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Digital strategies and non-conventional sources of innovation: Analysis of causal relationships using interpretive structural modeling

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A R T I C L E I N F O

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A B S T R A C T

Digitalization appears to have sped up in recent years, and many companies have seen their business models changed irreversibly. In this context, small and medium-sized enterprises (SMEs) should adopt different business approaches that help these firms thrive and maintain and/or create sustainable competitive advantages. SMEs' specificities can present obstacles to this adaptation process, yet these challenges may turn out to be the greatest allies of these companies if they stimulate swift, quick transformations. This study sought to develop an analysis system that identifies appropriate digital strategies and non-conventional sources of innovation, which can thus promote sustainable SME innovation. To achieve this goal, the research applied constructivist logic and combined cognitive mapping and interpretive structural modeling (ISM) to identify and analyze key variables and their respective cause-and-effect relationships that enhance successful innovation processes. A panel was formed of experts with professional experience and knowledge in this field, whose participation provided added value to the study's decision-making process through the incorporation of objective and subjective variables. The results and the analysis system's potential practical applications were validated in a final consolidation session with an expert from Portugal's *Agência Nacional de Inovação* (*i.e.*, National Innovation Agency). Theoretical and practical contributions are also discussed, as well as the limitations of the selected methodologies.

1. Introduction

In recent years, digitalization has clearly been intensifying (Gonçalves et al., 2024; Rodrigues et al., 2022), and the coronavirus disease-19 pandemic has accelerated the process. This transformation can be seen in interactions between companies and their customers and in internal operations. These changes have made many innovation and digitalization processes even more challenging for small and medium-sized enterprises (SMEs), which are currently dealing with an even more competitive business world in which their best allies are digital strategies—*i.e.*, structured plans and actions that organizations adopt to enhance performance, competitiveness, and innovation (Milici et al., 2023; Silva et al., 2025). SMEs' survival has thus become increasingly difficult, so these companies must take measures to encourage innovation and keep up with this process at all levels (Çipi et al., 2023; Silva et al., 2024; Verhoef et al., 2021).

Appropriate digitalization enables SMEs to perform better, differentiate themselves in the relevant markets, and draw closer to their customers, suppliers, and employees (Gonçalves et al., 2024; Granstrand & Holgersson, 2020). In this context, combining new digital strategies with non-conventional sources of innovation—*i.e.*, innovation inputs beyond traditional research and development (R&D), including digital

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communities, user-driven innovation, and open innovation networks (Guercini & Cova, 2018; Huang et al., 2023; Steiner, 1995)—can be the key to a successful innovation process. The adaptation and implementation of these strategies are, however, complex endeavors that depend on monetary resources and, above all, a willingness to change, which can be challenging given the organizational culture of many SMEs (Gantert et al., 2022; Macedo et al., 2024). These firms must first acknowledge that they need to change and then develop a plan that facilitates sustainable, effective innovations. Uninformed and naively optimistic decision making can threaten the success of the innovation process, so SMEs need to create a well-structured, clear, and adaptable approach that fits their realities and helps their decision-makers make good choices. To meet this need, the present study sought to develop a model that enables analyses of digital strategies and non-conventional sources of innovation that could improve SMEs' performance. This will allow us to address the following research questions.

- How are digital strategies and non-conventional sources of innovation interrelated?
- Which initiatives have the greatest impact on this interrelationship and should therefore be prioritized in organizational planning?

The existing literature underlines the conceptual multiplicity and complexity of this topic, which means research in this field needs to include a combination of constructivist techniques such as cognitive mapping and interpretive structural modeling (ISM). Together, these techniques can integrate subjectivity—an integral characteristic of decision-making processes—into analyses through decision-makers' debates and the exchange of knowledge and experiences. Cognitive mapping and ISM can be used to identify digital strategies and non-conventional sources of innovation that have positive and/or negative impacts on the innovation process. These techniques group the relevant components into areas of interest, identify cause-and-effect relationships between these variables, and rank them by their degree of importance to the process. In this way, the analysis model contributes to structuring the decision problem under analysis, assisting decision making in innovation contexts, and determining which variables can improve SMEs' outcomes. We have found no previously documented research applying this methodological approach to this study context.

Theoretically, this research advances the application of constructivist methodologies in innovation studies, bridging gaps in the existing literature by providing a robust decision-making process for understanding causal relationships and decision-making dynamics. Practically, it equips decision-makers with actionable insights and tools to navigate the challenges of digital transformation, fostering sustainable innovation and competitive advantage in resource-constrained environments. This dual contribution underscores the study's relevance to both academic and practitioner audiences.

This paper is organized into five sections. The next section presents a literature review focused on innovation and digitalization. The third section outlines the methodologies applied. Section four describes the results obtained. The final section presents this study's main conclusions and limitations, as well as suggestions for future research.

2. Related literature and research gaps

Çipi et al. (2023) and Verhoef et al. (2021) identify three phases of digital transformation: digitization, digitalization, and digital transformation. Digitization is the conversion of analog information into a digital format (Tan & Pan, 2003; Yoo et al., 2010). In contrast, digitalization refers both to this conversion and to the *"changes associated with the application of digital technology in all aspects of human society"* (Stolterman & Fors, 2004, p. 689). This transformation occurs on multiple levels, starting with processes that adopt new digital tools and optimize procedures by reducing manual operations. The second level involves organizations that offer new services and discard obsolete practices, while the third is businesses that experience distinct shifts in their role and value chain in economic ecosystems. The final level entails changes in societal structures (Parviainen et al., 2017; Silva et al., 2025). Finally, Ulas (2019, p. 663) states that "[digital transformation is] *a change in all job and income creation strategies*[; an] *application of a flexible management model* [for with] *standing* [...] *competition,* [and] *quickly meeting changing demands*[;] *a process of reinventing a business to digitise operations and formulate extended supply chain relationships*; [a] *functional use of* [the] *Internet in design, manufacturing, marketing, selling, and presenting*[;] *and* [... a] *data-based management model*".

Digital transformation, therefore, takes place not only at a digital level but also at organizations' structural, cultural, and strategic levels, and these alterations tend to bring added value to companies. This multidimensional perspective aligns with the broader theories of technology adoption (cf. Rogers, 2003) and organizational decision-making (cf. Simon, 1997), where the integration of digital technologies is viewed not only as a technological shift but also as a strategic and organizational change that redefines competitive advantage.

Granstrand and Holgersson (2020) report that innovation has a conceptual history of varied connotations and fluid denotations. Contemporary definitions see innovation as the result of a process with two characteristics: (1) the degree of the change's novelty; and (2) the successful application of something new so that it is perceived as novel by the world, a nation, or even a company (Granstrand & Holgersson, 2020). The theoretical foundation of innovation, as articulated by Schumpeter (1983), positions innovation as a key driver of competitive advantage and economic development. Nambisan et al. (2017) define digital innovation as a range of innovative outcomes including new products, platforms, and services, as well as fresh customer experiences and outcomes that, even if non-digital, are produced by digital tools. The authors also assert that this type of innovation relies on a variety of digital tools and infrastructure that enable innovation (*e.g.*, three-dimensional printing and data analytics). Nambisan et al. (2017) further highlight the possibility that the results of digital innovation will be diffused and assimilated in or adapted to specific contexts and are typically experienced through digital platforms. This definition supports a broader view of innovation that encompasses both digital and non-digital outcomes, expanding the scope of innovation beyond traditional boundaries.

Digital innovation is perceived as a driving force of economic development (Dougherty & Dunne, 2012; Loebbecke & Picot, 2015), generating competitive advantages in constantly changing and increasingly competitive business ecosystems. Currently, organizations must seek to position themselves advantageously in their markets by innovating on a regular basis to maintain or improve their standing with consumers (Gonçalves et al., 2024; Santos, Ferreira, Ferreira, & Carayannis, 2024). SME digital transformation is promoted by various factors, such as organizational flexibility, dynamism, knowledge spillovers, close cooperation with others, informality, and reduced bureaucracy (Macedo et al., 2024; Ulas, 2019). These factors resonate with the theoretical perspectives on organizational agility (cf. Doz & Kosonen, 2010), which emphasize the need for flexible, adaptive decision-making in rapidly changing environments. Specifically, Verhoef et al. (2021) state that three external factors have affected the need for digital transformation. First, organizations are increasingly adopting technological innovations ranging from the Internet to the latest technologies, which has accelerated the use of e-commerce on a daily basis. Second, a drastic change has occurred in the level of competitiveness, which has become both more global and intense as large, information-rich organizations have come to dominate multiple industries. Finally, consumer behavior has changed in response to the ongoing digital revolution, leading them to favor online shopping, making online channels an important part of today's more informed consumer journey (Çipi et al., 2023; Kannan & Li, 2017).

