborhood; (5) lower-density affluent and forested neighborhood; (6) waterfront hardscapes; (7) high-density residential neighborhood; (8) park tower; (9) higher-density affluent and forested neighborhood; (10) typical older and inner-city residential neighborhood; (11) downtown core; and (12) peri-urban forest.	– Generalized study that needs to be carried out again in the future in different areas where varied agglomerations of variables can be evaluated.
Nesticò and Bencardino (2016)	Neighborhood maps and geographic information system (GIS)	– Assessed real estate values and discrepancies between income estimates in a given geographical space using *Osservatorio del Mercato Immobiliare*, vector analysis, and a GIS tool. – Found that areas with the highest socioeconomic well-being are also the most expensive.	– Difficulty with analyzing relationships between variables. – Conclusions changed with the physical space analyzed. – Deeper territorial analysis needed to explore neighborhood culture.
Ferreira et al. (2018)	Cognitive mapping and measuring attractiveness by a categorical-based evaluation technique	– Provided an index that allows for the identification and prioritization of areas affected by blight.	– Geographic specificity of decision problem. – Limitations regarding the measuring attractiveness by a categorical-based evaluation technique methodology.
Pearson et al. (2019)	Regression model	– Identified a relationship between the human microbiome and neighborhood conditions, indicating opportunities for further research on green areas' effect on residents in the vicinity and blight's impact on health.	– The results are limited by a focus on only a short period. – The research only evaluated the conditions of one residential neighborhood, so the findings cannot be generalized.

End of Table 1

Authors	Methods	Results and contributions	Limitations
Sun et al. (2019)	Ordered logit model, ordinary least squares, hedonic model, factor analysis, and Shapley-Owen value	– Created a blight index for specific neighborhoods based on data from a previous study that assessed the individual blight score of each property in the city of Memphis USA, using a scale of 1 (*i.e.*, neighborhood without or with little evidence of blight) to 5 (*i.e.*, neighborhood significantly affected by blight) in order to facilitate the prevention of and fight against blight.	– The calculation of blight levels was limited because the index is an average of the individual scores for each property, which may not correctly reflect reality. – The initial data were restricted, and the dataset needs to be updated constantly so that the neighborhood index is as accurate as possible.
Lousada et al. (2021)	Cognitive mapping and system dynamics	– Proposed an integrated system that allows for the analysis of determinants of real-estate decay and respective cause-and-effect relationships.	– The results are limited to the analysis od cause-and-effect relationships. – No rankings are presented.

The studies summarized in Table 1 are part of the large number of models developed over the years to examine the characteristics of residential neighborhoods and group them according to variables reflecting multiple areas of activity. However, no research approach or model is free of limitations as ranking urban residential areas presents difficult challenges due to the ambiguity inherent to social science studies' findings, which depend on understanding individuals' needs and preferences. The more generalized limitations can be grouped into two main strands. The first is the definition of the criteria for ranking residential neighborhoods incorporated into the models (Ferreira, 2016; Ferreira et al., 2018). The determining factors are difficult to select largely because the existing decision-support systems have failed to consider neighborhoods' similarities and their intensifying cultural issues. The second strand is the way that the weights of these same criteria have been calculated, as well as the restricted analysis of the interrelationships between selected variables (Marques et al., 2018).

The present study, therefore, sought to develop a comprehensive, transparent, informed, and flexible analysis system in order to produce a coherent ranking of urban residential neighborhoods based on their sustainability. To this end, the aforementioned constructivist posture was adopted based on a combination of cognitive mapping techniques and the BWM (Rezaei, 2015; Silva et al., 2022). Specifically, two major factors impacted on the decision on which methods to use. First, cognitive mapping and BWM are two well-established methods in the operational research (OR) community, recognized for being simple and facilitating decision making across several organizational contexts. Second, we have found no prior documented evidence reporting their combined use to ranking residential neighborhoods based on their sustainability, allowing our study to add to the extant literature.

2. Methodological background

According to Belton and Stewart (2002), the decision-making process should consist of three fundamental phases. These are: (1) structuring to understand and organize the problem under analysis; (2) evaluation to construct a model that includes the decision makers' preferences; and (3) recommendations for how to apply the analysis system.

2.1. Problem-structuring methods (PSMs) and cognitive mapping

PSMs have been described as *"a key to producing agreements that would and could be implemented, particularly in situations where there was no clear agreement as to the exact problem or its solution"* (Ackermann, 2012, p. 652). PSMs provide better solutions to complex problems as compared to traditional approaches because PSMs provide the ideal conditions for decision makers to analyze the issues in question from a multi-criteria perspective. PSMs also enhance negotiations between stakeholders and facilitate the clarification of decision problems based on a clear, efficient representation process (Rosenhead, 1996).

