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RESEARCH ARTICLE

Optimising business models through digital alignment and strategic flexibility: Evidence from the manufacturing industry

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Abstract
The increasing integration of digital technologies in business processes calls for a deeper understanding of their impact on business model efficiency. This study explores how digital alignment, composed by strategic decision support and operational support, affects business model efficiency, while also examining the extent to which strategic flexibility moderates this relationship. To test the proposed hypotheses, we adopt a quantitative approach on a sample of Italian small and medium-sized enterprises in the manufacturing industry. In particular, a regression analysis, complemented by a necessary condition analysis, is performed. We find that digital alignment, both in terms of strategic decision support and operational support, fosters business model efficiency. Strategic flexibility strengthens the relationship between strategic decision support and business model efficiency. To the best of our knowledge, this study is the first to operationalise digital alignment as composed of strategic decision support and operational support. Accordingly, this study contributes to the extant literature on digital alignment and business models.

Keywords: digital alignment (DA); operational support (OS); strategic decision support (SDS); business model (BM) efficiency; strategic flexibility (SF); small and medium-sized enterprises (SMEs); necessary condition analysis (NCA)

Introduction

Business model (BM) efficiency, rooted in transaction cost economics, occupies a central position in management literature, focusing on replication and changes designed to optimise transactional efficiency (Pati, Nandakumar, Ghobadian, Ireland, & O'Regan, 2018; Zott & Amit, 2013). BM efficiency is multi-faceted, encompassing ease and accuracy of transactions, scalability, and the provision of relevant information for decision-making (Zott & Amit, 2010). This multidimensional concept gains particular salience for manufacturing small and medium-sized enterprises (SMEs), which are constrained by resource scarcity (Eggers, 2020). For these firms, efficiency mandates the refinement of internal processes and optimal utilisation of readily available resources, the elimination of operational slack, the cultivation of economies of scale, and the strategic deployment of cost advantages to undercut market rivals through more competitive pricing (Zott & Amit, 2013). Efficient BMs simplify transactions, minimise errors, and can adapt to different transaction volumes, thereby maintaining operational integrity and stakeholder trust (Han, Wang, & Naim, 2017). Efficient BMs also facilitate informed decision-making through transparency and the reduction of information asymmetry among stakeholders (Bohnsack, Kurtz, & Hanelt, 2021).

The drive for BM efficiency becomes increasingly relevant in the era of digital technologies (Chen, Liu, & Chen, 2020; Guo, Zhou, Chen, & Chen, 2021). As businesses evolve, the alignment of digital capabilities with overall strategy emerges as a vital component in this discourse (Canhoto, Quinton, Pera, Molinillo, & Simkin, 2021). In this view, digital alignment (DA) serves as an interface between an organisation's digital capabilities and its overarching business strategy. Indeed, previous studies on strategic alignment put it at the core of strategic management and information systems literature, allowing the analysis of BM change to cope with new challenges (Chan & Reich, 2007; Coltman, Tallon, Sharma, & Queiroz, 2015; Llamzon, Tan, & Carter, 2022; Tallon, Kraemer, & Gurbaxani, 2000). Despite its importance, BM efficiency has received limited attention in the existing literature (Zott & Amit, 2010). Particularly, we found a shortage of knowledge on how DA affects BM efficiency. Against this backdrop, we introduce a novel operationalisation of DA and explore the role of DA in enhancing BM efficiency.

To the best of our knowledge, previous literature did not introduce a measure of DA. Indeed, while Canhoto et al. (2021) have made a significant contribution by focusing on the strategic dimension of DA, it is essential to acknowledge that DA should also include an operational dimension. This can be suggested, for example, by existing studies about IT alignment (e.g., Tai, Wang, & Yeh, 2019), which included the operational dimension at the core. In particular, the operational side of IT alignment focused on improving day-to-day efficiency, supporting cross-functional coordination, and enabling detailed analyses of current business situations (Coltman et al., 2015; Gerow, Grover, Thatcher, & Roth, 2014). Here, we contend that the operational dimension is equally pertinent to DA. Incorporating these operational aspects provides a more holistic understanding of how digital technologies can be leveraged for both long-term strategic objectives and operational efficiencies. Consistently, we define DA as the dynamic and iterative process that harmonises an organisation's digital technology strategy with its business strategy across both strategic and operational dimensions. This definition captures the continuous adaptation of digital capabilities to meet evolving business objectives and is facilitated by the organisation's ability to sense opportunities, seize them, and reorganise resources accordingly (Teece, 2010). In the context of our research, DA promotes the ability of firms to effectively and simultaneously support strategic and operational activities in the face of business challenges.

Building on this conceptualisation of DA, we posit that DA fosters an enhanced BM efficiency. Accordingly, this expectation is grounded in a dual perspective, encompassing both strategic and operational dimensions. The strategic dimension involves integrating digital capabilities cohesively with the long-term goals of the organisation. This integration facilitates attributes associated with BM efficiency, including streamlined transactions and the potential for scalable growth. Simultaneously, the operational dimension concentrates on effectively leveraging digital capabilities to achieve immediate operational efficiencies. This encompasses tasks such as enhancing transactional accuracy and expediting transaction speed. Through this lens, DA constitutes a fundamental basis upon which optimal utilisation of digital capabilities is constructed. This, in turn, serves as a logical precursor to the intricate concept encapsulated by BM efficiency.

Achieving enhanced DA equips firms with a higher ability to develop strategic business plans, make bold decisions, and sharpen coordination across functions and product lines. This may be particularly true for SMEs (Canhoto et al., 2021; Li, Liu, Belitski, Ghobadian, & O'Regan, 2016), which often suffer from size-related disadvantages (Eggers, 2020). Indeed, by achieving a higher BM efficiency, SMEs can reduce slack, create economies of scale, and gain a cost advantage by charging lower prices than competitors. Specifically, with the support of digital technologies, SMEs can automate tasks, optimise resource allocation, and minimise wasteful activities (Sanchez, 1995; Zhou & Wu, 2010). This resource optimisation allows SMEs to make the most of their limited resources, improving their efficiency. Through DA, SMEs can automate production processes, improve production planning, and enhance supply chain coordination (Rayna & Striukova, 2016). This enables SMEs to increase their production capacity, reduce per-unit costs, and achieve economies of scale that were previously difficult to attain.

By combining strategic decision support (SDS) and operational support (OS) through an overall DA, organisations can align their digital technologies, decision-making processes, and operational activities with their BM. In addition, research has shown that strategic flexibility (SF) enhances a firm's ability to allocate resources, support a wider range of product applications, redefine product strategies, and reconfigure operational routines (Tai, Wang, & Yeh, 2019). In this sense, SF benefits strategic decision-making and provides OS during DA. Thus, SF may enable an organisation to re-allocate resources dynamically. When DA is high, the organisation is likely already employing its digital assets effectively (Brozovic, 2018). Strategic flexibility ensures that this alignment can be adapted to changing circumstances, thereby augmenting BM efficiency. As a result, we argue that SF could strengthen the positive effects of DA on BM efficiency by improving the firm's ability to make strategic decisions and deploy operational activities, optimising transaction execution, ease, transparency, and speed. As a result, we advance the following research question:

RQ: What is the role of digital alignment in shaping business model efficiency, and how does strategic flexibility moderate this relationship?

To answer this question, we rely on a sample of 156 managers from Italian manufacturing SMEs to investigate the relationship between DA and BM efficiency. The focus on this specific sector enhances the internal validity of our research by reducing sectoral heterogeneity. The Italian manufacturing sector's global significance and policy-driven digitalisation make the study both timely and geopolitically relevant. Lastly, the sector's composition, largely of SMEs, and the impact of the COVID-19 pandemic add contextual depth, making it a suitable setting to examine the efficacy of flexible business paradigms.

This study makes multiple contributions to extant literature. First, it augments the digital BM literature by underscoring the pivotal role of DA in optimising BM efficiency, specifically within the realm of manufacturing SMEs (Zhou & Wu, 2010; Zott & Amit, 2010). Notably, this study brings new insights into the role of strategic and operational alignment in the use of digital technologies. Second, the research enriches the ongoing scholarly dialogue on SF by elucidating its moderating influence on the nexus between DA and BM efficiency (Adler, Goldoftas, & Levine, 1999; Claussen, Essling, & Peukert, 2018; Eisenhardt, Furr, & Bingham, 2010). Third, the study employs a new methodological approach, incorporating necessary condition analysis (NCA) alongside regression analyses. This offers a more nuanced understanding of the essential conditions for achieving BM efficiency according to our sample.

The rest of this study is organised as follows: Section 2 presents the theoretical background and research hypotheses; Section 3 describes the methodology, including the setting and sample of the research, measures, and analytical techniques; and Section 4 describes the results, followed by the discussion (Section 5) and conclusions (Section 6).

