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Unraveling the path to smart manufacturing advancement: insights from necessary condition and fuzzy-set qualitative comparative analyses

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Abstract

Purpose – Smart manufacturing (SM), a key dimension of the Industry 4.0 paradigm, envisions the transformation of traditional production systems into autonomous, interconnected and data-driven networks. By leveraging advanced technologies, SM promises to enhance firms' competitiveness and operational efficiency. Despite its strategic relevance, many companies still struggle to achieve high levels of SM advancement. While the operations management literature has identified several technical and social factors crucial for SM advancement, there is little empirical evidence regarding the relevance of each factor in the SM path. Building on socio-technical systems theory, this study aims to understand the specific sequence in which firms need to deploy technical and social factors to advance in SM and whether specific combinations of factors enable firms to achieve higher levels of SM advancement.

Design/methodology/approach – This study combines necessary condition analysis (NCA) and fuzzy-set qualitative comparative analysis (fsQCA) using survey data from 234 firms in the automotive component industry.

Findings – The results of the NCA suggest that technical factors and social factors must be deployed in a specific sequence to advance in SM. Initial stages of SM adoption require a limited set of baseline factors, while advanced stages necessitate a broader array of factors. Additionally, the findings show that advancing in SM does not require firms to maximize the magnitude of every factor but rather to ensure a minimum presence of critical factors, indicating the existence of saturation effects. The outcomes of the fsQCA further reveal that certain factors, while not strictly necessary on their own, play a role within specific configurations, illustrating how the interplay of sequencing and tailored combinations drives successful SM advancement.

Research limitations/implications – Our study advances socio-technical systems theory and SM literature by reframing factor alignment as a dynamic and evolving process that adapts to varying operational and strategic priorities at different stages of SM advancement. By uncovering the technical and social factors critical for each stage, we provide a deeper understanding of how firms can navigate the SM complexities to achieve progress. Moreover, we enrich operations management research by demonstrating how enablers interact within broader systems and emphasizing the importance of tailoring strategies to context-specific requirements, moving beyond static frameworks to highlight stage-specific pathways that drive sustainable SM advancement.

Practical implications – The findings offer practical guidance for manufacturing executives, detailing how to allocate resources strategically and adapt configurations to align with the unique requirements of their SM transformation, thereby facilitating a more streamlined and effective progression toward advanced SM capabilities.

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Originality/value – This study is the first to provide empirical quantitative evidence on both the sequence in which firms need to deploy technical and social factors to reach higher stages of maturity in SM and the presence of specific configurations of factors that enable firms to achieve advanced levels of SM.

Keywords Smart manufacturing, Industry 4.0, Technical and social factors, Socio-technical systems theory, Necessary condition analysis, Fuzzy-set qualitative comparative analysis, Survey, Automotive industry
Paper type Research paper

1. Introduction

Over the past decade, Industry 4.0 has emerged as a transformative framework for the manufacturing sector, characterized by the integration of advanced digital technologies into industrial operations (Culot *et al*., 2020). Often regarded as the fourth industrial revolution, Industry 4.0 represents a systematic shift toward interconnected ecosystems in which physical and digital domains converge, enabling seamless data exchange and intelligent automation (Chiarello *et al*., 2018; Liao *et al*., 2017). Within the broad Industry 4.0 paradigm, Frank *et al*. (2019) identify four interrelated dimensions: Smart Manufacturing, Smart Products, Smart Supply Chains, and Smart Working. Among these, Smart Manufacturing (SM) lies at the core of Industry 4.0 and envisages the widespread use in production of smart technologies, including Big Data and Analytics, and Cloud Computing (Diaz and Ardalan, 2023; Kagermann *et al*., 2013; Frank *et al*., 2019). SM enables connected production systems that autonomously adjust to meet changing conditions and ensure optimal resource allocation (Kusiak, 2018), thus enhancing firms' operational performance and competitiveness (Arcidiacono and Schupp, 2024; Dalenogare *et al*., 2018). As a result, this manufacturing paradigm has gained increasing relevance for academia and practice (Culot *et al*., 2020; Min *et al*., 2018), and especially manufacturers operating in dynamic industries (e.g. automotive and consumer electronics) have directed consistent investments to introduce SM technologies in their plants (Kamble *et al*., 2020; Lin *et al*., 2018).

One of the unique characteristics of SM is that unlike previous technological shifts, such as information technology, it builds on multiple technologies, playing complementary rather than substitutable functions (e.g. Demeter *et al*., 2024; Battaglia *et al*., 2023; Culot *et al*., 2020; Frank *et al*., 2019). This paves the way for increasingly sophisticated managerial capacities of production processes, ranging from mere monitoring to full autonomy (Ancarani *et al*., 2020; Moeuf *et al*., 2018). However, progressing in SM poses complex challenges for manufacturers, as it requires firms to gradually incorporate various technological endowments rather than substituting one with another (Frank *et al*., 2019). This calls companies to overcome technical issues, such as those related to compatibility (Kamble *et al*., 2018), while simultaneously asking for increasingly relevant changes in workforce competences and culture (Arcidiacono *et al*., 2022; Sousa-Zomer *et al*., 2020). A considerable share of manufacturers is thus unable to translate SM investments into actual progress (Arcidiacono *et al*., 2022) and SM advancement across business partners is often fragmented (Lin *et al*., 2018), compromising its potential for value creation (Raj *et al*., 2020).

According to the tenets of socio-technical systems theory (Trist and Bamforth, 1951), the successful implementation of complex systems hinges on the integration between their social and technical subsystems (Chan and Reich, 2007; Orlikowski, 1992). Against this backdrop, operations management scholars have devoted significant efforts to investigating the factors that impact firms' ability to advance in SM (Csiki *et al*., 2023; Moeuf *et al*., 2020; Horváth and Szabó, 2019). In particular, research has stressed the relevance of technical factors pertaining to equipment currently in use at firms' sites (Kamble *et al*., 2018) and the competences of personnel involved in SM projects (Cagliano *et al*., 2019; Mittal *et al*., 2018). Equal importance has been attributed to social factors in the form of people (Ghobakhloo, 2020; Stornelli *et al*., 2021), organizational structures (Zheng *et al*., 2020), and culture (Benitez *et al*., 2020; Reis and Camargo Júnior, 2021). While these studies have provided valuable insights into the identification of social and technical factors influencing SM progression, they fail to shed light on how these factors should be prioritized and integrated. For instance, Kamble *et al.* (2018) emphasize the importance of upgrading equipment but overlook the need to assign specific responsibilities or establish dedicated roles to manage implementation effectively. Similarly, Lorenz *et al*. (2020) highlight the relevance of market scanning for identifying external opportunities but fail to examine the dependence on internal technical capabilities. In addition, there is uncertainty regarding how combinations of effective social and technical factors that impact on SM need to vary at different stages of advancement. This ambiguity leaves firms without a clear framework for resource allocation and prioritization, often resulting in unsustainable simultaneous deployments or the neglect of critical prerequisites, thus giving rise to inefficiencies, delays, or even project failure (Raj *et al*., 2020). Addressing this gap is relevant as it would provide firms with clear guidance on how to direct their efforts, enabling them to prioritize the most impactful factors and understand how their configurations can effectively tackle the complexities of SM adoption, thereby helping them fully harness the transformative potential of SM to drive long-term value creation.

With such objectives in mind, the following research questions (RQs) are posed:

RQ1. In what sequence do firms need to deploy technical and social factors to advance in Smart Manufacturing?

RQ2. Which configurations of technical and social factors enable firms to achieve higher levels of Smart Manufacturing advancement?

To answer these questions, a combination of necessary condition analysis (NCA) and fuzzy-set qualitative comparative analysis (fsQCA) was performed on survey data related to 234 firms operating in the automotive component industry. The NCA results showed that to advance in SM, technical and social factors need to be deployed following a defined sequence. While initial stages of SM adoption require a limited set of baseline factors, advanced stages necessitate multiple factors to be in place. It also emerged that advancing in SM does not require firms to maximize the magnitude of every factor, but rather to ensure a minimum presence of critical factors, thus suggesting the existence of saturation effects. The fsQCA findings further revealed that some factors, while not strictly necessary on their own, play a role within specific configurations that enable firms to reach higher levels of SM.

This study contributes to the operations management literature by quantitatively shedding light on the sequence in which firms should deploy technical and social factors to progress through higher stages of maturity in SM (Arcidiacono *et al*., 2022; Horváth and Szabó, 2019; Moeuf *et al*., 2020; Cagliano *et al*., 2019, among others), while also highlighting the importance of specific configurations of these factors. This provides a more nuanced understanding of the interplay between technical and social dimensions in SM progression and offers a complementary perspective to prior studies, which typically focused on identifying these factors without assessing their relative relevance or interactions. From a practical standpoint, the findings provide actionable insights for manufacturing executives, outlining not only how to strategically allocate resources but also how to tailor configurations to the specific needs of their SM transformation, ensuring a more efficient and effective path towards advanced manufacturing capabilities.

The remainder of this article is organized as follows. The next section introduces the relevant literature. Section 3 describes the methodology, and the results are presented in Section 4. Section 5 discusses the findings, and Section 6 concludes with the contributions and the limitations of the study.

2. Literature background

2.1 Smart manufacturing

The shift toward Industry 4.0 has brought significant transformations in the way firms approach value creation, leveraging emerging and converging technologies to optimize processes across the entire product lifecycle (Kagermann *et al.*, 2013). Among the various facets of this paradigm, the implementation of advanced technologies within production systems, often framed under the umbrella of Smart Manufacturing (Frank *et al.*, 2019), has gained particular attention. SM enables highly connected and integrated manufacturing systems (Dalenogare *et al.*, 2018; Kusiak, 2018) and has been identified as a means to preserve firms' competitiveness, given its potential to generate improvements in terms of cost, quality, delivery, and flexibility (Arcidiacono and Schupp, 2024; Bag *et al.*, 2021; Szász *et al.*, 2020).

