



Artificial intelligence and change management in small and medium-sized enterprises: an analysis of dynamics within adaptation initiatives

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Accepted: 21 December 2022

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Abstract

Given the increasingly significant role of small and medium-sized enterprises (SMEs) in the global economy and the ever more competitive markets in which these companies operate, SMEs' ability to adopt artificial intelligence (AI) technologies is of utmost importance. Due to constantly evolving social, environmental, and technological scenarios, the managers of these firms must increasingly focus on incorporating new tools such as AI into SME operations in order to enjoy their benefits. However, the subjectivity and complexity of this adaptation process makes integrated analyses of key factors challenging. The present study sought to develop a multi-criteria decision-support system that applies cognitive mapping and the decision-making trial and evaluation laboratory technique in a neutrosophic context. The main objective is to overcome the limitations of previous studies and models by structuring the decision problem and identifying and understanding which factors should be central to adaptation initiative analyses. A panel of experts in AI were recruited to facilitate the construction of an analysis system that takes into account indeterminacy in decision-making processes. The results were validated by both the panel members and project managers at COTEC Portugal—a leading think-and-action network that seeks to advance technology diffusion and business innovation cooperation. The proposed system's practical implications and benefits are also analyzed.

Keywords Artificial intelligence · Cognitive mapping · Decision-MAking Trial and Evaluation Laboratory (DEMATEL) · Neutrosophic logic · Small and medium-sized enterprise (SME)

1 Introduction

The transformation started by the industrial revolution has forced all companies— regardless of their size, industry, or location—to embark on the digitalization process. However,

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small and medium-sized enterprises (SMEs) have been especially slow to integrate digital technologies, with only one in five SMEs in the European Union currently running highly digitalized operations (Bettoni et al., 2021). As a result, these companies are under increasing pressure to implement complex growth plans that strengthen their competitiveness and help them stay abreast with constantly evolving technological and social innovations (De Marco et al., 2020; Falahat et al., 2020; Jung et al., 2018). For example, SMEs need to adapt to advances based on artificial intelligence (AI), which, according to Magistretti et al. (2019), is expected to become a complementary tool for SME decision-making processes. These firms' ability to adopt new technologies is, nevertheless, often restricted by SMEs' lack of resources and limited awareness of technological and social changes (Bettoni et al., 2021; Strotmann, 2007).

Although various authors have studied the basic nature of adaptation to new technologies, little is known about the actual impact of innovative tools on SMEs (*cf.* Mittal et al., 2018). The extant literature on this topic has limitations regarding: (1) the identification of evaluation and decision criteria; (2) definition of these criteria's relative importance; and (3) analysis of the dynamics of the criteria's causal interrelationships (Freire et al., 2021). To fill these significant gaps, the present research first applied the jointly understanding, reflecting, and negotiating strategy (JOURNEY) making approach via cognitive mapping techniques. The second phase then applied the decision-making trial and evaluation laboratory (DEMATEL) technique to process data in a neutrosophic context. This combination of methodologies facilitated both analyses of the dynamics of cause-and-effect relationships between the decision criteria identified and the incorporation of indeterminacy into the decision-making process.

With a view to increasing complementarity, two research questions were addressed:

- How can decision makers identify key initiatives that SMEs need to implement in order to manage change during adaptations to AI and how are these initiatives interrelated?
- Which drivers of adaptation have significant enough impacts that they should be given priority in order to facilitate SME adoption of AI tools?

The selected methodologies were implemented during two group work sessions with a panel of specialists (*i.e.*, professionals with practical knowledge about SME adaptation to AI technologies). Both meetings were held online due to coronavirus disease-19 (COVID-19) pandemic restrictions. These sessions comprised open discussions of how to structure the decision problem, which enabled the expert panel to identify the most relevant criteria and create a group cognitive map. The DEMATEL technique then helped the panel members examine the cause-and-effect relationships related to SME-AI adaptation processes and complete the necessary neutrosophic evaluations.

This study is the first to combine the DEMATEL technique and neutrosophic logic in order to conduct research on how SMEs can best adapt to AI tools, thereby contributing to the literature on this topic and generating opportunities for future investigations on related subjects.

This paper's remaining sections are as follows. The next section presents a literature review focused on AI and change management. Section three explains the methodologies applied, while section four covers the methodological application and main results. The final section offers conclusions, summarizes the insights gained, and makes recommendations for future research.

2 Literature review and research GAP

AI as a concept can be traced back to 1950, when the British mathematician Turing (1950) posed the following question: “Can machines think?”. The cited author states that, for a machine to be intelligent, it needs to “learn from experience” that is, the stimuli to which the machine is exposed. Nilsson (1984, p. 5) asserts that the term AI refers to a “*different class of machines [...] that can perform tasks requiring reasoning, judgment, and perception that previously could be done only by humans*”. In 1989, McCarthy (1989) used this term to describe computers that process large amounts of data in sophisticated ways.

According to Ayedee and Kumar (2020), SMEs’ biggest challenges when adopting AI include, among others, their employees’ less extensive training and limited skills. Ghobakhloo et al. (2011) observe that SMEs cannot easily adopt AI tools without adequate technological, financial, and human resources. These companies must thus overcome significant obstacles (e.g., the investment necessary to apply AI-related innovations) before adopting these tools. Grandon and Pearson (2004) predict that many firms will, nonetheless, adopt new technologies because of competitive pressure (i.e., the influence of the external environment) generated by the media, competitors, and customers, which significantly promotes SME adoption of new technologies. This pressure forces these firms to overcome related challenges and pushes SMEs to adapt to AI-based procedures.

Alharbi et al. (2016) mention other obstacles related to variations in countries’ requirements and/or other environmental factors that determine AI adoption. In this context, Grandon and Pearson (2004) argue that top-management involvement is fundamental to the implementation of new technologies in SMEs and that these individuals’ continuous support is necessary to ensure their organization is ready for change. Chen et al. (2015) and Priyadarshinee et al. (2017) also assert that senior management’s commitment to AI adaptation initiatives is vital because these decision makers enable the creation of technological ecosystems. Once top managers are involved, action plans can be carried out, such as providing training to human resources and communicating the benefits of implementing AI tools.

The role of change management has been analyzed in order to promote successful implementations and transformation processes. According to Bhatt (2017), organizational change can only be effective if it is managed well. Moran and Brightman (2001), specifically, define change management as a process of continuously renewing organizations’ direction, structure, and capabilities to meet external and internal stakeholders’ ever-changing needs. However, the multiple variables involved complicate decision makers’ attempts to measure and analyze the aspects that most influence change management as SMEs adapt to AI.

Various prior studies have concentrated on how adaptation to new technologies emerges in users (e.g., Fishbein & Ajzen, 1975; Ajzen, 1991; Venkatesh et al., 2003; Silva et al., 2021), but five types of limitations or gaps can still be widely found in the literature. The first is a lack of models that specifically focus on SMEs and AI, while the second is the absence of clarity regarding how variables are identified, selected, and defined in previous research. The third limitation is inconsistencies in how variables’ importance and/or explanatory power is determined in the context of SME behavior toward technology (i.e., subjective variables and insufficient attention paid to extrinsic factors or other important elements). The fourth gap is the scarcity of analyses of cause-and-effect relationship dynamics between the chosen variables, and the last limitation is the experts’ inability thus far to produce a clearly superior model of this adaptation process (cf. Milici et al., 2021; Silva et al., 2021).

Weber and Borchering (1993) observe that no methodology developed thus far is free of limitations. Therefore, a different tool is needed that can help decision makers overcome

these restrictions and enable real-life applications of and improvements in analytical models of how SMEs adapt to changes introduced by AI.

Given the above issues, the present research included an analysis of the dynamics inherent to adaptation initiatives, combining cognitive mapping and DEMATEL in a neutrosophic environment. This study also assumes a constructivist, process-oriented position (*cf.* Belton & Stewart, 2002; Bell & Morse, 2013). The main aim is to enable SME managers to develop concrete initiatives that ensure their company can more successfully adapt to the changes introduced by AI. In other words, the goal is to create a multi-criteria analysis system that allows SMEs to identify and overcome obstacles to AI technology adoption.

3 Methodological background

Complexity is an inherent property of decision-making processes (Dias & Clímaco, 2005; Tsotsolas & Alexopoulos, 2017). Related problem-solving support systems can be divided into three phases: (1) structuring; (2) evaluation; and (3) recommendation and/or implementation. In the present study, the first phase used cognitive mapping to identify the evaluation criteria (*i.e.*, factors affecting AI adaptation initiatives). In the second phase, the DEMATEL method was applied together with neutrosophic logic to analyze the criteria's interrelationships.