Theoretical background and hypotheses development

The relationship between strategic support and business model efficiency

Digital BMs need adaptive mechanisms to be put in place in order for them to unleash their high potential (Di Vaio, Palladino, Pezzi, & Kalisz, 2021; Urbinati, Bogers, Chiesa, & Frattini, 2019). According to Sjödin, Parida, Jovanovic, and Visnjic (2020), alignment is needed to assist the BM innovation success. For manufacturing firms, developing a digital BM implies a complex transformation process since it requires a DA involving operational and strategic decisions (Chen, Lassen, Chen, & Møller, 2022). DA ensures that digital technology-powered processes, operations, and capabilities are strategically integrated and aligned with the overall BM. Such a DA contributes to streamlining operations, reducing costs, eliminating bottlenecks, automating repetitive tasks, and improving analytics-powered strategy-making (Visnjic, Jovanovic, Neely, & Engwall, 2017; Zheng, Xiong, Chen, & Li, 2021).

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By pursuing both SDS and OS in their DA strategy, firms can achieve a holistic approach to digital transformation. SDS ensures that digital technologies are aligned with the organisation's long-term goals and objectives, while OS focuses on leveraging digital tools for higher day-to-day operational standards (Chen et al., 2022). These two aspects complement each other and contribute to defining cost strategies, pursuing asset maintenance, improving the BM architecture, product and service optimisation, and reaching operational efficiency (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Chen, Visnjic, Parida, & Zhang, 2021; Liu, Dong, Mei, & Shen, 2022; Porter & Heppelmann, 2014; Visnjic et al., 2017). In the absence of DA, firms may fail to effectively reach customers and capitalise on the created value since value creation and value capture mechanisms go in parallel (Sjödin et al., 2020).

Specifically, SDS involves the use of digital technologies to inform and facilitate strategic decisions. By leveraging digital technologies to support strategic decisions, firms can gain insights related to the latest market trends, customer preferences, and emerging technologies to identify new business opportunities and stay ahead of the competition (Urbinati et al., 2019). Through data analysis from multiple sources, digital technologies allow firms to make informed decisions about product development, expansion into new markets, mergers and acquisitions, or diversification strategies, as well as evaluate the potential impact of different strategic options and optimise decision outcomes (Chen et al., 2021; Porter and Heppelmann; Tu, Vonderembse, Ragu-Nathan, & Ragu-Nathan, 2004).

Thus, here, we contend that SDS exerts a positive influence on BM efficiency. The theoretical underpinning of this hypothesis relies on multiple aspects. To begin with, SDS, enabled by digital technologies, allows for the real-time assimilation and analysis of market data. This facilitates more informed and timely strategic decisions. On this aspect, Urbinati et al. (2019) posit that the integration of digital technologies enables firms to gain nuanced insights into market trends and customer preferences, thereby aligning their strategies more effectively with market demands.

Another critical dimension is the alignment of digital technologies with the strategic objectives of the firm, contributing to the optimisation of resource allocation, thereby enhancing BM efficiency. Consistently, Chen et al. (2022) argue that digital technologies allow firms to make informed decisions about product development, market expansion, and other strategic initiatives. From this angle, alignment is a complex transformative process that involves both operational and strategic decisions.

Furthermore, Sjödin et al. (2020) emphasise that alignment is crucial for the successful implementation and sustainability of innovative BMs. In this context, SDS ensures that digital technologies are well-integrated into the firm's operations while also aligned with its long-term goals and objectives. This alignment contributes to the efficiency of the BM by streamlining operations, reducing costs, and eliminating bottlenecks. Sjödin et al. (2020) also point out that in the absence of effective DA, firms may fail to reach customers effectively and capitalise on the value they create. SDS ensures that value creation and value capture mechanisms are aligned, thereby enhancing the efficiency of the BM.

Overall, SDS, facilitated by digital technologies, plays a pivotal role in enhancing BM efficiency. It does so by enabling informed decision-making, optimising resource allocation, fostering strategic alignment, and ensuring effective value creation and capture. Thus, we propose that:

Hypothesis 1: Strategic decision support of digital technologies positively affects the business model efficiency.

The relationship between operational support and business model efficiency

Extant literature has underscored how digital technologies can be functional in optimising a firm's operations and shaping its role in a supply chain or network (Belhadi et al., 2021). Indeed, digital technologies allow firms to convert their BMs into digital BMs, achieving higher levels of operational efficiency. For instance, Hsuan, Jovanovic, and Clemente (2021) showed that firms embrace digital servitization to achieve higher levels of operational efficiency and cost-effectiveness. Chen et al. (2021) showed that manufacturing firms embark on digital servitization by leveraging digital

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technologies (e.g., AI and IoT) to increase BM efficiency (e.g., enhanced value capture mechanisms by optimising internal activity systems and ease communication across the supply and distribution chain) (Murray, Papa, Cuozzo, & Russo, 2016). Digital technologies also help firms secure transactions, improve traceability and transparency, and, more in general, operations at a high speed, easily, and with limited costs (Chong, Lim, Hua, Zheng, & Tan, 2019; Warner & Wäger, 2019; Zheng et al., 2021). In this vein, OS focuses on using digital technologies to optimise and streamline the day-to-day operational activities of the business and includes activities such as production planning, inventory management, supply chain coordination, and process optimisation (Rayna & Striukova, 2016). OS is aimed at automating manual tasks and processes to reduce errors, improving BM efficiency, enabling real-time monitoring and control of production processes, freeing up resources for more value-added activities, and identifying opportunities for cost savings and process improvements (Bogers, Hadar, & Bilberg, 2016; Vial, 2019). Finally, OS allows firms to improve their BM efficiency (Kretschmer & Khashabi, 2020; Yoo, Boland, Lyytinen, & Majchrzak, 2012; Zhou & Wu, 2010), i.e., how firms design their activity system to reduce transaction costs and optimise internal processes (Zott & Amit, 2010). Thus, we contend that DA, including SDS and OS, can be instrumental in improving BM efficiency. In fact, digital technologies support firms to reach specific goals in terms of BM efficiency by enabling the translation of strategic assumptions into effective BM components (Casadesus-Masanell & Ricart, 2010; Teece, 2010; Volberda, Khanagha, Baden-Fuller, Mihalache, & Birkinshaw, 2021). In addition, digital technologies represent the architecture through which firms deploy their value systems and make decisions at an operational level (Al-Debei & Avison, 2010). To further corroborate this, we encompass the utilisation of digital technologies in activities such as production planning, inventory management, and supply chain coordination (Rayna & Striukova, 2016). The operational alignment enabled by digital technologies aims to automate manual tasks, thereby reducing errors and increasing the speed of operations (Bogers, Hadar, & Bilberg, 2016).

Also, Vial (2019) argues that digital technologies enable firms to improve their BM efficiency through real-time monitoring and control. This allows firms to identify and rectify inefficiencies promptly, thereby enhancing the overall efficiency of the BM. The immediate feedback loop enabled by digital technologies ensures that inefficiencies are not only identified but also addressed in a timely manner, thereby contributing to the long-term sustainability of the BM. Furthermore, the literature emphasises the role of digital technologies in reducing transaction costs and facilitating transaction processes. Zott and Amit (2010) discuss the importance of optimising internal processes and reducing transaction costs for enhancing BM efficiency. In this context, OS enabled by digital technologies can significantly reduce transaction costs and streamline transaction processes, thereby contributing to BM efficiency.

In sum, we argue that the OS, facilitated by digital technologies, plays a pivotal role in enhancing BM efficiency. Thus, we formulate the following hypothesis:

Hypothesis 2: Operational support of digital technologies positively affects the business model efficiency.

Strategic decision support: The moderating role of strategic flexibility

We contend that SF might serve as a key element that could enhance the positive impact of digital technologies on BM efficiency. This hypothesis is supported by a number of underlying mechanisms.

First, the role of SF in optimising operational efficiency functions as a central tenet. According to Zhou and Wu (2010), SF serves as a conduit through which technological capabilities are not just utilised but optimised. It allows firms to adapt to changing market conditions by reallocating resources in an agile manner. This adaptability is not an end in itself but a means to achieve operational efficiency. Sanchez (1995) and Bowman and Hurry (1993) further substantiate this by highlighting how SF provides firms with the latitude to explore multiple strategic pathways, thereby offering a cushion against market volatility and uncertainties (Brozovic, 2018).

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Second, Kretschmer and Khashabi (2020) and Zhou and Wu (2010) argue that the coordinated allocation of resources is pivotal for the effective utilisation of digital technologies. In environments characterised by high transaction volumes, such as e-commerce or financial trading platforms, the need for robust and available transactional processes becomes acute (Han, Wang, & Naim, 2017). Here, we believe that SF could act as an enabler, allowing firms to transition between different technological platforms without causing disruptions, thereby maintaining or even increasing operational efficiency. For example, the interplay between SF and supply chain processes is an important mechanism that contributes to BM efficiency. SF enables firms to allocate resources in a manner that is most conducive to the prevailing supply chain requirements (Bowman & Hurry, 1993; Chiang, Kocabasoglu-Hillmer, & Suresh, 2012; Singh, Singh Oberoi, & Singh Ahuja, 2013). This optimisation is not limited to internal processes but extends to external partnerships. By leveraging digital technologies, SF allows firms to forge beneficial partnerships with supply chain stakeholders, thereby gaining access to a broader array of resources and information that can be instrumental in enhancing efficiency (Han, Wang, & Naim, 2017).