SM builds on a wide array of technologies related to digitalization, connectivity, and automation (Battistoni *et al.*, 2023; Culot *et al.*, 2020; Semeraro *et al.*, 2021). Frank *et al.* (2019) cluster SM endowments into base and front-end. Base technologies constitute the backbone of SM, as they enable interconnected and intelligent manufacturing systems; they encompass Cloud Computing, the Internet of Things (IoT), and Big Data and Analytics (Tortorella *et al.*, 2020). Front-end technologies directly support operations and include vertical integration technologies, advanced robotics, artificial intelligence, and additive manufacturing, among others (Bag *et al.*, 2021). These technologies are not substitutable but rather have complementary roles (Battistoni *et al.*, 2023). Therefore, SM calls for firms to think systemically and adopt the entire set of SM technologies rather than focusing on a narrow subset (Frank *et al.*, 2019). In turn, the adoption of a broader set of SM technologies enables companies to advance in SM by conferring increasingly sophisticated managerial capacities to their processes.

Moeuf *et al.* (2018) define four SM-enabled managerial capacities of processes that identify higher stages of SM advancement (Figure 1). At the monitoring stage, firms apply baseline SM technologies, such as IoT and Cloud Computing, to surveil the status of production equipment and to provide alerts in the case of anomalies (Ancarani *et al.*, 2020). The control stage features the use of SM technologies to oversee production processes and identify conditions that require operators' intervention (Tao *et al.*, 2018). Optimization capacity extends previous capacities by using SM technologies to optimize production processes and allow for predictive diagnostics and the maintenance of machines (Chang *et al.*, 2022). Finally, autonomy, the most advanced capacity that can be conferred through SM, enables autonomous production systems that can learn and optimize themselves based on live parameters and lessons learned from past data (Bauer *et al.*, 2021).

2.2 Socio-technical systems theory and SM advancement

Since SM calls for the integration of cutting-edge technologies into configurations of people, competences, and processes (Frank *et al.*, 2019), it is often regarded as a "socio-technical paradigm" (Sony and Naik, 2020).

Socio-technical systems theory (STS henceforth; Trist and Bamforth, 1951) emerged in response to technocratic models, neglecting the influence of human factors (Trist, 1981). STS

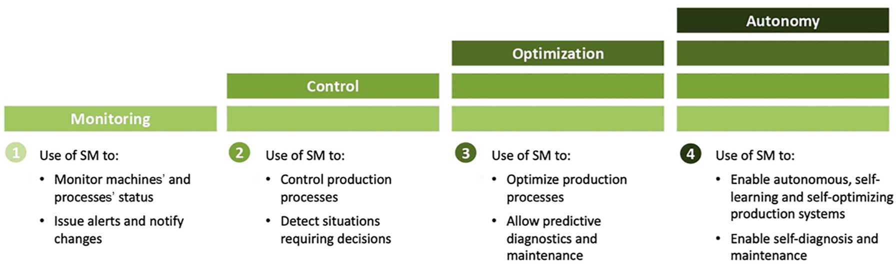

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Figure 1. SM advancement

builds on open system theory (von Bertalanffy, 1950) and posits that the success of a system depends on the interplay between its **social** and **technical** subsystems, which are seen as interrelated (Pasmore, 1988). The **technical** subsystem includes ***technologies, competences, workflows and procedures*** (Emery, 1993; Trist and Bamforth, 1951; Manz and Stewart, 1997). The **social** subsystem encompasses ***people***, ***culture***, and ***organizational structure*** (Trist and Bamforth, 1951). STS emphasizes that organizations should not focus solely on technology or human factors but rather on their integration to achieve the optimal outcome (Trist, 1981). In particular, the degree of "alignment" between these two components determines the effective implementation of complex systems (Chan and Reich, 2007).

Over the years, the holistic perspective of STS has proven valuable for investigating complex phenomena, such as the implementation of electronic health records (Sittig and Singh, 2015), the adoption of information systems (Orlikowski, 1992), and the deployment of advanced technologies in manufacturing (Kusiak, 2018; Marcon *et al*., 2022).

Building on this foundation, our study leverages STS to explore how firms align factors related to technologies, competences, workflows and procedures (i.e. technical subsystem) with people, organizational structures, and culture (i.e. social subsystem) to enable SM advancement.

2.3 Technical and social factors influencing SM advancement

To identify the main technical and social factors that impact SM advancement, a semi-structured review approach was followed (Snyder, 2019). This approach is especially suited to summarizing the state of knowledge in complex fields of research studied within different disciplines (Snyder, 2019). Three steps were followed in the analysis (Figure 2). First, a keyword search was performed in Scopus, as it constitutes the most relevant database for academic research (Culot *et al*., 2020). The search string was devised to include both a set of keywords pertaining to SM and keywords related to technical/social factors and enablers. Keywords were searched in the articles' titles, abstracts, and keywords. Articles published in English in peer-reviewed journals in the fields of Engineering; Business, Management and Accounting; Decision Sciences, Social Sciences were targeted. To build our review on highly reputed sources, only journals included in the Association of Business Schools Academic Journal Guide were retained (Culot *et al*., 2024). Titles, abstracts, and keywords of the 91 articles emerging from this first step were then examined independently by two researchers to evaluate the alignment with respect to the defined exclusion criteria. The full text of the preselected 36 articles was read by the research team, and the reference lists were examined, following a snowballing approach (Webster and Watson, 2002). The final list included 21 articles whose findings with respect to factors impacting SM advancement were coded and classified based on the tenets of STS theory (Table 1).

Accordingly, **technical factors (TFs)** impacting SM advancement have been categorized as ***technologies*** in use at firms' sites, technological ***competences*** of human resources, and ***workflows and procedures*** (Arcidiacono *et al*., 2022; Mittal *et al*., 2018; Trist and Bamforth, 1951). Starting with ***technologies***, studies emphasize the importance of a company's existing IT infrastructure, which serves as a foundational prerequisite for effectively capturing and storing data (Moeuf *et al*., 2020). Therefore, firms that can rely on a *state-of-the-art IT infrastructure* are better positioned to progress in SM (Kamble *et al*., 2018). Equal importance has been placed on evaluating the *interoperability between old and new equipment* (Kiel *et al*., 2017). Since advancing in SM requires the seamless integration of diverse technological components—often governed by undefined or evolving standards—companies must consider compatibility between legacy systems and new technologies from the outset to avoid issues related to functionality interplay (Horváth and Szabó, 2019). Along the same lines, the timely consideration of aspects connected to the *scalability of SM solutions* allows firms to easily broaden the scope of their digital projects (Xu *et al*., 2018). With respect to the technological ***competences*** of human resources, *digital competences provided through training* enable firms

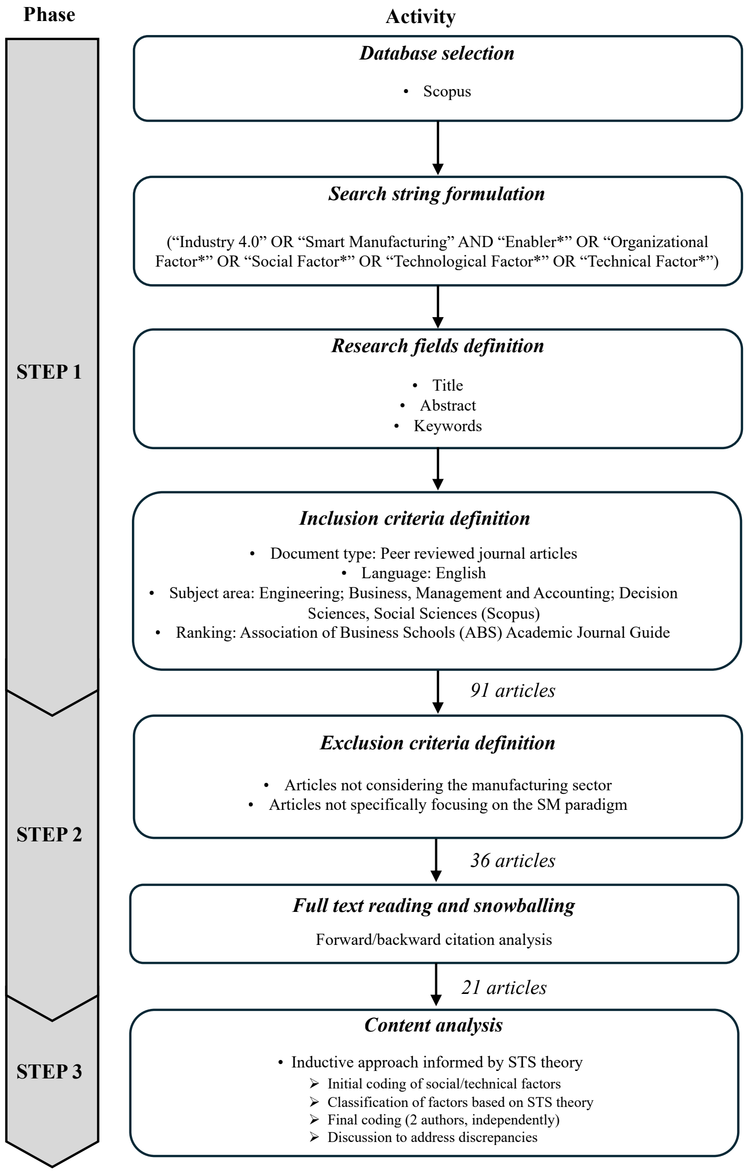

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Figure 2. Semi-structured literature review approach adopted to identify factors impacting on SM advancement

to fully leverage SM technologies, paving the way for progression to more advanced stages (Čater *et al.*, 2021; Sousa-Zomer *et al.*, 2020). Scholars have also highlighted the importance of supporting SM projects with ***workflows and procedures***. In particular, successful progression in SM requires the *definition of a clear roadmap for SM implementation* that aligns strategic priorities with SM initiatives and outlines the deployment path (Arcidiacono *et al.*, 2022; Raj *et al.*, 2020). In the same vein, regular *market scanning* has been recognized as