3.1 JOURNEY making, cognitive mapping, and neutrosophic logic

Problem structuring methods (PSMs) are defined as techniques that help decision makers make focused choices based on deliberative dialogue (Franco et al., 2004; Rosenhead & Mingers, 2001). As a PSM, the JOURNEY making approach produces structured visual representations of ideas, providing opportunities for critical dialogue, collaboration between decision makers, and reorganization of perspectives through collective consensual deliberation (Ackermann, 2012; Belton & Hodgkin, 1999; Eden & Ackermann, 2004; Tegarden & Sheetz, 2003). Cognitive mapping is often used when groups apply the JOURNEY making approach.

Eden (2004) and Marques et al. (2018) report that cognitive mapping has enormous potential as a tool for studying complex decision problems as it is a constructivist metacognitive technique that can take various visual, interactive forms (Pires et al., 2018; Reis et al., 2019). Cognitive maps are usually constructed as networks consisting of nodes (*i.e.*, concepts, ideas, or constructs) and arrows that connect the concepts so that the node at an arrow's tip is influenced by the concept at that arrow's tail (Eden, 2004). Arrows can represent positive or negative cause-and-effect relationships (Ferreira et al., 2017; Ribeiro et al., 2017). Montibeller and Belton (2006, p. 780) state that: “[a] *positive sign indicates a positive perceived causal connection, whereby an increase in a cause generates an increase in the linked effect*[, ... while] *a negative sign indicates a negative connection, whereby an increase in the cause leads to an increase in the opposite pole of the linked effect*”. The current research used cognitive-mapping results to support decision making in a neutrosophic environment.

The most fundamental principle of neutrosophic logic is that ideas not only have a degree of truth (T) but also a degree of falsity (F) and a degree of uncertainty/indeterminacy (I). All three must be included as independent components in decision-making processes (Ferreira & Meidutė-Kavaliauskienė, 2019). Neutrosophic logic is thus a multivalued logic in which truth values (*i.e.*, logical variable x) are given as a set of three components: T , I , and F

(Smarandache, 2007). These components are presented as any standard or nonstandard real subsets of $[-0, 1 +]$, in which $T = [- 0, 1 +]$; $I = [- 0, 1 +]$; and $F = [- 0, 1 +]$ (Smarandache, 2007).

Given C_i and C_j as two nodes, c_{ij} represents an arrow that connects the two concepts and represents their relationship as causal or indeterminate depending on the type of line (*i.e.*, filled or perforated, respectively) (Kandasamy & Smarandache, 2003). In addition, w_{ij} is the directed arrow's weight, and $w_{ij} \in \{- 1, 0, 1, I\}$. The relationship between the two concepts in question can have four values. The first is $w_{ij} = 0$ if C_i has no effect on C_j . The second value is $w_{ij} = 1$ if an increase (or decrease) in C_i causes an increase (or decrease) in C_j . The third option is $w_{ij} = - 1$ if an increase (or decrease) in C_i causes a decrease (or increase) in C_j . The last possible value is $w_{ij} = I$ if C_i 's relationship with or effect on C_j is undetermined.

According to Ghaderi et al. (2012), this methodological approach gives decision makers greater freedom to use their intuition as they can characterize impacts not only as positive and negative but also as indeterminant. This procedure is associated with a neutrosophic adjacency matrix of dimension $n \times m$ (*i.e.*, $n = m$ number of factors and/or criteria) that encompasses the values defined by neutrosophic evaluations of all cause-and-effect relationships between the relevant variables. Simplified neutrosophic matrix D is found using Eq. (1) (Ye, 2014), in which n decision criteria and their interrelationships' degree of intensity are represented as follows:

$$D = (\alpha_{ij})_{m \times n} = \begin{bmatrix} (t_{11}, i_{11}, f_{11}) & (t_{12}, i_{12}, f_{12}) & \dots & (t_{1n}, i_{1n}, f_{1n}) \\ (t_{21}, i_{21}, f_{21}) & (t_{22}, i_{22}, f_{22}) & \dots & (t_{2n}, i_{2n}, f_{2n}) \\ & \vdots & \vdots & \vdots \\ (t_{m1}, i_{m1}, f_{m1}) & (t_{m2}, i_{m2}, f_{m2}) & \dots & (t_{mn}, i_{mn}, f_{mn}) \end{bmatrix} \tag{1}$$

The three neutrosophic components (*i.e.*, T , I , and F) then need to be transformed into a single value and/or component (*i.e.*, crispification). Although there are several applicable functions in the course of neutrosophic aggregation (*cf.* Smarandache, 2020), one possible way to perform crispification of neutrosophic weights is Eq. (2) (Pramanik et al., 2016):

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

Pramanik et al. (2016) assert that Eq. (2) allows r specialists to determine their own neutrosophic decision weights (*i.e.*, w_1, w_2, \dots, w_r), so that each $w_k = (T_k, I_k, F_k)$ is represented by a neutrosophic number. Equation (2) stands out in the literature (*cf.* Smarandache, 2020), and makes it possible to crispify the three neutrosophic components, so that a single-component value (*i.e.*, crisp logic) is obtained, which facilitates the application of neutrosophic logic to other methodologies, including DEMATEL.

In the present study, the combined used of JOURNEY making, cognitive mapping and neutrosophic logic facilitated, first, the identification and analysis of the decision variables to be included in the evaluation model of SME adaptation to changes introduced by AI. Second, these methodologies clarified how the model variables interrelate in terms of dynamics of causality or indeterminacy. Third, deeper analyses could be conducted of adaptation initiatives to determine which sets of vertices should be addressed first. Last, the results add to the extant literature since apparently no prior research had yet applied this methodological combination in this study context.

3.2 DEMATEL

The DEMATEL technique was developed in the 1970s by Gabus and Fontela (1972) to construct matrices that help identify and analyze cause-and-effect relationships between criteria and/or sub-criteria (SCs) based on a structural model. This method highlights the interdependence between factors and produces a diagram that visualizes their behavior (Falatoonitoosi et al., 2013; Si et al., 2018). Dalvi-Esfahani et al., (2019, p. 5) report that this method “*determines the critical components of a system aided by impact relation diagrams*” that rely on numerical values expressing each criterion’s degree of influence. Specialists can use DEMATEL outputs to determine which criteria are causes (*i.e.*, have a greater effect on other factors and are higher priority) and which are effects (*i.e.*, receive more influence from other criteria and are lower priority) (Falatoonitoosi et al., 2013). This technique is applied in sequential steps (*cf.* Gabus & Fontela, 1972).

3.2.1 Step one

The first step is to create initial direct-relation matrix Z . Each specialist produces an $n \times n$ matrix, and each value represents the degree of influence between the relevant factors. When $i = j$ and $i, j \in \{1, 2, \dots, n\}$, the diagonal values in the matrix are equal to 0. Matrix Z of a specific group of variables is produced as shown in Eq. (3):

$$Z = \begin{matrix} C1 \\ C2 \\ \vdots \\ Cn \end{matrix} \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ a_{21} & 0 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 0 \end{bmatrix} \quad (3)$$

3.2.2 Step two

The second step is to calculate normalized direct-relation matrix X . This matrix can be developed when all elements’ degree of influence varies between 0 and 1, after applying the normalization constant λ and using Eqs. (4) and (5):

$$X = \frac{Z}{\lambda} \quad (4)$$

$$\lambda = \max \left(\max_{1 \leq i \leq n} \sum_{j=1}^n z_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^n z_{ij} \right) \quad (5)$$

3.2.3 Step three

The third step is to construct total-relation matrix T . Matrix X is used to create this matrix by adding up the values of each criterion’s direct and indirect effects. Overall, t_{ij} elements reflect the effects that factor i has on factor j , with matrix T representing the total relationships between each pair of factors. According to Chen et al. (2019), matrix T can be calculated using Eq. (6), in which I corresponds to identity matrix $n \times n$:

$$T = \lim_{h \rightarrow \infty} (X^1 + X^2 + \dots + X^h) = X(I - X)^{-1} \quad (6)$$

3.2.4 Step four

The fourth step is to calculate values for vectors R and C and the threshold (α) value. The columns and rows of total-relation matrix T are added up separately, so vectors R and C are obtained through Eqs. (7) and (8), respectively (Chen et al., 2019):

$$R = \left[\sum_{j=1}^n t_{ij} \right]_{n \times 1} = [r_i]_{n \times 1} \quad (7)$$

$$C = \left[\sum_{i=1}^n t_{ij} \right]_{1 \times n} = [c_j]_{1 \times n} \quad (8)$$

In this case, r_i (*i.e.*, the total of matrix T 's i th row) corresponds to the degree of influence that factor i has directly or indirectly on all the other criteria. In turn, c_j (*i.e.*, the total of matrix T 's j th column) represents the degree of influence that factor i receives directly or indirectly from the remaining criteria.