One of the most well-known PSMs is strategic options development and analysis (SODA)–also known as jointly understanding reflecting and negotiating strategy (*cf.* Ackermann & Eden, 2010). This method was developed by Eden and Ackermann (2001) to support decision-making processes and their facilitators when unstructured problems are involved, including the use of cognitive maps as a possible structuring tool. SODA is most commonly used in the first phase of solving complex decision problems and is defined as *"a general problem identification method that uses cognitive mapping as a modelling device for eliciting and recording individuals' views of a problem situation"* (Mingers & Rosenhead, 2004, p. 532).

Cognitive mapping is a graphical representation that seeks to reflect decision makers' values, objectives, ideas, and experiences regarding complex decision problems (Ackermann & Eden, 2010). Various authors (*e.g.*, Ackermann & Eden, 2001; Eden & Ackermann, 2001; Belton & Stewart, 2002; Eden, 2004; Vaz et al., 2022; Vieira et al., 2022) have advocated using cognitive mapping as a tool due to its great capability for structuring and clarifying complicated issues. According to Ferreira et al. (2016), cognitive mapping has three essential characteristics of which the first is that this technique promotes the discussion and sharing of important information among decision makers. The second and third characteristics are that cognitive mapping reduces the number of criteria omitted when decisions are made and stimulates synergies of knowledge through discussion and thoughtful analysis. This technique is thus a process of cognitive structuring that generates a map depicting the internal configuration of the decision problem (Wong, 2010). In other words, *"a cognitive map is the representation of thinking about a problem that follows from the process of mapping"* (Eden, 2004, p. 673).

Cognitive maps usually contain nodes that represent the concepts, variables, and/or decision criteria associated with the issue in question. In addition, arrows are used to indicate the cause-and-effect relationships of these components, which are associated with a positive (+) or negative (–) sign according to the nature of the link between each pair of concepts (Miguel et al., 2019). By enabling decision makers to structure complex decision problems, cognitive maps clarify the cause-and-effect relationships between existing variables related to the issue represented. These maps can thus play a fundamental role in supporting decision-making processes mainly because of the recursive, flexible character of these tools, which is strongly associated with constructivist principles. Following this, Ferreira et al. (2017) highlight that cognitive mapping has multiple advantages. The first is the interactive nature of how the maps are formed, while the second is flexibility, which allows actors to introduce different kinds of variables. The third advantage is simplicity of use, and the fourth is that this technique contributes to a fuller understanding of complicated decision problems through an easily grasped visual structure that fosters communication and cognitive associations. Last, cognitive mapping has a descriptive capability that enriches the informational context in which decision makers operate.

However, one possible disadvantage is any lack of sincerity that may filter into the process of elaborating a cognitive map (*e.g.*, the individuals involved failing to mention certain issues). In addition, facilitators may fail to guide the decision makers' discussion properly and recognize that the process is inherently subjective since maps are made based on mental representations (Faria et al., 2018). Mohammadi and Rezaei (2020) thus underline the importance of remembering that decision makers' subjective or biased value judgments can influence the final result.

2.2. Best-worst method

In the present study, the BWM was applied in the evaluation phase. This technique is considered a quite innovative tool with which to select the best alternative from a set of options (Rezaei et al., 2015). The BWM focuses on resolving the complexity inherent to peer-to-peer comparisons while providing results that reflect experts' preferences (Malek & Desai, 2019).

Rezaei (2015) explains that the BWM is based on specialists' specification of the best (*i.e.*, most important or most desirable) and the worst (*i.e.*, least important or least desirable) criteria of relevance to a decision problem. A comparison is then made between the best and worst variables in which they are individually compared to the other criteria. The variables' weights are then determined with reference to the final version of the analysis model (Amiri et al., 2020). In practice, the BWM consists of five stages.

2.2.1. Stage one

The first step is to define the number of evaluation criteria $\{a_1, a_2, \ldots, a_n\}$ to be considered.

2.2.2. Stage two

The second step is to identify the best criterion (*i.e.*, most important) and the worst criterion (*i.e.*, least important) based on the decision makers' personal opinion.

2.2.3. Stage three

Using a scale between 1 and 9, these experts need to express their preference for the best criterion as compared to all the other variables. A score of "1" denotes a specific criterion's equal importance or meaning in relation to the variable considered to be the best. If a criterion is assigned a score of "9", that value shows that the decision makers have an extreme preference of the best criterion over the variable valued as a 9. The result of this procedure is presented as the best-to-other vector, which is defined by Equation (1):

$$A_B = \left(a_{B1}, a_{B2}, a_{B3}, \ldots, a_{Bn}\right) \tag{1}$$

in which a_{Bj} represents the preference for the best criterion B over another criterion j, such that $a_{BB} = 1$.