Lastly, the shift in strategy formulation engendered by SF is predicated on several foundational principles, including resource allocation, structural modularity, and coordination mechanisms (Hayes & Pisano, 1994; Kandemir & Acur, 2012; Sanchez & Mahoney, 1996). These principles serve as the bedrock upon which digital technologies can be effectively deployed, especially in the context of SMEs (Eggers, 2020; Sen, Savitskie, Mahto, Kumar, & Khanine, 2022). They enable firms to navigate complex operational environments by providing a framework within which digital technologies can be utilised for identifying the most viable strategic options for both BM design and operational management (Kretschmer & Khashabi, 2020; Roberts, Campbell, & Vijayasarathy, 2016; Yoo et al., 2012).

In sum, SF emerges as a dynamic capability that optimises the deployment of digital technologies also enhancing the quality of strategic decision-making processes, culminating in more efficient BMs. Thus, taken together, these arguments suggest the following hypothesis:

Hypothesis 3: Strategic flexibility strengthens the relationship between strategic decision support of digital technologies and business model efficiency.

Operational support: The moderating role of strategic flexibility

In this section, we argue that SF could be a moderating force in the relationship between the OS of digital technologies and BM efficiency. We believe that multiple prior studies can support this hypothesis. For example, Kortmann, Gelhard, Zimmermann, and Piller (2014) argue that SF enhances the impact of digital technologies on operational efficiency by enabling firms to offer personalised products at scale. Da Silveira, Borenstein, and Fogliatto (2001) and Tu et al. (2004) contribute to this understanding by suggesting that mass customisation allows firms to adopt a customer-centric orientation, which can lead to an increase in transaction volume. Therefore, SF enables firms to meet individual customer needs while also allowing them to do so in an operationally efficient manner. Also, Sanchez (1995) argues that SF aids in the recombination of organisational resources, reducing both time and cost. This efficiency is crucial for adaptability in volatile market conditions. Aaldering and Song (2021) and Han, Wang, and Naim (2017) extend this by focusing on the role of SF in resource base management. They highlight the importance of aligning digital capabilities with the BM for operational efficiency. In this context, SF serves two primary functions. Internally, it optimises resource allocation and management, thereby contributing to operational efficiency. Externally, it enables firms to respond to market opportunities swiftly. The alignment of digital capabilities with the BM is not a static task but requires ongoing recalibration to adapt to technological advancements and market trends.

Thus, SF is a critical organisational capability that serves as a mechanism for both internal efficiency and external responsiveness. It facilitates the recombination of resources in a cost-effective

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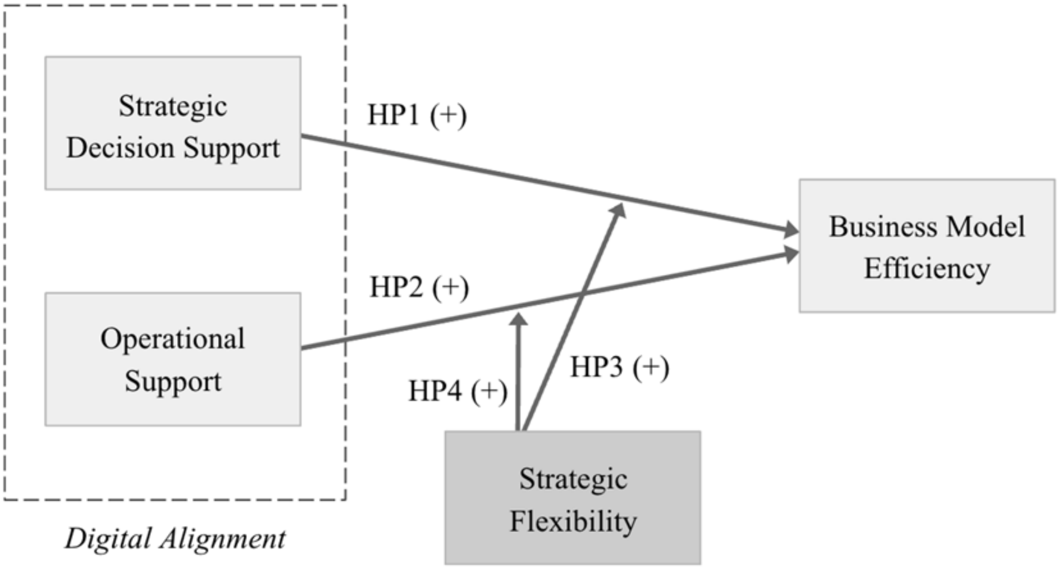

Figure 1. Research model.

and timely manner, while also enabling the dynamic alignment of digital capabilities with the evolving BM. This dual utility positions firms to navigate and capitalise on changing business conditions effectively.

Moreover, an enhanced ability to manage digital technology for operational purposes, when combined with higher levels of SF, can lead to strengthen customer relationships. Anupindi and Jiang (2008), Kandemir and Acur (2012), and Zhou and Wu (2010) provide evidence that this is achieved through more reliable transaction systems, price stability, and platforms that offer specific product information to customers. Thus, SF amplifies the benefits of digital technologies in customer operations.

Finally, SF enhances the potential of digital technologies for coordination across functions and product lines. Tu et al. (2004) and Zhang, Vonderembse, and Lim (2003) indicate that SF supports modularity and provides access to a broad range of products targeting different market segments and stakeholders. This flexibility in the use of digital technologies enhances the firm's ability to adjust manufacturing operations and reduce inefficiencies.

In summary, we advance that SF strengthens the relationship between OS of digital technologies and BM efficiency. Thus, we propose that:

Hypothesis 4: SF strengthens the relationship between operational support of digital technologies and business model efficiency

In Fig. 1, we report our research model.

Methodology

Setting and sample

Our data have been collected in Italy from November 2020 to January 2022 through a structured online survey, designed to capture both strategic and operational aspects of digital technology adoption in manufacturing SMEs. The covered manufacturing sectors include furniture, computer and electronics, textile, plastics and non-metallic, food, motor vehicles, and transports, among others.

Prior to administration, the survey was further validated with consultation from both academics and industry experts.

Invitations to participate in the survey were sent via email to CEOs or relevant decision-makers within these selected SMEs. To maximise response rates, two follow-up reminders were sent at 2-week intervals. The survey was administered using a secure online platform to ensure data integrity and confidentiality.

We believe this context is particularly suitable for testing our hypotheses for three main reasons. First, the focus on the manufacturing sector serves to reduce the heterogeneity that would otherwise arise from including firms from a variety of sectors. As noted by Laursen and Salter (2006), firms from disparate sectors such as manufacturing, services, and trading are typically characterised by different structures and organisational dynamics. These differences could considerably alter the analysis of the relationship between DA and BM efficiency. Natalicchio, Petruzzelli, Cardinali, and Savino (2018) further substantiate this by pointing out that the manufacturing sector exhibits a higher rate of developed innovations than other sectors, thereby enhancing the study of the digital realm across business contexts.

Second, the Italian manufacturing sector holds a position of considerable economic significance, being one of the largest worldwide. The Italian Ministry of Economic Development's 'Industry 4.0 National Plan', launched in 2016, has been a pivotal initiative in facilitating the implementation of digital technologies across the manufacturing sector (Chiarini, 2021). This national policy context not only increases the spread of digitalisation but also underscores the timeliness and relevance of studying digital technology adoption in Italian manufacturing SMEs.

Third, the structural composition of the Italian manufacturing sector, which is predominantly made up of SMEs, adds another layer of contextual suitability. These SMEs often exhibit structural fragility, making the effects of flexible business paradigms particularly relevant for increasing their overall efficiency (Cassetta, Dileo, & Pini, 2023). The observation period of our study coincides with the significant economic impact of the COVID-19 pandemic on the Italian economy, as noted by Rapaccini, Saccani, Kowalkowski, Paiola, and Adrodegari (2020). This environmental dynamism, exacerbated by the pandemic, provides an opportunity to closely analyse how SMEs adjust their organisational structures strategically by leveraging flexible approaches to preserve or enhance the overall efficiency of their BMs.

Our sample showed no clear pattern in the manufacturing sector, firm age, or employee number (within the constraints of the SME size of 250). This heterogeneity minimises the room for single-source bias (Avolio, Yammarino, & Bass, 1991). Moreover, to minimise the threat of response bias, we did not disclose the aim of the study. We randomly distributed the constructs in the survey, not suggesting clear paths of causality.

We collected 174 responses, 18 of which were removed due to missing data or failed attention checks. Thus, the final pool of respondents included 156 managers of Italian manufacturing SMEs. Table 1 reports the sample characteristics.

