Strengthening urban sustainability
Identification and analysis of proactive measures to combat blight
Barão, Madalena V.H.C.; Ferreira, Fernando A.F.; Spahr, Ronald W.; Sunderman, Mark A.; Govindan, Kannan; Meidutė-Kavaliauskienė, Ieva

Published in:
Journal of Cleaner Production

DOI:
10.1016/j.jclepro.2021.126026

Publication date:
2021

Document version:
Accepted manuscript

Document license:
CC BY-NC-ND

Citation for published version (APA):

Go to publication entry in University of Southern Denmark's Research Portal

Terms of use
This work is brought to you by the University of Southern Denmark. Unless otherwise specified it has been shared according to the terms for self-archiving.
If no other license is stated, these terms apply:

- You may download this work for personal use only.
- You may not further distribute the material or use it for any profit-making activity or commercial gain.
- You may freely distribute the URL identifying this open access version.

If you believe that this document breaches copyright please contact us providing details and we will investigate your claim. Please direct all enquiries to puresupport@bib.sdu.dk

Download date: 14. Sep. 2023
Citation:

STRENGTHENING URBAN SUSTAINABILITY: IDENTIFICATION AND ANALYSIS OF PROACTIVE MEASURES TO COMBAT BLIGHT

ABSTRACT

The process of identifying and analyzing proactive measures for the prevention of urban blight is complicated by its complexity and death of data. Blight affects people’s lives in many ways, including economically, socially, psychologically, and physically. The phenomenon comprises many factors, including making appropriate identification and eradication decisions that are challenging to analyze and structure. This study took a constructivist stance and sought to develop a new approach to identify and analyze proactive measures/tools to combat urban blight, complementing the existing literature. The methodology combined cognitive mapping techniques applied in decision conferences, and the decision making trial and evaluation laboratory (DEMATEL) technique based on the multiple-criteria decision analysis approach. This integrated approach facilitated the development of a multi-criteria model that identifies proactive anti-blight measures in a more complete, transparent way. This dual methodology enables incorporating objective and subjective elements, and field specialists’ knowledge and experiences, thereby reducing important decision criteria omissions. Additionally, this approach generates a transparent visualization of relationships among criteria. Identified blight determinants can be used to prevent blight, and improve the quality of life in the affected areas. These strategies were carefully analyzed by two independent experts from the Direção Geral do Território (General Directorate of the Territory of Portugal). The advantages and limitations of the proposed methodology are also deliberated.

Keywords: Proactive Anti-Blight Measures; Cognitive Mapping; Decision Conferencing; DEMATEL; MCDA; Urban Sustainability.

1. INTRODUCTION

Urban and neighborhood blight affect people’s lives worldwide, and is complicated by its complexity and death of data regarding multiple variables and dimensions. According to Darling (1943), Brueckner and Helsley (2011), and Ferreira et al. (2018), blight can arise due to varied situations including economic crises, urban sprawl, and inadequate urban planning. Various authors (e.g., Cohen et al., 2003; Han, 2014; Ferreira et al., 2018; Kondo et al., 2018; Marques et al., 2018) highlight negative aspects of blight that affect multiple dimensions in contemporary societies, such as: real estate markets; levels of violence, crime, and drug trafficking; or even the physical and mental health of residents of blighted areas. Even though multiple studies have attempted to define urban blight causes and eradication strategies, some more broadly than others, these strategies are highly complex (Ferreira et al., 2018). Beers et al. (2011: 8), for instance, define blight
As “deteriorating property conditions that have deleterious effects on the community in which the property is situated.”

Although the literature contains some studies regarding proactive anti-blight measures, these studies are uncommon (cf. Lousada et al., 2021). In addition, most studies fail to examine correlations and/or variable interactions among blight variables, failing to address blight from either an objective or subjective viewpoint, and rarely combining both approaches. To fill this apparent void, the present study sought to define proactive measures in combating blight by using a problem structuring method (PSM) (i.e., strategic options development and analysis (SODA)), and a multi-criteria evaluation technique (i.e., decision making trial and evaluation laboratory (DEMATEL)). The primary objective is to identify and analyze proactive blight prevention tools that benefit society at large and improve living standards in residential areas. Thus, this study answers the following research question:

- How can urban/neighborhood blight prevention strategies be identified, and how are they interrelated?

In attaining this main goal, three secondary goals need to be considered. The first is to conduct a literature review that facilitates the development of a theoretical framework for analyzing the blight problem. The second sub-goal is to organize two group sessions with a panel of experts who are asked to structure blight problems and identify proactive measures based on a group defined cognitive map. The last sub-goal is to analyze the relationships among decision criteria in order to understand interactions and influencing factors, using a multi-criteria technique (i.e., DEMATEL). In this sense, a major part of our contribution is bound with the methodology used. This methodology is novel because it integrates the use of cognitive mapping and DEMATEL for the first time in this study context, facilitating the identification of blight prevention strategies, and the examination of blight cause-and-effect relationships.

The remainder of this paper is organized as follows. Section two presents a brief literature review centered around blight identification, its causes and consequences. Section three clarifies the methodological aspects, while section four describes the methodological application and results. The final section concludes the paper and provides recommendations.

2. RELATED LITERATURE AND RESEARCH GAP

From a wider perspective, blight is a critical state of functional and social depreciation of properties whose presence or use is not accepted by the surrounding community (Breger, 1967). In other words, blight constitutes urban or neighborhood areas with rundown dwellings with deficient outdoor spaces, and include inadequate lighting and possibly air pollution. Generally, these areas are occupied by families with lower income than their community average (Darling, 1943). Haney (2007) characterizes blight as a group of abandoned or degraded properties accompanied by a damaged environment, abandoned and heaped garbage, vacant lots, vandalized properties, and graffiti, among other characteristics. Figure 1 provides two examples of urban blight.
Figure 1. Real-life Examples of Urban Blight

Source: Own illustration.
Urban and neighborhood blight may be caused by various factors, including deficient urban planning resulting in abnormally small lot sizes, lack of sufficient leisure areas, traffic and building congestion, nearby toxic industries, as well as other flawed planning issues. Other factors that commonly contribute to neighborhood decline are inadequate property maintenance, high delinquency rates and foreclosure on home mortgage loans for non-payment, crime, high population density, and general property negligence. A critical factor is that blighted areas are often occupied by families with lower incomes, and who may be considered unwanted by residents of “healthy” neighborhoods (Darling, 1943; Ferreira et al., 2018).

According to Bradbury et al. (1980), blight is caused by a phenomenon called “neighborhood effect”. This means that, if a property remains degraded or abandoned for a long time, its reputation and value is negatively affected, and, in turn, diminishes the attractiveness of the entire neighborhood. This downward neighborhood trend also causes the surrounding community to neglect its properties, and thus taint the entire surrounding area with blight (Brueckner and Helsley, 2011; Reis et al., 2019; Correia et al., 2020).

Since inadequate urban planning is considered by some authors to be a causal factor of blight (cf. Darling, 1943; Ferreira et al., 2018), urban planning needs to be defined and its role in daily lives clarified. Barton (2016: 15) broadly defines urban planning as “a generic activity, involving not only the state but also market and community interests which have an impact, or a stake, in the creation of human habitat”. Given this definition, urban planning is expected to manage neighborhood or urban area socioeconomic and environmental complexities. Thus, urban planning increases in importance both in residents’ daily life and the area environment in which they live, including transportation, green spaces, and exposure to traffic noise, which have a great impact on their physical, mental, environmental, and even economic wellbeing (Braubach et al., 2011; Barton et al., 2015; Carmichael et al., 2019). Inadequate urban planning may restrict area residence from obtaining healthy lifestyles, and may contribute to diseases such as diabetes or cardiovascular diseases (Carmichael et al., 2019).

Urban planning that contextualizes preventing and combating blight is critical for individuals living in today’s complex diverse society and extensive interconnectivity. Neighborhood and area land use and zoning must be clarified, including building types, and whether the neighborhood will be zoned as residential, commercial or industrial. These decisions impact traffic, the flow of people, noise, water quality and distribution, waste management, air quality, the location of infrastructure such as schools and hospitals, and the areas’ visual aspects.