To survive, SMEs have to become increasingly competitive, innovating creatively and regularly to remain viable and grow in harsh business environments. These companies' innovations need to revolutionize existing business models in unexpected ways, proposing new approaches to value propositions that, according to Gasparin et al. (2021) and Macedo et al. (2024), should be based on social transformation. Social innovation comprises new products and services that address social needs and that are disseminated through organizations whose primary focus is social relationships. However, SMEs face one major challenge: limited access to resources (Buckley, 1989; Kubíčková et al., 2014; Milici et al., 2023; Santos, Ferreira, Ferreira, & Carayannis, 2024). Thus, to maintain sustainable competitive advantages, companies need to possess valuable, rare, and inimitable resources (Grant, 2010), which requires these firms to tap into non-conventional sources of innovation. This aligns with the resource-based view (cf. Barney, 1991), where firms must leverage unique resources to gain and sustain competitive advantages.

During the 1970s and 1980s, Von Hippel (1988) conducted pioneering research on the sources of innovation, which was summarized in a book entitled *"The Sources of Innovation"*. Building on the cited work, scholars have identified three types of external sources of innovation: customers, suppliers, and third parties (*e.g.*, consultants and universities) (cf. Philipson, 2020). More recent studies (*e.g.*, Gantert et al., 2022; Gu et al., 2016) have shown that SMEs tend to turn to external sources for assistance due to their resource constraints. However, Tsai and Liao (2011) observe that organizations can also generate innovations by tapping into internal resources (*e.g.*, R&D or employee creativity). This highlights the importance of absorptive capacity (cf. Cohen & Levinthal, 1990), where SMEs must be capable of recognizing, assimilating, and applying external knowledge to innovate effectively. Investigations of makerspaces' ethical foundations (cf. Gantert et al., 2022; Gonçalves et al., 2024; Santos, Ferreira, Ferreira, & Carayannis, 2024) have found that these spaces are also potential non-conventional sources of innovation. Spaces such as coworking centers, coffee shops, and bars, among others, promote networking, knowledge exchange, and close collaboration among professionals (cf. Huang et al., 2023). These non-conventional innovation spaces resonate with the theory of open innovation (cf. Chesbrough, 2003), where organizations leverage external networks and knowledge flows to innovate more effectively. This process was quite recently identified and it is still underexplored, so future research may find other emerging non-conventional sources of innovation.

Non-conventional sources of innovation have been highlighted in recent studies in part due to policymakers' focus on encouraging large organizations to invest in sustainable innovation (cf. Tucci et al., 2020). Huang et al. (2023) , Rocha et al. (2022), and Steiner (1995) suggest that innovations' success is fostered by not only conventional science but also, more fundamentally, non-conventional individuals who are the key ingredient of creativity and innovation. This aligns with the concept of bricolage (cf. Baker & Nelson, 2005), where resourceful individuals within organizations draw on available materials to create novel solutions in resource-constrained environments. Both conventional and non-conventional sources of innovation are thus crucial to organizations' survival. Table 1 presents a summary of recent studies on non-conventional sources of innovation, highlighting their key points, focus areas, methodologies, and identified limitations.

Table 1 reveals three limitations shared by prior studies. The first is a lack of research that simultaneously addresses digital strategies and non-conventional sources of innovation. The second shortcoming is the absence of analyses of the causal relationships between the factors identified in SME contexts, and the last is a lack of cross-sectional analyses of these causal links over time (see also Santos, Ferreira, Ferreira, & Carayannis, 2024; Silva et al., 2025). While prior research has established the significance of digitalization and innovation in SMEs, there is a need for deeper theoretical synthesis to elucidate the role of non-conventional sources of innovation. This study seeks to bridge this gap by engaging more explicitly with foundational theories in innovation studies, technology adoption, and organizational decision-making,

Table 1
Recent studies: Key points in non-conventional sources of innovation research.

AUTHOR	METHODOLOGY	CONTRIBUTION	LIMITATION
Steiner (1995)	Conceptual paper and literature review	- Surveyed innovation managers regarding their innovation projects in terms of three human nature elements: (1) the in-depth involvement of actors from the settings where innovations will be applied, ensuring these participants exert a strong influence; (2) a large number of diverse individuals included in the creation process or opinions dominated by other actors due to their position, power, and expertise; and (3) room for testing and hypothesizing or pressures exerted on projects in any form. - Developed a framework for exploring different levels of organization-individual relationships or the effects of professional standards on innovation-project performance.	- The study was quite generic. - The research was based on a philosophy book about the meaning of being, which may have limited the topics covered.
Capdevila (2015)	Semi-structured interviews, direct observations, and qualitative analysis	- Considered the role of communities or individuals outside firms in innovation via formal and informal interactions. - Showed that co-working centers facilitate activities crucial to the emergence and development of innovation processes, such as sharing tacit knowledge, diffusing innovation, and coordinating diverse complementary knowledge bases. - Clarified the contributions of co-working centers to innovation dynamics at the individual, community, company,	-The study was restricted to Barcelona, Spain.

(*continued on next page*)

Table 1 (*continued*)

AUTHOR	METHODOLOGY	CONTRIBUTION	LIMITATION
		local, and global level.	
Guercini and Cova (2018)	Conceptual paper and literature review	- Found that entrepreneurship and innovation depend on the environment in which individuals operate. - Confirmed that non-conventional entrepreneurship is a new pattern that currently characterizes Western societies.	- The research was limited to non-conventional sources of entrepreneurship and failed to include digital strategies. - The study focused solely on small businesses and excluded SMEs.
Pagano et al. (2018)	Semi-structured interviews and qualitative analysis	- Described the characteristics of non-conventional innovation processes. - Demonstrated the importance of delving into individuals' interpersonal relationships and the ways these links affect non-conventional innovation processes. - Presented evidence of the role of community-organization interactions in non-conventional business processes.	- The research was restricted to one area (*i.e.*, industrial marketing and purchasing). - The data were related to a specific social event, which may have influenced or distorted the results.
Oeij et al. (2019)	Comparative qualitative analysis	- Identified the factors to consider when adopting social innovation. - Developed a comprehensive, consistent model for all types of solutions, with six distinct pathways and no one right road to social innovation. - Specified that the creation or presence of infrastructures in five of the six paths is a condition for adopting social innovation. - Confirmed that the innovation journey model can be applied in a social innovation context.	- The comparative qualitative analysis was quite generalized. - The researchers concluded that only one path can be chosen when adopting social innovation.
Gasparin et al. (2021)	Semi-structured interviews, direct observations, and qualitative analysis	- Explored SME business models that deliver social innovation in transition economies. - Focused on building a social business model and structuring strategy for social innovation. - Evaluated SMEs providing social innovations.	- The proposed model was developed in the context of a transition economy. - The interviewees were founders, directors, and managers, but workers at other levels were not included.
Gantert et al. (2022)	Survey	- Examined the moral foundations of makerspaces as non-conventional sources of innovation. - Identified three critical success factors of user-driven innovation, which were incorporated into a holistic makerspace model: (1) communication of the ethical foundations and corporate social responsibility of makerspaces; (2) makerspaces' user innovation improved through a variety of configuration; and (3) enough technical equipment to avoid a bottleneck in order to boost makerspaces' innovation performance. - Advocated neo-configurational approaches to theory building and makerspaces as non-conventional, inexhaustible sources of innovation.	- The study did not differentiate between subcategories of makerspaces (*i.e.*, overgeneralization). - Limited scenarios were covered by the methodology, which resulted in generalized results. - The respondents may have manipulated the data by not sharing the truth so that they could emphasize the success of their spaces. - The research only considered makerspaces in urban areas and failed to consider suburban and rural areas. - The study should have included purity and holiness among the measures of moral foundations.

thereby offering a more comprehensive framework for understanding the digital transformation of SMEs.

Specifically, the present study sought to explore more fully the conceptual complexity and multiplicity characteristic of non-conventional sources of innovation and their causal relationships with digital strategies, using the value-focused thinking (VFT) approach and the ISM technique. It employs VFT and ISM to analyze direct and indirect relationships among system elements. This methodological combination was chosen for its alignment with the problem characteristics and research objectives. Its strengths include its ability to identify structural patterns, handle complex relationships, and evaluate expert opinions, thus avoiding bias effects. According to Santos, Ferreira, Ferreira, Ferreira, and Meidutė-Kavaliauskienė (2024), it is well-suited for strategic analysis within complex frameworks and considers both direct and indirect relationships among elements, distinguishing it from other methods. In particular, the methodological combination applied in this study excels in visually and analytically elucidating cause-and-effect relationships among factors within complex systems, while also facilitating and debating expert opinions. Furthermore, its versatility extends across various domains (cf. Bai et al., 2024; Varela et al., 2025).

3. Methodological background

3.1. Value-focused thinking and cognitive mapping

Most individuals currently associate the word “problem” with a negative connotation, so they often fail to think about the problem itself and instead go straight to finding the “solution”. This approach may not generate the desired outcome, resulting in the right solution but for the wrong problem. Ferreira (2011) reports that a problem's structure can be understood differently by each individual, and its complexity depends on the manner and circumstances in which the problem is formulated, as well as who defines it. The author also observes that intrinsic values are frequently incorporated into decision-making processes in vague, imprecise ways. Important variables can thus be excluded, thereby contributing to decision-makers' inability to offer an appropriate, consciously thought-out solution to the problem under discussion.