Furthermore, to avoid jeopardising the validity of our analysis, we performed some robustness checks based on the recommendations by Podsakoff, MacKenzie, Lee, and Podsakoff (2003). We did not find any statistically significant differences between early and late respondents or subgroups based on size, age, industry, or export activity. We also checked for common method variance using Harman's single-factor test. Results indicated a total variance of 39.58%, considerably lower than the suggested threshold of 50.00%. Self-selection bias was inspected by comparing the directionality of responses of included and excluded participants, and no significant difference was found.

Measures

In this study, we relied on scales developed by or adapted from previous literature. A summary of the adopted latent constructs is reported in Table 2. All items were measured on a 1–7 Likert scale. As depicted in our research model, we set BM efficiency as the dependent variable of the study. Strategic

Table 1. Sample characteristics

Firm Size	*n*	%	*Manufacturing Sector*	*n*	%
Less than 20	31	19.87	Furniture	41	26.28
21–50	25	16.03	Computer and electronics	17	10.90
51–125	49	31.41	Textile	25	16.03
126–250	51	32.69	Plastics and non-metallic	38	24.36
			Food	9	5.77
Firm age			Motor vehicles and transports	13	8.33
Less than 3	16	10.26	Other	13	8.33
4–6	23	14.74			
7–20	60	38.46	*Exports*		
21–40	31	19.87	In the last 5 years,		
41–50	8	5.13	Your company export levels were:		
More than 50	18	11.54	No/Low	25	16.03
			Moderate	105	67.31
			High	26	16.67
$n = 156$					

decision and OS constitute our main independent variables, while SF is our moderator. Finally, size, age, sector, and export activity, presented in our sample characteristics table, were also inserted in our regression analysis to control how the key variables of the study behave when size, age, sector, and export activity are embedded in the models.

BM efficiency was measured by the nine items proposed by Pati et al. (2018). This measure of BM efficiency is related to its design, and it is anchored to transaction cost economics, encompassing replication and changes designed to enhance transaction efficiency (Zott & Amit, 2013). The objective is to minimise transaction costs for all transaction actors. Consistently, a focal firm can increase its overall BM efficiency by implementing new technologies, relocating, or recommitting key resources in its BM to reduce the transaction cost of the current organisational structure (Dunford, Palmer, & Benveniste, 2010).

SDS and OS were adapted from Tai, Wang, and Yeh (2019), focusing on digital technologies rather than IT levels of alignment. In particular, Tai, Wang, and Yeh (2019) proposed SDS and OS as two important components of IT alignment. Here, we adapted the Tai, Wang, and Yeh (2019) scale focused on IT alignment by embedding a digital technology view for a consistent measure of DA. The outcome is two scales of SDS and OS centred on digital technologies, as proposed in Table 2.

SF was measured by the six items proposed by Zhou and Wu (2010). This scale is derived from the theoretical contribution by Sanchez (1995), which focused on the flexible allocation and coordination of resources in response to changing environments.

Regarding the control variables, firm size was proxied by the number of employees currently operating in the SME, while other control variables including age, sector, and export activity (and their distribution in our sample) are in detail and presented in the sample characteristics table.

Methodological approach

The reliability of constructs is assessed in Table 2. Next, to estimate the latent variables, the items were calibrated utilising a congeneric methodology by using the Congeneric Latent Construct Estimator (CLC Estimator) developed by Marzi, Balzano, Egidi, and Magrini (2023) available at https://www.clcestimator.com/. The adoption of the CLC Estimator is congruent with the recommendations

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Table 2. Items and reliability of latent variables

	Omega	AVE
BM Efficiency – Nine items (Pati et al., 2018) 1. Our BM makes the transactions simple (ease of transaction) for all stakeholders. 2. Our BM enables a low number of errors in the execution of transactions. 3. Our BM is scalable (i.e., can handle a small and a large number of transactions). 4. Our BM enables stakeholders to make informed decisions. 5. Our BM makes transactions transparent. 6. As part of transactions, information is provided to stakeholders to reduce an asymmetric degree of knowledge among them regarding the quality and nature of the goods being exchanged. 7. Information is provided to stakeholders about each other. 8. Access to a large range of products, services, information, and other stakeholders is provided. 9. Our BM enables fast transactions.	.79	.53
SDS – Three items (adapted from Tai, Wang, & Yeh, 2019) 1. In our company, digital technologies support detailed analyses of major business decisions. 2. We use digital technologies to facilitate strategic business planning. 3. In our company, digital technologies help users in modelling possible courses of action.	.80	.55
OS – Three items (adapted from Tai, Wang, & Yeh, 2019) 1. We use digital technologies to improve the efficiency of our day-to-day business operations. 2. In our company, digital technologies support coordination across functions and product lines effectively. 3. In our company, digital technologies enable users to perform detailed analyses of present business situations.	.88	.63
SF – Six items (Zhou & Wu, 2010) *In responding to changes in the environment, your firm's strategy emphasises*: 1. The flexible allocation of marketing resources (including advertising, promotion, and distribution resources) to market a diverse line of products. 2. The flexible allocation of production resources to manufacture a broad range of product variations. 3. The flexibility of product design (such as modular product design) to support a broad range of potential product applications. 4. Redefining product strategies in terms of which products the firm intends to offer and which market segment it will target. 5. Reconfiguring chains of resources the firm can use in developing, manufacturing, and delivering its intended products to targeted markets. 6. Redeploying organisational resources effectively to support the firm's intended product strategies.	.84	.61
	$n = 156$	

posited by McNeish and Wolf (2020), advocating for the suboptimal practice of using sum score or unweighted means for item aggregation. Utilising the Maximum Likelihood technique for factor extraction, items were weighted according to their respective factor loadings into the target constructs (Marzi et al., 2023). As a result, this methodological choice has fortified the internal consistency of our measurements, thereby augmenting both the accuracy and the reliability of our sample (Marzi et al., 2023; McNeish & Wolf, 2020). After this phase, we ran multiple regressions (Allison, 1999) to predict the value of BM efficiency by considering multiple independent variables. Multiple regression allows adding a set of control effects on the main independent variables to analyse to which extent a hypothesised relationship provides additional insights in predicting the dependent variable (Allison, 1999). Regression models are built according to incremental logic to show prediction improvements and assess in a step-by-step approach how significance varies from one model to another.

Regression analysis is then complemented with an NCA. NCA is a method developed by Dul (2016) that can be applied both as a standalone method and/or confirmatory method for a variety

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Table 3. Correlation matrix

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. BM efficiency	2.95	.80	–							
2. SDS	2.98	1.02	.27***	–						
3. OS	3.31	.93	.29***	.19**	–					
4. SF	3.46	1.10	.13	.05	.24***	–				
5. Firm size	96.78	69.81	.09	−.10	.23***	.07	–			
6. Firm age	20.82	16.80	.08	−.03	−.07	−.24***	.41***	–		
7. Industry	–	–	−.05	.12	−.11	−.01	−.06	.14*	–	
8. Exports	2.01	.57	.14*	.17**	.11	−.01	−.02	−.05	.05	–

Numbers are rounded to the nearest hundredth. $n = 156$.
$^{*}p < 0.1$; $^{**}p < .05$; $^{***}p < .01$.

of more traditional techniques, such as multiple regressions or structural equation modelling. NCA aims to explore the relationship between two variables in terms of the necessary level of one variable X to predict a certain effect on the outcome variable Y (Dul, 2016).

As such, NCA is able to indicate specific bottlenecks and levels needed for variable X (condition) to generate the desired effect on variable Y (outcome), also showing the intensity of such an effect and the statistical significance of it. NCA is grounded in the calculation of ceiling lines. Although such calculations can be performed in different ways, the most robust approach rests on the 'ceiling envelope with free disposal hull' (CE-FDH). The result of CE-FDH is a graphical representation where the size of the empty space on the upper left corner of the graph shows the level of necessity requested from predictor X for generating outcome Y (Dul, 2016; Dul, Van der Laan, & Kuik, 2020). Next, the bottleneck table summarises the results of CE-FDH for each level of predictor X in generating the desired outcome Y. As a result, the bottleneck analysis is able to show the relation between X and Y at different degrees of X.

Dul (2016) also introduced the notion of the effect size (d), with a general guiding ratio where $0 < d < 0.10$ corresponds to a 'small' effect size, $0.10 \leq d < 0.30$ to a 'medium', $0.30 \leq d < 0.50$ to a 'large', and $0.50 \leq d < 1$ to a 'very large' effect size. Finally, NCA is accompanied by a statistical significance test, showing the necessity of the condition against the null hypothesis (Dul, Van der Laan, & Kuik, 2020). In the present study, we applied NCA as a data exploration technique to support multiple regression analysis by using CE-FDH calculation of the R package NCA developed by Dul (2022).

Results

Constructs' reliability and descriptive statistics

As illustrated in Table 2, Omega and Average Variance Extracted (AVE) for the adopted constructs are, respectively, equal to or above 0.79 and 0.53, suggesting acceptable levels of internal consistency, reliability, and validity.