Table 1. Technical and social factors influencing SM advancement

Technical factors	Technologies	State-of-the-art IT infrastructure (Kamble *et al.*, 2018; Moeuf *et al.*, 2020) Interoperability between old and new equipment (Horváth and Szabó, 2019; Kiel *et al.*, 2017; Müller *et al.*, 2018) Scalability of SM solutions (Xu *et al.*, 2018)
	Competences	Digital competences provided through training (Čater *et al.*, 2021; Cagliano *et al.*, 2019; Mittal *et al.*, 2018; Sousa-Zomer *et al.*, 2020)
	Workflows and procedures	Definition of a clear roadmap for SM implementation (Arcidiacono *et al.*, 2022; Moeuf *et al.*, 2020; Raj *et al.*, 2020) Market scanning (Arcidiacono *et al.*, 2022; Lorenz *et al.*, 2020) Staff are fully informed about the goals of SM projects (Moeuf *et al.*, 2020; Veile *et al.*, 2020) Employees exchange best practices concerning the use of SM (Veile *et al.*, 2020)
Social factors	People	Top management strong support (Ghobakhloo, 2020; Pozzi *et al.*, 2023; Stornelli *et al.*, 2021)
	Culture	Culture of openness to external partnerships (Arcidiacono *et al.*, 2022; Benitez *et al.*, 2020; Mittal *et al.*, 2018; Reis and Camargo Júnior, 2021; Sousa-Zomer *et al.*, 2020)
	Organizational structure	Dedicated roles to manage SM implementation (Horváth and Szabó, 2019; Tumbas *et al.*, 2018; Zheng *et al.*, 2020) Cross-functional integration teams for SM projects (Pozzi *et al.*, 2023; Veile *et al.*, 2020) Agile organizational structures (Veile *et al.*, 2020; Sousa-Zomer *et al.*, 2020)

Source(s): Authors' own work

essential for staying informed about the latest technological innovations and trends in the rapidly evolving SM landscape (Lorenz *et al.*, 2020). Additionally, ensuring that *staff are fully informed about the goals of SM projects* contributes to creating a climate of trust and facilitates acceptance, especially when such initiatives entail significant changes to employees' working routines (Moeuf *et al.*, 2020). Similarly, the *exchange of best practices concerning SM use* among employees fosters the full exploitation of technology potential, enhancing both individual competencies and overall organizational performance (Veile *et al.*, 2020).

The **social factors (SFs)** deemed relevant for SM advancement were categorized according to the three dimensions defined by the STS: ***people***, ***culture***, and ***organizational structure*** (Benitez *et al.*, 2020; Pozzi *et al.*, 2023; Trist and Bamforth, 1951). Starting with ***people***, one of the main challenges associated with SM implementation is potential resistance to change (Ghobakhloo, 2020). In this regard, *top management strong support* plays a crucial role in fostering a shared vision, motivating employees, and aligning organizational goals with the transformative potential of SM technologies (Pozzi *et al.*, 2023). The unique characteristics of SM make organizational ***culture***—particularly *openness to external partnerships*—crucial for advancing in SM. Since the SM knowledge base has become increasingly heterogeneous and complex as firms advance in SM (Frank *et al.*, 2019; Moeuf *et al.*, 2018), research has shown that manufacturers need to collaborate with external partners to access the specialized technological expertise required to successfully integrate additional technology blocks (Benitez *et al.*, 2020; Sousa-Zomer *et al.*, 2020). Conversely, firms that avoid external collaborations and rely solely on internal know-how are likely to remain confined to the low stages of SM (Arcidiacono *et al.*, 2022). As for factors related to the ***organizational structure***, *dedicated roles to manage SM implementation* act as boundary spanners and help reconcile the perceived contradiction between SM logic and prior, well-established IT logic (Horváth and Szabó, 2019; Tumbas *et al.*, 2018). In the same vein, the use of *cross-functional integration teams* allows for a comprehensive evaluation of the impact of the SM transition, which corroborates the technical perspective with considerations of the implications for the human resources and competences needed (Pozzi *et al*., 2023; Veile *et al*., 2020). Finally, *agile organizational structures*, characterized by weak hierarchies, enhance the utilization of shopfloor data within SM by enabling faster decision-making processes and fostering greater adaptability to dynamic industrial environments (Sousa-Zomer *et al*., 2020; Veile *et al*., 2020).

Overall, the analysis of the extant literature reveals a consensus on the TFs and SFs that contribute to firms' advancement in SM (e.g. Horváth and Szabó, 2019; Moeuf *et al*., 2020; Veile *et al*., 2020). However, limited attention has been paid to how TFs and SFs interrelate, whether an optimal deployment sequence exists, or which specific combinations yield the best results. A partial exception is the study by Arcidiacono *et al*. (2022), which explores enablers of firms' progression in SM through a focus on absorptive capacity. While valuable, the study considers a limited number of factors, relies on a small multiple-case sample, and presents findings that are not entirely conclusive. These limitations highlight the need for larger-scale research to validate, refine, and expand on existing insights (Eisenhardt, 1989). As highlighted in the introduction, this lack of evidence hinders the development of comprehensive frameworks to help firms effectively navigate the complexities of digital transformation and progress through the stages of SM. Addressing this gap would deliver critical insights, enabling firms to develop clear, actionable roadmaps for advancing to more sophisticated stages of SM and unlocking long-term value creation.

To contribute at filling this gap, survey data from 234 manufacturers operating in the automotive component industry were analyzed using NCA and fsQCA. Unlike prior studies relying on qualitative approaches or methods that assume uniform relationships among factors, NCA identifies critical thresholds and the minimum levels of specific factors required for progression, revealing the sequence in which these factors must be deployed. Complementing this, fsQCA identifies configurations of factors that lead to higher levels of SM advancement. By combining NCA and fsQCA, this dual-method approach provides a comprehensive understanding of both the individual necessary conditions and their interactions within broader configurations, thus overcoming the limitations of previous studies in the field of SM.

3. Methodology

This section provides a comprehensive explanation of the methodology underpinning the study. A visual summary is presented in Figure 3.

3.1 Measurement

To answer the RQs of interest, a cross-sectional, single-respondent survey was performed (Solaimani and Swaak, 2023; Arcidiacono and Schupp, 2024). The questionnaire, reported in full in the Online Appendix, measured the following aspects for each firm: (1) the presence of relevant TFs and SFs, and (2) SM advancement. Regarding the former, the factors emerging from the literature review were operationalized, building on the definitions and sources reported in Table 1, which ultimately resulted in eight constructs related to TFs (*State-of-the-art IT infrastructure, Interoperability between old and new equipment, Scalability of SM solutions, Digital competences provided through training, Definition of a clear roadmap for SM implementation, Staff are fully informed about the goals of SM projects, Employees exchange best practices concerning the use of SM, Market scanning*) and five concerning SFs (*Top management strong support, Culture of openness to external partnerships, Dedicated roles to manage SM implementation, Cross-functional integration teams for SM projects, Agile organizational structures*). A single-item approach was adopted to gather data in a more fine-grained and focused manner (e.g. Knol *et al*., 2018). Construct validity was verified through structured discussions within the author's team, the involvement of two external researchers, and a series of telephone interviews with manufacturing executives. Consensus on the adopted statements was quantified using a five-point Likert scale, where 1 signifies

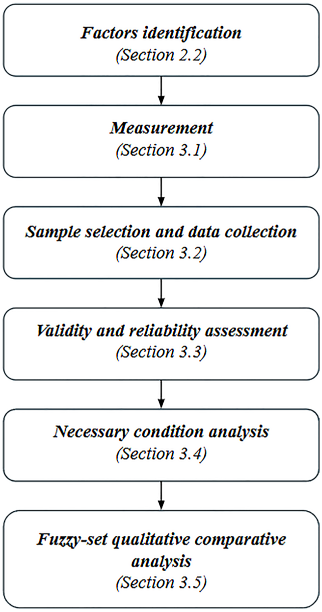

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Figure 3. Methodological approach adopted in the study

"I strongly disagree" and 5 indicates "I strongly agree". For SM advancement, we referred to the framework developed by Moeuf *et al*. (2018) and measured it with a four-level scale representing increasingly advanced operational capacities enabled by SM: *monitoring, control, optimization,* and *autonomy.* Respondents were asked to rate the most advanced capacity achieved thanks to SM at their plants. To enhance understanding, informants were provided with a visual representation and brief descriptions of these four capacities, arranged from the simplest to the most complex.

3.2 Sample selection and data collection

The automotive component industry was chosen as the setting for the analysis. This sector is highly competitive and capital intensive, requiring firms to balance multiple strategic priorities while optimizing production processes to achieve cost-efficiency and stay at the forefront of the industry (Hertenstein and Williamson, 2018). To meet these challenges, automotive firms have been pioneers in SM and investments in advanced technologies have been higher than in most other manufacturing sectors (Arcidiacono *et al.*, 2022). Nonetheless, extant research highlights that SM advancement in the automotive industry remains highly fragmented (Lin *et al.*, 2018). This fragmentation offers a unique opportunity to examine firms at different stages of SM adoption, ranging from initial implementation to more advanced levels. Moreover, as a globally influential sector, advancements in SM within automotive manufacturing often serve as a benchmark for other industries, enhancing the broader applicability of findings (Kamble *et al.*, 2020). Taken together, these features make the automotive component industry a particularly compelling setting for investigating the determinants of SM advancement.