The VFT approach was developed to deal with these issues. Keeney (1992) states that VFT consists of two steps: (1) decide what is wanted; and (2) figure out how to achieve it. A more common approach to problem solving, according to Keeney (1992), is alternative-focused thinking in which decision-makers first analyze the available alternatives and then choose the best option. The latter approach is, however, reactive rather than proactive, so VFT can generate better alternative solutions. Keeney (1992, p. 241) affirms that *“a decision problem may not be a problem at all but an opportunity”*. Decision-support methods and processes thus need to produce relevant insights, which means seeking optimum solutions is no longer the only approach available to decision-makers.

The first problem-structuring method (PSM), often referred to as soft operational research, was introduced by Rosenhead in 1989 (cf. Rosenhead, 2006), to facilitate the application of VFT (cf. Marttunen et al., 2017). Structuring and defining a decision problem has since become a constructive, continuous learning process and an essential phase that seeks to combine objective and subjective components that reflect significant actors' values (Bana e Costa et al., 1997; Ferreira et al., 2011). The structuring process thus comprises a flexible, context-adjusted phase that gives decision-makers time to learn about the problem (Bana e Costa et al., 1997). Mingers and Rosenhead (2004) argue that a PSM should have four functions. First, the method should facilitate the combination of various alternative solutions. Second, the PSM needs to be fully accessible to all actors so that any individual can use it without any specific specialization or training. Third, the selected technique must operate iteratively to ensure the problem's representation is adjusted to accommodate all actors' views. Finally, the method should allow for partial or local improvements after the structure has been identified and/or agreed upon by the decision-makers.

The present study applied the VFT approach via the strategic options development and analysis (SODA) methodology (Eden & Ackermann, 2001). SODA *“is a general problem identification method that uses cognitive mapping as a modelling device for eliciting and recording individuals' views of a problem situation”* (Mingers & Rosenhead, 2004, p. 532). Cognitive mapping techniques generate a graphic representation of how an individual or group perceives the key aspects of a decision problem and the causal relationships between them, with the ultimate goal of improving the decision-makers' understanding and ability to make appropriate choices (Eden, 1992). Fig. 1 provides an example cognitive map, which comprises a network of concepts connected by arrows that represent cause-and-effect relationships. Plus (+) or minus (−) signs are added to the arrows depending on the type of link between the variables (Macedo et al., 2024).

3.2. Interpretive structural modeling (ISM)

The ISM technique was developed by Warfield (cf. Watson, 1978) to structure and evaluate complex decision problems by identifying and analyzing the cause-and-effect relationships between components. This method can transform fuzzy ideas into an intuitive model that includes well-defined structural relationships, which allows decision-makers to analyze complex connections between specific variables (Bai et al., 2024; Çipi et al., 2023; Wu & Niu, 2017). The latter feature was deemed to be quite useful given the decision problem selected for the current research. The following subsections provide a more detailed discussion of these procedures.

3.2.1. Step one

The first step is to identify and list the variables that influence the outcome of the complex decision problem. In this procedure, the relevant factors are ascertained based on a group of experts' opinions and practical experiences and/or a literature review.

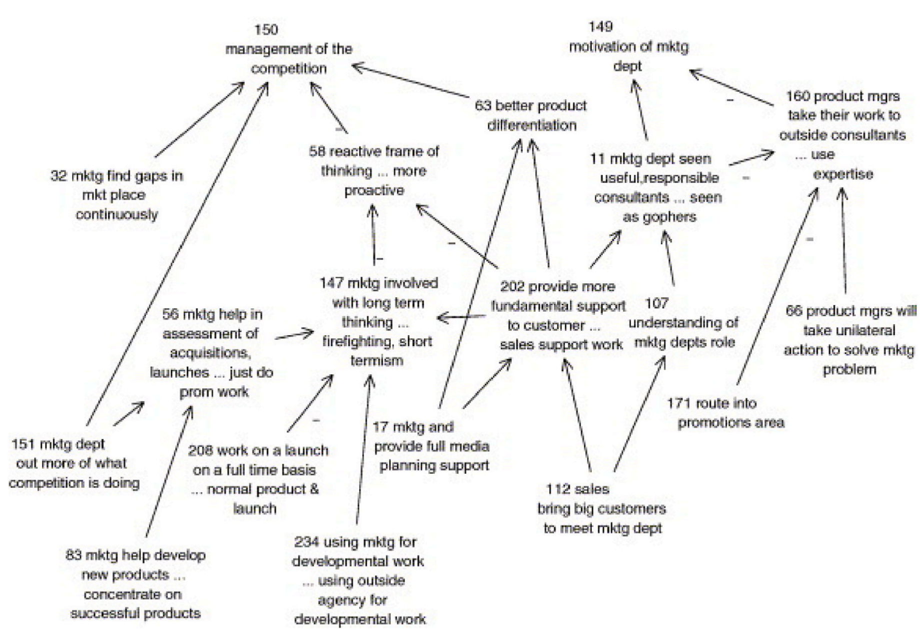

Fig. 1. Example of cognitive map.
Source: Eden (2004, p. 675)

3.2.2. Step two

The second step is to specify the contextualized relationships between the listed variables and their logical implications. The expert panel first discusses the relationship between each pair of factors. Fully established links are then defined by the group, that is, how the connections between pairs of variables can best be described (*e.g.*, one factor causes, supports, has a negative effect on, or is more important than the other factor).

3.2.3. Step three

The third step is to develop a structural self-interaction matrix (SSIM) (see Table 2), which reflects the interrelationships between the pairs of variables. The SSIM is created by assigning codes to each confirmed relationship between each variable *i* and *j* of the set of identified factors. Four types of connections exist between variables *i* and *j*, which are represented by the following four symbols.

- *V* = Variable *i* influences variable *j*.
- *A* = Variable *j* influences variable *i*.
- *X* = Variables *i* and *j* influence each other.
- *O* = Variable *i* and variable *j* have no relationship with each other.

3.2.4. Step four

The fourth step is to construct a reachability matrix using the SSIM. The information obtained thus far is translated into a binary format to allow for an analysis of the relationship between pairs of variables, replacing the inputs *V*, *A*, *X*, and *O* with a 1 and a 0 based on the following rules (Agarwal et al., 2007; Maheshwari et al., 2018).

- For any two variables, if the relationship is given as *V*, then the coordinates (*i*, *j*) are replaced with a 1 and the coordinates (*j*, *i*) are substituted by a 0.
- For any two variables, if the link is given as *A*, then the coordinates (*i*, *j*) are replaced with a 0 and the coordinates (*j*, *i*) are substituted by a 1.
- For any two variables, if the relationship is given as *X*, then the coordinates (*i*, *j*) and (*j*, *i*) are replaced with a 1.
- For any two variables, if the connection is given as *O*, then the coordinates (*i*, *j*) and (*j*, *i*) are substituted by a 0.

Replacing *V*, *A*, *X*, and *O* with binary digits produces the initial reachability matrix (IRM) depicted in Table 3.

3.2.5. Step five

The fifth step is to develop a final reachability matrix (FRM) such as the one depicted in Table 4, which includes transitivity relationships. Transitivity analysis consists of ascertaining if any indirect relationships exist between pairs of variables, keeping in mind that, if a first element *X* affects a second element *Y* and this second element, in turn, affects a third element *Z*, then the conclusion can be drawn that *X* affects *Z* indirectly. The absence of a direct relationship (*i.e.*, represented by 0) is then replaced by 1*. This analysis has to be conducted for all pairs of factors without a direct relationship in the IRM (Agarwal & Vrat, 2017; Çipi et al., 2023; Varela et al., 2025).

Table 2
Example of structural self-interaction matrix.

j→ / *i*↓	1	2	3	4	5	6	7
1		A	X	A	A	A	A
2			V	V	V	V	V
3				O	O	O	A
4					V	V	O
5						V	V
6							A
7							

Table 3
Example of initial reachability matrix.

j→ / *i*↓	1	2	3	4	5	6	7
1	1	0	1	0	0	0	0
2	1	1	1	1	1	1	1
3	1	0	1	0	0	0	0
4	1	0	0	1	1	1	0
5	1	0	0	0	1	1	1
6	1	0	0	0	0	1	0
7	1	0	0	0	0	1	1

Table 4
Example of final reachability matrix.

j→ / *i*↓	1	2	3	4	5	6	7
1	1	0	1	0	0	0	0
2	1	1	1	1	1	1	1
3	1	0	1	0	0	0	0
4	1	0	1*	1	1	1	1*
5	1	0	1*	0	1	1	1
6	1	0	1*	0	0	1	0
7	1	0	1	0	0	1	1

3.2.6. Step six

The sixth step is to define the reachability, antecedent, and intercept sets for each variable based on the FRM, according to the following guidelines.

- The reachability set considers all the factors that this variable can affect including the variable itself.
- The antecedent set takes into account all the factors that affect this variable including the variable itself.
- The intersection set considers all the factors that are held in common by each variable's reachability and antecedent sets.

3.2.7. Step seven

The seventh step is to classify the variables into partition levels based on the FRM. Using the intersection set, all the variables are associated with a level depending on the combined results for all the interactions. The intersection and reachability sets must be equal to qualify as a level, so the first equal combination becomes the top level. The procedure repeats until all the variables are assigned a level (Agarwal & Vrat, 2017).