When $i = j$ and $i, j \in \{1, 2, \dots, n\}$, the value of horizontal axis $R + C$ in the DEMATEL diagram is termed "prominence" because it represents the degree of importance of a given factor in the evaluation system. Similarly, vertical axis $R - C$ is labeled "relationship" because it reflects the overall degree of influence that a specific criterion has on the decision-support system. The $R + C$ and $R - C$ values can be used to divide the factors into groups of either causes (*i.e.*, donors) or effects (*i.e.*, recipients). Thus, if $r_i - c_j > 0$ (*i.e.*, a positive value), criterion i has a direct influence on the other factors. That is, criterion i is part of the causes group. However, if $r_i - c_j < 0$ (*i.e.*, a negative value), the remaining factors influence factor i , so it belongs to the effects group (Chen et al., 2019; Sumrit & Anuntavoranich, 2013; Tzeng et al., 2007). Finally, the α value is found as shown in Eq. (9):

$$\alpha = \frac{\sum_{i=1}^n \sum_{j=1}^n [t_{ij}]}{N} \quad (9)$$

The α value is defined in this step to eliminate any relatively insignificant elements from matrix T (Yang et al., 2008; Sumrit & Aunvoranich, 2013).

3.2.5 Step five

The last step is to develop an influence relationship map (IRM) or cause-and-effect diagram. An IRM is constructed by mapping the coordinate sets $(r_i + c_i, r_j - c_j)$, in which the $R + C$ and $R - C$ values refer to the horizontal axis and vertical axis of the diagram, respectively. The decision factors or criteria can fall into four quadrants (Si et al., 2018; Yazdi et al., 2020). The criteria are core factors if they belong to the first quartile (QI). They are driving factors if they are in the second quartile (QII). The criteria are independent factors if they fall into the third quartile (QIII), but they are impact factors if they are positioned in the fourth quartile (QIV) (see Fig. 1). Freire et al. (2021) observe that DEMATEL is widely respected as a simple, solid method that facilitates decision making.

4 Application and results

The structuring phase was of crucial importance to the current proposed decision-support system because its results can help SMEs analyze possible AI adaptation initiatives. At this

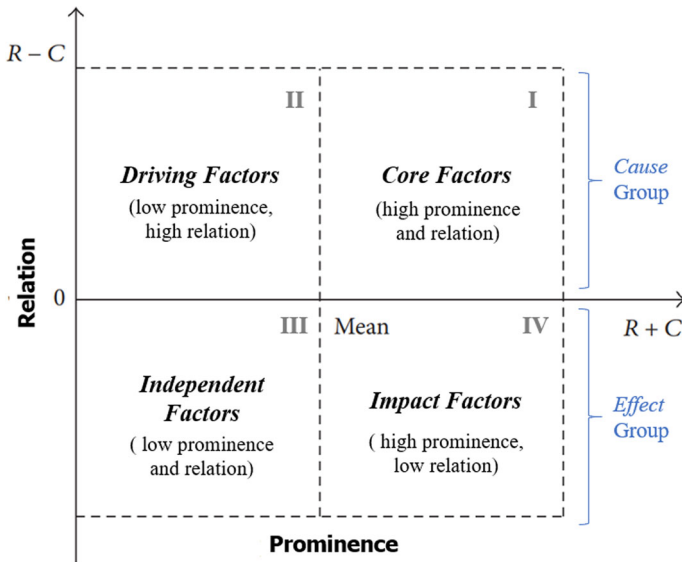


Fig. 1 Influence relationship map. *Source:* Adapted from Si et al. (2018)

stage, a panel of specialists was recruited from among professionals known in their field as decision makers who can clarify objectives, identify areas of concern, and organize ideas (Belton & Stewart, 2002). The number of experts on the panel can range from 5 to 12 members (Eden & Ackermann, 2004), so six decision makers (*i.e.*, professionals working in SMEs and with practical knowledge about AI) were recruited for the present study. Specifically, the panel members comprised an AI developer from SingularityNET, a Replai software engineer, a TNX Logistics software developer, and the Data Science Portuguese Association's executive director. The other two were the chief executive officer and data science specialist of ML Analytics and a data scientist from Border Innovation. These six specialists expressed an active interest in participating in this research and investigating the decision-making problem of SME adaptation to AI-based tools, which ensured that these experts would be available to share their experience and knowledge in group work sessions.

This study is process-oriented, so representativeness was not—and did not have to be—a point of concern. Bell and Morse (2013) note that the objective of the selected methodologies is not to make generalizations but rather to maintain a strong focus on process. In addition, once the expert panel was defined, the COVID-19 pandemic situation meant that the sessions had to be held online to guarantee the participants' safety and well-being. A facilitator and two technical assistants were also present to provide support and record the results when necessary.

4.1 Structuring phase: collective cognitive map

The first group session lasted approximately three hours and covered the first phase of analyzing the decision problem (*i.e.*, SME adaptation to AI tools). The main objective was to create a group cognitive map based on the panel members' interactions. The meeting began with the introduction of each expert and a brief overview of the study and its methodological

approach. The online platform used to conduct this session was the Miro platform (<http://www.miro.com>), which allowed the specialists to interact as needed.

A trigger question was then asked of the decision-maker panel: “Based on your professional experience, what initiatives can SMEs develop to facilitate change management while adapting to AI tools?”. This question encouraged the experts to exchange ideas and discuss the topic more fully. To identify significant factors affecting SME adaptation initiatives, the “post-its technique” (Ackermann & Eden, 2001) was applied to facilitate the collection of the input needed to construct the decision-support model. This procedure consisted of writing on post-it notes the decision criteria (*i.e.*, determinants of initiatives that help SMEs adapt to AI) that the specialists identified as relevant to the decision-making process and as an appropriate response to the trigger question.

The panel members were informed that only one digital post-it note could be used for each identified criterion (Ribeiro et al., 2017). In addition, given a positive or negative causal relationship to the problem, they had to include a positive (+) or negative (−) sign, respectively, in the note. In total, 112 criteria were identified and considered important to measures that allow SMEs to adapt to using AI. The results were in line with Eden and Ackermann’s (2004) suggestion that a cognitive map should normally contain between 90 and 120 criteria.

The next step was to organize the post-it notes (*i.e.*, established criteria) into areas of concern or clusters. The decision makers separated the criteria identified into five clusters labeled as follows: *Human Resources (C1)*; *Information Technology (IT) Infrastructure (C2)*; *Know-How and Knowledge (C3)*; *Organizational Policies and Management (C4)*; and *Leadership (C5)*. The last phase of the first group session consisted of an internal analysis of each cluster in order to establish the criteria’s hierarchy within each cluster. That is, the most important factors were placed at the top of their respective clusters, while the intermediate ones moved to the middle and the least important criteria at the bottom.

After the first group session, the five clusters were formatted into a group cognitive map using the Decision Explorer software (<http://www.banxia.com>). Figure 2 presents the map’s

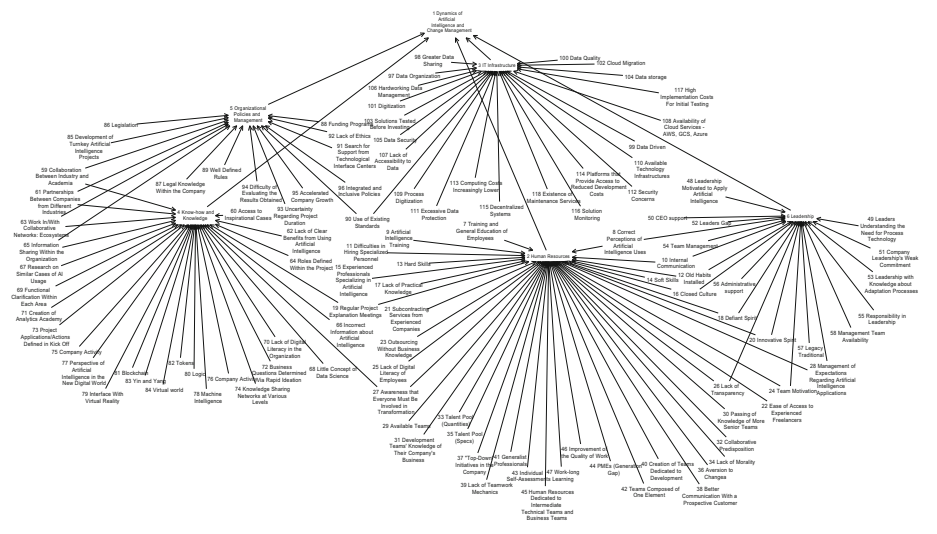


Fig. 2 Group cognitive map

final version, which was collectively validated by the participants in the second session. An editable version is available upon request from the authors.