2.2.4. Stage four

Using the same scale ranging between 1 and 9, the decision makers express their preference for each criterion with regard to the worst criterion identified in stage two. The result becomes the others-to-worst vector, which is determined using Equation (2):

$$A_W = \left(a_{1W}, a_{2W}, a_{3W}, \ldots, a_{nW}\right)^T. \tag{2}$$

Given that a_{jW} represents the preference of a given criterion j over the worst criterion W, $a_{WW} = 1$.

2.2.5. Stage five

The last step is to determine the criteria's optimal weights $\left(w_1^*, w_2^*, \ldots, w_n^*\right)$ such that these weights are the ones at which, for each pair w_B / w_j and $\frac{w_j}{w_w}$, $w_B / w_j = a_{Bj}$ and $w_j / w_w = a_{jW}$. To satisfy these conditions for all criteria j, a solution to the decision problem needs to be found in which the maximum absolute differences $\left|\frac{w_B}{w_j} - a_{Bj}\right|$ and

$\left|\frac{w_j}{w_w} - a_{jW}\right|$ are minimized. The non-negativity condition and sum-of-weights method are applied to obtain the required results, as shown in Equation (3):

$$min\,max_j \left\{ \left|\frac{w_B}{w_j} - a_{Bj}\right|, \left|\frac{w_j}{w_w} - a_{jW}\right| \right\};$$

$$\sum_j w_j = 1;$$

$$w_j \geq 0, for\,all\,j. \quad (3)$$

Equation (3) can further be transformed into a linear model expressed as Equation (4):

$$\min \ \xi^L, \text{ s.t.}$$

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi^L, for\,all\,j;$$

$$\left|\frac{w_j}{w_w} - a_{jW}\right| \leq \xi^L, for\,all\,j;$$

$$\sum_j w_j = 1;$$

$$w_j \geq 0, for\,all\,j. \quad (4)$$

Equation (4) is then used to calculate the optimal weights $\left(w_1^*, w_2^*, \ldots, w_n^*\right)$, and the level of consistency of the comparisons, represented by ξ^*. The consistency index is used to estimate the consistency ratio (*i.e.*, Key Success Indicator* (Ksi*)) with Equation (5) (*cf.* Rezaei et al., 2015):

$$\text{Ksi}^* = \frac{\xi^*}{\text{Consistency Index}}. \quad (5)$$

The lower the ξ^*, the lower the Ksi* becomes and the more consistent the vectors are. A ξ^* value close to zero confirms a high level of consistency (see Rezaei (2016) for consistency index values). This ratio can also indicate the reliability of the comparisons.

The BWM was developed to solve multi-criteria decision-making problems. This method is considered to be an extremely efficient way to identify the best alternative and provide a clearer understanding, in advance, of the evaluation interval, which contributes to stronger pairwise comparisons and more reliable weights (Mohammadi & Rezaei, 2020; Rezaei, 2020). According to Mohammadi and Rezaei (2020), Mendes et al. (2022) and Silva et al. (2022), another of the BWM main advantages is that it only requires pairs of reference (*i.e.*, 2n-3 pairwise comparisons) in contrast to other multi-criteria decision analysis and decision-making methods. In addition, the atypical structure of the BWM results is due to two vectors that include only integer numbers, which makes this method easier to use (Maghsoodi et al., 2020; Mohammadi & Rezaei, 2020; Silva et al., 2022).

Overall, the BWM has three primary advantages: (1) a reduced need for large amounts of data; (2) more reliable results; and (3) no use of fractional numbers. These features contribute to giving decision makers a better understanding of the problem under analysis. Compared to other multi-criteria decision-making approaches, the BWM is thus considered to be a robust, user-friendly technique.

The BWM limitations include that it determines the optimal weights of a set of criteria defined by only one group of decision makers' preferences (Mohammadi & Rezaei, 2020). Nonetheless, the BWM can play an important role in evaluations of residential areas as it facilitates the determination of criteria's relative importance in order to prioritize neighborhoods needing interventions. The results of this method are of great interest to urban planners, municipal administrators, and, above all, society at large. The process-oriented nature of the methodological framework adopted for the present study produced a final analysis model using cognitive mapping and the BWM, which can ensure accurate classifications of residential-area sustainability anywhere in the world.