3.2.8. Step eight

The eighth step is to remove the transitivity links based on the relationships confirmed by the FRM and used to create the ISM model.

3.2.9. Step Nine

The *matrice d'impacts croises-multiplication appliqué à un classement* (MICMAC) (see Fig. 2) seeks to provide a broader understanding of the variables of a given analysis system as determinant and dependent factors. According to Attri et al. (2013), variables can be classified according to their placement in four quadrants. Quadrant I (QI) contains *autonomous* factors with little or no dependence on other variables. Quadrant II (QII) holds *dependent* factors that are primarily dependent on other variables. Quadrant III (QIII) comprises *linkage* factors that are connected in some way to all the other variables. Quadrant IV (QIV) holds *independent* factors that are rarely influenced by other variables.

Attri et al. (2013) assert that the ISM technique offers multiple

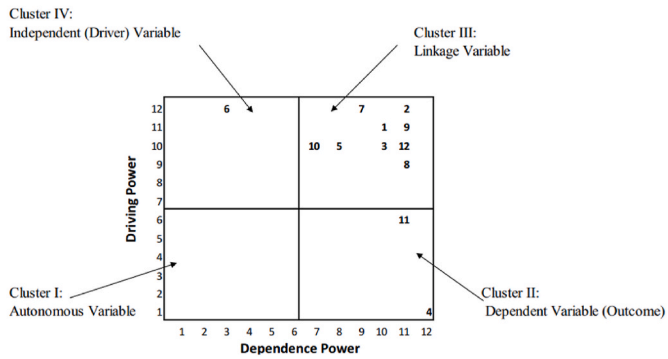

Fig. 2. Quadrants of *Matrice d'Impacts Croises-Multiplication Appliqué à un Classement.*
Source: Sindhu (2022, p. 108)

advantages. First, this method is a systematic procedure capable of considering all possible relationships between components via direct or transitive inference. Second, ISM is an efficient method that, depending on the context, uses transitive inference to reduce (*i.e.*, by between 50% and 80%) the number of relational queries required. Third, this technique does not require participants to have any understanding of the underlying process. Fourth, ISM guides—and records the results of—group deliberations in order to solve complex decision problems efficiently and systematically. Fifth, the results include a structured model or graphic representation of the original problem, which promotes more effective communication among decision-makers. Sixth, ISM enhances the quality of interdisciplinary and interpersonal interactions between experts within the problem-solving context by prioritizing and focusing on specific issues one at a time. Seventh, this technique encourages problem analyses that allow participants to explore the appropriateness of a proposed factor for a specific situation. Eighth, ISM is a learning tool that forces decision-makers to develop a fuller understanding of the meaning and importance of identified variables and their cause-and-effect relationships. Finally, this method facilitates action or policy analysis by helping participants to ascertain which specific areas offer advantages or leverage in terms of certain objectives.

Overall, ISM's greatest practical advantage is its constructivist logic as applications produce a series of structured directions for how to solve complex decision problems. The results ensure decision-makers perceive the problem at hand in realistic ways that take into account all the variables that condition it, including their precise identification and their interrelationships with the other determining factors and with the problem itself. This process allows groups of experts to identify key variables that can contribute to defining strategies that later solve the decision problem, which was the most concrete contribution of this technique to the present study. In addition, the lack of enough literature specifically focused on non-conventional innovation makes ISM particularly appropriate. This method is also based on decision-makers' experience, knowledge, and values, thereby generating new knowledge and approaches.

4. Application and results

The first step in developing a decision-support system is the structuring phase. As mentioned previously, the definition and organization of a decision problem is a constructive process of continuous learning. This phase also facilitates the incorporation of objective and subjective components into the system (Bana e Costa et al., 1997; Çipi et al., 2023). A well-formulated framework is fundamental to ensuring a solid operational basis for problem-solving procedures (Bana e Costa et al., 1997), which, in the current research, was achieved by applying the SODA approach. Using cognitive mapping techniques, the decision-makers were able to identify and structure the evaluation criteria that were included in the analysis model.

The study began with the recruitment of a panel of decision-makers with specialized expertise in the topic under study. According to Eden and Ackermann (2001), cognitive mapping is most effective when the facilitator engages directly with a small group of participants, typically between three and ten individuals. Following this recommendation, we selected five decision-makers with extensive expertise, ensuring diversity in gender, age, and professional experience. Specifically, each participant had over a decade of relevant professional experience and held a strategic decision-making role. Although based in Portugal, these specialists had prior experience in European projects, providing them with a broader perspective. Their voluntary participation ensured genuine engagement with the problem under discussion. Our approach prioritizes expertise and experience over statistical representativeness, aligning with the process-oriented nature of the study (cf. Bell & Morse, 2013). Experts were selected based on their deep knowledge and practical involvement in digital strategies and non-conventional sources of innovation, ensuring a well-informed and meaningful discussion. While we did not restrict the selection to a specific industry or geographic region, we sought a diverse group with varied backgrounds to capture a broad range of perspectives. Two facilitators coordinated the group work sessions, recorded results, and encouraged discussion within the group. The meetings took place online, which made scheduling them much easier, on the *Zoom* platform (see https://zoom.us/), which recreated a face-to-face meeting environment via shared images and sound. In addition, the *Miro* platform (see https://miro.com/) enabled the application of the "post-its technique" (Eden & Ackermann, 2001) in order to construct the group cognitive map.

4.1. Structuring phase: group cognitive map

The structuring phase was completed in a session of approximately 4 h. The basic problem under study was first presented to the panel as the following trigger question: *"Based on your knowledge and professional experience, what digital strategies and non-conventional sources of innovation would you recommend to SMEs?"*. The experts' subsequent identification of relevant criteria was facilitated by the post-its technique. Each criterion had to consist of a concept, expression, or phrase and be written on a post-it note with a "+" or "–" according to the positive or negative impact of that variable on the success of SMEs' innovation processes. To avoid any repetition of criteria, the facilitators encouraged the experts to exchange their ideas freely.

This first phase produced a list of 161 factors after a consensus was reached about the number and appropriateness of the criteria identified. The next step was to aggregate these variables into areas of interest (*i.e.*, clusters). Throughout the decision-making process, the facilitators helped the participants reach an agreement, in this case, on the creation and labeling of each cluster, allocation of each criterion to a specific cluster, and placement of specific factors in more than one cluster. The result was four distinct clusters: *Organizational Factors* (C1); *Tools* (C2); *Methodologies and Strategies* (C3); and *Stakeholders* (C4). Finally, the panel conducted an internal analysis of each cluster, in which the experts categorized each criterion according to its importance within the cluster (s) to which it belongs in terms of promoting SMEs' innovation process. The ranking by importance had three levels: high (H); medium (M); and low (L). The most significant criteria were thus placed at the top of the respective cluster, and the least important factors were allocated to the bottom. The information gathered in the first session was processed by the *Decision Explorer* software (see http://www.banxia.com) to generate a cognitive map that consolidated the group's ideas and experiences. This map was developed by the panel of decision-makers, so this visual representation reflects their knowledge, experiences, and values, as well as the discussions held during the first session. Notably, the result of these procedures will always be unique, namely different from the contents that would have been produced by a different group of experts,