A nonrandom sampling approach was followed (Arcidiacono and Schupp, 2024; Camuffo and Poletto, 2023). A leading European original equipment manufacturer (OEM) in the automotive component sector made available an initial list of 800 contacts that included OEMs and their suppliers. Each contact was carefully reviewed and verified to eliminate duplicates or incomplete entries, and an invitation letter, which included a link to the online questionnaire, was sent to the chief executive officers (CEOs) of 569 manufacturing firms. The CEOs were requested to complete the questionnaire (or delegate it to a manager within their organization who possessed the relevant SM expertise) only if their company had adopted at least one SM technology (Frank *et al.*, 2019). For companies with multiple plants, the respondents were instructed to provide details about the plant that was the most advanced in terms of SM technology (Arcidiacono *et al.*, 2023; Ferdows, 1997). During the data collection process, two reminders were sent. The final sample resulted in 234 usable responses (Table 2), corresponding to a response rate of 41%.

While nonrandom sampling might limit the generalizability of the findings, several aspects justify its use in this study. First, purposive sampling is widely used in studies on technology adoption because it enables a focus on firms with relevant experience, reducing the risk of including respondents without adequate knowledge (Arcidiacono and Schupp, 2024; Arcidiacono *et al.*, 2022; Frank *et al.*, 2019; Lorenz *et al.*, 2020). Second, in our specific case, reliance on the contact list provided by the OEM ensured that the research team had direct access to key decision-makers, such as CEOs and high-level managers, likely increasing firms' willingness to participate in the survey (Cousin *et al.*, 2018). Third, a random sampling approach would have required access to a broader and less targeted pool of firms, increasing costs and complexity while introducing noise into the dataset (Forza, 2002; Tortorella *et al.*, 2024). Finally, while the sampling was nonrandom, the firms included were diverse in terms of country, industry, and size (Table 2) and represent some of the most prominent players in the global automotive component industry. These characteristics strengthen the representativeness of the dataset and ensure insights that are both actionable and reflective of key dynamics within the automotive component industry.

3.3 Validity and reliability assessment

The survey methodology used in this study entailed gathering data from a single respondent within each organization. This approach could subject the study to potential respondent and common-method biases (CMB). Specifically, some scholars (e.g. Flynn *et al.*, 2018;

Table 2. Sample demographics

Respondents' role		Respondents' seniority	
CEO	59 (25%)	>5 years	149 (64%)
Plant manager	39 (17%)	2–5 years	48 (20%)
CDO	34 (15%)	<2 years	37 (16%)
R&D manager	27 (11%)		
Other	75 (32%)		

Country		Industry (NACE CODE)	
Germany	85 (36%)	Manufacture of fabricated metal products (C25)	65 (28%)
China	27 (12%)	Manufacture of basic metals (C24)	52 (22%)
France	17 (7%)	Manufacture of rubber and plastic components (C22)	46 (20%)
Italy	15 (6%)	Manufacture of machinery and equipment n.e.c (C28)	26 (11%)
Other	90 (39%)	Other	45 (19%)

Plant size	
>249 employees	147 (63%)
50–249 employees	74 (32%)
<50 employees	13 (5%)

Source(s): Authors' own work

Montabon *et al.*, 2018) have argued that using single respondents could be particularly problematic in investigations concerning multiple levels of analysis or that build on constructs that lack a singular, objective definition and are therefore polyadic in nature (e.g. relationship strength). Conversely, single-respondent designs that operate at a single level of analysis and center around monadic constructs are generally less prone to respondent bias, although they still face the risk of CMB.

This research concentrated on the firm level, and all constructs can be reasonably viewed as monadic. According to Ketokivi and Schroeder (2004) and Flynn *et al*. (2018), TFs can be considered "quasi-objective." The same can be said for the SFs included in this analysis—except for *Top management strong support*, which is "perceptual" in nature. As for SM advancement, it should be acknowledged that this metric could be affected by a certain degree of subjectivity. Nonetheless, it conceptually overlaps and shows a statistically significant correlation ($p < 0.01$) with the number of foundational technologies a firm has adopted (Arcidiacono *et al*., 2023)—a measure included in the survey questionnaire.

To further reduce the risk of CMB, we implemented various precautions and procedural solutions (e.g. Podsakoff *et al*., 2012). First, we conducted a preliminary test of the questionnaire with two practitioners and two researchers who suggested minor revisions to improve clarity and minimize ambiguity in the questions. Second, the questionnaire was structured to separate independent and dependent variables. Third, to encourage unbiased and honest responses, we added a statement at the beginning of the survey assuring participants that their responses would remain anonymous, be used solely for research purposes, and be combined with those of other respondents. Fourth, we ensured that our respondents were knowledgeable about the issues under study by selecting informants who held managerial roles and possessed expertise in SM.

In terms of diagnostic checks, we verified the extent of CMB, the presence of multicollinearity issues, and nonresponse bias (e.g. Solaimani and Swaak, 2023; Czakon *et al*., 2023; Patil *et al*., 2024). Regarding CMB, we resorted to Harman's single-factor test (Fuller *et al*., 2016). The results suggested that a single factor explained 56% of the total variance—well beyond the common threshold of 70% (Czakon *et al*., 2023). Spearman correlation coefficients were used to assess multicollinearity (e.g. Murray, 2013), with no problematic values detected (i.e. they were all <0.7; Ratner, 2009). To further ensure that there were no issues related to either CMB or multicollinearity, we employed the approach proposed by Sukhov *et al*. (2023). First, we estimated a linear model and examined the variance inflation factor (VIF). Subsequently, we generated a new random dependent variable and incorporated it into the model, using all latent variables as predictors for this single criterion. In both cases, the VIF was <3.3, indicating that multicollinearity and CMB were not present (Kock and Lynn, 2012; Kock, 2015). Following Wagner and Kemmerling's (2010) recommendations, nonresponse bias was verified by performing *t*-tests and Levene's tests to examine differences in means and variances between early (i.e. companies that replied within a month from when the survey was received) and late respondents (i.e. companies that responded after two follow-ups). No significant differences were found.

3.4 Necessary condition analysis

To shed light on RQ1, we employed the NCA method (e.g. Czakon *et al*., 2023; van der Valk *et al*., 2016; Solaimani and Swaak, 2023; Battistoni *et al*., 2023). NCA is a bivariate data analysis technique used to define critical success factors that enable (but do not guarantee) the outcome when present and inhibit it when absent (Hauff *et al*., 2021; Dul, 2019; Cepeda *et al*., 2024). In the necessity logic of NCA, each level of the dependent (Y) and independent (X) variables is examined to test the relationship "Is the level of X critical for a specific level of Y?" This helps identify necessary success factors for achieving desired outcomes as well as detect elements like constraints and bottlenecks. In other words, NCA allows for defining both the relevant factors and the sequence in which they should be deployed (Dul *et al*., 2021). Previous uses of NCA have been found to shed light on, for example, critical success factors in the adoption of lean principles (Knol *et al.*, 2018) and artificial intelligence (Solaimani and Swaak, 2023).

The NCA posits that an X (input) condition limits a Y (output) result by drawing a ceiling line above a set of values displayed on a scatter plot of X vs Y. Extant research has mainly referred to two types of ceiling lines: ceiling envelopment with free disposal hull (CE-FDH), which represents a step function line through the upper-left data points, and ceiling regression with free disposal hull (CR-FDH), which represents the least-squares trend line through the upper-left data points (van der Valk *et al.*, 2016; Knol *et al.*, 2018; Dul, 2016).

The area beyond the ceiling is known as "empty space," indicating that higher output levels (Y) cannot be attained with lower input levels (X). The effect size (*d*) statistic is obtained by calculating the ratio of the empty space to the total space of the plot, which "quantifies the degree of necessity." A larger area above the ceiling line corresponds to a greater effect size (constraint), thereby indicating higher criticality (Dul, 2016; Hauff *et al.*, 2021).

According to Dul (2016), a success factor is deemed critical if it meets three specific criteria: (1) *the existence of a ceiling zone*, (2) *statistical significance*, and (3) *ceiling line accuracy*. The ceiling zone is identified by visually inspecting the upper-left section of the scatterplot for empty space. Statistical significance is reached when $p < 0.1$ (i.e. when the effect size is > 0). The precision of the ceiling line is assessed by the ratio of observations outside the ceiling zone to the total number of observations (Dul, 2016). A higher number of data points beyond the ceiling line results in a less accurate measure of criticality for the evaluated success factor. A ceiling line accuracy >95% is considered satisfactory (Hauff *et al.*, 2021; Arenius *et al.*, 2017; Dul, 2016; van der Valk *et al.*, 2016).

To conclude, a bottleneck table is constructed. This table presents the NCA analysis of each critical success factor in a tabular representation of the ceiling line. The word "bottleneck" underscores its function in revealing the minimum levels of critical success factors required to attain a specific outcome level—that is, the bottleneck table allows us to identify the sequence in which success factors become critical per outcome level (Dul, 2016).

3.5 Fuzzy-set qualitative comparative analysis

To answer RQ2, we employed fuzzy-set Qualitative Comparative Analysis (e.g. Fiss, 2011; Schneider and Wagemann, 2012; Greckhamer *et al.*, 2018). FsQCA is a configurational comparative method that examines how different combinations of causal conditions (akin to independent variables) jointly produce a specific outcome (akin to a dependent variable). Unlike traditional regression-based approaches that focus on isolating the effects of individual variables, fsQCA uncovers causal complexity by identifying multiple, equally valid pathways (equifinality) leading to the same outcome (Ragin, 2008; Fiss, 2011).

FsQCA operates under the logic of set theory, treating variables as fuzzy sets and analyzing the degree to which cases belong to these sets. The first step involves calibrating raw data into membership scores, typically ranging from 0 (full nonmembership) to 1 (full membership), using either direct calibration (based on theoretical thresholds) or indirect calibration (e.g. quartiles or percentiles) (Schneider and Wagemann, 2012). Due to the lack of substantive knowledge and established theoretical benchmarks specific to this study's context (e.g. Chen and Chen, 2024; Marrucci *et al.*, 2023), we employed an indirect calibration method. Anchor points were set at the 5th percentile (full nonmembership), 50th percentile (crossover point), and 95th percentile (full membership), adhering to widely accepted guidelines (Fiss, 2011). To ensure the inclusion of cases with raw scores of exactly 0.5 in the truth table analysis, a small constant (0.01) was added to these values (Du and Kim, 2021; Ding, 2022).