Blighted areas suffer from consequences of negative social and economic tendencies. Blight affects residents’ lifestyle and quality of life. This is especially true for children, because urban blight often facilitates unsafe urban environments due to drug trafficking and prostitution (Ferreira et al., 2018). Children cannot safely move freely through neighborhood streets, forcing residents to retreat into their homes and refraining from outdoor activities (Cohen et al., 2003; Turcu, 2012; Fernandes et al., 2018). Additionally, individual property blight not only negatively impacts its value, but also tends to impact adjacent neighborhood property values. As the proportion of blighted properties increase in a neighborhood, property values are reduced for the entire
neighborhood. The cancer of extensive neighborhood blight negatively impacts all neighborhood properties (Bradbury et al., 1980).

Previously, other authors have conducted studies attempting to identify potential blight prevention and eradication strategies. However, effective studies are relatively rare. Table 1 illustrates some blight-related studies, highlighting respective contributions and limitations.
<table>
<thead>
<tr>
<th>AUTHOR</th>
<th>APPROACH/METHOD</th>
<th>CONTRIBUTION</th>
<th>LIMITATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beers et al. (2011)</td>
<td>Legal approach</td>
<td>Examined a set of laws enacted for the state of Pennsylvania in the United States (US) to prevent, control, and combat the problem of blighted areas.</td>
<td>▪ The definition of preventive measures is limited as these laws were developed based on the characteristics of a specific area (i.e., Pennsylvania).</td>
</tr>
<tr>
<td>Brueckner and Helsley</td>
<td>Quantitative approach using Lagrange equations,</td>
<td>Defined the relationship between urban sprawl and blight and corrective policies to combat urban sprawl, such as “congestion price, open-space amenity tax and impact fees”, which can have a positive impact on the prevention of blight.</td>
<td>▪ This study only considered one aspect of a complex phenomenon (i.e., market failures affecting urban real estate markets), ignoring poverty and neighborhood externalities that are also significant causes of urban blight.</td>
</tr>
<tr>
<td>(2011)</td>
<td>mathematical conditions, and Cobb-Douglas</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>production functions</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leland and Read (2013)</td>
<td>Quantitative approach using ordinal logistic</td>
<td>Provided a fuller understanding of how urban planners’ demographic characteristics (i.e., age, gender, race, political ideology, and education) tend to influence their willingness to support specific development projects, most notably those that prevent and eliminate blight, as well as encouraging diversity in this profession to take varied interests into account.</td>
<td>▪ The range of people involved was limited specifically regarding the number and type of professionals. ▪ The study also did not take into account the individuals’ level of authority in the workplace.</td>
</tr>
<tr>
<td></td>
<td>regression models</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Authors</td>
<td>Methodology</td>
<td>Description</td>
<td>Limitations</td>
</tr>
<tr>
<td>------------------</td>
<td>--------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| Reyes *et al.*  (2016) | Machine learning model                           | Developed a classification model that determines proactively if properties will have building code violations in order to detect the presence of blight and intervene by inspecting properties earlier, based on data from the city of Cincinnati in the US. | - The model validity is weakened by limitations regarding the data collected and used to develop the model. Thus, the information extracted from the model in the field needs to be validated in order to avoid ethical issues.  
- At the time of the paper publication, the model had not yet been tested in an actual neighborhood. |
| Hosseini *et al.* (2017) | Qualitative approach through questionnaires and quantitative methods using chi-squared and Spearman’s correlation tests | Provided a fuller understanding of citizens’ willingness to participate actively and jointly in the planning, creation, and implementation of policies to improve the conditions in which they live, as well as to intervene in their area’s organization and preservation in order to prevent and combat blight | - Limitations exist regarding the definition of preventive measures as the results reflect a sample from a specific area (*i.e.*, Laleh-Zar neighborhood in Tehran, Iran). |
| Ferreira *et al.* (2018) | Multiple-criteria decision analysis (MCDA) approach, through cognitive mapping and measuring attractiveness by a categorical-based evaluation technique | Developed an index that facilitates the identification of blighted areas and prioritization of interventions to combat and prevent blight. | - The findings are limited by the peculiarities of the adopted methodology and results.  
- The study scale was restricted, and the index was not tested on a larger dataset. |
| Sun *et al.* (2019) | Quantitative approach using an 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 in the US, 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. |
Generally, all prior studies have limitations. However, these investigations serve as catalysts for future research, and expand existing knowledge. The limitations listed in Table 1 are quite heterogeneous due to the variety of studies and approaches. Study limitations may be grouped into five areas. First, there is a lack of clarity and rationality in the definition of preventive measures to combat blight (Beers et al., 2011; Hosseini et al., 2017). A second area limitation is the absence of analyses of the causal relationships between the variables (Brueckner and Helsley, 2011). A third area limitation is the scale size (Ferreira et al., 2018), while the fourth is the type of data used (Reyes et al., 2016; Sun et al., 2019). The final and fifth area limitation is the formation of specific indices.

Urban blight is a complex problem with multiple interrelated variables and players. Therefore, blight analyses must consider multiple interrelationships and perspectives rather than merely correlating variables or using only one specific type of approach (i.e., qualitative or quantitative). Most studies presented in Table 1 each limit their respective methodology to one technique. Overall, the intricate nature of the neighborhood blight problem requires a method developed to structure complex decision problems, such as the SODA approach, which, according to Rosenhead (2006), enables the incorporation of various decision-problem perspectives.

The present study applies cognitive maps as a structuring technique that, in the context of a decision conference (Phillips & Bana e Costa, 2007; Lousada et al., 2021), facilitates the inclusion of both quantitative and qualitative factors. Subsequent to the generation of the cognitive map, the DEMATEL technique is applied as part of the multiple-criteria decision analysis (MCDA) approach, thereby allowing for a causal-relationship analysis to cognitive map factors (Kumar and Dixit, 2018), thus combining qualitative and quantitative approaches. The adoption of this methodological approach enables the development of a more complete, transparent study that overcomes some previous study limitations, as previously illustrated.

3. METHODOLOGICAL BACKGROUND

The selected methodology is based on constructivism, and was divided into three phases: (1) structuring; (2) evaluation; and (3) recommendations. The SODA approach was used in the structuring phase in combination with cognitive mapping. In the evaluation phase, DEMATEL was applied as part of the MCDA approach.

Although it is widely recognized in the literature that each MCDA method has strengths and weaknesses (cf. Belton and Stewart, 2002), leading several authors to argue that there is no such thing as an overall superior method or technique (e.g., Weber & Borcherding, 1993; Zhou & Ang, 2009; Ferreira & Santos, 2016), three major factors influenced the selection of methods in the present study. First, cognitive mapping and DEMATEL are two well-established socio-technical methods recognized as being simple to apply and facilitating decision making across various organizational contexts (cf. Belton & Stewart, 2002). Second, two of DEMATEL’s key features are the capacity to include qualitative and quantitative criteria and deal with the interdependence between
them during analyses of cause-and-effect relationships. Last, despite cognitive mapping and DEMATEL’s relative popularity, their combined use is quite scarce, and the literature offers no prior evidence of their combined used in this study context, supporting the assumption that the proposed framework is a novelty in the field of urban blight.

3.1 SODA, Cognitive Mapping, and Decision Conferencing

SODA was developed by Eden and Ackermann (2001) as a PSM. This method is based on representations of various points of view in a diagram, namely, causal or cognitive map (Sørensen and Vidal, 2008; Ackermann, 2012; Guarnieri et al., 2016; Smith and Shaw, 2019; Duburgo, 2020).

To understand cognitive mapping better, PSMs first need to be defined as these include the SODA approach, and thus cognitive maps. PSMs—also known as soft operational research (soft OR)—emerged between 1970 and 1980 as a way to eliminate some limitations identified by managers and researchers while using traditional quantitative OR methods (Mingers, 2000; Mingers and Rosenhead, 2004; Ackermann, 2011, 2012; Castanho et al., 2019; Marques et al., 2020). According to Rosenhead (2006: 759), “PSM[s] […] have been one of the growth points for OR, extending its fundamentally analytic approach into problem domains with which OR had previously failed to, or not purported to, engage”.

PSMs such as SODA provide assistance in analyzing complex decision problems characterized by: (1) multiple actors; (2) divergent perspectives; (3) conflicting interests; (4) intangible factors; and (5) uncertainty (Rosenhead, 2006; Mingers and White, 2010). SODA allows decision makers to manage the complexity of these problems rather than reduce it, which allows the relevant groups of participants to see the entire problem, and share their knowledge through the construction of cognitive maps (Smith and Shaw, 2019). According to Ackermann (2012), PSMs also have other advantages, such as certainty that the situation is being fully explored by taking into account various perspectives, thereby contributing to the development of a representative understanding of reality. Other advantages include widening the number of alternatives generated, and formulating and elaborating new options.