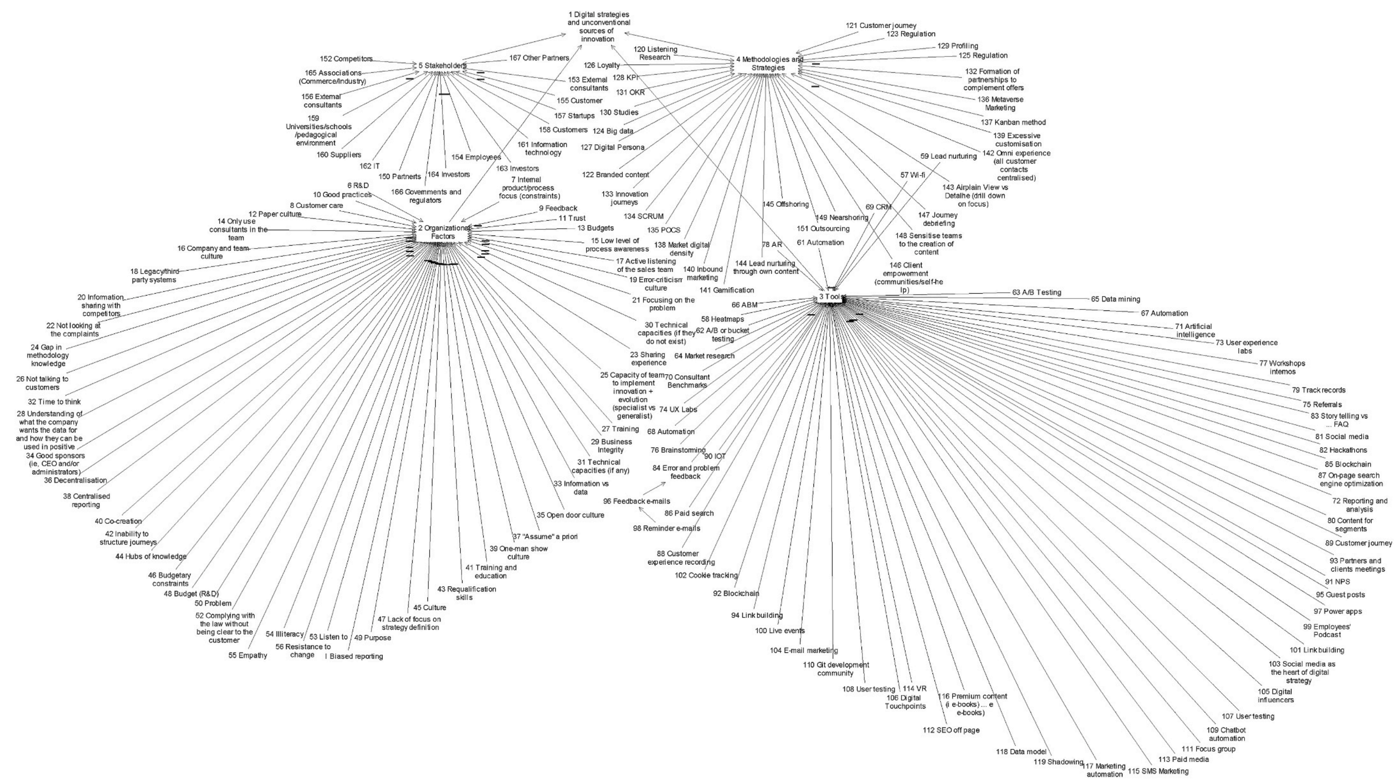

Fig. 3. Group cognitive map.

Table 5
Key criteria for successful innovation.

CLUSTER (C)	#	SUBCRITERION (SC)
Organizational Factors (C1)	SC41	Training and education
	SC16	Company and team culture
	SC28	Understanding of what the company wants the data for and how they can be used in positive ways
	SC56	Resistance to change (−)
	SC9	Feedback
	SC34	Good sponsors (*i.e.*, chief executive officer and/or administrators)
	SC40	Co-creation
Tools (C2)	SC62	A/B or bucket testing
	SC107	User testing
	SC67	Automation
	SC73	User experience labs
	SC82	Hackathons
	SC87	On-page search engine optimization
	SC71	Artificial intelligence
Methodologies and Strategies (C3)	SC121	Customer journey
	SC124	Big data
	SC127	Digital persona
	SC132	Formation of partnerships to complement offers
	SC141	Gamification
	SC135	Proof-of-concept switch
	SC136	Metaverse marketing
Stakeholders (C4)	SC150	Partners
	SC154	Employees
	SC158	Customers
	SC161	Information technology
	SC166	Governments and regulators (−)

Note: (−) = negative effect on the resolution of the decision problem.

which highlights the contextualized nature of the findings. As Bell and Morse (2013) note, the objective of these methodologies is not to make generalizations but rather to maintain a strong focus on process. Fig. 3 shows the final version of the cognitive map.

4.2. Evaluation phase: ISM and MICMAC analysis

The next phase was an evaluation of the criteria using the ISM technique. The second group work session lasted approximately 3 h and began with an introduction of the methodology used to identify the most crucial factors and the causal relationships between them. The facilitators first presented the cognitive map based on the previous session to the panel for validation. The key criteria in each cluster were then identified using the nominal group technique (NGT) and multi-voting. Table 5 lists the results (*i.e.*, the four clusters and their most significant variables).

The decision-makers were next asked to work together to reach a consensus on the type of relationship between each pair of criteria, namely to follow the third step of the ISM method (see subsection 3.2.3). An inter-cluster analysis (*i.e.*, links between clusters) was performed first, followed by an intra-cluster evaluation (*i.e.*, connections within each cluster). The SSIM produced by the first kind of analysis highlights the causal relationships between the four clusters (see Table 6). C1 is not influenced by C2, but C1 affects C2. The latter cluster, in turn, does not influence C3, but C2 is affected by C3.

The intra-cluster analysis, in turn, generated an SSIM for each cluster

Table 6
Structural self-interaction matrix for inter-cluster evaluation.

	C1	C2	C3	C4
C1		V	X	X
C2			A	X
C3				X
C4				

Table 7
Structural self-interaction matrices (SSIMs) for intra-cluster evaluation.

SSIM for Organizational Factors (C1)

	SC9	SC16	SC28	SC34	SC40	SC41	SC56
SC9		X	X	X	X	X	X
SC16			X	X	X	X	X
SC28				V	X	X	X
SC34					X	X	X
SC40						X	X
SC41							X
SC56							

SSIM for Tools (C2)

	SC62	SC67	SC71	SC73	SC82	SC87	SC107
SC62		X	X	X	O	V	X
SC67			X	O	O	X	X
SC71				X	X	A	X
SC73					A	O	V
SC82						O	X
SC87							O
SC107							

SSIM for Methodologies and Strategies (C3)

	SC121	SC124	SC127	SC132	SC135	SC136	SC141
SC121		X	X	X	X	X	X
SC124			X	X	X	X	X
SC127				X	X	X	X
SC132					X	X	X
SC135						X	V
SC136							X
SC141							

SSIM for Stakeholders (C4)

	SC150	SC154	SC158	SC161	SC166
SC150		X	X	X	X
SC154			X	X	A
SC158				X	X
SC161					X
SC166					

Note: SC = subcriterion or specific criterion.

Table 8
Initial reachability matrix: Inter-cluster evaluation.

	C1	C2	C3	C4
C1	1	1	1	1
C2	0	1	0	1
C3	1	1	1	1
C4	1	1	1	1

to determine the causal links among the key criteria in each cluster. Table 7 contains the SSIMs for the four clusters. An analysis of the four matrices confirmed that most causal relationships between the variables are bidirectional (*i.e.*, criteria that influence each other), which tends to reinforce cross-criteria links.

4.2.1. Inter-cluster assessment

Using the inter-cluster SSIM (see Table 6), the IRM was created by replacing *V*, *A*, *X*, and *O* with the binary digits 1 and 0 to reflect the

Table 9
Final reachability matrix: Inter-cluster assessment.

	C1	C2	C3	C4	Dr Pw
C1	1	1	1	1	4
C2	1*	1	1*	1	4
C3	1	1	1	1	4
C4	1	1	1	1	4
Dp Pw	4	4	4	4	

Note: Dr Pw = driving power; Dp Pw = dependence power.

Table 10
Reachability, antecedent, and intersection sets and partition levels: Inter-cluster evaluation.

	REACHABILITY SET	ANTECEDENT SET	INTERSECTION SET	LEVEL
C1	C1, C2, C3, C4	C1, C2, C3, C4	C1, C2, C3, C4	1
C2	C1, C2, C3, C4	C1, C2, C3, C4	C1, C2, C3, C4	1
C3	C1, C2, C3, C4	C1, C2, C3, C4	C1, C2, C3, C4	1
C4	C1, C2, C3, C4	C1, C2, C3, C4	C1, C2, C3, C4	1

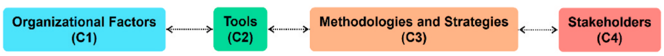

Fig. 4. Interpretive structural modeling graph: Inter-cluster evaluation.

	DP PW (x)	DR PW (y)	TYPE	QUADRANT
C1	4	4	Linkage	III
C2	4	4	Linkage	III
C3	4	4	Linkage	III
C4	4	4	Linkage	III

Note: Dp Pw = dependence power; Dr Pw = driving power.

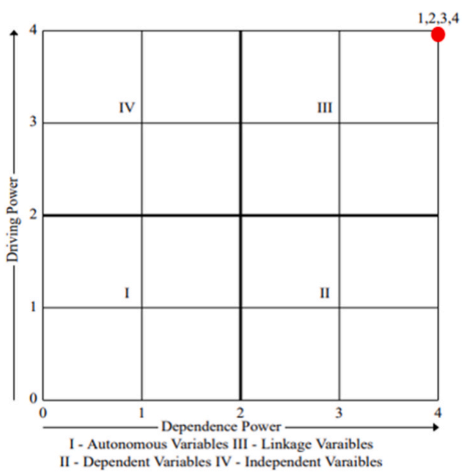

Fig. 5. Micmac analysis: Inter-cluster evaluation.

relationships between each pair of clusters. Table 8 presents the IRM for the inter-cluster analysis.

The next procedure involved analyzing the transitivity present between clusters in order to verify whether indirect relationships exist between the pairs of clusters (*i.e.*, represented by 0 in the IRM). Transitivity was identified using the three-step matrix method and the inter-cluster IRM. The first step was to find one line that contained at least one 0. In this case, the C2 row needed to be isolated. The second step was to eliminate the rows corresponding to the clusters that contain 0 in the isolated row, which took out the C1 and C3 lines. The last step was to verify, in the columns with 0 in the isolated row, if at least one 1 appeared in the columns of the remaining clusters. If this condition is fulfilled, a transitivity relationship is found to be present, and the cell that contains the 0 is changed to 1*. In the present case, both the C1 and C3 columns have at least one 1, so the cells that contained a 0 were modified to 1*.