In Table 3, we present descriptive statistics (means, standard deviations, and correlations) for the variables adopted in this study. As shown in Table 3, SDS and OS are positively and significantly correlated ($\rho = 0.19$, $p < .05$). To detect whether the regressions might have suffered from multicollinearity issues, we computed the variance inflation factors (VIFs). All VIF scores are lower than 1.5, significantly below the threshold of 10 recommended by Chatterjee and Hadi (2006).

Regression analysis

Table 4 illustrates the main results of the multiple regression analysis. Model 1 includes control variables only. Model 2 adds to Model 1 the direct effect of SDS. Model 3 adds to Model 1 the direct effect

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Table 4. Regression models

	Hypotheses	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Independent variables										
SDS	***Hypothesis 1***		.31 (.09)***		.25 (.09)***	.31 (.09)***	.29 (.09)***			.23 (.09)***
OS	***Hypothesis 2***			.28 (.08)***	.23 (.08)***			.26 (.08)***	.29 (.09)***	.25 (.08)***
SF						.14 (.07)*	.16 (.07)**	.09 (.08)	.07 (.08)	.10 (.07)
Interaction effects										
Strat. Dec. X Strat. Flex.	***Hypothesis 3***						.22 (.09)**			.24 (.09)***
Operational X Strat. Flex.	***Hypothesis 4***								.07 (.07)	.05 (.06)
Control variables										
Firm size		.05 (.08)	.07 (.08)	−.03 (.08)	.01 (.08)	.05 (.08)	.07 (.08)	−.04 (.08)	−.05 (.08)	.01 (.08)
Firm age		.05 (.06)	.05 (.06)	.09 (.06)	.08 (.06)	.09 (.06)	.05 (.07)	.11 (.07)	.10 (.07)	.06 (.06)
Industry		−.03 (.04)	−.05 (.04)	−.02 (.04)	−.04 (.04)	−.05 (.04)	−.04 (.04)	−.03 (.05)	−.02 (.04)	−.03 (.04)
Export		.26 (.14)*	.18 (.14)	.20 (.14)	.15 (.13)	.18 (.14)	.15 (.13)	.21 (.14)	.23 (.14)*	.13 (.13)
Model fit										
Adjusted *R*-Squared		.01	.08	.08	.12	.09	.12	.08	.08	.16
n		156	156	156	156	156	156	156	156	156

Both dependent and independent variables are standardised, and the dependent variable is BM efficiency.
*$p < 0.1$; **$p < .05$; ***$p < .01$ (standard errors in parentheses). Numbers are rounded to the nearest hundredth.

of OS. Model 4 adds to Model 1 both the direct effect of SDS and OS. Model 5 adds to Model 2 the direct effect of SF. Model 6 adds to Model 5 the interaction effect between SDS and SF. Model 7 adds to Model 3 the direct effect of SF. Model 8 adds to Model 7 the interaction effect between OS and SF. Model 9 reports all direct and indirect effects considered in the study.

Hypothesis 1 states that there is a positive effect of SDS on BM efficiency. As reported in Table 4, this hypothesis receives strong empirical support (in Model 2, $\beta = 0.31, p < .01$). Hypothesis 2 states that there is a positive effect of OS on BM efficiency. In addition, this hypothesis receives strong empirical support (in Model 3, $\beta = 0.28$, $p < .01$). Hypothesis 3 states that there is a positive interaction effect of SDS and SF on BM efficiency. This hypothesis is empirically supported (in Model 6, $\beta = 0.22$, $p < .05$). Finally, Hypothesis 4 states that there is a positive interaction effect of OS and SF on BM efficiency. As can be observed in Model 8, the interaction coefficient is positive as expected ($\beta = 0.07$), but the p-value is too high to justify empirical support of Hypothesis 4 ($p > .10$). Thus, Hypothesis 4 is not supported.

Moreover, it can be noted that the incremental logic of the proposed multiple regression model exhibits a notable appreciation of adjusted R-squared values, raised from 0.01 in Model 1 (control variables only) to 0.16 in Model 9 (full model, Table 4). This manifests the augmented predictive power in the baseline models when adding the key variables of the study.

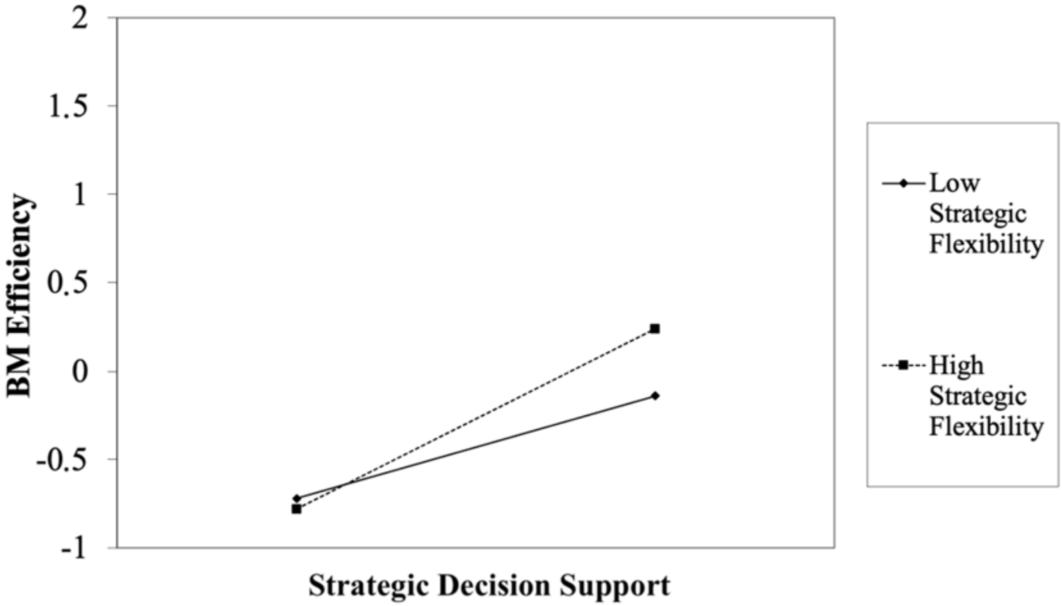

Figure 2. Significant interaction effect.

Turning to examine the significant moderation effect of SF in the relationship between SDS and BM efficiency, we report the interaction patterns (Aiken, West, & Reno, 1991). SDS has a more positive relationship with BM efficiency when SF is high (gradient = 0.51, $t = 4.66$, $p < .00$) than when it is low (gradient = 0.29, $t = 6.49$, $p < .00$) (Fig. 2). To assess the robustness of our results, we conducted additional analyses employing a model that included only the independent variables, eschewing control variables. The outcomes of these supplementary tests were corroborative, thereby bolstering the validity of our results.

Necessary condition analysis

The results of the NCA analysis are presented in Table 5. As suggested by Dul (2016), we used the same latent scores calculated for the multiple regression presented above, using standardised values. The CE-FDH showed that, among the three variables involved in the present study, only two have statistical significance (SDS and OS). The CE-FDH shows that both variables have a medium effect (0.25 and 0.23, respectively) on being a necessary condition of BM efficiency. The results of CE-FDH are also graphically shown in Figs. 3 and 4.

The bottleneck analysis, presented in Table 5, also shows that to reach a high level of BM efficiency (60.00%), the necessary levels of SDS and OS should be at 16.67% and 30.00%, respectively. The levels of both necessary conditions steadily increase until 83.33% and 60.00% when the required level of BM efficiency is 80.00% and above. Such results show that both conditions have a medium effect, as they are necessary only when high levels of outcome (BM efficiency) are requested.

Discussion

This study undertakes an investigation into the potential impact of DA, consisting of SDS and OS, on the efficiency of BMs. Prior literature has emphasised the significance of digital technologies and the alignment process in achieving successful BM innovation (Akter et al., 2016; Baden-Fuller & Haefliger, 2013; Sjödin et al., 2020). Alignment across distinct activity domains seeks to achieve a

Table 5. Necessary condition analysis (NCA)

Effect size of condition X on Y	CE-FDH	*p*-value	Effect
SDS	0.25	0.01	Medium ($0.10 \leq d < 0.30$)
OS	0.23	0.06	Medium ($0.10 \leq d < 0.30$)
SF	0.18	0.36 n.s.	Not supported
Bottlenecks CE-FDH X on Y			
BM efficiency (Y)	*SDS*	*OS*	
0.00%	–	–	
10.00%	–	–	
20.00%	–	–	
30.00%	–	–	
40.00%	–	–	
50.00%	–	–	
60.00%	16.67%	30.00%	
70.00%	16.67%	30.00%	
80.00%	83.33%	60.00%	
90.00%	83.33%	60.00%	
100.00%	83.33%	60.00%	