Cognitive maps are a structuring tool appropriate for complex decision problems (Ferreira et al., 2016a; Jalali et al., 2016; Ribeiro et al., 2017; Abuabara et al., 2018; Faria et al., 2018; Ferreira et al., 2018; Brito et al., 2019). These maps represent networks in which each node represents a concept or an idea, while the arrows connecting the nodes represent cause-and-effect relationships, implications, or influences (Eden, 2004; Montibeller and Belton, 2006; Ackermann and Eden, 2010; Assunção, et al., 2020). The arrowhead concepts are usually wanted or unwanted objectives, while tail concepts are options (Eden, 2004).

According to Ferreira et al. (2012), Ferreira et al. (2016b), and Miguel et al. (2019), cognitive maps allow researchers to promote discussions between the decision makers involved and reduce the omission of important criteria. In addition, these maps foster learning by enhancing decision makers’ understanding of the causal relationships between criteria. Filipe et al. (2015) and Oliveira et al. (2017) further report that these
maps enable decision makers to deal simultaneously with quantitative and qualitative factors, structure complex decision situations, and benefit from group work. Cognitive maps also facilitate the development and implementation of strategic decisions.

In the present study, a group cognitive map was developed in a decision conference (Phillips & Bana e Costa, 2007; Lousada et al., 2021), that is, a meeting of people willing to solve an important decision problem that affects their organization. This meeting was conducted by a neutral facilitator who is a specialist in decision analysis, and who works as a consultant in this type of process. The decision conference relied on a model created specifically in the meeting to aggregate the relevant data and opinions in order to help the group to think more clearly about their decision problem (Mustajoki et al., 2007; Phillips and Bana e Costa, 2007; Vieira et al., 2020). According to Vieira et al. (2020: 1), “[This approach] has proven to be effective, in a variety of contexts, in [terms of] creating a collaborative environment that enables […] individual beliefs [to surface], [as well as] identifying common concerns, managing eventual value conflicts and promoting agreement in group model building”. Marttunen et al. (2017) assert that a good problem structuring process is extremely important to the subsequent MCDA evaluation phase because the latter’s success will be strongly influenced by the results of the previous structuring procedure.

3.2 DEMATEL

The DEMATEL technique was developed by the Batelle Memorial Institute of Geneva’s Science and Human Affairs Program between 1972 and 1976 (Gabus and Fontela, 1972). This method is a mathematical technique that facilitates analyses of causality, and other associations between various dimensions in complex decision problems (Sumrit and Anuntavoranich, 2013; Kumar and Dixit, 2018; Du and Zhou, 2019). According to Chang et al. (2011: 1852), “DEMATEL can convert the relationship[s] between cause and effect factors into an intelligible structural model of the system”.

This method was applied during the second phase of the MCDA approach (i.e., evaluation phase), which is a branch of OR focused on supporting decision making involving complex problems (Bana e Costa et al., 1997; Doumpos and Zopounidis, 2002; Ferreira et al., 2011). DEMATEL is based on matrices and digraphs (Chang et al., 2011; Falatoonitoosi et al., 2013; Bacudio et al., 2016; Kumar et al., 2017). Digraphs visually represent the cause-and-effect relationships between criteria, as well as clarifying their direction (Wu and Lee, 2007; Kumar et al., 2017; Si et al., 2018), and dividing the factors into causes and effects (Chang et al., 2011; Lin, 2013; Si et al., 2018).

The DEMATEL technique generates a correlation matrix based on expert opinions about the cause-and-effect relationships between factors. A scale of 0 to 4 is used to measure these relationships, in which “0” is no influence, “1” little influence, “2” medium influence, “3” strong influence, and “4” very strong influence (Gabus and Fontela, 1972; Kumar et al., 2017; Atthirawong et al., 2018; Kumar and Dixit, 2018). To apply this method, four steps had to be completed (Tzeng et al., 2007; Li and Tzeng, 2009; Vujanović et al., 2012; Falatoonitoosi et al., 2013; Hsu et al., 2013; Lee et al., 2013; Si et al., 2018).
3.2.1 Step One

The average matrix was calculated using the above scale of 0 to 4. \( H \) is the number of experts and \( n \) the number of factors. Each expert’s score formed a non-negative matrix \( n \times n \) \( B^k = [b_{ij}^k] \) \( n \times n \) with \( 1 \leq k \leq H \). Next, the scores average was calculated by using Equation (1) to create the average matrix \( A = [a_{ij}] n \times n \):

\[
a_{ij} = \frac{1}{H} \sum_{k=1}^{H} b_{ij}^k
\]  

(1)

3.2.2 Step Two

The normalized direct relation or influence matrix—matrix \( D \)—was calculated by normalizing the average matrix using Equations (2) and (3). Matrix \( D \) was obtained by dividing the elements of matrix \( A \) by \( S \), and the matrix values were kept between 0 and 1:

\[
S = \max(\max_{1 \leq i \leq n} \sum_{j=1}^{n} a_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^{n} a_{ij})
\]  

(2)

\[
D = \frac{A}{S}
\]  

(3)

3.2.3 Step Three

The total relation matrix—matrix \( T \)—was calculated using Equation (4), in which \( I \) is an identity matrix \( n \times n \):

\[
T = \lim_{n \to \infty} (D + D^2 + \cdots + D^m) = D(I - D^{-1})
\]  

(4)

3.2.4 Step Four

The last step was to set a threshold value \( p \) and build an impact relationship map (IRM), which is the final result of the DEMATEL technique (i.e., “a visual representation of the mind […] with] which the respondent organizes his or her own action in the world” (Li and Tzeng, 2009: 9892)). The threshold value \( p \) is the average of the values in matrix \( T \), represented as Equation (5), and this value is used to filter out the values that are too low in matrix \( T \):

\[
p = \frac{1}{n^2} \sum_{i,j=1}^{n} t_{ij}
\]  

(5)
The DEMATEL technique has various advantages, but, as can be expected with any technique, it is not without limitations. As previously mentioned, one of its strengths is that it allows researchers to analyze the causal relationships between the factors, and to visualize more easily the structure of complex causal relationships through digraphs (Chang et al., 2011; Falatoonitoosi et al., 2013; Zhou et al., 2017). According to Hsu et al. (2013: 171), “DEMATEL can deal with [...] complicated and intertwined problems and determine the causal relationships among [...] evaluation criteria”.

Chang et al. (2011) assert that DEMATEL does not require a large amount of data or independence between elements, which other traditional techniques do (Vujanović et al., 2012; Wu and Chang, 2015). The DEMATEL method uses a “structural modeling technique” (Wu and Chang, 2015: 396) to identify possible interdependence between elements. Falatoonitoosi et al. (2013: 3477) report that “this methodology enables business managers to reach a high [level of] performance regarding [...] the effect[s] group criteria [...] [have on] all fields”. DEMATEL has been used in various areas to make better decisions about practices because “many real-world systems include imprecise and uncertain information” (Si et al., 2018: 1).

Kumar and Dixit (2018: 118) assert that “DEMATEL is a robust tool for gaining an improved view of the problem and [...] [for] assist[ing] the various stakeholders [...] [by] making their decision process [...] [transparent] and reliable”. However, the cited authors also point out that the limitations of this tool include the “biased judgement[s] of the experts and the non-unification of the judgment scales of the DEMATEL technique” (Kumar and Dixit, 2018: 118). Si et al. (2018: 12) mention other limitations, such as that “it determines the ranking of alternatives based on interdependent relationships among them [...] but other criteria are not incorporated in the decision making problem”. A third limitation is that “the relative weights of experts are not considered [...] [when] aggregating [the] personal judgements of experts into group assessments”.

Finally, Li and Tzeng (2009) report a limitation in the way the threshold value is defined. According to the cited authors, this value is usually chosen in conversations with specialists or in a subjective process by the researchers. Li and Tzeng (2009) highlight that an appropriate definition of the threshold value is important because it affects the information used to form the IRM.
4. APPLICATION AND RESULTS

As mentioned previously, the main objective of this study was to identify and analyze proactive measures and/or tools to combat blight. To achieve this goal, SODA and cognitive mapping were combined with the DEMATEL technique to evaluate the cause-and-effect relationships between these measures.