The map in Fig. 2 has three significant features. First, each cause-and-effect relationship is represented by an arrow. Second, some criteria are linked to more than one cluster. Last, the negative signs next to arrows indicate the criteria that negatively influence SME adoption of AI. In short, cognitive mapping helped the expert panel identify decision criteria, thereby facilitating the search for appropriate solutions for the specific decision problem under study through intensive debate and knowledge sharing (Barão et al., 2021). The mapping process proved to be an important step toward communicating about and structuring the issue in question and provided the necessary conditions for the DEMATEL subsequent application in a neutrosophic context.

4.2 Evaluation phase: DEMATEL and neutrosophic logic

After the structuring phase was completed, the panel members could move on to the evaluation phase, which took place during the second group session held online via Zoom. First, the group cognitive map was shown to the panel members so that they could make any adjustments needed. The next techniques to be used were then presented. The facilitator emphasized the advantage of integrating the two approaches selected (*i.e.*, DEMATEL in a neutrosophic environment) due to the uncertainty and indeterminacy inherent to decision-making processes (Ferreira & Meidutė-Kavaliauskienė, 2019).

During this session, the specialists thus focused on completing six relation matrices (*i.e.*, a first matrix indicating the relationships between clusters and five matrices corresponding to the expected reality within each cluster). Because of the clusters' size, nominal group and multivoting techniques were used to select the most significant criteria to be included in the last five matrices. Once the most important factors were identified, the decision makers assessed these criteria's interrelationships on a DEMATEL scale ranging from 0 to 4 (0 = "No influence"; 1 = "Little influence"; 2 = "Medium influence"; 3 = "Strong influence"; 4 = "Very strong influence").

The experts could then conduct neutrosophic assessments of these relationships (*i.e.*, to identify how likely—expressed as a percentage—their judgment was to be true (T), uncertain (I), or false (F)). The panel was informed that, within neutrosophic logic, the total of the percentages attributed to T , I , and F can differ from 100%.

After finishing the evaluation using neutrosophic values, the specialists next aggregated the values (*i.e.*, crispification) to obtain the initial inputs needed to apply the DEMATEL technique. This procedure involved performing an extra calculation for all values obtained during the evaluation phase, which utilized the crispification Eq. (2) (see Sect. 3.1). The crisp values were then ready for the five DEMATEL steps (see Sect. 3.2).

The first round of analysis focused on the relationships between the previously identified clusters listed in Table 1. The panel created the matrix shown in Table 2, which includes the neutrosophic values assigned by the decision makers and subjected to crispification. The results of this step are given in Table 3.

Table 3 shows that the final values used to create the DEMATEL direct-relation matrix (see Table 4) were produced by multiplying each crisp neutrosophic value (*i.e.*, the crispification equation numerator) by the degree of influence assigned by the panel. The DEMATEL scale value x was in this way estimated for each causal relationship. The results were incorporated into direct-relation matrix Z (*i.e.*, DEMATEL step one (see Sect. 3.2.1)) presented in Table

Table 1 Clusters identified

Clusters	
C1	Human Resources
C2	Information Technology Infrastructure
C3	Know-How and Knowledge
C4	Organizational Policies and Management
C5	Leadership

Table 2 Matrix with neutrosophic values for clusters

	C1	C2	C3	C4	C5
C1	–	3 (0.8, 0.6, 0.4)	3 (0.8, 0.4, 0.2)	2 (0.8, 0.3, 0.2)	3 (0.6, 0.5, 0.4)
C2	3 (0.9, 0.5, 0.5)	–	3 (0.9, 0.4, 0.1)	1 (0.8, 0.1, 0.1)	1 (0.7, 0.2, 0.2)
C3	4 (0.9, 0.5, 0.1)	4 (0.9, 0.5, 0.1)	–	2 (0.7, 0.5, 0.3)	2 (0.9, 0.4, 0.1)
C4	3 (0.6, 0.7, 0.3)	2 (0.6, 0.6, 0.4)	3 (0.8, 0.5, 0.2)	–	1 (0.9, 0.1, 0)
C5	4 (0.9, 0.5, 0.1)	3 (0.9, 0.5, 0.1)	2 (0.5, 0.7, 0.7)	3 (0.8, 0.3, 0.2)	–

4. This step enabled the panel to proceed to the remaining steps (*i.e.*, steps two through five in Sect. 3.2).

The initial direct-relation matrix (see Table 5) was subsequently normalized by performing the required intermediate calculations using Eqs. (4) and (5) (see Sect. 3.2.2). Next, total-relation matrix T (see Table 6) was created based on Eq. (6) (see Sect. 3.2.3) after the three imperative matrices needed for this procedure (*i.e.*, matrices I , $I - X$, and $(I - X)^{-1}$) were constructed.

In matrix T , column R corresponds to each row's total obtained with Eq. (7), and row C is each column's total calculated using Eq. (8) (see Sect. 3.2.4) in DEMATEL step four. The R value corresponds to the degree of total influence that a specific cluster has on all the other clusters. Thus, C3 has the greatest impact on the remaining clusters (*i.e.*, 4.0691). Line C , in turn, represents the degree of influence that a given cluster receives from the other clusters, which shows that C1 is the most influenced (*i.e.*, 4.2543). The results further reveal that C5 has the least effect (*i.e.*, 2.4579) on the remaining clusters.

The α value was calculated using Eq. (9) (see Sect. 3.2.4), namely by averaging all of matrix T 's values. With an α value of 0.6937, the most influential relationships could be retained, and all values with a lesser effect on this matrix were eliminated (see the values in red and green in Table 6). The definition of the α value thus plays a fundamental role in shaping the DEMATEL diagram of cause-and-effect relationships (*i.e.*, IRM), as shown in Fig. 3.

Figure 3 provides a quick, clear overview of the importance and significant influences with regard to SME-AI adaptation initiatives. $R + C$ (*i.e.*, the horizontal axis in Fig. 3) reveals the total effects given and received by the clusters in question, highlighting the clusters' order of importance (*i.e.*, the higher a cluster's $R + C$ value is, the more important that cluster will be and the greater its impact will be on the analysis system). Based on the IRM, C1 is the most important cluster, with the highest $R + C$ value of 7.8355, although this number is quite close to C3's value. C4 is the least significant, with the lowest $R + C$ value of 5.8529. The

Table 3 Crisp Neutrosophic Values for Clusters

Relationship analyzed	DEMATEL scale (X)	Neutrosophic values (T, I, F)			Neutrosophic Crispification		
		T	I	F	Crispification equation numerator	Crisp weight W	Final value in matrix Z
<i>Clusters matrix</i>							
C1–C2	3.0	0.80	0.60	0.40	0.56795	0.04211	1.70
C1–C3	3.0	0.80	0.40	0.20	0.71716	0.05318	2.15
C1–C4	2.0	0.80	0.30	0.20	0.76195	0.05650	1.52
C1–C5	3.0	0.60	0.50	0.40	0.56411	0.04182	1.69
C2–C1	3.0	0.90	0.50	0.50	0.58769	0.04358	1.76
C2–C3	3.0	0.90	0.40	0.10	0.75505	0.05599	2.27
C2–C4	1.0	0.80	0.10	0.10	0.85858	0.06366	0.86
C2–C5	1.0	0.70	0.20	0.20	0.76195	0.05650	0.76
C3–C1	4.0	0.90	0.50	0.10	0.70000	0.05190	2.80
C3–C2	4.0	0.90	0.50	0.10	0.70000	0.05190	2.80
C3–C4	2.0	0.70	0.50	0.30	0.62141	0.04608	1.24
C3–C5	2.0	0.90	0.40	0.10	0.75505	0.05599	1.51
C4–C1	3.0	0.60	0.70	0.30	0.50334	0.03732	1.51
C4–C2	2.0	0.60	0.60	0.40	0.52390	0.03885	1.05
C4–C3	3.0	0.80	0.50	0.20	0.66834	0.04956	2.01
C4–C5	1.0	0.90	0.10	0.00	0.91835	0.06809	0.92
C5–C1	4.0	0.90	0.50	0.10	0.70000	0.05190	2.80
C5–C2	3.0	0.90	0.50	0.10	0.70000	0.05190	2.10
C5–C3	2.0	0.50	0.70	0.70	0.35969	0.02667	0.72
C5–C4	3.0	0.80	0.30	0.20	0.76195	0.05650	2.29
$\sum_{k=1}^r w_k^c = 1$; complies with Eq. (1) conditions (see Sect. 3.1)				Crispification Equation Denominator	13.48648	1	