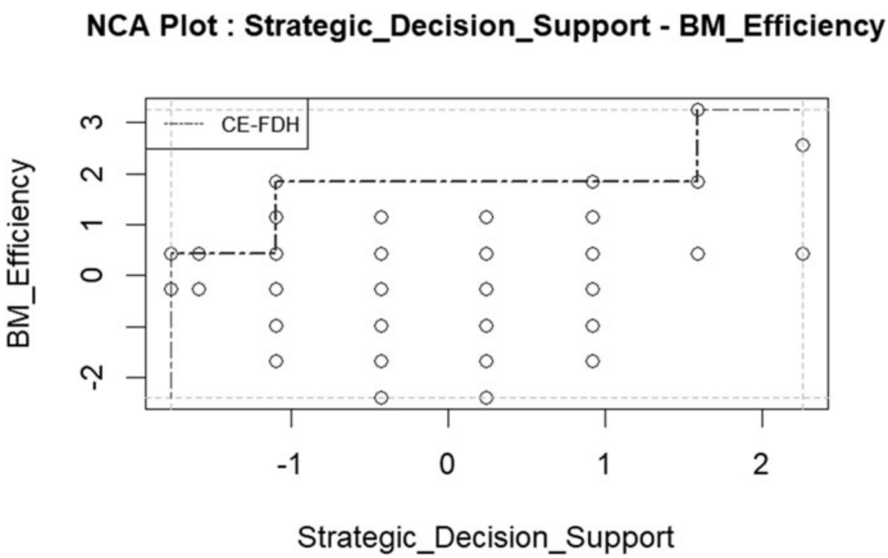

Figure 3. CE-FDH plot for the relationship between SDS and BM efficiency.

fit between systems of value creation and value capture (Demil & Lecocq, 2010; Kaplan & Norton, 2008; Leppänen, George, & Alexy, 2021; Tidhar & Eisenhardt, 2020). A firm's capacity to consistently synchronise its revenue and cost architecture with sources of value creation directly influences performance outcomes (Velu, 2017; Warner & Wäger, 2019).

Digital technologies facilitate detailed analyses of pivotal business decisions and aid strategic business planning (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013), assisting decision-makers in modelling potential courses of action (Tai, Wang, & Yeh, 2019). Consistently, our results point out a

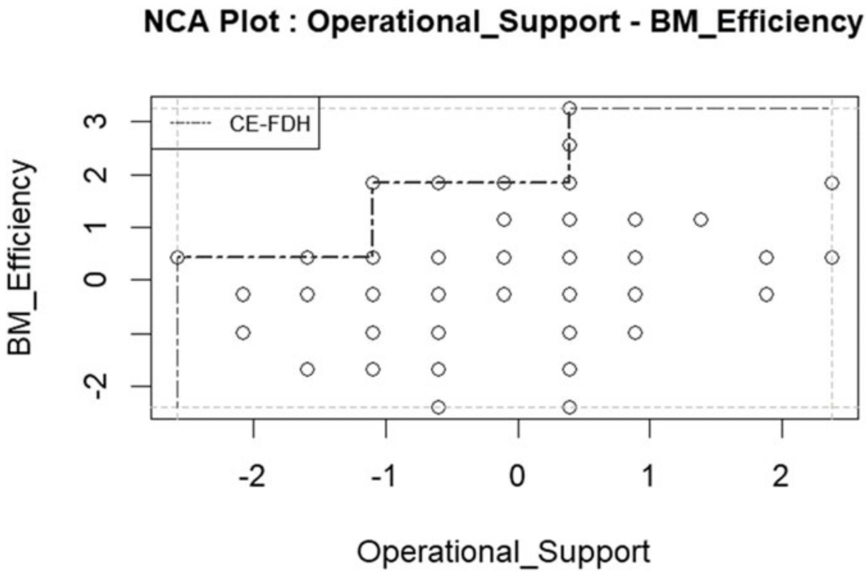

Figure 4. CE-FDH plot for the relationship between OS and BM efficiency.

positive interaction effect between SDS and SF concerning BM efficiency. Moreover, the favourable moderating effect of SF on the relationship between SDS and BM efficiency could manifest as enhanced product strategies through more effective reallocation of organisational resources and identification of optimal market segments for investment (Zhou & Wu, 2010). In this context, SF can enhance the positive impact of digital technologies on BM efficiency by allowing flexible allocation of marketing and production resources (Kretschmer & Khashabi, 2020; Yoo et al., 2012). SF empowers firms to adapt strategic decisions concerning factors such as product design modularity (Zhou & Wu, 2010).

Furthermore, this study identifies SDS and OS as pivotal factors in achieving BM efficiency. These variables exert a medium-level influence, growing increasingly crucial as the target efficiency level escalates. Specifically, to attain a 60.00% efficiency level, SDS should stand at 16.67%, while OS should reach 30.00%. These thresholds exhibit a progressive rise when aiming for an 80.00% efficiency level. Consequently, these variables cease to be optional and evolve into essential components for attaining higher echelons of business efficiency.

Theoretical implications

This study contributes significantly to the existing body of literature in multiple ways. First, we introduce a novel operationalisation of DA within the context of digital BMs. We believe that this conceptual advancement could serve as a linchpin in broadening the academic dialogue surrounding the strategic implications of digitalisation for business efficacy. Our empirical results corroborate a dual impact stemming from both SDS and OS on the level of BM efficiency. This result contributes to the ongoing conversation on the pivotal role of alignment in unlocking the latent potential of BMs (Sjödin et al., 2020), by highlighting the efficacy of DA as a precursor to achieving BM efficiency.

Second, our study contributes to the ongoing discourse concerning the interplay between SF and BM efficiency (Eisenhardt, Furr, & Bingham, 2010). Our empirical investigation reveals that superior SF augments firms' capacity to enhance SDS for achieving BM efficiency. This study improves our understanding of the role of SF (Zhou & Wu, 2010) in organisations, facilitating BM efficiency through a positive interaction with DA. Grounded in the subdimensions of SF, such as the

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flexible allocation of resources and reconfiguring chains of resources, our empirical findings elucidate that SF, in synergy with the strategic decisional support of digital technologies, facilitates a more agile resource reallocation and operational recalibration in response to market dynamics (Chiang, Kocabasoglu-Hillmer, & Suresh, 2012; Han, Wang, & Naim, 2017). This process optimises the utility of digital capabilities also leading to higher operational efficiency and, thus, a more effective BM. The contingent effect of SF engenders theoretical reflections on the intricate interplay between digital strategies and operational efficiency, offering a nuanced framework for understanding this complex relationship (Hayes & Pisano, 1994; Sanchez, 1995). However, SF exerts a non-significant influence in the relationship between OS and BM efficiency. This observation underscores the proposition that SF is a capability intricately tied to strategic pursuits and decision-making processes (Kandemir & Acur, 2012; Nadkarni & Narayanan, 2007), thereby amplifying its potency when directed towards strategic endeavours. At the same time, our study sheds light on the role of SF in augmenting BM efficiency. This is evidenced by instances, such as those within the domain of SMEs operating in the manufacturing sector, wherein alternative pathways to bolstering BM efficiency are pursued, distinct from the avenue of SF development.

In addition, we combine regression analysis and NCA. Particularly, our study delves into the identification of essential prerequisites for the realisation of BM efficiency. Leveraging on NCA, we elucidate the requisite thresholds of SDS and OS necessary to attain specific levels of BM efficiency. The optimal degree of DA for enhancing BM efficiency is contingent upon a firm's strategic approach to BM design. Drawing from the categorisation proposed by Zott and Amit (2010) encompassing novelty, lock-in, complementarities, and efficiency, our results expound that firms prioritising efficiency as a dominant facet of their operational framework necessitate a pronounced level of DA. In contrast, firms allocating partial emphasis on efficiency can suffice with moderate levels of DA.

Practical implications

This study provides significant insights into the intricate relationship between DA and BM efficiency. Through a detailed analysis of the DA and BM efficiency, this study yields a number of practical implications. First, the results underscore the imperative of instating digital technology-enabled BMs to augment efficiency. The results illuminate that the assimilation of digital technologies into the existing BM architecture holds the promise of engendering heightened efficiency.

Second, in the pursuit of attaining optimal efficiency levels, managers are encouraged to meaningfully align both operational and strategic activities. This strategic alignment assumes preeminent significance, as the nexus between OS and SDS is fundamentally symbiotic (Kortmann et al., 2014). For example, firms that have transitioned to digital BMs ought to seamlessly integrate OS systems, such as enterprise resource planning (ERP) software, with the fabric of strategic decision-making processes. This amalgamation ensures that operational data captured by the ERP system contribute substantially to well-informed strategic analyses and decision-making. Such a synergistic approach empowers firms to make informed decisions, leveraging real-time operational insights to not only enhance short-term efficiency but also elevate long-term strategic effectiveness.

Moreover, the study corroborates the pivotal role of aligning digital technologies through the prism of performance metrics and balanced scorecards. The establishment of key performance indicators calibrated to gauge both process and strategic effectiveness empowers manufacturing enterprises to ensure that endeavours geared towards operational efficiency harmonise with the pursuit of overarching long-term strategic objectives. This strategic alignment underscores a comprehensive approach to BM efficiency, striking an intricate equilibrium between immediate operational performance and enduring strategic outcomes.