After the matrix method was applied, the results were compared with those of a deductive method. In addition, the outcomes of the matrix method were put side by side with the results produced by the *SmartISM* software (Ahmad & Qahmash, 2021), which uses the Floyd-Warshall algorithm to evaluate transitivity (see also Çipi et al. (2023) and Santos, Ferreira, Ferreira, Ferreira, and Meidutė-Kavaliauskienė (2024)). No differences were found between the outcomes of the three methods for the present analysis. Table 9 shows the inter-cluster transitivity relationship results.

Using the FRM of the inter-cluster analysis, the degrees of influence and dependence of each cluster could be determined. The degrees of the four clusters are the same, so these areas of interest are equally important to each other and fundamental to innovation processes. This result confirms that the clusters have the same mutual influence and dependence on each other. The clusters were then categorized by partition level. Since their reachability and intersection sets are identical, all the clusters were allocated to the same partition level (*i.e.*, level one). Table 10 lists the defined reachability, antecedent, and intersection sets, as well as the partition levels detected by the inter-cluster analysis.

The next step was to reduce the matrix to its canonical form and create the ISM digraph, which only represents the direct relationships of the clusters. Fig. 4 presents the ISM produced by the inter-cluster analysis.

Finally, MICMAC analysis was conducted to classify the clusters according to the previously estimated degrees of influence and dependence. Fig. 5 provides the resulting MICMAC diagram.

All four clusters show a high degree of influence and dependence, so they have a great capacity to influence or be influenced by each other. The conclusion was thus reached that, in an innovation process, SMEs should focus equally intensively on these clusters.

4.2.2. Intra-cluster assessment

After the inter-cluster analysis was completed, the same steps were followed to analyze the key criteria of each cluster (*i.e.*, hereafter referred to as subcriteria or specific criteria (SCs)) defined by the decision-maker panel. In this procedure, the impact of the SCs' relationships was evaluated for each pair of factors in the same cluster.

C1 included 51 criteria. Thus, as mentioned previously, the experts were asked to select the variables they considered to be the most significant in innovation processes using NGT and multi-voting. The panel also specified the cause-and-effect relationships between the pairs of SCs to produce the IRM for this cluster. The pairs were then checked for possible transitivity links. As had been done previously, the results produced by the matrix method were compared with those obtained with the deductive method and *SmartISM* software. Again, no differences were detected, namely the three techniques confirmed that only one pair of variables is a transitive relationship. Next, the FRM was drawn up in order to measure the degrees of influence and dependence of each SC. The reachability, antecedent, and intersection sets are equal to each other, so the SCs were all included in level one. The matrix was then reduced to its canonical form, and MICMAC analysis was carried out for C1. All the C1 SCs were categorized as linkage factors as they are located in QIII (see Fig. 6). The results thus support the conclusion that a strong relationship exists between these variables and that they are all highly relevant to the analysis model.

C2 comprised 62 criteria, which meant that the decision-makers first needed to select the factors that most influence SMEs' innovation process in order to simplify the analyses. The causal relationships between these SCs were identified and translated into the IRM for this cluster, which was used to identify possible transitivity relationships and thus construct the FRM. One difference was found in the results produced by the three methods (*i.e.*, matrix, deductive, and *SmartISM* software or Floyd-Warshall algorithm) for C2. Thus, only the first two methods' parallel outcomes were used. The SCs all have a high degree of influence and dependence, which underlines the strong influence and dependence between them. After the reachability, antecedent, and intersection sets were defined, the variables were assigned into the same level: SC62, SC67, SC71, SC73, SC82, SC87and SC107. The MICMAC analysis for C2 placed the criteria at coordinates (7, 7). All the SCs are located in QIII (*i.e.*, linkage factors). Overall, a strong relationship exists between this

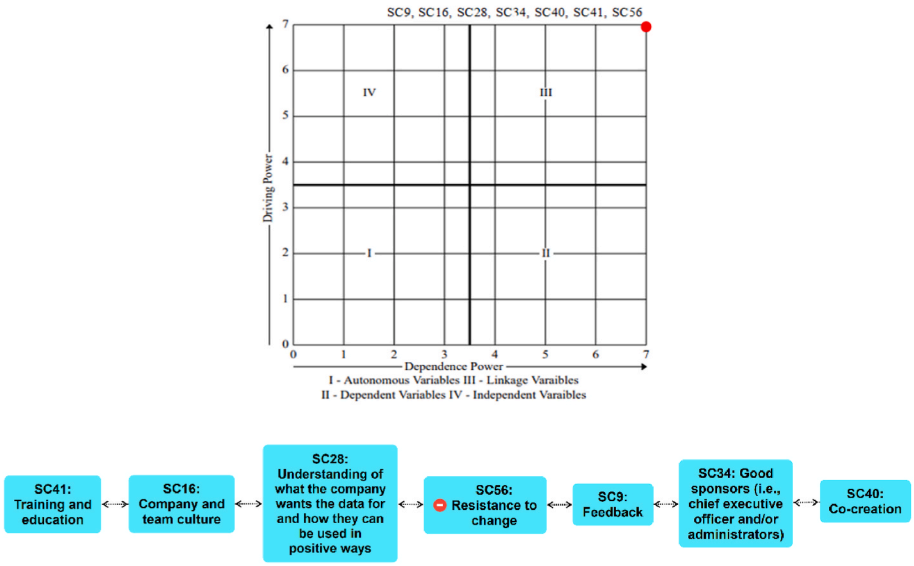

Fig. 6. Micmac analysis and digraph for C1.
Note: SC = subcriterion or specific criterion.

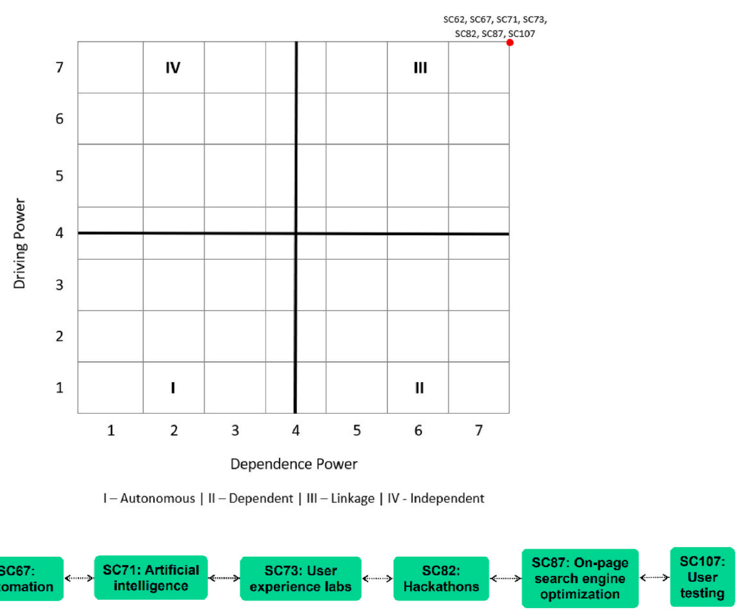

Fig. 7. Micmac analysis and digraph for C2.

clusters' key variables, and they are of great importance to the decision-support model. Fig. 7 shows the MICMAC analysis and digraph for C2.

C3 contains 31 criteria out of which the decision-makers first selected the SCs they considered most important to ensuring successful innovation processes. The causal relationships between these variables were defined to produce the C3 IRM. Only one transitivity relationship was identified in the procedure followed to construct this cluster's FRM. The results are similar for all three transitivity analysis methods. Next, the degrees of influence and dependence between the SCs were defined, which proved to be both high and identical for all the key variables. That is, the reachability, antecedent, and intersection sets are equal, and the SCs are all at the same partition level (*i.e.*, level one). Finally, the matrix was reduced to its canonical form, and MICMAC analysis was conducted, placing all the factors in QIII (*i.e.*, linkage variables). The SCs thus have the same influence and dependence relationships, which again suggests strong links exist between these variables and they play an important role in the analysis model. The MICMAC analysis and ISM digraph for C3 are presented in Fig. 8.