A truth table was then constructed to summarize all observed combinations of conditions and their corresponding outcomes. Each row of the table represents a unique configuration of conditions, indicating whether it consistently leads to the desired outcome. To ensure robustness, we applied a consistency threshold of 0.80 and a frequency threshold of ≥3 cases. On one hand, the consistency threshold represents the widely adopted minimum level in the literature, providing a rigorous basis to confirm that configurations reliably produce the outcome (Ragin, 2008; Greckhamer *et al.*, 2018; Fiss, 2011; Schneider and Wagemann, 2012; Rubinson *et al.*, 2019). On the other hand, the frequency threshold reflects the medium-sized sample used in this study and filters out configurations supported by a limited number of cases, ensuring that the results remain empirically relevant and are not driven by idiosyncratic cases (Greckhamer *et al.*, 2018; Sukhov *et al.*, 2023; Russo *et al.*, 2019; Mason *et al.*, 2022).

The analysis proceeds with the application of Boolean algebra to identify sufficient configurations of conditions for achieving the outcome. FsQCA generates three types of solutions—parsimonious, intermediate, and complex. Following mainstream practice (Cantele *et al.*, 2023; Paykani *et al.*, 2018; Ragin, 2008; Fiss, 2011; Greckhamer *et al.*, 2018) and considering the high number of variables included in the analysis, we focused on intermediate solutions to balance the meaningfulness of the findings with their interpretability (Schneider and Wagemann, 2012; Fiss, 2011). While the complex solution may overfit the data by including all possible configurations, and the parsimonious solution risks oversimplification by excluding potentially relevant conditions, the intermediate solution strikes a balance between empirical complexity and theoretical parsimony (Cantele *et al.*, 2023; Ragin, 2008; Greckhamer *et al.*, 2018).

4. Results

4.1 Necessary condition analysis

The X vs Y scatterplots for each success factor are reported in Figure 4. The *x*-axis represents the level of the factor, while the *y*-axis corresponds to the stage of SM adoption. The dotted and solid lines illustrate the CE-FDH and CR-FDH ceiling lines, respectively. As stated above, three conditions are necessary for a factor to be considered critical: the existence of a ceiling zone, $p < 0.1$, and ceiling line accuracy >95%.

Visual analysis reveals a ceiling zone (i.e. an empty space in the upper-left corner) for the following factors: *State-of-the-art IT infrastructure*, *Interoperability between old and new equipment*, *Scalability of SM solutions*, *Digital competences provided through training*, *Market scanning*, *Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM*, *Top management strong support*, *Culture of openness to external partnerships*, *Dedicated roles to manage SM implementation*, *Cross-functional integration teams for SM projects*, and *Agile organizational structures).*

As for *p*-value and accuracy, Table 3 shows that *Scalability of SM solutions*, *Digital competences provided through*, *Market scanning*, *Employees exchange best practices concerning the use of SM*, *Top management strong support*, *Culture of openness to external partnerships*, *Dedicated roles to manage SM implementation*, *Cross-functional integration teams for SM projects*, and *Agile organizational structures* all have a *p*-value <0.1 (effect size >0) and accuracy >95%. Hence, these factors are found to be critical for SM advancement. Conversely, *State-of-the-art IT infrastructure*, *Interoperability between old and new equipment*, *Definition of a clear roadmap for SM implementation*, and *Staff are fully informed about the goals of SM projects* have no role in SM advancement.

To identify the sequence in which firms need to deploy TFs and SFs to advance in SM, a bottleneck table was constructed (Table 4), where the rows represent the levels of SM advancement and the columns indicate the minimum value of each critical success factor necessary for achieving the respective level of SM advancement.

The results show that *Top management strong support* is the most critical factor for firms initiating their journey in SM (monitoring). As companies progress from the initial stage to a more integrated level of SM adoption (control), the necessity of this factor intensifies and the

Scalability of SM solutions comes into play. Moving to the next stage (optimization), both factors become even more important, while a group of equally critical factors also emerges: *Digital competences provided through training*, *Culture of openness to external partnerships*, *Market scanning*, *Dedicated roles to manage SM implementation*, and *Cross-functional integration teams for SM projects*. At the highest stage of SM implementation (autonomy), the magnitude of the previously identified factors increases and two additional factors appear: *Employees exchange best practices concerning the use of SM* and *Agile organizational structures*. To conclude, it is worth noting that none of the success factors reaches a value of 5, with magnitudes slightly exceeding a value of 3 at the most advanced stages.

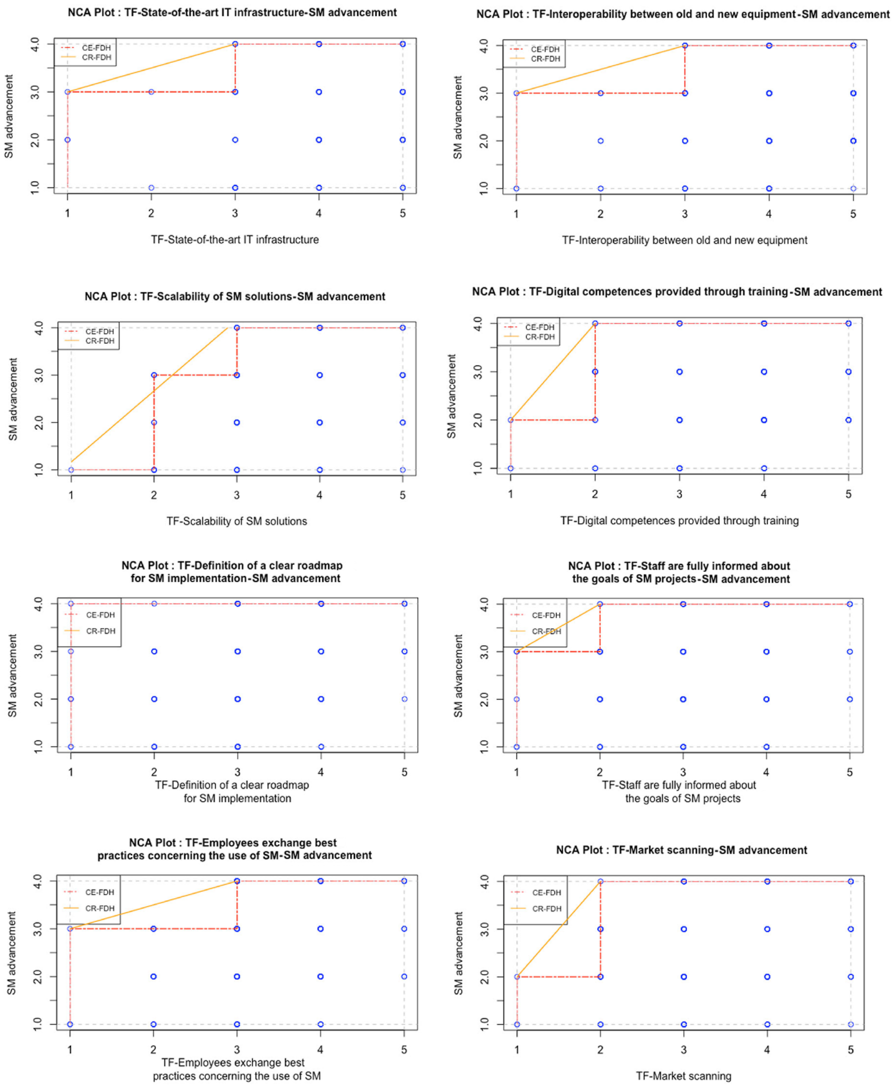
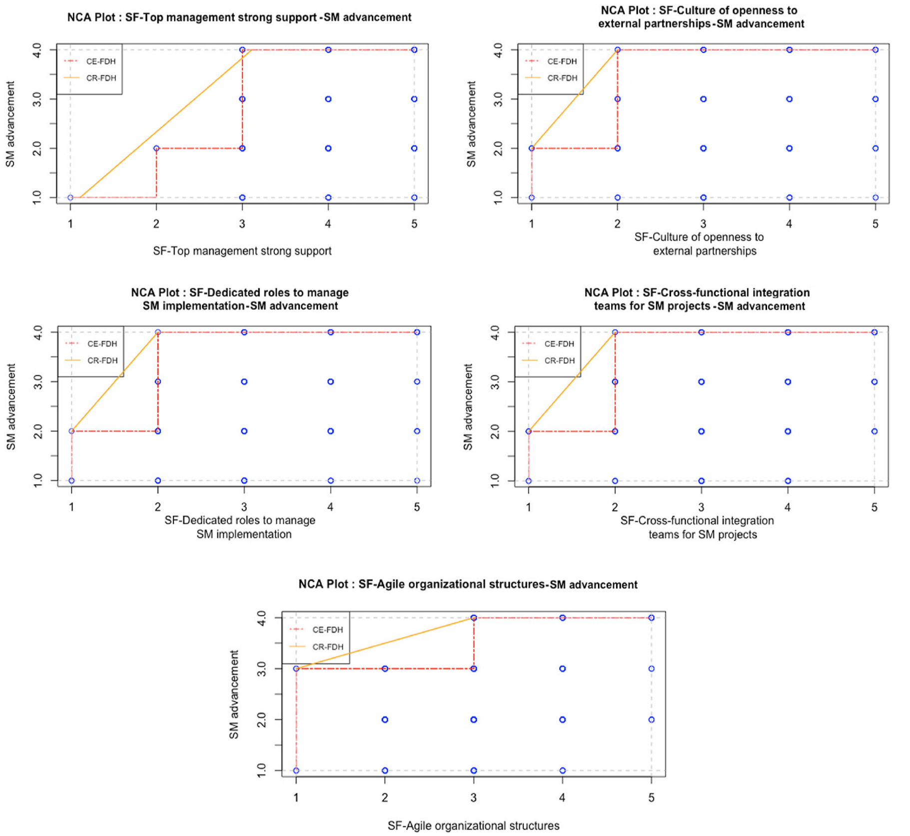


Figure 4. NCA scatterplots



Source(s): Authors' own work

Figure 4. (*continued*)

4.2 Fuzzy-set qualitative comparative analysis

The results of the fsQCA are reported in Table 5, with both configurations leading to high (i.e. autonomy) and low (i.e. monitoring) stages of SM advancement. On one side, identify five configurations (S1–S5) that explain the presence of high SM advancement, reflecting different combinations of technical and social conditions that act as sufficient pathways for achieving this outcome. On the other side, two configurations (L1 and L2) describe the conditions associated with low SM advancement, emphasizing the absence or irrelevance of key factors that hinder progress. Black circles (●) indicate the presence of a condition, reflecting its essential role in the configuration. Barred circles (Ø) denote the absence of a condition, indicating that its exclusion is critical for the outcome. Blank cells signify irrelevant conditions, meaning that the presence or absence of a factor does not influence the outcome in that particular configuration.