Within the context of SMEs, a challenge resides in achieving the alignment of operational activities and strategic decisions within their digital BMs. Strategic alignment proves vital in unlocking the full potential of efficiency enhancements. Moreover, strategically agile manufacturing enterprises can thoughtfully invest in mass customisation capabilities to amplify OS for digital technologies, thereby optimally leveraging the influence on BM efficiency. Alternatively, by accentuating semi-structured mechanisms, firms can foster BM efficiency through a symbiosis of SDS and OS measures, encompassing heuristic-based processes and strategic alliance networks.

Furthermore, to optimise the harmonious interplay between digital technology-propelled SDS and SF in fostering BM efficiency, managers can operationalise an array of measures. The integration of meta routines, job enrichment, task-switching, and partitioning mechanisms empowers enterprises to harness the generative potential of SF while concurrently upholding operational efficiency (Adler, Goldoftas, & Levine, 1999). The capacity of digital technologies to facilitate multitasking and foster combinatorial innovation further augments this strategic initiative (Thomas & Tee, 2022; Yoo et al., 2012). However, the study also underscores that while SF bears a pivotal role in enhancing the impact of SDS on BM efficiency, it might not necessarily bear a direct influence on OS. The pursuit of SF could potentially divert resources and attention away from optimising operational efficiency and the existing BM. Moreover, the allocation of resources towards strategic initiatives might inadvertently leave limited resources accessible for OS, thereby potentially undermining endeavours to augment operational efficiency. Consequently, it is incumbent upon firms to strike a balance in their resource allocation, ensuring a meaningful trade-off between fostering SF and enhancing OS to achieve optimal levels of BM efficiency.

Limitations, conclusions, and future work

This study provides a novel perspective on the importance of DA in accomplishing BM efficiency. In addition, it investigates the role played by SF in the previous relationships, contributing to the academic debate about the flexibility-efficiency trade-off.

While the study provides valuable original insights, it is not free of limitations. One such constraint pertains to the omission of external environmental factors as potential moderating variables. Prior literature suggests that elevated levels of SF are requisite in increasingly unstable environments (Akhtar & Sushil, 2018). As such, future inquiries should incorporate environmental contingencies to better elucidate the interplay between DA and SF.

Another methodological limitation lies in the study's cross-sectional design. To substantiate the causal relationships posited, future research could benefit from employing a longitudinal approach. In addition, the study's reliance on self-reported metrics and the absence of temporal separation between the independent and dependent variables introduce potential biases. These methodological choices may compromise the validity of the results undermining the causal pathways under investigation. Therefore, interpretative caution is advised when generalising these results.

Lastly, the study's focus on manufacturing SMEs could limit the generalisability of its results to other sectors or cross-national contexts. Future research could employ cross-country designs to assess the extent to which these results are applicable beyond the specific context examined herein.

References

Aaldering, L. J., & Song, C. H. (2021). Of leaders and laggards – Towards digitalization of the process industries. *Technovation*, *105*, 102211.

Adler, P. S., Goldoftas, B., & Levine, D. I. (1999). Flexibility versus efficiency? A case study of model changeovers in the Toyota production system. *Organization Science*, *10*(1), 43–68.

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. Thousand Oaks, CA: Sage.

Akhtar, M., & Sushil, S. (2018). Strategic performance management system in uncertain business environment: An empirical study of the Indian oil industry. *Business Process Management Journal*, *24*(4), 923–942.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113–131.

Al-Debei, M. M., & Avison, D. (2010). Developing a unified framework of the business model concept. *European Journal of Information Systems*, *19*(3), 359–376.

Allison, P. D. (1999). *Multiple regression: A primer*. Thousand Oaks, CA: Pine Forge Press.

Anupindi, R., & Jiang, L. (2008). Capacity investment under postponement strategies, market competition, and demand uncertainty. *Management Science*, *54*(11), 1876–1890.
Avolio, B. J., Yammarino, F. J., & Bass, B. M. (1991). Identifying common methods variance with data collected from a single source: An unresolved sticky issue. *Journal of Management*, *17*(3), 571–587.
Baden-Fuller, C., & Haefliger, S. (2013). Business models and technological innovation. *Long Range Planning*, *46*(6), 419–426.
Belhadi, A., Kamble, S., Jabbour, C. J. C., Gunasekaran, A., Ndubisi, N. O., & Venkatesh, M. (2021). Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. *Technological Forecasting and Social Change*, *163*, 120447.
Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. V. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, *37*(2), 471–482.
Bogers, M., Hadar, R., & Bilberg, A. (2016). Additive manufacturing for consumer-centric business models: Implications for supply chains in consumer goods manufacturing. *Technological Forecasting and Social Change*, *102*, 225–239.
Bohnsack, R., Kurtz, H., & Hanelt, A. (2021). Re-examining path dependence in the digital age: The evolution of connected car business models. *Research Policy*, *50*(9), 104328.
Bowman, E. H., & Hurry, D. (1993). Strategy through the option lens: An integrated view of resource investments and the incremental-choice process. *Academy of Management Review*, *18*(4), 760–782.
Brozovic, D. (2018). Strategic flexibility: A review of the literature. *International Journal of Management Reviews*, *20*(1), 3–31.
Canhoto, A. I., Quinton, S., Pera, R., Molinillo, S., & Simkin, L. (2021). Digital strategy aligning in SMEs: A dynamic capabilities perspective. *The Journal of Strategic Information Systems*, *30*(3), 101682.
Casadesus-Masanell, R., & Ricart, J. E. (2010). From strategy to business models and onto tactics. *Long Range Planning*, *43*(2-3), 195–215.
Cassetta, E., Dileo, I., & Pini, M. (2023). Linking external collaborations, eco-innovation and sustainable growth. An empirical analysis on the Italian manufacturing firms. *Industry and Innovation*, *30*(4), 452–479.
Chan, Y. E., & Reich, B. H. (2007). IT alignment: What have we learned? *Journal of Information Technology*, *22*(4), 297–315.
Chatterjee, S., & Hadi, A. S. (2006). *Regression analysis by example*. New York, NY: Wiley.
Chen, K. L., Lassen, A. H., Chen, L., & Møller, C. (2022). Exploring the value of IoT data as an enabler of the transformation towards servitization: An action design research approach. *European Journal of Information Systems*, *32*(2), 1–27.
Chen, Y., Liu, H., & Chen, M. (2020). Achieving novelty and efficiency in business model design: Striking a balance between IT exploration and exploitation. *Information & Management*, *59*(3), 103268.
Chen, Y., Visnjic, I., Parida, V., & Zhang, Z. (2021). On the road to digital servitization – The (dis)continuous interplay between business model and digital technology. *International Journal of Operations and Production Management*, *41*(5), 694–722.
Chiang, C., Kocabasoglu-Hillmer, C., & Suresh, N. (2012). An empirical investigation of the impact of strategic sourcing and flexibility on firm's supply chain agility. *International Journal of Operations and Production Management*, *32*(1), 49–78.
Chiarini, A. (2021). Industry 4.0 technologies in the manufacturing sector: Are we sure they are all relevant for environmental performance? *Business Strategy and the Environment*, *30*(7), 3194–3207.
Chong, A. Y. L., Lim, E. T., Hua, X., Zheng, S., & Tan, C. W. (2019). Business on chain: A comparative case study of five blockchain-inspired business models. *Journal of the Association for Information Systems*, *20*(9), 9.
Claussen, J., Essling, C., & Peukert, C. (2018). Demand variation, strategic flexibility and market entry: Evidence from the US airline industry. *Strategic Management Journal*, *39*(11), 2877–2898.
Coltman, T., Tallon, P., Sharma, R., & Queiroz, M. (2015). Strategic IT alignment: Twenty-five years on. *Journal of Information Technology*, *30*(2), 91–100.
Da Silveira, G., Borenstein, D., & Fogliatto, F. S. (2001). Mass customization: Literature review and research directions. *International Journal of Production Economics*, *72*(1), 1–13.
Demil, B., & Lecocq, X. (2010). Business model evolution: In search of dynamic consistency. *Long Range Planning*, *43*(2–3), 227–246.
Di Vaio, A., Palladino, R., Pezzi, A., & Kalisz, D. E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. *Journal of Business Research*, *123*, 220–231.
Dul, J. (2016). Necessary condition analysis (NCA) logic and methodology of "necessary but not sufficient" causality. *Organizational Research Methods*, *19*(1), 10–52.
Dul, J. (2022). *Necessary Condition Analysis. R Package Version 3.2.1*. Retrieved May 23, 2023, from https://cran.r-project.org/web/packages/NCA/
Dul, J., Van der Laan, E., & Kuik, R. (2020). A statistical significance test for necessary condition analysis. *Organizational Research Methods*, *23*(2), 385–395.
Dunford, R., Palmer, I., & Benveniste, J. (2010). Business model replication for early and rapid internationalisation: The ING direct experience. *Long Range Planning*, *43*(5), 655–674.
Eggers, F. (2020). Masters of disasters? Challenges and opportunities for SMEs in times of crisis. *Journal of Business Research*, *116*, 199–208.
Eisenhardt, K. M., Furr, N. R., & Bingham, C. B. (2010). CROSSROADS – Microfoundations of performance: Balancing efficiency and flexibility in dynamic environments. *Organization Science*, *21*(6), 1263–1273.