T = degree of truth; I = degree of uncertainty/indeterminacy; F = degree of falsity

Table 4 Direct-relation matrix Z for clusters

	C1	C2	C3	C4	C5	Total
C1	0.00	1.70	2.15	1.52	1.69	7.07
C2	1.76	0.00	2.27	0.86	0.76	5.65
C3	2.80	2.80	0.00	1.24	1.51	8.35
C4	1.51	1.05	2.01	0.00	0.92	5.48
C5	2.80	2.10	0.72	2.29	0.00	7.91
TOTAL	8.87	7.65	7.14	5.91	4.88	

Table 5 Normalized direct-relation matrix X for clusters

Max.	8.9	8.4			
1/max	0.112700	0.119719			
1/s	0.112700				
	C1	C2	C3	C4	C5
C1	0.0000	0.1920	0.2425	0.1717	0.1907
C2	0.1987	0.0000	0.2553	0.0968	0.0859
C3	0.3156	0.3156	0.0000	0.1401	0.1702
C4	0.1702	0.1181	0.2260	0.0000	0.1035
C5	0.3156	0.2367	0.0811	0.2576	0.0000

overall order of importance can be expressed as $C1 > C3 > C2 > C5 > C4$. In addition, Fig. 3 reveals that C3 is the core factor cluster (*i.e.*, QI), C5 is the driving factor cluster (*i.e.*, QII), C4 and C2 are independent factor clusters (*i.e.*, QIII), and C1 is an impact factor cluster (*i.e.*, QIV).

After analyzing this first matrix and respective IRM, the same five steps were completed for each individual cluster. As mentioned previously, the specialists had to first select the most important criteria within each cluster using nominal group and multivoting techniques. The initial DEMATEL matrices (*i.e.*, direct-relation matrix Z) incorporate crisp weights produced by following the same procedures used in the above inter-cluster analysis.

The C1 criteria listed in Table 7 were considered by the decision-maker panel to be of greater importance. After selecting the criteria, the experts crispified the values in the neutrosophic matrix (see Table 8) so that direct-relation matrix Z could be completed with crisp values (see Table 9) and the final results could be analyzed.

Table 10 confirms that SC17 has the most influence on the other criteria because it has an R value of 1.5872, followed immediately by SC15 with an R value of 1.5395. SC28 is the most influenced by all the remaining SCs, with a C value of 1.9488. Figure 4 also shows that the SCs of this cluster can be listed by order of importance as follows: $SC28 > SC24 > SC31 > SC15 > SC17$. SC28 thus has the greatest significance overall, with an $R + C$ value of 2.7440.

Regarding the $R - C$ values, the SCs belonging to the effects group (*i.e.*, negative $R - C$) are SC31, SC24, and SC28, which are located at the bottom half of the respective DEMATEL diagram. The causes group (*i.e.*, positive $R - C$) is composed of SC17 and SC15, which affect the other factors more than these two SCs are influenced. This group appears in the IRM's upper half. The DEMATEL-diagram quartiles organize the criteria as follows. SC15 and SC17 are driving factors. SC31 can be considered an independent factor, and SC24 and SC28 are impact factors.

The analysis next focused on C2. The decision makers again selected the criteria to be included in this cluster (see Table 11) so that, at a later stage, the neutrosophic matrix could be created more easily (see Table 12). This matrix served as the basis for C1's initial direct-relation matrix, which contained the crisp weights needed to conduct this analysis (see Table 13).

As Table 14 shows, SC114 has the most influence on the other SCs (*i.e.*, $R = 3.0746$), while SC101 is the most affected by the other SCs in this cluster (*i.e.*, $C = 2.8633$). SC101,

Table 6 Total-relation matrix T for clusters I

	C1	C2	C3	C4	C5
C1	1.0000	0.0000	0.0000	0.0000	0.0000
C2	0.0000	1.0000	0.0000	0.0000	0.0000
C3	0.0000	0.0000	1.0000	0.0000	0.0000
C4	0.0000	0.0000	0.0000	1.0000	0.0000
C5	0.0000	0.0000	0.0000	0.0000	1.0000

 $I - X$

	C1	C2	C3	C4	C5
C1	1.0000	-0.1920	-0.2425	-0.1717	-0.1907
C2	-0.1987	1.0000	-0.2553	-0.0968	-0.0859
C3	-0.3156	-0.3156	1.0000	-0.1401	-0.1702
C4	-0.1702	-0.1181	-0.2260	1.0000	-0.1035
C5	-0.3156	-0.2367	-0.0811	-0.2576	1.0000

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

	C1	C2	C3	C4	C5
C1	1.7165	0.8052	0.8156	0.6420	0.6018
C2	0.7656	1.5439	0.7296	0.5002	0.4545
C3	1.0539	0.9758	1.7111	0.6817	0.6466
C4	0.7236	0.6289	0.6888	1.3986	0.4540
C5	0.9947	0.8606	0.7462	0.7365	1.4669

Matrix T

	C1	C2	C3	C4	C5	R
C1	0.7165	0.8052	0.8156	0.6420	0.6018	3.5812
C2	0.7656	0.5439	0.7296	0.5002	0.4545	2.9937
C3	1.0539	0.9758	0.7111	0.6817	0.6466	4.0691
C4	0.7236	0.6289	0.6888	0.3986	0.4540	2.8940
C5	0.9947	0.8606	0.7462	0.7365	0.4669	3.8050
C	4.2543	3.8145	3.6915	2.9589	2.6237	

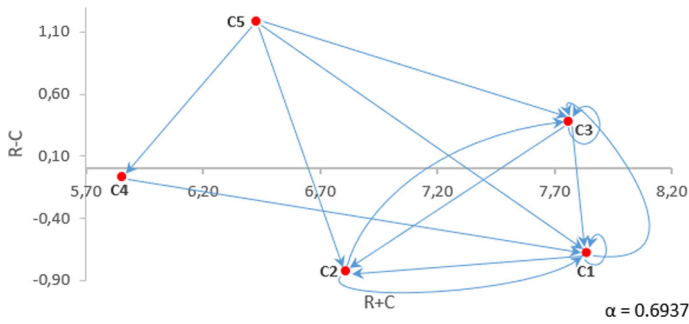


Fig. 3 Influence relationship map for clusters

Table 7 Most significant criteria: human resources cluster

Selected sub-criteria

SC17	Lack of practical knowledge
SC15	Experienced professionals specializing in artificial intelligence
SC31	Development teams' knowledge of their company's business
SC24	Team motivation
SC28	Management of expectations regarding artificial intelligence applications

Table 8 Matrix with neutrosophic values: human resources cluster

	SC17	SC15	SC31	SC24	SC28
SC17	–	4 (1, 0.1, 0)	3 (0.8, 0.5, 0.2)	2 (0.7, 0.2, 0.2)	4 (0.9, 0.1, 0.1)
SC15	3 (0.8, 0.5, 0.2)	–	4 (0.8, 0.5, 0.2)	4 (1, 0.5, 0)	4 (0.9, 0.1, 0.1)
SC31	1 (0.8, 0.2, 0)	3 (0.9, 0.5, 0.2)	–	3 (0.8, 0.4, 0.2)	4 (0.9, 0.1, 0.1)
SC24	1 (0.5, 0.8, 0.5)	1 (0.4, 0.8, 0.3)	2 (0.8, 0.7, 0.2)	–	4 (0.9, 0.1, 0.1)
SC28	0 (0.8, 0.2, 0)	0 (0.8, 0.2, 0)	4 (0.7, 0.5, 0.3)	4 (0.9, 0.1, 0.1)	–

Table 9 Direct-relation matrix Z: human resources cluster

	SC17	SC15	SC31	SC24	SC28	TOTAL
SC17	0.00	3.77	2.01	1.52	3.60	10.90
SC15	2.01	0.00	2.67	2.85	3.60	11.12
SC31	0.00	2.05	0.00	2.15	3.60	7.80
SC24	0.38	0.40	1.13	0.00	3.60	5.51
SC28	0.00	0.00	2.49	3.60	0.00	6.09
TOTAL	2.39	6.22	8.29	10.12	14.40	