As for the specific findings,

(1) S1 builds on the presence of *State-of the-art IT infrastructure*, *Interoperability between old and new equipment*, *Scalability of SM solutions*, *Digital competences provided through training*, *Definition of a clear roadmap for SM implementation*, *Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM*, *Top management strong support*, *Dedicated roles to manage*

Table 3. Parameters of the NCA

Construct	Ceiling line	Accuracy (%)	Ceiling zone	Effect size	*p*-value
TF-state-of the-art IT infrastructure	CE-FDH	100	2.000	0.167	0.309
	CR-FDH	100	1.000	0.083	0.279
TF-interoperability between old and new equipment	CE-FDH	100	2.000	0.167	0.161
	CR-FDH	100	1.000	0.083	0.102
TF-scalability of SM solutions	CE-FDH	100	4.000	0.333	0.005***
	CR-FDH	98.3	2.676	0.223	0.005***
TF-digital competences provided through training	CE-FDH	100	2.000	0.167	0.088*
	CR-FDH	100	1.000	0.083	0.088*
TF-definition of a clear roadmap for SM implementation	CE-FDH	100	0.000	0.000	1.000
	CR-FDH	NA[a]	0.000	0.000	1.000
TF-market scanning	CE-FDH	100	2.000	0.167	0.083*
	CR-FDH	100	1.000	0.083	0.083*
TF-staff are fully informed about the goals of SM projects	CE-FDH	100	1.000	0.083	0.283
	CR-FDH	100	0.500	0.042	0.283
TF-employees exchange best practices concerning the use of SM	CE-FDH	100	2.000	0.167	0.037**
	CR-FDH	100	1.000	0.083	0.001***
SF-top management strong support	CE-FDH	100	5.000	0.417	0.019**
	CR-FDH	97.9	3.333	0.278	0.018**
SF-culture of openness to external partnerships	CE-FDH	100	2.000	0.167	0.015**
	CR-FDH	100	1.000	0.083	0.015**
SF-dedicated roles to manage SM implementation	CE-FDH	100	2.000	0.167	0.079*
	CR-FDH	100	1.000	0.083	0.079*
SF-cross-functional integration teams for SM projects	CE-FDH	100	2.000	0.167	0.015**
	CR-FDH	100	1.000	0.083	0.015**
SF-agile organizational structures	CE-FDH	100	2.000	0.167	0.035**
	CR-FDH	100	1.000	0.083	0.000***

Note(s): (1) $*p < 0.1$ $**p < 0.05$ $***p < 0.01$; (2) The accuracy of the CE-FDH ceiling lines is always 100% because it is a piecewise linear function passing through the upperpoints (Dul, 2019); (3) [a]CR-FDH accuracy for non-critical factors (i.e. $d = 0$) cannot be calculated due to the absence of a ceiling zone, impeding the construction of the CR-FDH line (Solaimani and Swaak, 2023), (4) NCA focuses on identifying conditions that must be present for an outcome to occur (i.e. it operates in isolation from the rest of the causal structure), making control variables unnecessary (Bokrantz and Dul, 2023; van der Valk *et al.*, 2016)
Source(s): Authors' own work

SM implementation, *Cross-functional integration teams for SM projects*, and *Agile organizational structures. Market scanning* and *Culture of openness to external partnerships* are not relevant in this configuration.

(2) S2 involves the presence of *State-of the-art IT infrastructure*, *Interoperability between old and new equipment*, *Scalability of SM solutions*, *Digital competences provided through training*, *Definition of a clear roadmap for SM implementation*, *Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM*, *Top management strong support*, *Dedicated roles to manage SM implementation*, and *Agile organizational structures*, but with the absence of *Market scanning* and *Culture of openness to external partnership. Cross-functional integration teams for SM projects* are not relevant.

(3) S3 is defined by the presence of *State-of the-art IT infrastructure*, *Interoperability between old and new equipment*, *Scalability of SM solutions*, *Digital competences provided through training*, *Definition of a clear roadmap for SM implementation*, *Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM*, *Market scanning*, *Top management strong support*, *Culture of openness to external partnerships*, *Dedicated roles to manage SM implementation*,

Table 4. Bottleneck analysis

Y/X	TF Scalability of SM solutions	TF Digital competences provided through training	TF Employees exchange best practices concerning the use of SM	TF Market scanning	SF Top management strong support	SF Culture of openness to external partnerships	SF Dedicated roles to manage SM implementation	SF Cross-functional integration teams for SM projects	SF Agile organizational structures
1.0 monitoring	NN	NN	NN	NN	1.111	NN	NN	NN	NN
2.0 control	1.556	NN	NN	NN	1.778	NN	NN	NN	NN
3.0 optimization	2.222	1.500	NN	1.500	2.444	1.500	1.500	1.500	NN
4.0 autonomy	2.889	2.000	3.000	2.000	3.111	2.000	2.000	2.000	3.000

Note(s): (1) Only critical success factors are represented; (2) NN denotes not necessary
Source(s): Authors' own work

Table 5. Configurations for predicting SM advancement

	High stage of SM advancement (i.e. autonomy)					Low stage of SM advancement (i.e. monitoring)	
	S1	S2	S3	S4	S5	L1	L2
TF-state-of-the-art IT infrastructure	●	●	●	●	●	Ø	●
TF-interoperability between old and new equipment	●	●	●		●	Ø	●
TF-scalability of SM solutions	●	●	●	●		Ø	Ø
TF-digital competences provided through training	●	●	●	●	●	Ø	●
TF-definition of a clear roadmap for SM implementation	●	●	●	●	●	●	●
TF-staff are fully informed about the goals of SM projects	●	●	●	●	●	●	●
TF-employees exchange best practices concerning the use of SM	●	●	●	●	●	●	●
TF-market scanning		Ø	●	●	●	Ø	Ø
SF-top management strong support	●	●	●	●	●	Ø	Ø
SF-culture of openness to external partnerships		Ø	●	●	Ø	Ø	Ø
SF-dedicated roles to manage SM implementation	●	●	●	●	●	●	●
SF-cross-functional integration teams for SM projects	●			●	Ø	Ø	Ø
SF-agile organizational structures	●	●	●	●	●	●	●
Raw coverage	0.373	0.328	0.336	0.359	0.262	0.216	0.218
Unique coverage	0.009	0.030	0.003	0.036	0.029	0.070	0.071
Consistency	0.851	0.864	0.877	0.873	0.859	0.807	0.830
Overall solution coverage	*0.482*					*0.288*	
Overall solution consistency	*0.822*					*0.830*	

Note(s): Full circles (●) indicate the presence of a condition. Barred circles (Ø) indicate the absence of a condition. Blank cells indicate that a specific causal condition is not relevant
Source(s): Authors' own work

and *Agile organizational structures. Cross-functional integration teams for SM projects* are instead not relevant.

(4) S4 requires the presence of *State-of the-art IT infrastructure*, *Scalability of SM solutions*, *Digital competences provided through training*, *Definition of a clear roadmap for SM implementation, Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM, Market scanning, Top management strong support, Culture of openness to external partnerships, Dedicated roles to manage SM implementation, Cross-functional integration teams for SM projects,* and *Agile organizational structures. Interoperability between old and new equipment* is not relevant in this configuration.

(5) S5 is characterized by the presence of *State-of the-art IT infrastructure*, *Interoperability between old and new equipment*, *Digital competences provided through training*, *Definition of a clear roadmap for SM implementation*, *Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM, Market scanning, Top management strong support, Dedicated roles to manage SM implementation,* and *Agile organizational structures. Culture of openness to external partnerships* and *Cross-functional integration teams for SM projects* are absent in this configuration, while *Scalability of SM solutions* is not relevant.