4.1 Structuring Phase: Participants and Procedures

The techniques were applied using a group of seven professionals specializing in areas that directly deal with urban blight. One expert was a senior technical architect in the Sintra City Council’s Urban Planning Department, while another was the head of the Urban Renewal Division of the Loures City Council’s Department of Planning and Urban Management. Two other experts were members of the Alvalade County Council’s Public Spaces Department, and another was a member of the Campolide County Council’s Innovation Department. The last two experts were an architect specializing in urban renewal from the Associação Portuguesa para a Reabilitação Urbana e Proteção do Património (Portuguese Association for Urban Renewal and Heritage Protection), and the division head of the Lisbon City Council’s Local Development Department. All seven specialists made themselves available to share their knowledge, and showed interest in analyzing the decision problem in question. Figure 2 depicts the methodological procedures followed.

Figure 2. Methodological Processes Followed
The results reflect the ideas and experience of a particular group of participants, but, when the procedures followed are correctly applied, they can work equally well with different decision-maker panels or in other contexts. Thus, representativeness is not—and does not need to be—a matter of concern. The findings reflect the research constructivist orientation, which means that the proposed methodology is more focused on process than specific desired outcomes (for further discussion, see Bell and Morse (2013), Fonseca et al. (2018), Ormerod (2018), Ackermann (2019), and Ormerod (2020)).

An experienced facilitator (i.e., one of the authors of this paper) conducted the group meetings and recorded the outcomes. The first session focused on structuring the decision problem, and lasted approximately four hours. This session was attended not only by the specialists, but also by the facilitator and two technical assistants who recorded the entire process, ensured that everything went as intended, and facilitated communication between the decision makers. First, a brief presentation of the methodology was given, and each expert was invited to introduce him- or herself to the other members of the panel. Next, to start the process of structuring the decision problem, a question was asked of the decision makers (i.e., a trigger question): “Based on your knowledge and professional experience, what proactive strategies, measures, and/or actions would you suggest to combat blight?”. This question provided the impetus needed to implement the “post-its technique” (Ackermann and Eden, 2001), and identify proactive measures to prevent blight. In the “post-its technique”, each decision maker is invited to write any criterion that answers the trigger question on post-it notes (i.e., one per note). Every time an item has a negative effect on the objective in question (i.e., every time a criterion negatively influences the prevention of blight), a minus sign (−) is written in the upper right corner of the post-it note. The decision makers repeat the process until they agree that no more significant criteria need to be added (Ferreira et al., 2014; Pires et al., 2018).

The decision makers talked, discussed ideas, and wrote down criteria for as long as needed. The post-it notes were placed on a whiteboard visible to everyone, and, whenever criteria appeared to be exactly the same, they were eliminated. At the end of the session, the post-it notes were grouped into five clusters by the decision makers (i.e., governance, community involvement, economy, territorial planning, and operationalization). Finally, the decision makers were asked to reorder the criteria inside each cluster, putting the most important ones at the top, and the least significant ones at the bottom. In the end, after removing repeated criteria, the map contained about 120 criteria. A group cognitive map was then generated using the Decision Explorer software (www.banxia.com). According to Eden and Ackermann (2001: 36), this software is “non-prescriptive in use or outcome. It is deliberately designed to help the skilled professional consultant manage the complexity and richness that arises when working [with] large amounts of interrelated qualitative data”. Figure 3 shows the final version of the group cognitive map, which was validated by the panel members through collective analysis and discussion.
Overall, the development of the collective cognitive map was useful in terms of both structuring and improving the decision makers’ understanding of blight prevention strategies. As reported in the literature (e.g., Eden and Ackermann, 2001), cognitive mapping significantly reduced the number of omitted dimensions and determinants in the analysis of anti-blight strategies. In addition, the map improved the panel’s understanding of the cause-and-effect relationships between the criteria. The mapping process was thus fundamental to ensuring the success of the subsequent evaluation phase, in which DEMATEL was applied.

4.2 Evaluation Phase

The second session with the decision makers involved putting the second phase of the multi-criteria decision support process (i.e., evaluation) into practice. In this meeting, the group reviewed the map and applied the DEMATEL technique, as well as discussing the causal relationships between clusters and the links between the criteria within each cluster. This session was held with only five of the seven panel members due to scheduling conflicts and illness—a situation mentioned in the literature, which researchers have confirmed does not compromise the results obtained (cf. Azevedo and Ferreira, 2019). Table 2 presents the clusters identified. Table 3 represents the average matrix (i.e., matrix A) based on the analysis carried out of relationships between clusters in the first step of the DEMATEL application procedure (see section 3.2.1).

<table>
<thead>
<tr>
<th>CLUSTERS</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>Governance</td>
</tr>
<tr>
<td>C2</td>
<td>Community Involvement</td>
</tr>
<tr>
<td>C3</td>
<td>Economy</td>
</tr>
<tr>
<td>C4</td>
<td>Territorial Planning</td>
</tr>
<tr>
<td>C5</td>
<td>Operationalization</td>
</tr>
</tbody>
</table>
Table 3. Average Matrix for Clusters

<table>
<thead>
<tr>
<th></th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>0.0</td>
<td>2.0</td>
<td>2.5</td>
<td>4.0</td>
<td>3.5</td>
<td>12.0</td>
</tr>
<tr>
<td>C2</td>
<td>1.5</td>
<td>0.0</td>
<td>0.5</td>
<td>2.0</td>
<td>2.0</td>
<td>6.0</td>
</tr>
<tr>
<td>C3</td>
<td>2.0</td>
<td>3.0</td>
<td>0.0</td>
<td>3.0</td>
<td>3.0</td>
<td>11.0</td>
</tr>
<tr>
<td>C4</td>
<td>2.0</td>
<td>3.0</td>
<td>3.0</td>
<td>0.0</td>
<td>2.5</td>
<td>10.5</td>
</tr>
<tr>
<td>C5</td>
<td>2.0</td>
<td>4.0</td>
<td>4.0</td>
<td>3.0</td>
<td>0.0</td>
<td>13.0</td>
</tr>
<tr>
<td>TOTAL</td>
<td>7.5</td>
<td>12.0</td>
<td>10.0</td>
<td>12.0</td>
<td>11.0</td>
<td></td>
</tr>
</tbody>
</table>

In step two, the maximum value of the sum totals of the columns and rows of matrix A in Table 3 was calculated using Equation (2), which produced the results shown in Table 4. The normalized direct-relation matrix (i.e., matrix D in Table 5) was obtained by multiplying matrix A by the inverse of S using Equation (3).

Table 4. Step 2 Calculations for DEMATEL Cluster Analysis

<table>
<thead>
<tr>
<th></th>
<th>MAX</th>
<th>1/Max</th>
<th>1/s</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12.0</td>
<td>13.0</td>
<td>0.076923077</td>
</tr>
</tbody>
</table>

Table 5. Direct-Relation Matrix

<table>
<thead>
<tr>
<th></th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>0.0000</td>
<td>0.1538</td>
<td>0.1923</td>
<td>0.3077</td>
<td>0.2692</td>
</tr>
<tr>
<td>C2</td>
<td>0.1154</td>
<td>0.0000</td>
<td>0.0385</td>
<td>0.1538</td>
<td>0.1538</td>
</tr>
<tr>
<td>C3</td>
<td>0.1538</td>
<td>0.2308</td>
<td>0.0000</td>
<td>0.2308</td>
<td>0.2308</td>
</tr>
<tr>
<td>C4</td>
<td>0.1538</td>
<td>0.2308</td>
<td>0.2308</td>
<td>0.0000</td>
<td>0.1923</td>
</tr>
<tr>
<td>C5</td>
<td>0.1538</td>
<td>0.3077</td>
<td>0.3077</td>
<td>0.2308</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Step three required the creation of three matrices (see Table 6) to obtain the total relation matrix (i.e., matrix T) using Equation (4). First, an identity matrix (i.e., matrix I) was generated, after which matrix D—obtained in the previous step—was subtracted (I – D). The inverse matrix was thus calculated using the expression I – D⁻¹. Finally, matrix T was calculated using Equation (4), and thus multiplying matrix D by the inverse matrix (see Table 7).
Table 6. Calculations for Total Relation Matrix