Gerow, J. E., Grover, V., Thatcher, J., & Roth, P. L. (2014). Looking toward the future of IT–business strategic alignment through the past. *MIS Quarterly*, *38*(4), 1159–1186.

Guo, J., Zhou, S., Chen, J., & Chen, Q. (2021). How information technology capability and knowledge integration capability interact to affect business model design: A polynomial regression with response surface analysis. *Technological Forecasting and Social Change*, *170*, 120935.

Han, J. H., Wang, Y., & Naim, M. (2017). Reconceptualization of information technology flexibility for supply chain management: An empirical study. *International Journal of Production Economics*, *187*, 196–215.

Hayes, R. H., & Pisano, G. P. (1994). Beyond world-class: The new manufacturing strategy. *Harvard Business Review*, *72*(1), 77–86.

Hsuan, J., Jovanovic, M., & Clemente, D. H. (2021). Exploring digital servitization trajectories within product–service–software space. *International Journal of Operations and Production Management*, *41*(5), 598–621.

Kandemir, D., & Acur, N. (2012). Examining proactive strategic decision-making flexibility in new product development. *Journal of Product Innovation Management*, *29*(4), 608–622.

Kaplan, R. S., & Norton, D. P. (2008). Mastering the management system. *Harvard Business Review*, *86*(1), 62.

Kortmann, S., Gelhard, C., Zimmermann, C., & Piller, F. T. (2014). Linking strategic flexibility and operational efficiency: The mediating role of ambidextrous operational capabilities. *Journal of Operations Management*, *32*(7–8), 475–490.

Kretschmer, T., & Khashabi, P. (2020). Digital transformation and organization design: An integrated approach. *California Management Review*, *62*(4), 86–104.

Laursen, K., & Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal*, *27*(2), 131–150.

Leppänen, P., George, G., & Alexy, O. (2021). When do novel business models lead to high firm performance? A configurational approach to value drivers, competitive strategy, and firm environment. *Academy of Management Journal*, *66*(1), 164–194.

Li, W., Liu, K., Belitski, M., Ghobadian, A., & O'Regan, N. (2016). e-Leadership through strategic alignment: An empirical study of small-and medium-sized enterprises in the digital age. *Journal of Information Technology*, *31*(2), 185–206.

Liu, Y., Dong, J., Mei, L., & Shen, R. (2022). Digital innovation and performance of manufacturing firms: An affordance perspective. *Technovation*, *119*, 102458.

Llamzon, R. B., Tan, F. T. C., & Carter, L. (2022). Toward an information systems alignment framework in the wake of exogenous shocks: Insights from a literature review. *International Journal of Information Management*, *63*, 102450.

Marzi, G., Balzano, M., Egidi, L., & Magrini, A. (2023). CLC estimator: A tool for latent construct estimation via congeneric approaches in survey research. *Multivariate Behavioral Research*, *58*(6), 1160–1164.

McNeish, D., & Wolf, M. G. (2020). Thinking twice about sum scores. *Behavior Research Methods*, *52*(6), 2286–2305.

Murray, A., Papa, A., Cuozzo, B., & Russo, G. (2016). Evaluating the innovation of the Internet of Things: Empirical evidence from the intellectual capital assessment. *Business Process Management Journal*, *22*(2), 341–356.

Nadkarni, S., & Narayanan, V. K. (2007). Strategic schemas, strategic flexibility, and firm performance: The moderating role of industry clockspeed. *Strategic Management Journal*, *28*(3), 243–270.

Natalicchio, A., Petruzzelli, A. M., Cardinali, S., & Savino, T. (2018). Open innovation and the human resource dimension: An investigation into the Italian manufacturing sector. *Management Decision*, *56*(6), 1271–1284.

Pati, R. K., Nandakumar, M. K., Ghobadian, A., Ireland, R. D., & O'Regan, N. (2018). Business model design–performance relationship under external and internal contingencies: Evidence from SMEs in an emerging economy. *Long Range Planning*, *51*(5), 750–769.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879.

Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, *92*(11), 64–88.

Rapaccini, M., Saccani, N., Kowalkowski, C., Paiola, M., & Adrodegari, F. (2020). Navigating disruptive crises through service-led growth: The impact of COVID-19 on Italian manufacturing firms. *Industrial Marketing Management*, *88*, 225–237.

Rayna, T., & Striukova, L. (2016). From rapid prototyping to home fabrication: How 3D printing is changing business model innovation. *Technological Forecasting and Social Change*, *102*, 214–224.

Roberts, N., Campbell, D. E., & Vijayasarathy, L. R. (2016). Using information systems to sense opportunities for innovation: Integrating postadoptive use behaviors with the dynamic managerial capability perspective. *Journal of Management Information Systems*, *33*(1), 45–69.

Sanchez, R. (1995). Strategic flexibility in product competition. *Strategic Management Journal*, *16*(S1), 135–159.

Sanchez, R., & Mahoney, J. T. (1996). Modularity, flexibility, and knowledge management in product and organization design. *Strategic Management Journal*, *17*(S2), 63–76.

Sen, S., Savitskie, K., Mahto, R. V., Kumar, S., & Khanine, D. (2022). If it ain't broke, don't fix it? Indian manufacturing SMEs' quest for strategic flexibility. *Journal of Business Research*, *143*, 27–35.

Singh, D., Singh Oberoi, J., & Singh Ahuja, I. (2013). An empirical investigation of dynamic capabilities in managing strategic flexibility in manufacturing organizations. *Management Decision*, *51*(7), 1442–1461.

Sjödin, D., Parida, V., Jovanovic, M., & Visnjic, I. (2020). Value creation and value capture alignment in business model innovation: A process view on outcome-based business models. *Journal of Product Innovation Management*, *37*(2), 158–183.

Tai, J. C., Wang, E. T., & Yeh, H. Y. (2019). A study of IS assets, IS ambidexterity, and IS alignment: The dynamic managerial capability perspective. *Information & Management*, *56*(1), 55–69.

Tallon, P. P., Kraemer, K. L., & Gurbaxani, V. (2000). Executives' perceptions of the business value of information technology: A process-oriented approach. *Journal of Management Information Systems*, *16*(4), 145–173.

Teece, D. J. (2010). Business models, business strategy and innovation. *Long Range Planning*, *43*(2-3), 172–194.

Thomas, L. D., & Tee, R. (2022). Generativity: A systematic review and conceptual framework. *International Journal of Management Reviews*, *24*(2), 255–278.

Tidhar, R., & Eisenhardt, K. M. (2020). Get rich or die trying… finding revenue model fit using machine learning and multiple cases. *Strategic Management Journal*, *41*(7), 1245–1273.

Tu, Q., Vonderembse, M. A., Ragu-Nathan, T. S., & Ragu-Nathan, B. (2004). Measuring modularity-based manufacturing practices and their impact on mass customization capability: A customer-driven perspective. *Decision Sciences*, *35*(2), 147–168.

Urbinati, A., Bogers, M., Chiesa, V., & Frattini, F. (2019). Creating and capturing value from Big Data: A multiple-case study analysis of provider companies. *Technovation*, *84*, 21–36.

Velu, C. (2017). A systems perspective on business model evolution: The case of an agricultural information service provider in India. *Long Range Planning*, *50*(5), 603–620.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118–144.

Visnjic, I., Jovanovic, M., Neely, A., & Engwall, M. (2017). What brings the value to outcome-based contract providers? Value drivers in outcome business models. *International Journal of Production Economics*, *192*, 169–181.

Volberda, H. W., Khanagha, S., Baden-Fuller, C., Mihalache, O. R., & Birkinshaw, J. (2021). Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms. *Long Range Planning*, *54*(5), 102110.

Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52*(3), 326–349.

Yoo, Y., Boland, R. J. Jr, Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, *23*(5), 1398–1408.

Zhang, Q., Vonderembse, M. A., & Lim, J. S. (2003). Manufacturing flexibility: Defining and analyzing relationships among competence, capability, and customer satisfaction. *Journal of Operations Management*, *21*(2), 173–191.

Zheng, L. J., Xiong, C., Chen, X., & Li, C. S. (2021). Product innovation in entrepreneurial firms: How business model design influences disruptive and adoptive innovation. *Technological Forecasting and Social Change*, *170*, 120894.

Zhou, K. Z., & Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. *Strategic Management Journal*, *31*(5), 547–561.

Zott, C., & Amit, R. (2010). Business model design: An activity system perspective. *Long Range Planning*, *43*(2-3), 216–226.

Zott, C., & Amit, R. (2013). The business model: A theoretically anchored robust construct for strategic analysis. *Strategic Organization*, *11*(4), 403–411.

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