Table 10 Total-relation matrix *T*: human resources cluster

	SC17	SC15	SC31	SC24	SC28	R
SC17	0.0558	0.3326	0.3259	0.3555	0.5174	1.5872
SC15	0.1648	0.1042	0.3481	0.4146	0.5079	1.5395
SC31	0.0332	0.1788	0.1338	0.3118	0.4144	1.0720
SC24	0.0391	0.0651	0.1664	0.1294	0.3500	0.7501
SC28	0.0155	0.0471	0.2373	0.3362	0.1590	0.7952
C	0.3084	0.7278	1.2115	1.5475	1.9488	

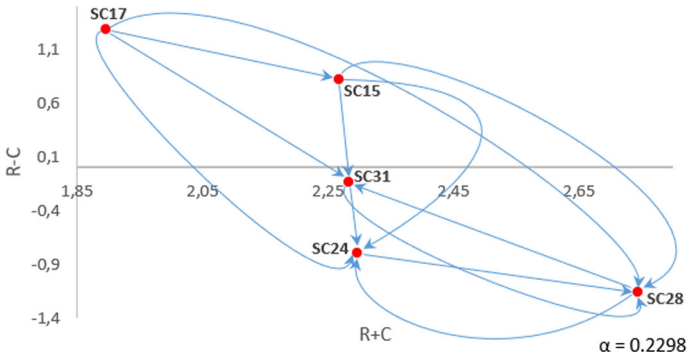


Fig. 4 Influence relationship map for human resources cluster

Table 11 Most significant criteria: information technology infrastructure cluster

Selected sub-criteria	
SC97	Data organization
SC100	Data quality
SC103	Solutions tested before investing
SC101	Digitalization
SC114	Platforms that provide access to reduced development costs

Table 12 Matrix with neutrosophic values: information technology infrastructure cluster

	SC97	SC100	SC103	SC101	SC114
SC97	–	3 (0.8, 0.2, 0.2)	3 (0.8, 0.5, 0.2)	4 (0.8, 0.5, 0.2)	0 (0.9, 0.5, 0.1)
SC100	3 (0.7, 0.2, 0.2)	–	3 (0.8, 0.5, 0.2)	4 (0.9, 0.5, 0.1)	0 (0.9, 0.5, 0.1)
SC103	1 (0.8, 0.3, 0.1)	2 (0.6, 0.5, 0.4)	–	2 (0.8, 0.5, 0.2)	3 (0.6, 0.6, 0.2)
SC101	4 (0.8, 0.5, 0.2)	4 (0.8, 0.5, 0.2)	3 (0.8, 0.5, 0.2)	–	1 (0.6, 0.7, 0.5)
SC114	4 (0.5, 0.5, 0.5)	4 (0.8, 0.5, 0.2)	4 (0.8, 0.5, 0.2)	4 (0.9, 0.5, 0.1)	–

Table 13 Direct-relation matrix: information technology infrastructure cluster

	SC97	SC100	SC103	SC101	SC114	TOTAL
SC97	0.00	2.40	2.01	2.67	0.00	7.08
SC100	2.19	0.00	2.01	2.74	0.00	6.93
SC103	0.78	1.13	0.00	1.34	1.70	4.95
SC101	2.67	2.67	2.01	0.00	0.36	7.71
SC114	2.00	2.67	2.67	2.80	0.00	10.15
TOTAL	7.64	8.87	8.69	9.55	2.06	

Table 14 Total-relation matrix *t*: information technology infrastructure cluster

	SC97	SC100	SC103	SC101	SC114	<i>R</i>
SC97	0.3436	0.5648	0.5257	0.6058	0.1098	2.1497
SC100	0.5150	0.3670	0.5196	0.6026	0.1086	2.1128
SC103	0.3472	0.4021	0.2954	0.4348	0.2329	1.7124
SC101	0.5814	0.6149	0.5575	0.4322	0.1444	2.3304
SC114	0.6525	0.7471	0.7356	0.7879	0.1515	3.0746
<i>C</i>	2.4398	2.6959	2.6337	2.8633	0.7471	

however, stands out as the most prominent (*i.e.*, $R + C = 5.1937$). SC114, in contrast, has an $R + C$ value equal to 3.8218, so this factor is the least important because it has an extremely low C value (*i.e.*, 0.7471) compared to the remaining SCs. Thus, the C2 SCs' order of importance is as follows: SC101 > SC100 > SC97 > SC103 > SC114.

SC114 is the only member of the causes group, with a positive $R + C$ value of 2.3275. The remaining SCs of this cluster (*i.e.*, SC97, SC100, SC103, and SC101) are part of the effects group. Figure 5 reveals the SCs' position in terms of their most important connections. That is, SC114 is a driving factor, SC103 is an independent factor, and SC97, SC100 and SC101 are impact factors.

C3 was analyzed next using the SCs selected as the most important (see Table 15). Table 16 is the matrix of neutrosophic values, and Table 17 presents the results of crispification.

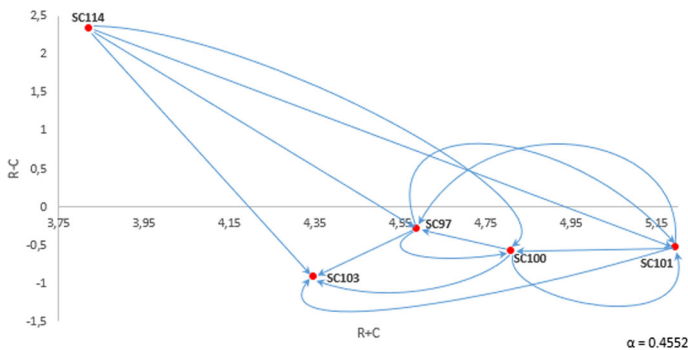


Fig. 5 Influence relationship map for information technology infrastructure cluster

Table 15 Most significant criteria: know-how and knowledge cluster

Selected sub-criteria	
SC67	Research on similar cases of artificial intelligence usage
SC66	Incorrect information about artificial intelligence
SC62	Lack of clear benefits from using artificial intelligence
SC72	Business questions determined via rapid ideation
SC65	Information sharing within the organization

Table 16 Matrix with neutrosophic values: know-how and knowledge cluster

	SC67	SC66	SC62	SC72	SC65
SC67	–	2(0.6, 0.5, 0.1)	3(0.9, 0.1, 0.1)	4(0.9, 0.5, 0.1)	3(0.7, 0.2, 0.3)
SC66	4(0.9, 0.1, 0.1)	–	3(0.9, 0.1, 0.1)	4(0.9, 0.5, 0.1)	2(0.7, 0.2, 0.3)
SC62	3(0.8, 0.2, 0.1)	2(0.5, 0.7, 0.5)	–	4(0.9, 0.5, 0.1)	1(0.7, 0.2, 0.3)
SC72	4(0.9, 0.5, 0.1)	3(0.7, 0.3, 0.3)	4(0.9, 0.5, 0.1)	–	4(0.9, 0.5, 0.1)
SC65	3(0.8, 0.2, 0.2)	2(0.6, 0.5, 0.1)	3(0.8, 0.2, 0.2)	3(0.8, 0.2, 0.2)	–

Table 17 Direct-relation matrix: know-how and knowledge cluster

	SC67	SC66	SC62	SC72	SC65	TOTAL
SC67	0.00	1.25	2.70	2.80	2.19	8.94
SC66	3.60	0.00	2.70	2.80	1.46	10.56
SC62	2.48	0.85	0.00	2.80	0.73	6.86
SC72	2.80	2.10	2.80	0.00	2.80	10.50
SC65	2.40	1.25	2.40	2.40	0.00	8.45
TOTAL	11.28	5.45	10.60	10.80	7.18	

Table 18, in turn, characterizes the degree of influence attributed to the five selected SCs.

Table 18 confirms that SC66 is the most influential factor in this cluster, with a total R value of 4.4713, but SC72 has an only slightly lower value. SC67, in contrast, is the most affected by the other SCs in this cluster, with a C value of 4.6252. SC72 is again a close second, with a value of C equal to 4.5482, so the latter factor plays a prominent role because it is also influenced by the remaining SCs. Thus, SC72 is a more significant factor in the overall decision-support system, whereas SC65 is the least important SC in C3. The following order of importance was confirmed: $SC72 > SC67 > SC62 > SC66 > SC65$.