<table>
<thead>
<tr>
<th>Matrix I</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>1.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>C2</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>C3</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>C4</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>C5</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>I-D</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>1.0000</td>
<td>-0.1538</td>
<td>-0.1923</td>
<td>-0.3077</td>
<td>-0.2692</td>
</tr>
<tr>
<td>C2</td>
<td>-0.1154</td>
<td>1.0000</td>
<td>-0.0385</td>
<td>-0.1538</td>
<td>-0.1538</td>
</tr>
<tr>
<td>C3</td>
<td>-0.1538</td>
<td>-0.2308</td>
<td>1.0000</td>
<td>-0.2308</td>
<td>-0.2308</td>
</tr>
<tr>
<td>C4</td>
<td>-0.1538</td>
<td>-0.2308</td>
<td>-0.2308</td>
<td>1.0000</td>
<td>-0.1923</td>
</tr>
<tr>
<td>C5</td>
<td>-0.1538</td>
<td>-0.3077</td>
<td>-0.3077</td>
<td>-0.2308</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(I-D)^-1</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>1.5682</td>
<td>0.9970</td>
<td>0.8902</td>
<td>1.0690</td>
<td>0.9866</td>
</tr>
<tr>
<td>C2</td>
<td>0.4101</td>
<td>1.4666</td>
<td>0.4377</td>
<td>0.5794</td>
<td>0.5485</td>
</tr>
<tr>
<td>C3</td>
<td>0.6425</td>
<td>0.9635</td>
<td>1.6456</td>
<td>0.9287</td>
<td>0.8796</td>
</tr>
<tr>
<td>C4</td>
<td>0.6204</td>
<td>0.9287</td>
<td>0.8030</td>
<td>1.7092</td>
<td>0.8239</td>
</tr>
<tr>
<td>C5</td>
<td>0.7083</td>
<td>1.1154</td>
<td>0.9633</td>
<td>1.0229</td>
<td>1.7813</td>
</tr>
</tbody>
</table>

Table 7. Total Relation Matrix

<table>
<thead>
<tr>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>0.5682</td>
<td>0.9970</td>
<td>0.8902</td>
<td>1.0690</td>
<td>0.9866</td>
</tr>
<tr>
<td>C2</td>
<td>0.4101</td>
<td>0.4666</td>
<td>0.4377</td>
<td>0.5794</td>
<td>0.5485</td>
</tr>
<tr>
<td>C3</td>
<td>0.6425</td>
<td>0.9635</td>
<td>0.6456</td>
<td>0.9287</td>
<td>0.8796</td>
</tr>
<tr>
<td>C4</td>
<td>0.6204</td>
<td>0.9287</td>
<td>0.8030</td>
<td>0.7092</td>
<td>0.8239</td>
</tr>
<tr>
<td>C5</td>
<td>0.7083</td>
<td>1.1154</td>
<td>0.9633</td>
<td>1.0229</td>
<td>0.7813</td>
</tr>
<tr>
<td>C</td>
<td>2.9496</td>
<td>4.4712</td>
<td>3.7397</td>
<td>4.3092</td>
<td>4.0198</td>
</tr>
</tbody>
</table>
In matrix $T$ in Table 7, a row and a column were added to represent the $C$ and $R$ values, respectively. $C$ values are the total of each column, which represents the influence that all criteria have on the criterion in question. For example, the effects of the other clusters on C1 (i.e., governance) have a value of 2.9496. The $R$ values are the totals of each line, which indicate the overall influence that each cluster has on the others. For instance, C1 has a total influence of 4.5111 on the other clusters. The results show that C5 (i.e., operationalization) and C1 have the greatest influence over the remaining clusters, with an $R$ value of 4.5912 and 4.5111, respectively. In contrast, C2 (i.e., community involvement) has the smallest impact on the other clusters, with an $R$ of 2.4422. Notably, this cluster is also the most affected by all the other clusters, based on a $C$ value of 4.4712.

Matrix $T$ reveals that all the criteria are related to each other, but that some relationships are more significant than others are. In step four, the threshold value $p$ was calculated as 0.7796 based on Equation (5). This value highlights which are the most important relationships, placing values above $p$ in green and values below or equal to $p$ in red (see Table 7). Table 8 contains two columns representing the addition and subtraction of the $R$ and $C$ values, respectively. The column showing the combination of these values provides a fuller understanding of the criteria importance. The greater this total value, the more significant the criterion is because the relationships established with the other criteria are stronger. In this case, the operationalization cluster is the most important in the model, with a value of 8.6110.

<table>
<thead>
<tr>
<th></th>
<th>R</th>
<th>C</th>
<th>R+C</th>
<th>R-C</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>4.5111</td>
<td>2.9496</td>
<td>7.4606</td>
<td>1.5615</td>
</tr>
<tr>
<td>C2</td>
<td>2.4422</td>
<td>4.4712</td>
<td>6.9134</td>
<td>-2.0289</td>
</tr>
<tr>
<td>C3</td>
<td>4.0598</td>
<td>3.7397</td>
<td>7.7995</td>
<td>0.3201</td>
</tr>
<tr>
<td>C4</td>
<td>3.8851</td>
<td>4.3092</td>
<td>8.1943</td>
<td>-0.4241</td>
</tr>
<tr>
<td>C5</td>
<td>4.5912</td>
<td>4.0198</td>
<td>8.6110</td>
<td>0.5714</td>
</tr>
</tbody>
</table>

The column showing the subtraction of the $R$ and $C$ values helps decision makers visualize the nature of the relationship between criteria and understand which criteria are causes or effects. A negative value means that a criterion is more affected by other criteria than it influences them, that is, an effect criterion. A positive value indicates that the criterion affects others more than it is affected, so it is a cause criterion. As previous analyses also confirmed, C2 (i.e., community involvement) is the most influenced cluster with a value of −2.0289.

The last step produced the final results of the DEMATEL technique (i.e., IRMs). In this first map or diagram (see Figure 4), the clusters that appear below $R+C$ are those that have a negative value regarding the difference between $R$ and $C$, and thus are more affected than they affect others. These criteria represent the effects clusters (i.e., C2 and C4). Clusters above the $R+C$ axis are those whose difference between $R$ and $C$ is positive,
so they influence other clusters more than they are influenced and constitute the causes clusters (i.e., C1, C3, and C5).

![DEMATEL - Cause Effect Diagram](image)

**Figure 4.** IRM for Clusters

On the right side of the graph are the most important clusters in terms of further analysis since they have more relationships, that is, those clusters whose values for the addition of $R$ and $C$ are higher (i.e., C5 and C4). On the left side are those clusters that are less significant, in this case only C2. The arrows in the diagram (see Figure 3) show the direction of the relationships between each cluster. Only the links considered significant for the present analysis based on the threshold value $p$ are included, that is, those in green in matrix $T$ (see Table 7).

The four steps were carefully followed for the remaining five matrices, which comprised analyses of the criteria influence on each other within the five clusters as discussed further below. Due to the large number of criteria identified in each cluster, nominal group and multi-voting techniques were used to identify the most important criteria for further analysis (i.e., significant proactive anti-blight measures and actions).

Regarding the first cluster (i.e., governance), seven criteria—identified as sub-criterion (SC) to differentiate them from the main clusters—were chosen by the decision-maker panel, as shown in Table 9. This cluster has a threshold value $p$ of 0.2673.

<table>
<thead>
<tr>
<th>CHOSEN CRITERIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC7 Development of renewal incentive programs</td>
</tr>
<tr>
<td>SC8 Promotion of cost-controlled housing programs</td>
</tr>
<tr>
<td>SC19 Streamlining of administrative processes</td>
</tr>
<tr>
<td>SC31 Co-governance</td>
</tr>
<tr>
<td>SC33 Municipalities’ greater capacity to control and monitor</td>
</tr>
</tbody>
</table>
The $R$ values (see Table 10) reveal that SC31 (i.e., co-governance) has the greatest influence on all other criteria, with an $R$ value of 2.7288. In contrast, SC8 (i.e., promotion of cost-controlled housing programs) has the least impact on the other criteria, with an $R$ value of just 1.1997. The $C$ values show that SC7 (i.e., development of renewal incentive programs) is the most strongly influenced by the rest of the criteria, with a value of 2.6901.