3. Application and results

3.1. Structuring phase: causal map

The SODA approach was applied in the structuring phase, during which cognitive mapping was used to identify the evaluation criteria and examine their cause-and-effect relationships. This approach required the recruitment in advance of a multidisciplinary panel of specialists with diverse areas of expertise in sustainable urban residential neighborhoods. In two group work sessions, these specialists exhaustively debated the decision problem in question. The literature provides flexible guidelines for the composition of decision-maker panels (*i.e.*, ideally 6 to 10 members) (*cf.* Ackermann & Eden, 2001). Thus, a panel of seven experts participated in the current research to ensure that the analysis model incorporated different management perspectives and social and geographical differences. Due to this research's constructivist and process-orientated nature, it is worth noting that the objective of the group meetings was not to achieve representativeness or make generalizations but rather to ensure a strong focus on process (Belton & Stewart, 2002; Bell & Morse, 2013; Mendes et al., 2022). A facilitator was also present to ensure the correct application of the methodologies and record the results.

The first session corresponded to the structuring phase of the decision-making process, which was organized into three parts. These were the: (1) definition of criteria to be included in the model by the decision-maker panel; (2) organization of the criteria into clusters; and (3) validation of the results (*i.e.*, the causal map). This session lasted approximately four hours and took place on the Miro platform (https://miro.com/platform/) due to coronavirus disease-19 restrictions. The process began with the introduction of all the invited experts and the facilitator, after which the subject matter and methodologies were presented to the group to ensure that the procedures were clear and the panel understood the important role they had to play.

Next, the facilitator asked the following trigger question: *"Based on your professional experience, what factors can limit or boost residential areas' sustainability in the Autonomous Region of Madeira?"*. The "post-its technique" (Ackermann & Eden, 2001) was then applied to organize the responses of the decision-maker panel, thereby facilitating the identification of decision criteria and definition of links between them. The experts shared their values and experiences to find the most relevant evaluation criteria for sustainable residential neighborhoods. Using the Miro platform, the participants wrote the criteria defined on digital post-it notes. These experts were asked to mark the notes with a minus (–) sign whenever a negative causality relationship was present (*i.e.*, when the criterion under analysis limited residential-area sustainability) or a plus (+) sign if the criterion boosted sustainability. This procedure was followed for a controlled period and was enriched by the panel's constant exchange of ideas, which produced a list of 126 different criteria.

In the second part of the first session, the decision makers were invited to create clusters (*i.e.*, areas of interest) with the criteria identified in the preceding discussion. The criteria were grouped into five areas: (1) *energy and environment* (C1); (2) *social dimension* (C2); (3) *accessibility and mobility* (C3); (4) *infrastructure* (C4); and (5) *governance and citizenship* (C5). In the final part of this session, the decision makers were asked to rearrange the criteria within each cluster by order of importance so that the results would reflect their perspective. Subsequently, all the information gathered using the post-its technique was translated into a group cognitive map using the *Decision Explorer* software (http://www.banxia.com). This map was discussed and approved by the panel at the beginning of the second group work session. Figure 1 shows the final version of the group cognitive map (size restrictions prevent a better visualization, but an editable version of the entire map can be obtained from the corresponding author upon request).

The cognitive map presented in Figure 1 reflects the criteria chosen in response to the trigger question, the panel members' experience and values, and their shared vision. One of the greatest benefits associated with constructing the map was the discussion generated, which increased the transparency of the decision-making process and the participants' understanding of the causal relationships between criteria.

3.2. Evaluation phase

The evaluation phase coincided with the second session. The BWM was explained to the decision makers until everyone understood the reasons for using this method at that stage. The session lasted approximately three hours.

As the criteria had already been identified in the first session, the procedure started with the second step in the BWM application, namely the panel's joint determination of which was the best (*i.e.*, most important) and worst (*i.e.*, least important) cluster. Next, the participants quantified the relative importance of the best cluster versus all the other clusters on a scale ranging from 1 to 9. In this case, a "1" indicated that the two clusters compared were equally important and a "9" suggested that the best cluster was much more important than the other cluster. The decision makers then discussed their preferences for all clusters compared to the worst (*i.e.*, least important) cluster using the same scale. In the final step, each cluster's weight was calculated using the BWM (see Section 2). Table 2 and Figure 2 present the clusters' weights.