On the contrary,

(1) L1 is defined by the presence of *Definition of a clear roadmap for SM implementation*, *Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM*, *Dedicated roles to manage SM implementation,*

and *Agile organizational structures.* It is further characterized by the absence of *State-of-the-art IT infrastructure*, *Interoperability between old and new equipment*, *Scalability of SM solutions*, *Digital competences provided through training*, *Market scanning*, and *Top management strong support*, *Culture of openness to external partnerships,* and *Cross-functional integration teams for SM projects.*

(2) L2 is characterized by the presence of *State-of the-art IT infrastructure*, *Interoperability between old and new equipment*, *Digital competences provided through training*, *Definition of a clear roadmap for SM implementation*, *Staff are fully informed about the goals of SM projects*, *Employees exchange best practices concerning the use of SM*, *Dedicated roles to manage SM implementation,* and *Agile organizational structures.* However, it shows the absence of *Scalability of SM solutions*, *Market scanning*, *Top management strong support*, *Culture of openness to external partnerships,* and *Cross-functional integration teams for SM projects.*

Key metrics, such as overall solution consistency and coverage, were used to assess the robustness and relevance of the results. Coverage values, akin to R^2 in regression (Fiss, 2011; Deng *et al*., 2022), reflect the empirical relevance of the configurations. The overall solution coverage for high SM advancement was 0.482. For low SM advancement, the overall solution coverage was lower at 0.288, consistent with expectations in QCA studies, as conditions leading to suboptimal outcomes are often more fragmented (Ragin, 2008; Dușa, 2018). While no explicit threshold for coverage is universally established, values above 0.2 are generally considered meaningful in QCA, as they highlight configurations with sufficient empirical relevance (Fiss, 2011; Ragin, 2008; Sukhov *et al*., 2023; Li *et al*., 2023). Overall solution consistency measures how reliably the configurations lead to the outcome, analogous to the concept of model fit (Deng *et al*., 2022; Fiss, 2007). For both high and low SM advancement, consistency values exceed the commonly accepted threshold of 0.8 (Ragin, 2008; Li *et al*., 2023; Shao, 2024), with values of 0.822 and 0.830, respectively. These high consistency levels confirm the robustness of the causal pathways, ensuring confidence in the validity of the results.

5. Discussion

By combining NCA and fsQCA, this study investigated the sequence in which firms are called to deploy TFs and SFs to progress in SM, as well as the specific combinations of factors that enable firms to achieve higher stages of SM advancement. This section discusses the main findings in relation to the SM and STS literature.

Starting with RQ1, at a high level, our findings suggest that SFs are as critical as TFs in advancing SM. This challenges the purely technology-focused perspective of earlier studies on SM enablers (Culot *et al*., 2020; Kiel *et al*., 2017), which emphasized digital technologies as central to SM advancement but overlooked the significant structural and cultural transformations required for successful adoption (Moeuf *et al*., 2018). In line with the tenets of STS, which emphasize the interplay between technical and social subsystems (Trist and Bamforth, 1951), our findings confirm that in the context of SM, SFs are not merely ancillary to TFs, but rather serve as critical enablers, ensuring that technological advancements are effectively integrated into organizational routines. By fostering adaptability across workflows, leadership, and organizational structures, SFs equip firms to navigate the complexities of SM transformation, underscoring that technological progress cannot occur without a robust social foundation.

Second, our results highlight that firms do not need to introduce all factors simultaneously but can deploy them gradually, following a defined sequence. This reflects the progressive nature of SM transformation and quantitatively supports observations from prior qualitative studies (Arcidiacono *et al*., 2022). Notably, the bottleneck analysis revealed that advancing in SM does not require firms to achieve high levels of critical success factors; their magnitude only slightly exceeds a value of 3 at the highest stage (i.e. autonomy). This indicates a saturation effect, as additional investments in critical success factors beyond a certain threshold would not yield proportional advancements. Instead, the simultaneous presence of multiple TFs and SFs of a medium magnitude appears to be more relevant for sustaining progress. STS resonates with these findings by underscoring the importance of "synchronizing" technical and social subsystems for effective project implementation (Trist, 1981). While SM research acknowledges that the successful deployment of digital technologies hinges on the simultaneous presence of relevant technical and social factors (Arcidiacono *et al.*, 2022; Čater *et al.*, 2021; Moeuf *et al.*, 2020; Veile *et al.*, 2020, among others), the idea that advancements between these two dimensions need to be balanced and synchronized generally does not emerge. In this regard, our findings complement the SM literature by highlighting that incremental improvements across both technical and social dimensions may be more fruitful than disproportionate investments in individual factors.

With respect to the detailed findings regarding the sequence in which firms are called to deploy critical factors, strong support from top management is already critical at the very early stages of the SM transformation. Within the STS literature, leadership plays a pivotal role in aligning technical advancements with organizational readiness (Pasmore, 1988). SM literature supports the importance of leaders who convey an appealing vision of the technological future to trigger the digital transition (Pozzi *et al.*, 2023). Our results confirm these theoretical insights by demonstrating that top management support is necessary for establishing monitoring capabilities, which form the foundation for subsequent stages of SM advancement.

TFs, in the form of the scalability of SM solutions, become particularly relevant from the control stage onwards. Building on STS, scalability reflects the ability to extend and adapt a company's systems to support growing demands and complexities without compromising systemic stability (Trist and Bamforth, 1951). This adaptability ensures that technological advancements contribute to sustainable growth and cohesive progression through SM stages, avoiding costly disruptions or overhauls while addressing the evolving needs of the organization (Horváth and Szabó, 2019; Xu *et al.*, 2018).

Overall, the findings nuance literature that has conceptualized SM advancement as a series of stages of growing complexity (Frank *et al.*, 2019; Moeuf *et al.*, 2018) by suggesting that monitoring and control are baseline capabilities achievable with a limited set of critical factors. In fact, these capabilities primarily enhance the understanding of internal processes through the deployment of user-friendly SM technologies, such as the IoT and Cloud Computing, for which firms often have in-house expertise (Ancarani *et al.*, 2020; Dalenogare *et al.*, 2018; Maroufkhani *et al.*, 2023).

Conversely, our results suggest that from the optimization stage onwards, greater efforts are to be deployed in mobilizing key factors. From this perspective, procedures aimed at regularly scanning the market and a culture of openness to external collaborations become relevant. This is because optimization and autonomy aim to improve production processes by leveraging advanced technologies such as artificial intelligence and virtualization technologies (Lee *et al.*, 2018; Culot *et al.*, 2024; Cannas *et al.*, 2024). Given the complexity and specialized nature of the knowledge required for these technologies, firms are called to rely on external sources to access cutting-edge expertise and solutions (Sousa-Zomer *et al.*, 2020). Moreover, the optimization stage necessitates a shift in employee competences, as workers must be capable of translating process data and analyses into actionable insights (Čater *et al.*, 2021). Previous SM literature has suggested that the successful integration of SM knowledge hinges on adaptive social subsystems capable of assimilating and operationalizing these inputs (Arcidiacono *et al.*, 2022). Our findings further detail this claim by showing that SFs are instrumental in this process. In particular, dedicated managerial roles provide the oversight necessary to strategically integrate such inputs with organizational objectives (Horváth and Szabó, 2019). Cross-functional teams integrate diverse expertise, enabling comprehensive evaluations of SM initiatives (Pozzi *et al.*, 2023). These findings also reflect the principle that socio-technical systems must evolve collaboratively, with social subsystems serving as the bridge between external expertise and internal advancements (Trist and Bamforth, 1951; Pasmore, 1988).

As for the progression toward autonomy, the results highlight the importance of establishing agile organizational structures. While organizational agility is acknowledged as an enabler of SM (Veile *et al*., 2020), extant literature has not explicitly linked agile structures to the achievement of very advanced stages of SM. This can be elucidated in light of the peculiar characteristics of autonomous production systems, which are inherently adaptable and self-adjusting (Moeuf *et al*., 2018). In this respect, their full potential can be exploited only in conjunction with organizational structures that enable rapid decision-making and swift configuration of resources. Furthermore, given that autonomous production systems necessitate significant changes in routines and employee attitudes (Bauer *et al*., 2021), the exchange of best practices emerges as a critical SF. This finding can be interpreted under the lens of STS theory, which posits that shared learning through best practices enables social subsystems to dynamically adjust to the evolving requirements of automation while preventing misalignments between technical advancements and organizational practices (Chan and Reich, 2007; Pasmore, 1988).

As for RQ2, the fsQCA results identify five configurations (S1–S5) associated with high SM advancement (i.e. autonomy capability) and two configurations (L1 and L2) linked to low SM advancement (i.e. monitoring capability). L1 and L2 consistently lack foundational factors crucial for the monitoring and control stages, such as top management support and the scalability of SM solutions. Even when higher-level technical and social factors are present, the absence of these prerequisites significantly hinders progress. This insight reinforces the necessity of establishing a robust foundation in the early stages of SM transformation to enable advancement.