### Table 10. Total Relation Matrix for Governance Cluster

<table>
<thead>
<tr>
<th></th>
<th>SC34</th>
<th>SC19</th>
<th>SC8</th>
<th>SC7</th>
<th>SC31</th>
<th>SC35</th>
<th>SC33</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC34</td>
<td>0.1932</td>
<td>0.1927</td>
<td>0.4045</td>
<td>0.4122</td>
<td>0.2561</td>
<td>0.2962</td>
<td>0.2377</td>
<td>1.9926</td>
</tr>
<tr>
<td>SC19</td>
<td>0.3601</td>
<td>0.1184</td>
<td>0.4454</td>
<td>0.4996</td>
<td>0.2662</td>
<td>0.3301</td>
<td>0.3288</td>
<td>2.3485</td>
</tr>
<tr>
<td>SC8</td>
<td>0.1868</td>
<td>0.0620</td>
<td>0.1746</td>
<td>0.2819</td>
<td>0.1885</td>
<td>0.2178</td>
<td>0.0881</td>
<td>1.1997</td>
</tr>
<tr>
<td>SC7</td>
<td>0.2080</td>
<td>0.0725</td>
<td>0.3730</td>
<td>0.1996</td>
<td>0.1909</td>
<td>0.2412</td>
<td>0.1648</td>
<td>1.4500</td>
</tr>
<tr>
<td>SC31</td>
<td>0.4209</td>
<td>0.2927</td>
<td>0.5280</td>
<td>0.5382</td>
<td>0.2213</td>
<td>0.4321</td>
<td>0.2956</td>
<td>2.7288</td>
</tr>
<tr>
<td>SC35</td>
<td>0.2453</td>
<td>0.0769</td>
<td>0.4048</td>
<td>0.4013</td>
<td>0.1863</td>
<td>0.1675</td>
<td>0.1787</td>
<td>1.6608</td>
</tr>
<tr>
<td>SC33</td>
<td>0.2651</td>
<td>0.1892</td>
<td>0.2442</td>
<td>0.3575</td>
<td>0.2537</td>
<td>0.2703</td>
<td>0.1355</td>
<td>1.7154</td>
</tr>
<tr>
<td>C</td>
<td>1.8795</td>
<td>1.0045</td>
<td>2.5745</td>
<td>2.6901</td>
<td>1.5630</td>
<td>1.9552</td>
<td>1.4292</td>
<td></td>
</tr>
</tbody>
</table>

An examination of each criterion in the DEMATEL diagram (see Figure 5) revealed that the SC farthest to the right in the chart is SC31 (i.e., co-governance). Thus, this SC is the most important measure as it is the one that has the highest value for the addition of $R$ and $C$ (4.2918). The least significant SC in the present analysis is SC33 (i.e., municipalities’ greater capacity to control and monitor) as it is the farthest to the left in the diagram and the SC with the lowest value for $R+C$ (3.1446).
The criterion that has the smallest difference between $R$ and $C$ and that is in the lowest position in the IRM is SC8 (i.e., promotion of cost-controlled housing programs), with a value of $-1.3749$. In contrast, the SC that has the highest $R-C$ value is SC19 (i.e., streamlining of administrative processes). Overall, the cause criteria are SC19, SC31, SC33, and SC34, while the effect criteria are SC7, SC8, and SC35.

In the second cluster (i.e., community involvement), seven SCs were also selected. The criteria are listed in Table 11, and they have a threshold value $p$ of 0.8275.

**Table 11. Identification of Criteria for Community Involvement Cluster**

<table>
<thead>
<tr>
<th>CHOSEN CRITERIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC39 Citizenship education</td>
</tr>
<tr>
<td>SC43 Residents’ new transformative skills</td>
</tr>
<tr>
<td>SC44 Participation in decision-making processes</td>
</tr>
<tr>
<td>SC47 Identification of local stakeholders</td>
</tr>
<tr>
<td>SC50 Creation of a sense of belonging</td>
</tr>
<tr>
<td>SC55 Development of strategies for appropriations of public spaces</td>
</tr>
<tr>
<td>SC60 Initiatives and activities involving the community</td>
</tr>
</tbody>
</table>

As seen in Table 12, the most influential SC is SC50 (i.e., creation of a sense of belonging), with an $R$ value of 6.1672. The second most important criterion is SC55 (i.e., development of strategies for appropriations of public spaces), with an $R$ value of 6.1602, which is extremely close to the value of the first SC. In contrast, the SC most influenced by other criteria is SC60 (i.e., initiatives and activities involving the community), with a $C$ value of 6.6383, while the second most affected is SC50, with 6.6297.

**Table 12. Total Relation Matrix for Community Involvement Cluster**

<table>
<thead>
<tr>
<th></th>
<th>SC44</th>
<th>SC60</th>
<th>SC50</th>
<th>SC43</th>
<th>SC55</th>
<th>SC39</th>
<th>SC47</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC44</td>
<td>0.7599</td>
<td>0.9486</td>
<td>0.9826</td>
<td>0.7720</td>
<td>0.9445</td>
<td>0.8246</td>
<td>0.5666</td>
<td>5.7988</td>
</tr>
<tr>
<td>SC60</td>
<td>0.8885</td>
<td>0.8395</td>
<td>0.9947</td>
<td>0.8350</td>
<td>0.9386</td>
<td>0.8171</td>
<td>0.5739</td>
<td>5.8874</td>
</tr>
<tr>
<td>SC50</td>
<td>0.9593</td>
<td>1.0331</td>
<td>0.8816</td>
<td>0.8503</td>
<td>0.9944</td>
<td>0.8514</td>
<td>0.5973</td>
<td>6.1672</td>
</tr>
<tr>
<td>SC43</td>
<td>0.7651</td>
<td>0.8629</td>
<td>0.8795</td>
<td>0.6174</td>
<td>0.8276</td>
<td>0.7351</td>
<td>0.5171</td>
<td>5.2048</td>
</tr>
<tr>
<td>SC55</td>
<td>0.9244</td>
<td>1.0326</td>
<td>1.0338</td>
<td>0.8677</td>
<td>0.8382</td>
<td>0.8667</td>
<td>0.5967</td>
<td>6.1602</td>
</tr>
<tr>
<td>SC39</td>
<td>0.9415</td>
<td>1.0124</td>
<td>0.9979</td>
<td>0.8326</td>
<td>0.9407</td>
<td>0.7137</td>
<td>0.5853</td>
<td>6.0242</td>
</tr>
<tr>
<td>SC47</td>
<td>0.8463</td>
<td>0.9092</td>
<td>0.8596</td>
<td>0.7288</td>
<td>0.8429</td>
<td>0.6749</td>
<td>0.4420</td>
<td>5.3036</td>
</tr>
</tbody>
</table>

The most significant criterion for the current analysis, that is, the one farthest to the right in the diagram (see Figure 5) is SC50 (i.e., creation of a sense of belonging), with an $R+C$ value of 12.7970. The criterion that has the weakest relationships with the
other SCs is SC47 (i.e., identification of local stakeholders) as it is the farthest to the left in the graph, with an $R+C$ value of 9.1825. The IRM in Figure 6 reveals that most the criteria are below the $R–C$ axis, so all these criteria have a negative value, making them effect criteria (i.e., SC43, SC44, SC50, SC55, and SC60). SC39 and SC47 are above the $R–C$ axis, with positive values, and thus these are cause criteria. SC47 (i.e., identification of local stakeholders) is the criterion that has the highest value for the difference between $R$ and $C$ (1.4248), while SC60 (i.e., initiatives and activities involving the community) has the lowest value (–0.7509).
In the third cluster (i.e., economy), the panel members chose only five criteria for analysis, which reflects the small size of this cluster. These criteria are listed in Table 13. The cluster has a threshold value $p$ of 1.1453.