Table 2. Best-worst method application to clusters

Number of clusters = 5	C1	C2	C3	C4	C5
Names of clusters	Energy and environment	Social dimension	Accessibility and mobility	Infrastructure	Governance and citizenship
Best cluster	–	–	–	–	Governance and citizenship
Worst cluster	–	Social dimension	–	–	–
Best-to-other vector	Energy and environment	Social dimension	Accessibility and mobility	Infrastructure	Governance and citizenship
Entrepreneur profile	2	5	3	4	1
Others-to-worst vector					
Energy and environment	–	6	–	–	–
Social dimension	–	1	–	–	–
Accessibility and mobility	–	3	–	–	–
Infrastructure	–	5	–	–	–
Governance and citizenship	–	8	–	–	–
Weights	0.259	0.052	0.173	0.129	0.388
Ksi*	0.129				

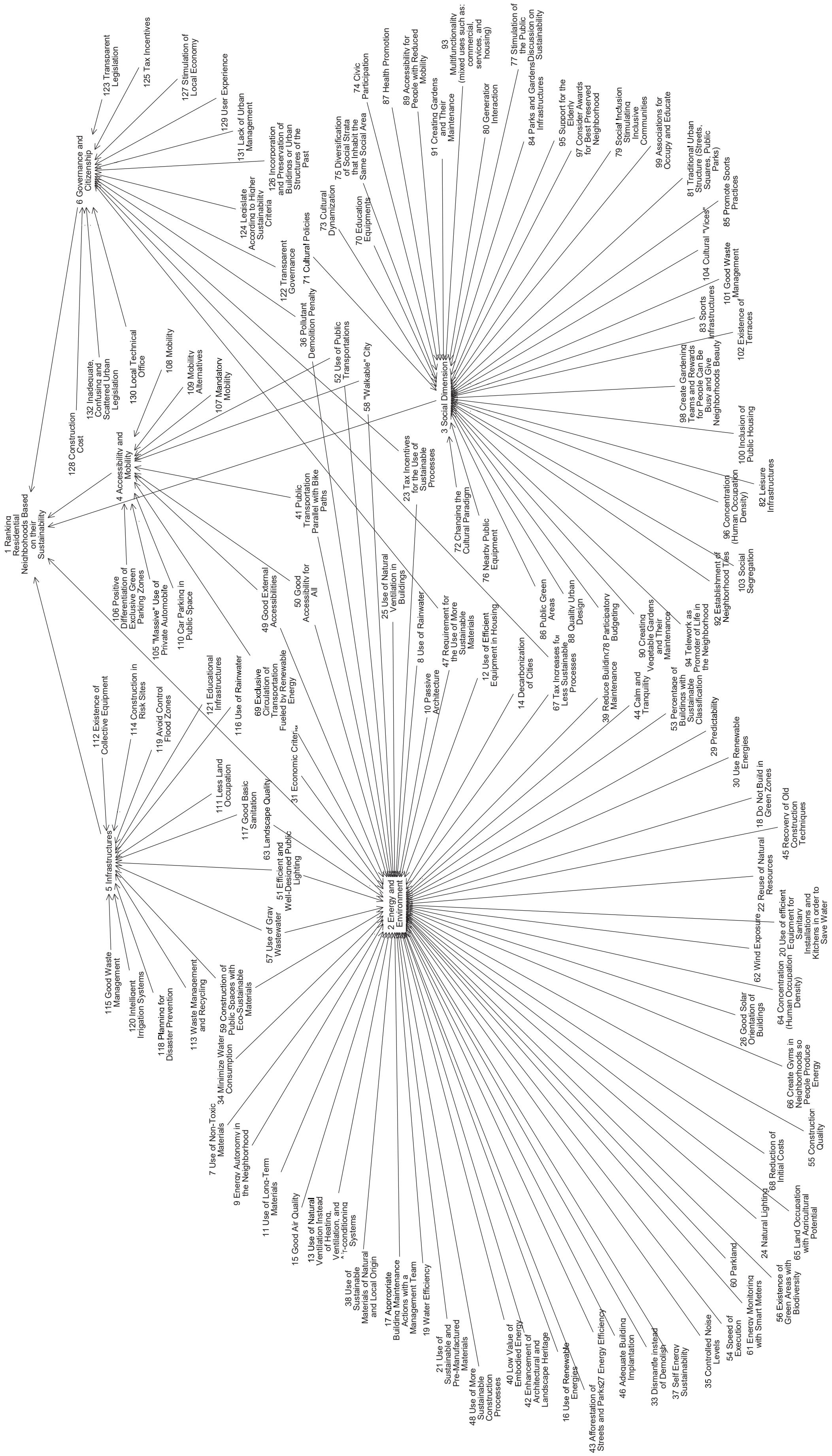

Figure 1. Group cognitive map

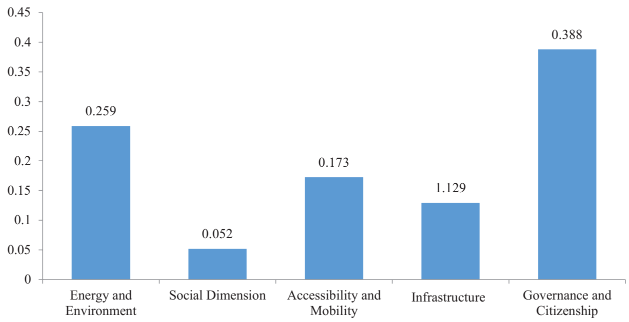

Figure 2. Clusters' weight

The results reveal that C5 has the greatest weight in evaluations of residential-area sustainability. In contrast, C2 is the least important since it has the lowest weight compared to the other clusters. Based on the cognitive map previously validated by the decision makers, the next step consisted of choosing the set of criteria to be kept in each of the five clusters for subsequent analysis. The choices were made collectively using nominal group technique (NGT) and multi-voting method. Table 3 contains the criteria receiving the most votes in each area of interest, which were then analyzed by again applying the BWM. The criteria weights defined are presented in Table 4.