C4 embraces 17 criteria initially defined by the decision-maker panel, who later picked out the factors with the most significant impact on innovation processes' success. The cause-and-effect relationships between the SCs were specified, and the IRM of this cluster was constructed. The possibility of transitivity between pairs of variables was then checked to identify any indirect relationships. No differences were found for C4 between the outcomes of the three transitivity analysis methods. The FRM of this cluster was constructed next, after which the degrees of influence and dependence between SCs could be estimated. The degrees were again equal for all the variables, as were the reachability, antecedent, and interaction sets. The latter were allocated together to partition level one. The matrix for this cluster was reduced to its canonical form, and MICMAC analysis was carried out, revealing that all the SCs are again located in QIII and that they have equal influence and dependence relationships. These findings indicate that strong links exist between the factors, and the C4 SCs are extremely

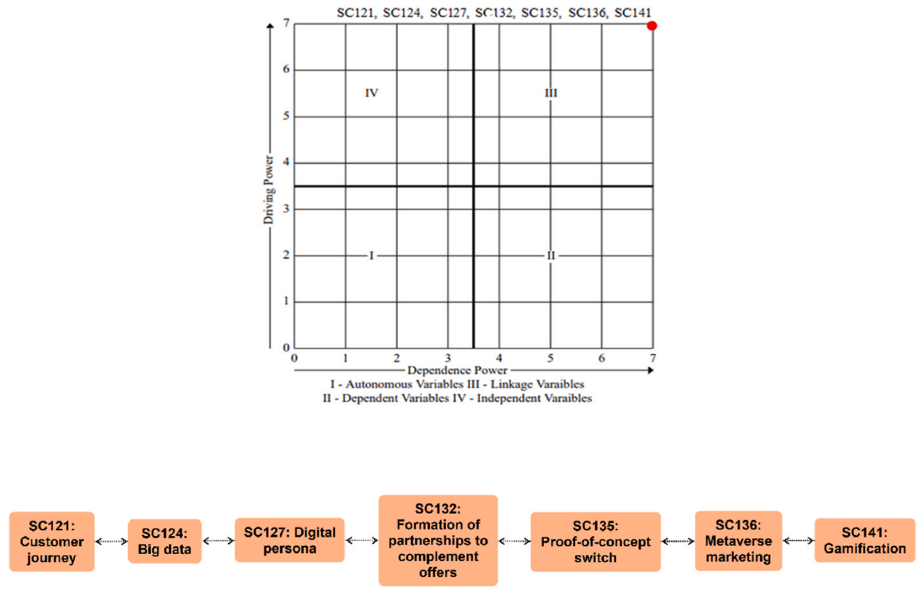

Fig. 8. Micmac analysis and digraph for C3.

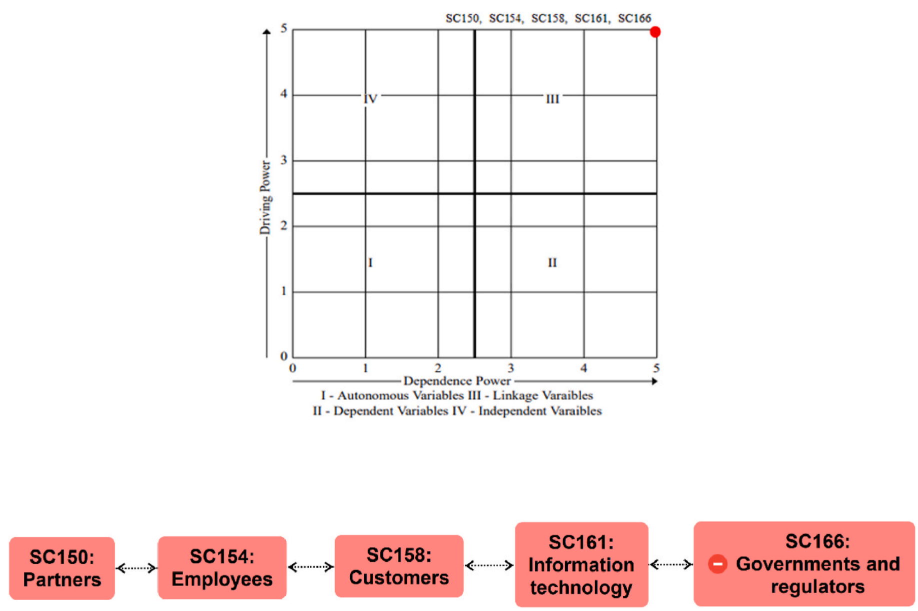

Fig. 9. Micmac analysis and digraph for C4.

important to the decision-support model. Fig. 9 shows the C4 MICMAC results. The next subsection discusses how these findings can be used to guide decisions about which key aspects should be taken into account when SMEs plan innovation projects.

4.3. Recommendation phase: discussion and consolidation of results

The analysis and discussion of the results was followed by a consolidation procedure to ensure SMEs' innovation processes are fruitful. The findings were used to generate a guide (see Fig. 10) divided into four crucial areas that affect innovation's success: (1) organizational factors; (2) tools; (3) methodologies and strategies; and (4) stakeholders. The analysis model in Fig. 10 was developed using the *Mind Map Pro* software (see https://simplemind.eu). The upper area of the decision-support system contains aspects related to the SME and its stakeholders, while the lower area comprises variables related to the methods that promote successful innovation processes.

To consolidate the analysis model further, a third session was held with an expert who was external to—and neutral about—the decision-maker panels' previous group work. This professional was the head of the Monitoring Unit at Portugal's *Agência Nacional de Inovação* (ANI) (National Innovation Agency). ANI seeks to develop initiatives that support technological and business innovation at the national level.

The final session was held online in the *Zoom* platform for approximately 1 h. The meeting followed a five-part agenda in which the first segment was dedicated to introducing the topic under study, as well as the theoretical assumptions that shaped the decision-makers' interactions. The second part outlined the methodologies applied, while the third described their application during the empirical research. The fourth and last segments were an analysis of the results and of the model's practical applicability, ending with an opportunity to suggest improvements.

The consolidation session thus began with an explanation of the conceptual framework that channeled how the expert panel identified

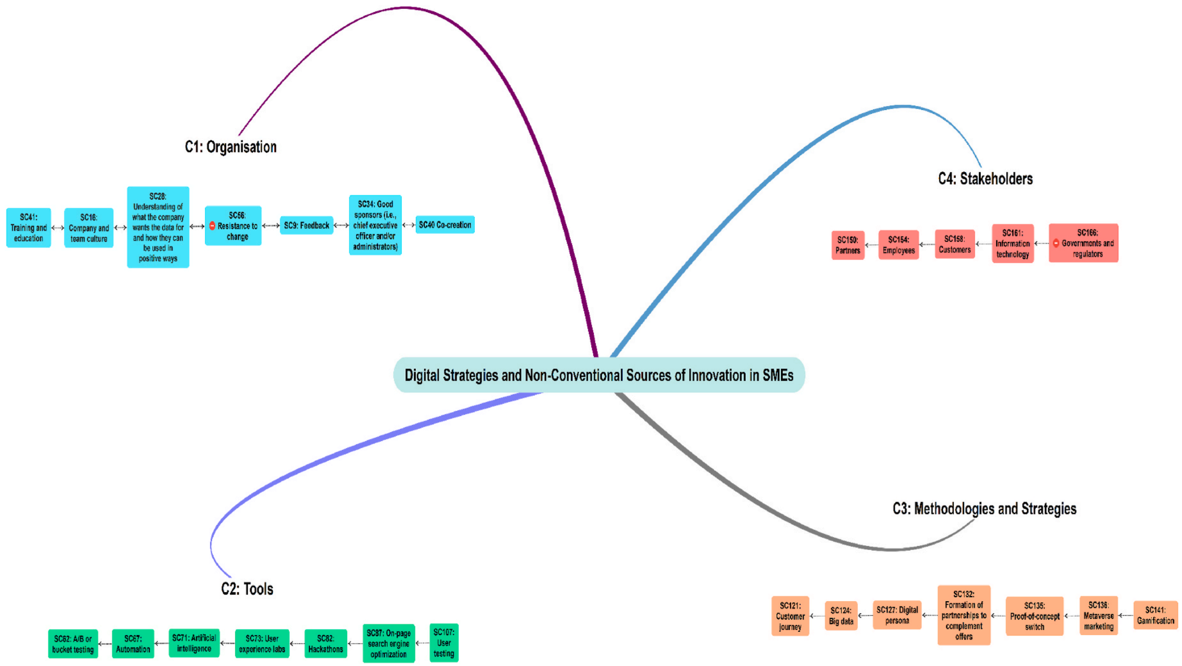

Fig. 10. Analysis model of digital strategies and non-conventional sources of innovation for SMEs.

the variables they considered fundamental to SMEs' innovation processes. Next, the methodologies were described, which proved necessary because they were unfamiliar to the ANI professional. He found these techniques quite appropriate, although he noted that the results would vary depending on *"the previous experience of the people selected. People more connected to academia have a certain type of vision and make different choices than people more connected to the business environment or people connected to the public sector"* (in his own words). This expert also observed that, *"if the panel had been larger, it would have provided a greater diversity of views"* (also in his words). In his opinion, the inter-cluster analysis should have placed financial variables in a separate cluster instead of in C1: *"It is not enough to have the will, need, resources, and knowledge. It is necessary to finance projects because everything you want to do will have an associated cost. Organizations also think about innovating in response to the availability of* funding (in the expert's words).

Turning to the intra-cluster results, he generally agreed with the criteria defined and emphasized, especially, SC40 in C1: *"Of course, collaboration is one of the most important factors since alone we do very little. When it comes to more advanced knowledge, it is very difficult for organizations to have within them—or to have access to—the necessary people and knowledge they need to innovate, and therefore collaboration is absolutely essential"* (in the expert's words).