**Table 13. Identification of Criteria for Economy Cluster**

<table>
<thead>
<tr>
<th>CHOSEN CRITERIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC110 Revitalization of urban centers</td>
</tr>
<tr>
<td>SC111 Creation of hubs of attractiveness for trade and proximity services</td>
</tr>
<tr>
<td>SC112 Synergies with bordering areas</td>
</tr>
<tr>
<td>SC114 Investment in self-employment and local economy</td>
</tr>
<tr>
<td>SC120 Artistic and cultural interventions</td>
</tr>
</tbody>
</table>

Table 14 shows that the most influential SC is SC111 (i.e., creation of hubs of attractiveness for trade and proximity services) since it is the one with the highest $R$ value (6.5369). In contrast, the SC most affected by the other criteria is SC110 (i.e., revitalization of urban centers), with a $C$ value of 6.1446.
Table 14. Total Relation Matrix for Economy Cluster

<table>
<thead>
<tr>
<th></th>
<th>SC112</th>
<th>SC114</th>
<th>SC111</th>
<th>SC110</th>
<th>SC120</th>
<th>R</th>
<th>C</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC112</td>
<td>0.8760</td>
<td>0.9956</td>
<td>1.0256</td>
<td>1.0825</td>
<td>0.9645</td>
<td>4.9442</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SC114</td>
<td>1.0509</td>
<td>0.8910</td>
<td>1.0989</td>
<td>1.1592</td>
<td>1.0092</td>
<td>5.2093</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SC111</td>
<td>1.3588</td>
<td>1.3167</td>
<td>1.1564</td>
<td>1.4537</td>
<td>1.2514</td>
<td>6.5369</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SC110</td>
<td>1.2918</td>
<td>1.2276</td>
<td>1.2882</td>
<td>1.1589</td>
<td>1.1886</td>
<td>6.1551</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SC120</td>
<td>1.2038</td>
<td>1.1401</td>
<td>1.2001</td>
<td>1.2902</td>
<td>0.9522</td>
<td>5.7864</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>5.7813</td>
<td>5.5710</td>
<td>5.7693</td>
<td>6.1446</td>
<td>5.3659</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The most important SC for the present analysis is SC111 (i.e., creation of hubs of attractiveness for trade and proximity services), with a $R+C$ value of 12.3062. This SC is the farthest to the right in the IRM (see Figure 7). SC110 (i.e., revitalization of urban centers) has a quite similar $R+C$ value (12.2997), making this SC a close second in terms of the most significant relationships. In contrast, the least significant SC, that is, the one that has the least number of links with the other criteria, is SC112 (i.e., synergies with bordering areas), with the lowest $R+C$ value (10.7255).

![DEMATEL - Cause effect diagram](image)

**Figure 7. IRM for Economy Cluster**

The results for the difference between $R$ and $C$ reveal that SC111 (i.e., creation of hubs of attractiveness for trade and proximity services) has a stronger effect on the other criteria, as opposed to being influenced, because it has a positive value (0.7677). In contrast, the SC that is most affected by the remaining criteria is SC112 (i.e., synergies with bordering areas), with the lowest $R–C$ value (–0.8370) and the lowest position in the IRM (see Figure 7). In this chart, the cause criteria are SC110, SC111, and SC120, and the effect criteria are SC112 and SC114.

Regarding the fourth cluster (i.e., territorial planning), five criteria were also selected, which are presented in Table 15. This cluster has a threshold value $p$ of 0.6770.
Table 15. Identification of Criteria for Territorial Planning Cluster

<table>
<thead>
<tr>
<th>CHOSEN CRITERIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC11 Urban, social, and financial planning with intervention strategies</td>
</tr>
<tr>
<td>SC73 Planning instruments</td>
</tr>
<tr>
<td>SC82 Creation of green and leisure spaces</td>
</tr>
<tr>
<td>SC84 Existence of equipment for groups</td>
</tr>
<tr>
<td>SC88 Upgrading of public areas</td>
</tr>
</tbody>
</table>

The SCs that most influence the rest are SC11 (*i.e.*, urban, social, and financial planning with intervention strategies) and SC73 (*i.e.*, planning instruments), which have the same $R$ value of 4.1852. SC88 (*i.e.*, upgrading of public areas) is the least influential, with an $R$ value of 2.6543 (see Table 16). An analysis of the $C$ values revealed that the most strongly affected SC is SC88, with a $C$ value of 4.1852, while the least affected criteria are SC11 and SC73, with the same $C$ value (2.7407).

Table 16. Total Relation Matrix for Territorial Planning Cluster

```
<table>
<thead>
<tr>
<th></th>
<th>SC11</th>
<th>SC82</th>
<th>SC84</th>
<th>SC73</th>
<th>SC88</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC11</td>
<td>0.5481</td>
<td>0.9396</td>
<td>0.9123</td>
<td>0.7481</td>
<td>1.0370</td>
<td>4.1852</td>
</tr>
<tr>
<td>SC82</td>
<td>0.4938</td>
<td>0.5179</td>
<td>0.6550</td>
<td>0.4938</td>
<td>0.7901</td>
<td>2.9506</td>
</tr>
<tr>
<td>SC84</td>
<td>0.4938</td>
<td>0.6758</td>
<td>0.4971</td>
<td>0.4938</td>
<td>0.7901</td>
<td>2.9506</td>
</tr>
<tr>
<td>SC73</td>
<td>0.7481</td>
<td>0.9396</td>
<td>0.9123</td>
<td>0.5481</td>
<td>1.0370</td>
<td>4.1852</td>
</tr>
<tr>
<td>SC88</td>
<td>0.4568</td>
<td>0.6251</td>
<td>0.5848</td>
<td>0.4568</td>
<td>0.5309</td>
<td>2.6543</td>
</tr>
<tr>
<td>C</td>
<td>2.7407</td>
<td>3.6979</td>
<td>3.5614</td>
<td>2.7407</td>
<td>4.1852</td>
<td></td>
</tr>
</tbody>
</table>
```

The criteria that have the largest number of significant relationships are SC11 (*i.e.*, urban, social, and financial planning with intervention strategies) and SC73 (*i.e.*, planning instruments), with the same $R+C$ value (6.9259). These SCs are the farthest to the right on the IRM (see Figure 8). The two criteria also have the highest $R–C$ value, with a positive value of 1.444, which places them at the top of the diagram.
SC84 \textit{(i.e., existence of equipment for groups)} is the farthest left on the IRM, and this criterion has a lower $R+C$ value (6.5120), showing that SC84 has the least important relationships with the other criteria. The lowest SC on the IRM is SC88 \textit{(i.e., upgrading of public areas)}, with a $R–C$ value of −1.5309. In this cluster, the cause criteria are SC11 and SC73, while the effect criteria are SC82, SC84, and SC88.

Finally, in the fifth cluster \textit{(i.e., operationalization)}, five criteria were also chosen by the expert panel (see Table 17). The threshold value $p$ is 0.1634.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|}
\hline
\textbf{CHOSEN CRITERIA} & \textbf{SC99} \textit{Lack of human resources (HR) in local councils with the education and availability to do hands-on work in the field} \\
\hline
SC100 & Promote regular maintenance of spaces and buildings \\
\hline
SC102 & Lack of control \\
\hline
SC105 & Organize seminars and/or debates about blight \\
\hline
SC106 & Removal of degraded buildings to prevent them from becoming the basis of further urban blight \\
\hline
\end{tabular}
\caption{Identification Criteria for \textit{Operationalization} Cluster}
\end{table}

In this cluster, two SCs have the strongest effect on the others. The first is SC99 \textit{(i.e., lack of HR in local councils with the education and availability to do hands-on work in the field)}, with the highest $R$ value (1.5960), and the second is SC102 \textit{(i.e., lack of control)}, with an $R$ value of 1.1743 (see Table 18). The SC that has the least influence is SC100 \textit{(i.e., promote regular maintenance of spaces and buildings)}, with an $R$ of just 0.4027. In contrast, the most strongly affected SC is SC106 \textit{(i.e., removal of degraded buildings to prevent them from becoming the basis of further urban blight)}, with a $C$ value of 1.6497, while the least influenced is SC99 \textit{(i.e., lack of HR in local councils with the education and availability to do hands-on work in the field)}, with a $C$ value of 0.2197.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|l|l|l|l|}
\hline
 & SC100 & SC106 & SC102 & SC99 & SC105 & \textbf{R} \\
\hline
SC100 & 0.0538 & 0.3106 & 0.0231 & 0.0033 & 0.0118 & 0.4027 \\
\hline
SC106 & 0.1883 & 0.0872 & 0.0810 & 0.0116 & 0.0413 & 0.4093 \\
\hline
\end{tabular}
\caption{Total Relation Matrix for Operationalization Cluster}
\end{table}
An analysis of the addition and subtraction of $R$ and $C$ revealed that the SC at the farthest right on the IRM (see Figure 9) is SC106 (i.e., removal of degraded buildings), with an $R+C$ value of 2.0590. In contrast, the SC the farthest to the left in the graph is SC105 (i.e., organize seminars and/or debates about blight), with an $R+C$ value of only 0.8581.