Table 3. Criteria selected for analysis

Clusters	Most significant criteria	Least significant criteria	Observations
Energy and environment	Energy efficiency	Use of natural ventilation instead of heating, ventilation, and air-conditioning systems	The two criteria of use of more sustainable construction processes and afforestation of streets and parks were both given the same weight (i.e., the third most significant criterion). The two criteria of nearby public equipment and quality of urban design were both given the same weight (i.e., the second most significant criterion). The two criteria of walkable city and mobility alternatives were both given the same weight (i.e., the second most significant criterion).
Social dimension	Multifunctionality (mixed uses such as commercial, services, and housing)	Education equipment	
Accessibility and mobility	Good accessibility for all	Public transportation parallel with bike paths	
Infrastructure	Waste management and recycling	Use of gray wastewater	
Governance and citizenship	Transparent governance	Local technical office	

Table 4. Criteria selected for analysis and clusters' and criteria's weights

Clusters	Weights	Criteria	Weights
Energy and environment	0.259	– Energy efficiency – Passive architecture – Use of renewable energies – Use of more sustainable construction processes – Use of public transportation – Afforestation of streets and parks – Use of natural ventilation instead of heating, ventilation, and air-conditioning systems	0.217 0.292 0.097 0.146 0.073 0.146 0.029
Social dimension	0.052	– Multifunctionality (mixed uses such as commercial, services, and housing) – Education equipment – Civic participation – Nearby public equipment – Quality urban design – Inclusion of public housing – Public green areas	0.301 0.033 0.124 0.187 0.187 0.075 0.093
Accessibility and mobility	0.173	– Public transportation parallel with bike paths – Good accessibility for all – Walkable city – Mobility alternatives – Exclusive circulation of transportation fueled by renewable energy	0.070 0.323 0.253 0.253 0.101
Infrastructure	0.129	– Waste management and recycling – Use of gray wastewater – Existence of collective equipment – Use of rainwater – Planning for disaster prevention	0.200 0.050 0.300 0.150 0.300
Governance and citizenship	0.388	– Tax incentives for the use of sustainable processes – Transparent governance – Transparent legislation – Local technical office – Stimulation of local economy	0.089 0.407 0.268 0.055 0.179

The next part of the second session was devoted to testing the validity of the evaluation system in a real-life setting. The decision makers were asked to classify different residential areas in the 11 municipalities of the Autonomous Region of Madeira, Portugal. The BWM was again applied to create a ranking of these neighborhoods. The overall score was calculated based on a simple additive model. Table 5 and Figure 3 present the results.

The top-ranked alternative is Amparo in the parish of São Martinho and municipality of Funchal, with a score of 5.013. The next most sustainable is the residential area at the center of Ribeira Brava in the parish and municipality of Ribeira Brava, with 4.387 points. This neighborhood only obtained a higher score than Amparo in C5. The neighborhoods of Neves in the parish of São Gonçalo and municipality of Funchal and of Carmo in the parish of Câmara de Lobos in the same municipality also were given a good score. In contrast, the least sustainable residential areas are the center of São Vicente in the parish and municipality of São Vicente, Faial in the municipality of Santana, Arco da Calheta in the municipality of Calheta, and Garajau in the parish of Caniço and municipality of Santa Cruz. Notably, the last alternative received a score of 2.525, so city planners will need to implement multiple initiatives to improve the sustainability of this neighborhood.

Urban planners, municipal administrators, and politicians with decision-making power can thus analyze the partial assessments of residential neighborhoods and propose ways to improve these areas based on which dimensions should be given priority in interventions. For example, Figure 4 shows the partial assessments of Neves, Faial, and Garajau using C1, C3, and C5's criteria. These residential areas were chosen for analysis because Neves and Faial's scores are below the trendline, while Garajau has the worst score in the ranking.