In addition, Fig. 6 presents SC66 and SC65 as having a positive $R - C$ value, which places them in the causes group, while the other SCs (*i.e.*, SC67, SC62 and SC72) have a negative $R - C$ value and belong to the effects group. This DEMATEL-diagram quartiles similarly reveal that SC66 and SC65 are driving factors, SC62 is an independent factor, and SC67 and SC72 are impact factors (see Fig. 6).

Table 18 Total-relation matrix T : know-how and knowledge cluster

	SC67	SC66	SC62	SC72	SC65	R
SC67	0.7513	0.5172	0.9257	0.9418	0.7001	3.8362
SC66	1.1275	0.4853	1.0483	1.0669	0.7433	4.4713
SC62	0.7916	0.4146	0.5968	0.8043	0.5100	3.1173
SC72	1.0626	0.6313	1.0382	0.8514	0.8143	4.3978
SC65	0.8922	0.4974	0.8739	0.8838	0.5132	3.6605
C	4.6252	2.5457	4.4831	4.5482	3.2809	

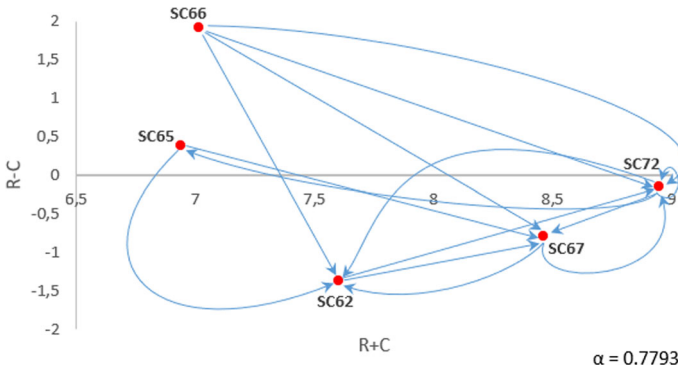


Fig. 6 Influence relationship map for know-how and knowledge cluster

The most important SCs from C4 are listed in Table 19. After crispification, this cluster’s matrix could be transformed—using neutrosophic values calculated in the second group work session (see Table 20)—into the direct-relation matrix shown in Table 21.

In Table 22, the SC with the greatest impact within C4 is SC94 as this factor has the highest R value (*i.e.*, 4.1112). SC85 exhibits the highest C value (*i.e.*, 3.6266), so it receives the most influence from the other SCs. SC94 stands out as having the highest $R + C$ value in this matrix (*i.e.*, 7.5106), so this factor is the most prominent than the remaining SCs. SC88, in contrast, is the least important with an $R + C$ value of 5.1763. The SCs’ order of importance in this cluster is confirmed by Fig. 7 (*i.e.*, $SC94 > SC63 > SC85 > SC90 > SC88$). Based on this IRM, SC94 and SC63 are core factors, while SC90 is the driving factor. Finally, SC88 is an independent factor, and SC85 is an impact factor.

Table 19 Most significant criteria: organizational policies and management cluster

Selected criteria	
SC88	Funding programs
SC63	Work in/with collaborative networks: ecosystems
SC90	Use of existing standards
SC94	Difficulty of evaluating the results obtained
SC85	Development of turnkey artificial intelligence projects

Table 20 Matrix with neutrosophic values: organizational policies and management cluster

	SC88	SC63	SC90	SC94	SC85
SC88	–	2(0.6, 0.3, 0.4)	1(0.8, 0, 0.2)	0(0.9, 0.1, 0.1)	2(0.9, 0.5, 0.1)
SC63	3(0.8, 0, 0.2)	–	1(0.8, 0, 0.2)	2(0.9, 0.1, 0.1)	2(0.9, 0.5, 0.1)
SC90	1(0.8, 0, 0.2)	1(0.8, 0, 0.2)	–	2(0.9, 0.1, 0.1)	2(0.5, 0.5, 0.5)
SC94	1(0.8, 0, 0.2)	3(0.8, 0.1, 0.2)	2(0.7, 0.4, 0.3)	–	3(0.8, 0.3, 0.2)
SC85	1(0.8, 0, 0.2)	1(0.8, 0, 0.2)	1(0.8, 0, 0.2)	3(0.9, 0.5, 0.1)	–

Table 21 Direct-relation matrix: organizational policies and management cluster

	SC88	SC63	SC90	SC94	SC85	TOTAL
SC88	0.00	1.26	0.84	0.00	1.40	3.50
SC63	2.51	0.00	0.84	1.80	1.40	6.55
SC90	0.84	0.84	0.00	1.80	1.00	4.47
SC94	0.84	2.48	1.33	0.00	2.29	6.93
SC85	0.84	0.84	0.84	2.10	0.00	4.61
TOTAL	5.02	5.41	3.84	5.70	6.09	

Table 22 Total-relation matrix *T*: organizational policies and management cluster

	SC88	SC63	SC90	SC94	SC85	R
SC88	0.3347	0.4915	0.3610	0.3878	0.5490	2.1241
SC63	0.8586	0.6230	0.5611	0.8264	0.8549	3.7240
SC90	0.5422	0.5930	0.3511	0.7040	0.6565	2.8469
SC94	0.7569	0.9573	0.6596	0.7264	1.0110	4.1112
SC85	0.5597	0.6170	0.4744	0.7548	0.5552	2.9610
C	3.0522	3.2819	2.4072	3.3993	3.6266	

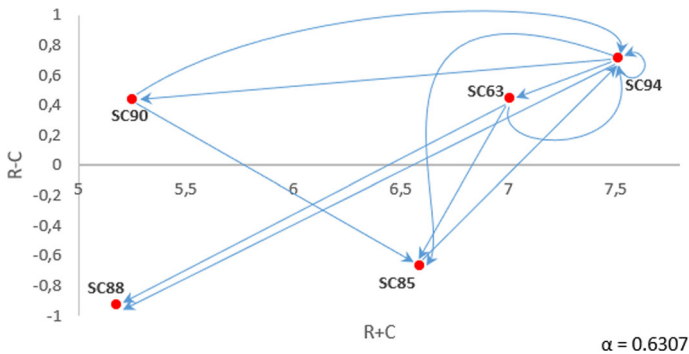


Fig. 7 Influence relationship map for organizational policies and management cluster

Table 23 Most significant criteria: leadership cluster

	Selected sub-criteria
SC53	Leadership with knowledge about adaptation processes
SC24	Team motivation
SC51	Company leadership's weak commitment
SC8	Correct perceptions of artificial intelligence uses
SC48	Leadership motivated to apply artificial intelligence

Table 23 lists the most significant SCs selected from C5 for analysis. Table 24 presents this cluster's neutrosophic matrix. Table 25 then reveals C5's direct-relation matrix after the values were subjected to crispification.

According to Table 26, SC8 has the greatest total effect on the other SCs, with an R value of 4.0115. SC24 receives the most influence from the other factors, with the highest C value of 3.9519. The totals of these variables' R and C confirm that SC53 is easily spotted as the most important SC (*i.e.*, 7.1543). The selected SCs can be ranked by order of importance as follows: SC53 > SC24 > SC51 > SC8 > SC48.

In the last step of this cluster's analysis (see Fig. 8), SC53 and SC8 were allocated to the causes group (*i.e.*, $R - C > 0$), and SC48, SC51, and SC24 were placed in the effects group. The conclusion was also reached that SC53 is a core factor, SC53 is a driving factor, and SC51 is an independent factor. Finally, SC24 is an impact factor.