![DEMATEL - Cause Effect Diagram](image)

**Figure 9. IRM for Operationalization Cluster**

An examination of the relationships between criteria showed that the SC at the top of the diagram is SC99 (i.e., lack of HR in local councils with the education and availability to do hands-on work in the field), with an $R–C$ value of 1.3763. SC99 thus influences more criteria than it is influenced by them. In contrast, the SC that is more affected than it influences is SC106 (i.e., removal of degraded buildings), with an $R–C$ value of $-1.2403$. For this cluster, the cause criteria are SC99, SC102, and SC105, while the effect criteria are SC100 and SC106.

In summary, five clusters including 29 major SCs (i.e., proactive anti-blight measures) were identified and analyzed in this study. Based on the above analysis, it is possible to identify the top seven SCs. In no particular order, these are:

- Co-governance (government cluster),
- Creation of a sense of belonging (community involvement cluster),
- Creation of hubs of attractiveness for trade and proximity services (economy cluster)
- Revitalization of urban centers (economy cluster)
- Urban, social, and financial planning with intervention strategies (territorial planning cluster)
- Planning instruments (territorial planning cluster)
- Removal of degraded buildings (operationalization cluster)

In addition, it is also possible to identify the SCs that seem to be less effective, such as organize seminars and/or debates about blight. With this information, it is easier to identify and analyze proactive measures and/or tools to combat blight.
4.3 Consolidation, Discussion, and Recommendations

To consolidate the results obtained with the proposed methodology, a meeting was held with two architects from Direção Geral do Território (Directorate General for Territory of Portugal). One was a senior technician in the Territorial Information and Management Division, and the other was a senior technician of the Division of Territorial Development and Cities Policy. This final session focused on eliciting these experts’ opinions regarding the study approach and results. Due to the restrictions implemented during the COVID-19 pandemic, the meeting was held using the Zoom platform to ensure the required social distance.

The consolidation session lasted about an hour, starting with a briefing on the blight phenomenon and its causes, effects, and consequences, as well as the methodologies used. Next, the interviewer explained how the methods (i.e., SODA and DEMATEL) were applied and the results obtained, namely, the group cognitive map and the IRMs. According to the interviewees, these methodologies “have great potential, and the results are extremely interesting and valid” (in their words). The experts also pointed out that the analyses of the causal relationships between the criteria (i.e., using DEMATEL) “are also very interesting” (also in their words).

However, these professionals felt that, because the results relied on a specific group of specialists comprising a limited number of participants, the approach is limited in terms of generalization. At this point, the interviewer underlined the process-oriented nature of the proposed framework, which does not seek to achieve representativeness or optimal solutions. Instead, the primary focus is on the process and ways that new insights can be obtained based on the techniques used to identify and inter-relate proactive anti-blight measures and actions.

Subsequently, the interviewees pointed out that the panel composition was quite heterogeneous as the experts were linked to different aspects of the blight problem, which the two senior technicians said was an extremely positive aspect. This meeting with two specialists who had not participated in the group sessions provided further evidence of the relevance of the proposed framework and its results.

5. CONCLUSION

The combined used of cognitive mapping and DEMATEL facilitates a more complete, transparent approach to the issue of blight, providing a holistic view of the phenomenon through the inclusion of objective and subjective elements in the analyses. In addition, the proposed methodology also offers a clearer understanding of the preventative measures that can be adopted, and a way to analyze their cause-and-effect relationships, thereby answering the research question presented (i.e., “How can urban/neighborhood blight prevention strategies be identified, and how are they interrelated?”). Specifically, the application of the methodology used allowed over 120 proactive strategies to be identified and divided into five clusters: (1) governance; (2) community involvement; (3) economy; (4) territorial planning; and (5) operationalization. The first two clusters contain the largest number of proactive measures. An analysis was then carried out of the cause-and-effect relationships between clusters and between criteria within each cluster.

The results reveal that the operationalization cluster has the greatest number of relationships with the other clusters. When this cluster is combined with the governance cluster, the two clusters have the most influence on the cognitive structure developed based on the expert panel’s expertise. Thus, they comprise a set of key measures closely linked to the realization of other cluster measures. These two clusters were thus classified as cause criteria. In contrast, the community involvement cluster proved to contain primarily effect criteria, and this cluster is the most strongly affected by the other clusters, showing that the implementation of its measures are influenced by other actions.
While this methodology has many strengths, it also has some limitations. Being constructivist in nature, its results depend on the context in which they were obtained, and the findings are difficult to generalize to other contexts. The cognitive map and the configuration of its contents were obtained through group sessions, and thus the results depend on a specific context and subjective views of the expert panel. The same limitation applies to the degree of influence calculated for each criterion using DEMATEL. The results could have been different if the panel participants were other people or the facilitator replaced by another researcher.

Some difficulty was also experienced during the recruitment of specialists for the panel due to the study extensive requirements of participants both in terms of time—a total of about eight hours—and schedules. Notably, although the blight prevention model created is constructivist in nature, and its results are based on subjective opinions and a specific context, the specialists involved in this study were quite enthusiastic about the results.

A review of the existing literature on this topic reveals that attempts to identify measures to prevent blight had already been made in various parts of the world, especially in the US. However, the previous studies summarized in Table 1 have limitations, namely, regarding the identification of measures and lack of dynamic analyses of variables. Thus, the present research sought to complement the existing literature to enable the creation and analysis of proactive measures to combat blight, and take into account objective and subjective aspects and causal relationships between variables.

No prior studies on blight prevention were found that combined PSM and the DEMATEL technique. The proposed methodology provides a new decision-support system covering the full scope of the blight problem. The combination of these two approaches facilitated the development of a more complete, transparent framework, as well as the participants’ sharing of experience and knowledge, thereby integrating people into the problem solution. Overall, this multi-criteria approach to identifying and analyzing proactive measures to prevent blight constitutes a significant contribution that improves the existing knowledge in this field of study and, once the findings are put into practice, the quality of life in affected areas.

Theoretically, although the findings are idiosyncratic in nature, they can be an important starting point for other researchers and practitioners who analyze proactive anti-blight measures. Thus, our contribution will be available as a springboard for additional studies, and complements previous contributions in the field. From a methodological point of view, our contribution is two-fold: one coming from the integration of methodologies used, which we believe to be novel in this study context, and second from the description of the process followed, which allows for replications in other contexts and/or with different groups of experts, due to the process-oriented nature of the framework. Specially, this methodology facilitated the development of a system that identifies proactive anti-blight measures in a simple, transparent, and structured approach. Again, no prior evidence reporting the combined used of cognitive mapping and DEMATEL to analyze proactive anti-blight measures has been found. This allows us to assume the novelty of our study.

This research approach by no means exhausts the possibilities for applying constructivist methodologies to the blight phenomenon. Thus, future studies may benefit from identifying and analyzing anti-blight measures with other multi-criteria techniques. In addition, since the above results are constructivist—and thus context dependent—the present study could be repeated with different panels with other types of experience and backgrounds to obtain new results adapted to the situations under analysis. Our findings, therefore, complement the existing knowledge about blight, and the proposed approach can serve as a starting point for future investigations, generating added value for those involved in the fight against blight.

ACKNOWLEDGMENTS
This study results from a larger research project on urban blight that includes causes of blight, its consequences, and blight preventive initiatives and remediation strategies. Funding for this study was received from the Portuguese Foundation for Science and Technology (Grant UIDB/00315/2020), the University of Memphis Fogelman College of Business and Economics Department of Finance, Insurance and Real Estate, and from the Morris Fogelman Real Estate Chair of Excellence. Records of the expert panel meetings, including pictures, software output and non-confidential information of the study, can be obtained from the corresponding author upon request. The authors gratefully acknowledge the exceptional contribution of the panel members: Ana Luís, Carmen Lemos, Cátia Godinho, João Pedro Santos, José Carvalho Ferreira, José Ferreira, and Pedro Hébil. We also wish to acknowledge the extraordinary contribution of Luísa Almeida and Rita Zina—senior representatives of the General Directorate of the Territory of Portugal—for the insights provided during the consolidation phase.

REFERENCES