An analysis of Figure 4 reveals which dimensions of each neighborhood need improvement. The criteria included in Figure 4 must all be strengthened for these residential areas to become more sustainable. However, a greater balance can be seen between the scores assigned to C5, which is the cluster with the greatest weight in this decision-support model, as compared to the scores of C1 and C3. Those entities that are responsible for managing– and making decisions for–these neighborhoods thus need to take into account what dimensions should be given priority in terms of improvement interventions. These residential areas will then improve their position in the overall ranking. Despite Faial's partial score for C3, this cluster does not have as much influence on the overall ranking of the three alternatives as C3's weight in the analysis system is lower than C1 and C5's weight.

Table 5. Ranking of alternative neighborhoods using the evaluation system created

Ranking of alternatives		
Number	Alternative	Score
1	Funchal: Amparo (S. Martinho)	5.013
2	Ribeira Brava: Centro (R. Brava)	4.387
3	Funchal: Neves (S. Gonçalo)	4.279
4	Câmara de Lobos: Carmo (C. Lobos)	4.187
5	Porto Santo: Vila Baleira (P. Santo)	4.113
6	Ponta do Sol: Centro (P. Sol)	4.099
7	Machico: Centro (Machico)	3.685
8	Porto Moniz: Seixal	3.498
9	São Vicente: Centro (S. Vicente)	3.342
10	Santana: Faial	2.744
11	Calheta: Arco da Calheta	2.688
12	Santa Cruz: Garajau (Caniço)	2.525

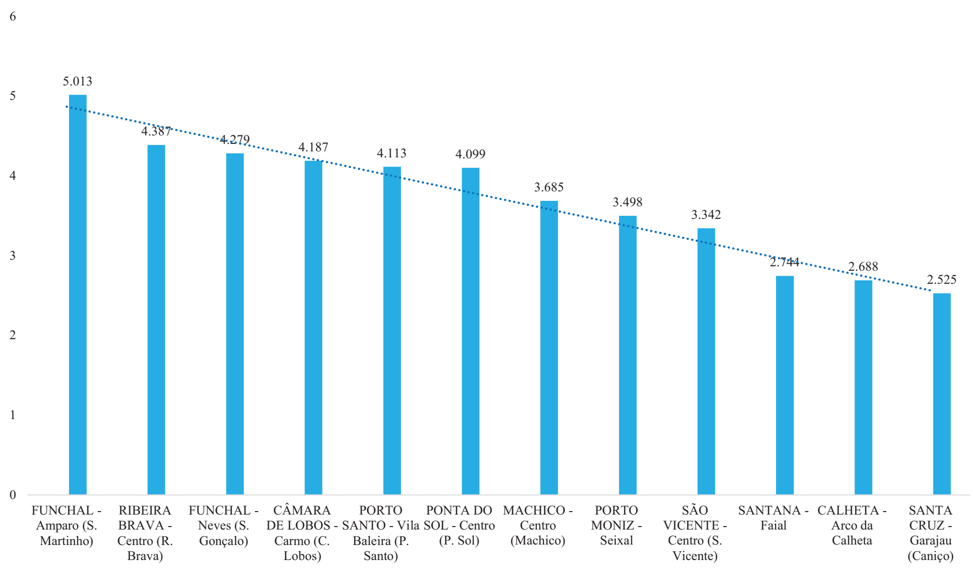

Figure 3. Madeira residential areas ranked by sustainability using analysis model

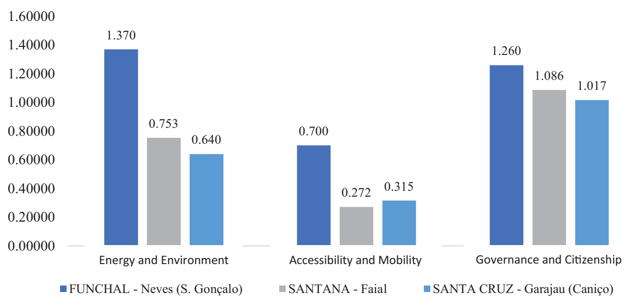

Figure 4. Weighted partial assessments of Neves, Faial, and Garajau residential areas

The recommendations phase of this study is presented in the next subsection. The results from the evaluation procedures were discussed with a neutral expert who had not participated in the first two phases. This specialist formulated recommendations for how to improve the sustainability classification system developed by the decision-maker panel.

3.3. Consolidation, limitations, and recommendations

The final consolidation session was conducted to analyze and examine the findings produced by applying the selected methodologies and to elicit an impartial expert's validation and advice regarding the proposed model. The specialist in question is the city councilor of the Municipality of Funchal, Madeira, who is responsible for urban planning. This professional was considered to have, due to his functions, expertise in the classification of residential areas according to their sustainability.