Table 24 Matrix with neutrosophic values: leadership cluster

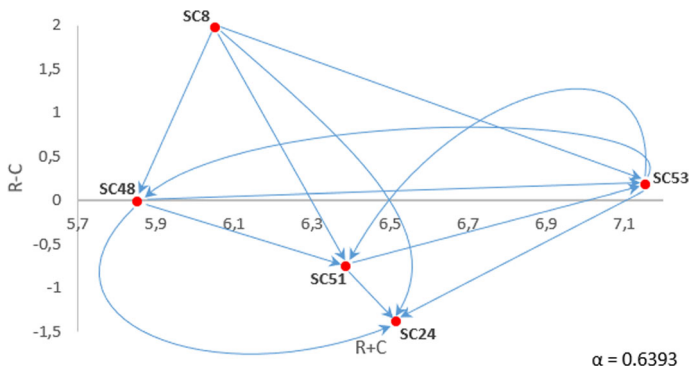
	SC53	SC24	SC51	SC8	SC48
SC53	–	4(0.9, 0.5, 0.1)	4(0.9, 0.2, 0.1)	3(0.9, 0.3, 0.3)	4(0.9, 0.1, 0.1)
SC24	3(0.7, 0.3, 0.3)	–	3(0.7, 0.3, 0.3)	3(0.9, 0.3, 0.3)	2(0.6, 0.5, 0.2)
SC51	4(0.9, 0.1, 0.1)	4(0.9, 0.2, 0.1)	–	2(0.5, 0.9, 0.5)	2(0.6, 0.5, 0.2)
SC8	4(0.9, 0.1, 0.1)	4(0.9, 0.2, 0.1)	4(0.7, 0.5, 0.2)	–	4(0.9, 0.1, 0.1)
SC48	3(0.7, 0.3, 0.3)	4(0.9, 0.2, 0.1)	4(0.9, 0.2, 0.1)	2(0.5, 0.9, 0.5)	–

Table 25 Direct-relation matrix: leadership Cluster

	SC53	SC24	SC51	SC8	SC48	TOTAL
SC53	0.00	2.80	3.43	2.25	3.60	12.08
SC24	2.10	0.00	2.10	2.25	1.23	7.67
SC51	3.60	3.43	0.00	0.68	1.23	8.94
SC8	3.60	3.43	2.58	0.00	3.60	13.21
SC48	2.10	3.43	3.43	0.68	0.00	9.65
TOTAL	11.40	13.10	11.55	5.85	9.65	

Table 26 Total-relation Matrix T :
leadership cluster

	SC53	SC24	SC51	SC8	SC48	R
SC53	0.6382	0.9007	0.8644	0.5144	0.7503	3.6680
SC24	0.5872	0.5067	0.5935	0.4103	0.4666	2.5643
SC51	0.7056	0.7612	0.5026	0.3520	0.4982	2.8195
SC8	0.9120	0.9992	0.8811	0.4115	0.8076	4.0115
SC48	0.6433	0.7841	0.7276	0.3524	0.4116	2.9189
C	3.4863	3.9519	3.5692	2.0406	2.9343	

**Fig. 8** Influence relationship map for city leadership cluster

4.3 Consolidation, discussion, and recommendations

After the multi-criteria analysis model was developed, a consolidation meeting was held with two project managers from COTEC Portugal to strengthen the proposed decision-support system and the reliability of results. Founded in 2003, COTEC Portugal is a leading think-and-action network for advancing technology diffusion and business innovation cooperation. This final meeting was also held in the Zoom platform.

First, the facilitator gave a brief overview of the research topic and objectives and then presented the methodologies applied (*i.e.*, cognitive mapping and DEMATEL techniques in a neutrosophic environment). Next, the two COTEC staff members focused on the results. These specialists highlighted that the qualitative research component (*i.e.*, cognitive mapping) was quite fully developed and interesting insofar as the main areas of concern identified were correctly represented.

Both interviewees also expressed great interest in the quantitative methodology used (*i.e.*, DEMATEL in a neutrosophic environment), mentioning that the extremely specific purpose of the proposed model (*i.e.*, to help SMEs) is important. According to one expert, “*this [area] is where projects and models like this can help*” (in his words). One interviewee also noted that the proposed model is an instrument capable of identifying not only “*expected relationships*” but also relationships that “*may not have correlations as strong as expected*” (also in the interviewee’s words). This feature underscores the ability of decision-support system created in this study to clarify specific issues that are initially more difficult to grasp.

When asked about the model’s practical applicability, the specialists jointly highlighted four points. First, “*the value proposition that this model offers to companies must first be*

made clear” (in their words). Second, “*in terms of visualization, [...] an effective presentation model*” is needed (also in their words) because, no matter how good the model and results are, SMEs still have a somewhat “closed” mentality and culture with regard to change. Third, “*practical cases of implementations in SMEs must be presented*” (again in their words). The interviewees stressed how real examples of initiative would add greater solidity and credibility to the model as SMEs are quite market-oriented. Last, an effort “*needs to be made to encourage and support its [the model’s] implementation*” (in the interviewees’ words), including helping managers understand how each adaptation initiative can be positioned and identifying, for the future, which main action plans will be needed. In this way, “*the risk of the process dying along the way*” can be avoided (in their words).

At the end, the two experts emphasized the model’s potential importance as a decision-support system since indecision often prevents the application of recommended measures and solutions. This final session thus provided an important opportunity to consolidate the results as the meeting ensured more empirically robust findings based on a greater transparency regarding how the proposed model was interpreted. In addition, these external, neutral specialists’ observations added value by providing a validation of the decision-support system in a real-life context.

5 Conclusion

Major challenges are associated with change management in SMEs seeking to adopt AI tools. Despite their subjectivity and complexity, relevant adaptation initiatives are crucial to these companies’ success. Thus, managers urgently need to pay full attention to this issue. The main objective of the present research was to develop a multi-criteria analysis system based on constructivist thinking and a combination of cognitive mapping and DEMATEL techniques applied in a neutrosophic environment. The proposed model could then be used to analyze SME adaptation initiatives with regard to AI.

The selected methodology comprised a decision-support system facilitating analyses of dynamics within factors affecting adaptation initiatives in order to identify a set of criteria and characteristics that can contribute to better change management in SMEs. The proposed model, first, incorporates a large number of factors and decisive initiatives because it structures the decision problem based on the different perspectives of a group of specialists in this area. Second, the analysis system reveals which dimensions have the greatest and least impact (*i.e.*, importance) on SME successful adaptation to AI. This approach can help professionals develop a clearer, more focused and transparent understanding of possible interventions by not only incorporating objective and subjective elements into the decision-making process but also enhancing learning through participation. Third, the proposed model includes uncertainty and insecurity (*i.e.*, neutrosophic logic), thereby providing a closer approximation to human thinking. Last, this decision-support system produces more authentic, understandable, and real results for SME managers due to the crispification of neutrosophic values.

The present findings answer the two predefined research questions. The first was how decision makers can identify key initiatives that SMEs need to implement in order to manage change during adaptations to AI and how these initiatives are interrelated. The second question was which drivers of adaptation have a significant enough impact to be prioritized over other factors in order to facilitate SME adoption of AI tools. Specifically, the results reveal three categories of factors that affect SME change management related to AI adoption, namely: *human resources; IT infrastructure; know-how and knowledge; organizational policies and*

management; and *leadership*. In addition, studies of this topic using neutrosophic logic are relatively scarce, so the present findings provide added value to the academic literature on AI, SMEs, and operational research/management science.

This study has limitations that need to be taken into account. The first is that the results cannot be generalized without appropriate adaptations (*i.e.*, findings shaped by the specific research setting). The second limitation is that the expert panel's specific profile directly influenced the results, so the findings would probably change given a different panel. The third restriction is the panel's lack of heterogeneity as only one female specialist was recruited. The fourth was online group work sessions that, due to virtual-environment constraints, did not facilitate direct or more engaging physical interactions. The last limitation was the large number of procedures required to quantify degrees of influence between the various clusters and criteria, which added extra hours to the two group sessions and, consequently, caused the participants to experience greater fatigue. Nevertheless, this research's main objective was achieved, and the promising results provide a clearer understanding of the topic under study.

These limitations can be seen as opportunities for further investigation, thereby suggesting avenues for future research focused on AI adaptation in SMEs. Additional studies could recruit a more heterogeneous panel with members from different regions. Researchers can also apply the selected methodologies to large companies or monitor the results of real-life implementations of the proposed model, which might serve as practical application cases. Finally, further investigations may want to combine neutrosophic logic with other multi-criteria analysis methods (*e.g.*, analytic hierarchy process or best–worst method). SME adaptation of AI tools is an emerging topic that is currently attracting much interest, so all those involved would welcome any future studies that can contribute with more empirically robust results to the existing body of research on this subject.

Acknowledgements This work was partially funded by the Portuguese Foundation for Science and Technology (Grants UIDB/00315/2020 and UIDB/04630/2020). Records of the expert panel meetings, including photographs, software output, and non-confidential information, can be obtained from the corresponding author upon request. The authors gratefully acknowledge the contribution of the panel members: André Lago, André Miranda, Douglas Amante, Guilherme Pereira, Marília Simões and Miguel Santos. The authors are also grateful to Rui Gonçalves and Guilherme Santos at COTEC Portugal—a leading think-and-action network for advancing technology diffusion and business innovation cooperation—for their availability and the important insights they provided during the validation phase.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Informed consent Informed consent was obtained from all individual participants included in the study.

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