The fsQCA outcomes reflected in configurations S1–S5 complement findings from the NCA by demonstrating that SM advancement has a context-specific nature and that interactions between TFs and SFs can potentially compensate for the absence of critical factors [1]. For example, S1 highlights a comprehensive strategy where foundational TFs—such as state-of-the-art IT infrastructure and interoperability—are bolstered by SFs in the form of agile organizational structures, cross-functional teams, and informed staff. This configuration suggests that balancing operational stability with structural adaptability is crucial for fully leveraging SM technologies. Notably, S1 identifies external engagement (e.g. market scanning or partnerships) as not relevant for achieving high SM advancement in this specific context. This indicates that while such engagement may be present or absent, it does not significantly influence the outcome in this configuration. Instead, the emphasis is on optimizing internal capabilities to seamlessly integrate technological advancements into existing structures. From a socio-technical perspective, this alignment reflects how internal coherence provides systemic resilience, enabling firms to absorb technological advancements without creating misalignments between technical and social subsystems (Trist, 1981). S2 shares many foundational elements with S1 but diverges in its approach to external engagement. Unlike S1, S2 explicitly excludes factors such as market scanning and culture of openness to external partnerships. This strategic choice may reflect a deliberate effort to minimize potential disruptions arising from external dependencies, particularly in contexts where higher internal complexity demands greater coordination and control (Contieri *et al*., 2024; Piccarozzi *et al*., 2024). Configurations S3 and S4 represent a shift from the sole internal focus observed in S1 and S2. Specifically, the inclusion of market scanning and partnerships in S3 suggests that firms adopting this configuration actively seek external expertise and innovations to complement their existing capabilities. This strategic orientation aligns with the results of previous studies that have suggested the importance of developing dynamic capabilities aimed at assimilating externally generated technological knowledge in the context of SM (Sousa-Zomer *et al*., 2020). From an STS perspective, S3 demonstrates how stable internal systems provide the foundation for selectively integrating external inputs, ensuring that these contributions align with organizational goals (Pasmore, 1988). S4 builds on the external orientation observed in S3 but places additional emphasis on internal collaboration. Specifically, the presence of cross-functional teams highlights a deliberate effort to integrate external expertise while harmonizing diverse internal capabilities. Interestingly, S4 does not consider interoperability between old and new equipment as a critical factor. This may indicate that firms adopting this configuration have either transitioned to modernized systems or operate in environments with modular infrastructures that reduce dependency on interoperability (Burns *et al.*, 2019; Pedone and Mezgár, 2018). Alternatively, the irrelevance of interoperability could reflect a forward-looking investment strategy that prioritizes new technologies over legacy system adaptation (Alqoud *et al.*, 2022). Finally, S5 presents a distinct configuration that diverges from the outward-facing strategies observed in S3 and S4 by emphasizing internal focus and cautious external engagement. Notably, it excludes external partnerships while incorporating market scanning, suggesting a strategy to remain informed about external developments without directly collaborating with external actors (Arcidiacono *et al.*, 2022). The absence of cross-functional teams in S5 further reinforces this localized and compartmentalized approach, in which decision-making processes are streamlined within specific domains rather than distributed across broader organizational structures (Culot *et al.*, 2019). This configuration reflects an effort to maintain tighter control over specific aspects of SM implementation, potentially simplifying coordination demands and reducing organizational complexity. Equally significant in S5 is the nonrelevance of scalability as a critical factor. This absence suggests that firms adopting this configuration are less concerned with broad, scalable SM transformations and instead focus on localized optimization. By prioritizing depth within specific processes over organization-wide scalability, these firms can achieve targeted advancements that align with immediate operational needs.

Taken together, S1–S5 provide a nuanced perspective on how external engagement interacts with internal mechanisms to drive advancements in SM. While earlier SM literature consistently highlighted collaborations with external partners as a universal enabler of SM transformation (Arcidiacono *et al.*, 2022; Benitez *et al.*, 2020; Sousa-Zomer *et al.*, 2020), the insights from S1, S2, and S5 challenge and expand upon this view. Specifically, they highlight that deliberately limiting reliance on external engagement to avoid excessive dependencies does not necessarily hinder progress toward advanced stages of SM, provided that companies maintain access to specialized SM knowledge. From a socio-technical perspective, these findings illustrate the adaptability of firms in aligning internal and external strategies to advance SM while minimizing potential risks.

6. Conclusions

6.1 Contributions to theory

Our study responds to previous calls for additional empirical research on SM (Arcidiacono and Schupp, 2024; Koh *et al.*, 2019; Stentoft *et al.*, 2021) and offers several theoretical contributions.

First, while STS theory acknowledges that the successful implementation of complex systems hinges on the alignment of social and technical dimensions (Chan and Reich, 2007), the precise nature of this "alignment" often remains elusive. By identifying the TFs and SFs critical at each stage of SM advancement, our study offers a more granular understanding of what "alignment" entails within the context of SM. Our findings also reconceptualize "alignment" as a dynamic, evolving process rather than a static state, underscoring how the relevance of specific TFs and SFs shifts depending on the targeted stage of SM advancement. This dynamic perspective broadens the theoretical scope of STS by framing alignment as an adaptive process that requires continuous recalibration to address changing operational and strategic priorities. Furthermore, by uncovering multiple pathways to achieving high SM advancement, our study enriches STS by demonstrating that "alignment" is not a singular, optimal state but rather a spectrum of diverse, context-sensitive configurations tailored to the unique operational and strategic priorities of the firm. Next, our study contributes to the stream of operations management research that has identified and listed enablers of SM advancement (Benitez *et al*., 2020; Čater *et al*., 2021; Lorenz *et al*., 2020; Moeuf *et al*., 2020; Veile *et al*., 2020, among others) by clarifying the sequence in which these factors are to be deployed to successfully advance in SM. By moving beyond static lists of enablers, our study offers a dynamic perspective, demonstrating that the relevance and interaction of technical and social factors evolve across different stages of SM advancement. Moreover, we shed light on the specific configurations of factors leading to higher levels of SM advancement, demonstrating that no single pathway is universally optimal. Instead, firms combine technical and social dimensions in diverse, context-sensitive ways to navigate their SM journey. This perspective underscores the importance of understanding how enablers interact within broader systems, revealing that their efficacy depends not only on their presence but also on how they are integrated and adapted to fit specific operational contexts.

Finally, our study employs a methodological approach that combines NCA and fsQCA, two methods rarely used together in operations management research. NCA identifies the necessary conditions for achieving specific outcomes, highlighting critical constraints and their influence on SM advancement. FsQCA complements this by revealing how combinations of technical and social factors interact to drive high SM advancement, capturing the equifinality inherent in socio-technical systems. Together, these methods provide a comprehensive framework for examining both the prerequisites and the diverse configurations of factors that lead to high outcomes. By integrating these approaches, our study underscores their potential for advancing operations management research and encourages further exploration of these methods to address the complexity of organizational systems and their pathways to strategic objectives.

6.2 Contributions to practice

Our findings offer multiple implications for business leaders involved in the SM transformation. First, our results demonstrate that SM advancement is a progressive journey that does not entail the simultaneous deployment of critical factors. Instead, firms can commit resources over time, aligning investments with the specific demands of each stage. This phased approach allows managers to manage risks effectively and maintain operational stability while gradually building the capabilities required for the advanced stages of SM transformation. In this direction, by identifying the factors critical at different stages of SM advancement, our study provides a roadmap for adoption, thus helping leaders to deploy resources when they will have the greatest impact and to avoid unnecessary expenditures on factors that are not impactful at a given level of SM advancement. Further, as the relevance of critical factors shifts across different stages of SM advancement, our findings stress the importance of managerial adaptability in navigating the socio-technical complexities of SM transformation. In this respect, leaders must continuously reassess and recalibrate their strategies to succeed in SM. Developing a culture of organizational flexibility and learning ensures that firms can respond dynamically to evolving technical and social demands. This adaptability is key to sustaining progress amid rapid technological advancements and shifting market conditions. Finally, our findings highlight that high levels of SM advancement can be achieved through diverse configurations of technical and social factors, emphasizing that there is no single pathway to success. The effectiveness of enablers is context dependent, requiring managers to tailor the adopted approaches to their specific operational and strategic environments.

To conclude, this study provides relevant implications for policymakers tasked with designing and implementing policies aimed at fostering SM and Industry 4.0. By identifying the existence of saturation effects, our study reveals that fostering a holistic approach that values the integration of technologies with processes, organizational structures, cultural features, and competences is more impactful than focusing solely on isolated factors. In this direction, policies should not only incentivize technological adoption but also support complementary investments in workforce training, organizational restructuring, and the development of collaborative ecosystems. Moreover, recognizing the heterogeneous nature of firms, policymakers should tailor interventions to accommodate varying levels of readiness. By embracing this multi-faceted strategy, policymakers can create an enabling environment that facilitates sustainable and widespread progress in the transition toward advanced manufacturing.

6.3 Limitations and future research

This study has several limitations. First, it is confined to firms in the automotive industry. Given its global influence, the automotive sector often sets the pace for other domains by showcasing innovative practices and driving technological advancements (Kamble *et al.*, 2020). These attributes make it a compelling and highly relevant context for investigating SM implementation. However, this focus inherently limits the generalizability of the findings. Future contributions could extend the analysis to other industries with varying levels of technological maturity and competitive dynamics to validate and expand these insights. Cross-sector comparisons could further illuminate how specific characteristics, such as regulatory requirements or operational practices, influence the adoption and progression of SM initiatives.

Second, the study focuses on intra-firm factors without considering the role of external environmental elements. Aspects such as competitive pressures, customer demands, and mimetic behaviors may significantly influence the implementation of SM initiatives and their evolution over time. Future research could adopt a broader framework that incorporates multiple levels of analysis, exploring how external forces interact with internal dynamics to offer a more comprehensive understanding of the conditions that drive or hinder SM progression.

Third, our research design relied on single respondents within each firm, which, despite careful mitigation strategies, increases the risk of CMB. While the use of procedural and post hoc techniques provided robust evidence supporting the reliability of our findings, future studies should prioritize the collection of data from multiple respondents to further enhance the validity of the results. For example, triangulating perspectives from managers across different functional areas—such as operations and IT—as well as involving employees with more operational roles could provide a richer and more nuanced understanding of SM dynamics.

Fourth, the cross-sectional nature of our data constrains our ability to capture the temporal and evolutionary aspects of SM adoption and progression. SM transformation is inherently dynamic, involving iterative feedback loops and adjustments over time. To address this limitation, future research could adopt longitudinal designs that would allow scholars to observe how technical and social factors develop, interact, and influence firm performance over time. Such an approach would also enable the establishment of stronger causal inferences, moving beyond the conditional and configurational relationships explored in this study.

Finally, the integration of methodological diversity could further advance this field of research. Future studies could complement survey-based approaches with mixed-method research (e.g. secondary data and case studies) to explore contextual nuances and uncover mechanisms that might not be evident through quantitative analyses alone.

Notes

1. The divergence between NCA and QCA results stems from their distinct analytical logics: NCA identifies a factor as necessary due to its indispensable role in enabling the outcome, whereas QCA reveals that the same factor can be absent in specific configurations where other conditions interact to achieve the outcome (Dul, 2016; Ding, 2022; Sukhov *et al.*, 2023). This highlights that SM advancement exhibits characteristics of equifinality—that is, multiple distinct configurations of complementary elements can lead to similar outcomes in achieving high advancement levels (Fiss, 2011; Cantele *et al.*, 2023).

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Supplementary material

The supplementary material for this article can be found online.

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