The consolidation session lasted approximately one hour and took place in the Municipality of Funchal Urban Planning Office. Four points were covered of which the first was the theoretical framework of the decision-support model for ranking city-neighborhood sustainability. The second was a discussion of the results and of the advantages and disadvantages of the classification system. The third point was an analysis of the possible practical implementation of the proposed model, while the last was recommended improvements.

The final session started with a brief explanation of the subject matter under study and the methods applied to create an analysis system for classifying residential areas according to their sustainability. The interviewee was informed that the development of the ranking system was based on a constructivist logic and the decision-maker panel's values and experiences. Next, the city councilor proceeded to analyze the cognitive map, weights assigned using the BWM, and ranking of alternatives.

This expert said that the methodology, *"in terms of structure, is very well organized"* (in his words) and the cognitive map, criteria, and clusters *"were very well chosen by the decision makers"* (also in his words). The interviewee also shared that he *"agree*[d] *with most of the results obtained but that it would be interesting to know what the results would be with a different panel of decision makers"* (citing the expert). At that point, the councilor was told that the subjectivity inherent to this process is recognized in the literature as being part of the methods applied, and thus integrated into the decision process. Regarding the advantages of the evaluation system, the expert asserted that this model *"allows us to identify the points where sustainability gaps appear and prioritize interventions to deal with them"* (again in his words). Another advantage mentioned was that the *"model can be applied to any residential area that needs to be classified* […] *at the parish, county, region, or country level"* (citing the expert). He pointed out that a disadvantage is the decision-maker panel, whose members had reportedly *"very similar training, but, if the panel were more multidisciplinary, it could lead to other results"* (again in his words). The interviewee was again reminded that the procedures are process-oriented, so representativeness or generalization need not be of concern (*cf.* Bell & Morse, 2013; Silva et al., 2022).

When asked if the present classification model could be implemented in practice, the city council expert indicated that *"entities with interests linked to land use and planning, the environment, and infrastructure could be contacted. After a presentation of this classification system, they would certainly be interested in using this methodology for future practical applications"* (in the decision maker's words). He also suggested that *"persistence would be needed in terms of the presentation and dissemination of this model to the right entities"* (also in his words) because this was the only way to ensure the ranking system created would be fully understood and used.

The decision maker suggested that the decision-support model should *"be applied experimentally in residential areas of interest to different entities such as the City Council, Regional Directorate for Planning, Regional Directorate for Environment and Climate Change, and Regional Secretariat of Infrastructure. The classification results should be presented to these entities"* (he said) in order to enhance the credibility and reliability of the proposed analysis model. At the end of the session, the specialist said the study and findings were *"very interesting"* (in his words), and that great benefits could be obtained by applying the urban residential area classification system to real-life neighborhoods.

Conclusions

The main objective of the present research was to create a multi-criteria evaluation model that facilitates the ranking of residential neighborhoods based on their sustainability. The methodologies selected combined cognitive mapping techniques and the BWM, which relied on the input of a panel of experts with varied backgrounds in sustainability and urbanism. The results can thus support decision making in cities, especially for managers, urban planners, and policymakers since they develop policies regarding residential-neighborhood sustainability. The methodology could be extrapolated to other contexts as long as the procedures adopted are carefully adjusted. The resulting rankings should also be compared with classifications based on previously used criteria to verify whether city-residential areas are sustainable. Further applications may also get interesting results by computerizing the proposed model and using an operating system that would provide users easy access to the findings.

Overall, we believe that our study produces important theoretical and practical contributions to the literature. In theory, these contributions can be an important starting point for other researchers and practitioners who analyze the sustainability of residential neighborhoods. Methodologically, they are two-fold. First, we combine methodologies (*i.e.*, cognitive mapping and BWM), which we believe to be a novel approach in the analysis of sustainability in residential neighborhoods. Second, our contribution is derived from the description of the applied process, which allows for replications in different contexts and/or with different groups of experts. This results from the process-oriented nature of the framework.

Although the present results confirm the usefulness of the evaluation system for gathering evidence with which residential neighborhoods can be classified according to their sustainability, no methodological approach is free from limitations. In this case, our study is idiosyncratic, context dependent. Thus, researchers, in the future, need to apply different multi-criteria methods, conduct comparative studies, or even replicate the entire process with a different group of experts. In this way, the results could be generalized more easily to other contexts.

Finally, a critical mass needs to get involved (*i.e.*, different private entities and government organizations with decision-making power) in order to facilitate comparisons between rankings of residential neighborhoods. These assessments could include comparing areas with similarities, residential neighborhoods in the same municipality, and/or residential areas with worse and better sustainability ratings to be able to develop more detailed comparative analyses. Methodological comparisons are also encouraged. Any contributions to advancing this field of research will be beneficial to–and allow significant advances to be made in–urban residential areas' increased sustainability.

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