The expert also offered the *"practical advice* [that decision-makers need] *to prioritize the factors depending on the innovation's objective"* (in his words). He further mentioned that an added value from a practical point of view would have been weighting the key criteria so that they could be more easily prioritized. Despite making a similar point about the clusters, the expert acknowledged the importance of using a process-oriented methodological framework. Overall, he found the proposed model to be of great interest, as well as being globally valid, adhering closely to reality, and thus easy to apply within an organization. Finally, he suggested the decision-support system should be tested in an SME for further refinement of the model.

Overall, the four clusters identified (*i.e.*, *Organizational Factors* (C1), *Tools* (C2), *Methodologies and Strategies* (C3), and *Stakeholders* (C4)) align with the main topics described in the literature review section (*e.g.*, Macedo et al., 2024; Santos, Ferreira, Ferreira, & Carayannis, 2024). The key variables associated with these four clusters represent the subcriteria, demonstrating the relevance of these themes to innovation. In other words, these clusters serve as both the source and direct catalysts for innovation. Furthermore, these clusters are interrelated and mutually influential, demonstrating a two-way influence. As also discussed in the literature review section, particularly concerning the importance of the digital strategy topic (cf. Gonçalves et al., 2024; Silva et al., 2025), these clusters are intricately connected to various factors such as strategy, employee performance, technology (*e.g.*, digitalization, IT, digital platforms), and the process of digital transformation leading to innovation.

The mutual influences between the *Organizational Factors* and *Tools* clusters exemplify characteristics of organizational aspects within companies, including employees' educational levels and organizational culture. These aspects contribute to faster, more effective adoption, and better utilization of tools, such as digitalization. Similarly, tools positively impact organizational aspects across all subcriteria, except for decreasing resistance to change. The interrelationship between tools, methodologies, and strategies underscores the dependency between technological and methodological aspects. In essence, the use of tools corresponds to the availability of data and the capability for methodological use. Furthermore, methodologies and strategies are linked to various stakeholders. While stakeholders can influence the application of specific methodologies, methodologies can, in turn, impact stakeholders' behaviors.

The seven key variables within the *Organizational Factors* cluster are mutually associated. Innovation in SMEs hinges on the combination of training, a supportive culture, understanding data purpose, addressing resistance, feedback mechanisms, and strong executive sponsorship. The factors related to the *Tools* cluster directly influence innovation. For instance, user testing contributes to search engine optimization, which, in turn, extends to hackathons and user experience labs. This directly impacts the utilization of AI and automation, and indirectly influences A/B testing. User testing is significant in innovation due to its pivotal role in digital ecosystems and the transformation process. *Methodologies and Strategies* (C3) are crucial across all areas and stages of digital platform transformation. For example, gamification influences metaverse marketing and subsequently proof of concepts. The cause-and-effect direction leads to finding partners and the capability to manage digital data in response to customer journeys. Cluster C4, regarding stakeholders, demonstrates consecutive and indirect cause-and-effect relationships among the actors involved in digital transformation for innovation. The government sector, associated with regulations, is perceived to have negative effects on innovation. This implies a direct impact on IT and indirect effects on other stakeholders.

We acknowledge that the composition of the expert panel may affect the generalizability of the findings. However, our goal is not to produce universally applicable results but to develop a framework that can be adapted and applied across different contexts. Drawing on the perspective of Bell and Morse (2013), the methodologies used in this study align with the principle that the aim is not to generate generalized solutions but to focus on the decision-making process itself. This approach allows for flexibility, enabling organizations to tailor the framework to their specific needs and circumstances. By emphasizing process over generalization, the study ensures that the proposed decision-support model remains adaptable to the unique characteristics of SMEs, enhancing its relevance and applicability. This process-oriented approach also underscores the constructivist nature of the research, which values the iterative exploration of variables, the dynamic interactions within decision-making contexts, and the co-creation of knowledge through dialogue.

Naturally, we recognize that other decision-makers may wish to apply our methodology to their specific contexts. Even if they do not fully grasp the entire process, they may still be interested in our final recommendations. In such cases, we suggest that these decision-makers examine the cognitive map (Fig. 3) and the ISM diagrams (Figs. 6–10) to identify the determinants most relevant to their unique situations. While we could prioritize factors with the greatest potential impact and propose targeted intervention strategies, this would need to be determined on a case-by-case basis, considering the specific characteristics of each SME, context, and situation. Ultimately, this approach not only enriches theoretical insights but also provides practitioners with adaptable tools to navigate the evolving challenges of innovation across diverse SME environments.

5. Conclusion

In recent decades, digital evolution has generated significant disruption in societies and businesses. Given SMEs' limited resources, innovation must clearly be a top priority to ensure their survival. These firms represent the majority of companies, so researchers need to create tools that can support their innovation processes.

The scarcity of literature on non-conventional sources of innovation is coupled with a lack of expertise on how to exploit them. This challenging context underscores the importance of structuring this decision problem and creating evaluation models that can guide SMEs toward successful innovation. The complexity of this topic is magnified by the conceptual multiplicity of non-conventional sources of innovation. The intricacy of the decision problem reinforces the need to incorporate subjective aspects into analysis models, including values, social proficiency, and professional experience and knowledge, so that these decision-support systems better align with SMEs' unique characteristics.

The methodologies applied in this study made use of the decision-maker panel's expertise to provide a deeper understanding of digital strategies and non-conventional sources of innovation, as well as the causal relationships between related variables, allowing the two research questions presented to be answered (*i.e.*, How are digital strategies and non-conventional sources of innovation interrelated? Which initiatives have the greatest impact on this interrelationship and should therefore be prioritized in organizational planning?).

This study offers significant theoretical, practical, and societal contributions, which can facilitate the identification and prioritization of digital strategies and non-conventional sources of innovation that enhance innovation processes. Theoretically, it advances the understanding of how digital strategies and non-conventional sources of innovation interact, particularly in the context of SMEs. By employing a novel integration of cognitive mapping and ISM, the research bridges existing gaps in the literature by providing a structured framework to analyze the complexity and subjectivity inherent in innovation processes.

From a practical standpoint, the proposed decision-support model equips SMEs with the necessary tools to identify and prioritize critical innovation drivers, strengthening their ability to adapt and thrive in rapidly evolving digital environments. A key contribution is the development of a cognitive map encompassing 161 criteria relevant to SME innovation, alongside the identification of four key areas of interest and their respective criteria, which collectively support successful innovation efforts. Additionally, the constructed matrices clarify the cause-and-effect relationships among the four clusters and their associated variables, ensuring a structured approach to decision-making. The decision-support tool integrates both objective and subjective components, providing decision-makers with actionable insights into these causal relationships and facilitating more effective resource allocation and strategic planning. Furthermore, the methodologies employed actively engaged the expert panel, fostering discussions that enriched the collective understanding of SMEs' innovation processes.

Beyond organizational benefits, the cognitive mapping process and expert panel discussions underscored the growing relevance of non-conventional sources of innovation, such as digital communities, user-driven innovation, collaborative networks, and open-source innovation networks. These insights point to the need for targeted policy measures that enable SMEs to fully leverage these emerging innovation pathways. Based on this, we recommend that policymakers introduce subsidies for SMEs adopting digital tools that enhance remote collaboration, such as project management software and cloud-based communication platforms. These tools not only facilitate operational efficiency but also enable SMEs to tap into distributed knowledge networks, fostering open innovation. Another key recommendation is financial support for SMEs integrating AI-driven solutions, particularly in areas such as customer service automation and predictive analytics, where machine learning can uncover new market trends and enhance decision-making. Furthermore, the expert panel emphasized the importance of cross-industry learning and collective intelligence, leading us to propose the creation of government-led platforms where SMEs can access case studies, workshops, and mentorship programs showcasing successful applications of non-conventional innovation sources. By tailoring these policy measures to the distinct challenges faced by SMEs across different sectors and regions, policymakers can drive more impactful and sustainable digital transformation efforts, ultimately contributing to economic resilience, job creation, and long-term sustainable development.

Regardless of the results, this study was subject to certain limitations. First, the findings are context specific, so they cannot be directly generalized to other settings. Second, the techniques applied provided no clear hierarchy of the clusters' importance. Third, the proposed model may not fully represent the range of non-conventional sources of innovation as the analysis system focuses more strongly on digital strategies. Finally, the methodologies used made prioritization of the key criteria in terms of practice quite difficult. Nonetheless, the combination of cognitive mapping and ISM produced a well-structured and easy-to-understand overview of the variables that should be considered in the innovation process and of their relative importance in SME contexts.

Future research could strengthen the present findings by comparing them with the results produced by another panel of decision-makers or, as suggested by the ANI expert, applying the proposed model to an actual SME in order to fine tune the decision-support system. Further studies are also needed to apply other multi-criteria methodologies in combination with cognitive mapping and ISM to obtain a clearer ranking of the key criteria by priority, thereby facilitating practical applications of the model. The topic under study is highly complex, so additional research on this area would benefit both the academic and business communities.

CRediT authorship contribution statement

Inês M. Farinha: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fernando A.F. Ferreira:** Writing – review & editing, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Neuza C.M.Q. F. Ferreira:** Writing – original draft, Methodology, Formal analysis, Data curation. **Edwin Garces:** Writing – review & editing, Methodology, Formal analysis. **Tugrul Daim:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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Data availability

Data will be made available on request.

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