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RESEARCH ARTICLE

How manufacturing firms navigate through stormy waters of digitalization: the role of dynamic capabilities, organizational factors and environmental turbulence for business model innovation

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Abstract
Although research has shown that business model innovation (BMI) is an effective means to remain competitive in the digital age, many firms do not respond appropriately and often fail to exploit new digital opportunities. In this study, we adopt a microfoundational approach to understand the role and effects of dynamic capabilities (DCs) on BMI in the context of digitalization. Furthermore, we test how this relationship is influenced by contextual factors. Our results from a survey of German manufacturing firms demonstrate the importance of building strong DCs for effective BMI in the context of digitalization. We also highlight the advantages of an entrepreneurial leadership and mindset in this context. The study further suggests that environmental turbulence in the digital context acts as an antecedent to DCs and BMI, rather than moderating their relationship. While strategic factors indirectly affect BMI as antecedents of DCs, we found no evidence of an influence of the organizational structure.

Key words: Business model innovation; digitalization; dynamic capabilities; environmental turbulence; microfoundations; organizational factors

Introduction

Historically, firms have always been exposed to environmental changes and uncertainties. However, today's business environment has changed enormously. In contrast to previous developments, digitalization significantly affects the nature, scale and speed of environmental change and has the potential to break down traditional industry boundaries and business logics (Brenk, Lüttgens, Diener, & Piller, 2019). Digitalization undoubtedly opens numerous business opportunities, but there are also downsides as current strategies, business models (BMs) and capabilities become obsolete (Rachinger, Rauter, Müller, Vorraber, & Schirgi, 2019; Witschel, Döhla, Kaiser, Voigt, & Pfletschinger, 2019).

Given the highly volatile, uncertain, complex and ambiguous environment (Schoemaker, Heaton, & Teece, 2018), firms need guidance on how to overcome these threats. This is true even for traditional success stories, as in the case of the German industry and its world-renowned label 'made in Germany'. Although digitalization is challenging for firms of all sizes, ages and industries (McAfee & Brynjolfsson, 2017), it is recognized that manufacturing firms are particularly affected by these changes (Björkdahl, 2020; Laudien & Daxböck, 2016). To cope with environmental dynamism, firms need to innovate or adapt their current BMs (Kiel, Arnold, & Voigt, 2017; Rachinger et al., 2019; Saebi, Lien, & Foss, 2017; Westerman, Bonnet, & McAfee, 2014; Zott & Amit, 2017). Yet, only a few manufacturers are responding in a comprehensive and coordinated way and often fail to exploit new digital opportunities, which threatens their competitiveness (Björkdahl, 2020). Most manufacturing firms are predominantly preoccupied with achieving greater efficiency through digital technologies rather than focusing on growth-oriented strategies, such as business model innovation (BMI) (Björkdahl, 2020). Often path dependencies, resource rigidity, missing responsibilities and fear of cannibalization hinder BMI (Chesbrough, 2007; Doz & Kosonen, 2010). However, to take advantage of digitalization, technological issues are not primarily decisive for the effectiveness of digitalization; it is also about building new capabilities and adapting existing resources, organizational activities and structures (Björkdahl, 2020). As the radical change associated with BMI in the digital context implies high requirements to the organization and management of a firm (Leih, Linden, & Teece, 2015; Schoemaker, Heaton, & Teece, 2018), firms need specific capabilities, such as dynamic capabilities (DCs), to build and sustain competitive advantage and thus compete in the digital age. DCs are defined as a 'firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments' (Teece, Pisano, & Shuen, 1997, p. 516) and describe the set of required capabilities for BMI, as enabling resources and structural changes represent the core elements of this explanatory approach (Achtenhagen, Melin, & Naldi, 2013; Leih, Linden, & Teece, 2015; Teece, 2018a).

Despite the research progress related to the important role of DCs for firms adaptability in turbulent environments (Teece, 2007; Wilden, Devinney, & Dowling, 2016) and more recently in the context of BMI (e.g., Achtenhagen, Melin, & Naldi, 2013; Inigo, Albareda, & Ritala, 2017; Leih, Linden, & Teece, 2015; Loon, Otaye-Ebede, & Stewart, 2020; Mezger, 2014; Teece, 2018a), its implication for BMI in times of digitalization remain understudied. Considering that particularly in highly turbulent environments, as in the context of digitalization, DCs are continuously required to sense, seize and transform new digital business opportunities (Teece, 2018a; Warner & Wäger, 2019; Witschel et al., 2019), it is surprising that this research stream is still underdeveloped. Similarly, Vial (2019) notes, 'there is an interesting fit between DC as a conceptual foundation and DT as a phenomenon of interest (…) The ability for firms to design mechanisms that enable repeatable, continuous adaptation in spite of such rapid changes is therefore an important question' (p. 133). Another unresolved question concerns the underlying components that explain how these DCs are developed and how they contribute to effective BMI (Loon, Otaye-Ebede, & Stewart, 2020). Notwithstanding ongoing advances in the microfoundation movement, only a few studies focus on microfoundations relevant to BMI in the digital age (Warner & Wäger, 2019; Witschel et al., 2019). However, understanding microfoundations that represent distinct individual's skills, routines, organizational and managerial process as well as structures (Felin, Foss, Heimeriks, & Madsen, 2012; Teece, 2007) is important, since it reveals relevant factors that affect DCs for BMI (Loon, Otaye-Ebede, & Stewart, 2020) and thus enrich theoretical understanding and practical knowledge on how firms identify, develop and implement digital BMs (Warner & Wäger, 2019; Witschel et al., 2019).

Given the aforementioned research shortcomings, this work echoes ongoing calls that emphasize the need to broaden our understanding of DCs from a microfoundational perspective (Barney & Felin, 2013; Fainshmidt & Frazier, 2017; Fallon-Byrne & Harney, 2017; Loon, Otaye-Ebede, & Stewart, 2020; Schilke, Hu, & Helfat, 2018; Vial, 2019). In this work, we argue that different environmental conditions and contexts, such as BMI in the digital age, require different capabilities, processes and structures. Therefore, adopting a microfoundational lens, we examine the relationship between DCs and BMI in the context of digitalization. Through our partial least square structural equation modeling (PLS-SEM) study among German manufacturing firms, we empirically confirm the positive effects of DCs and highlight the important role of strong DCs for BMI in the context of digitalization. Particularly, using a validated measurement construct that takes into account the underlying processes and structures of DCs that are

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becoming increasingly important in the digital age (Warner & Wäger, 2019; Witschel et al., 2019), we extend the current understanding of microfoundations and thus contribute to DC research, but also to the growing field of research investigating BMI from a DC perspective. Likewise, we contribute to the business perspective in digitalization research, which is still in its nascent stage and lacks empirical evidence on the question how and under what conditions firms can respond to digitalization (Hausberg, Liere-Netheler, Packmohr, Pakura, & Vogelsang, 2019; Vial, 2019; Warner & Wäger, 2019; Witschel et al., 2019).

Given that the development and effectiveness of DCs is influenced by context-specific variables (Baía & Ferreira, 2019; Teece, Pisano, & Shuen, 1997; Wilden, Devinney, & Dowling, 2016; Wilden, Gudergan, Nielsen, & Lings, 2013; Zahra, Sapienza, & Davisson, 2006), we also examine whether and to what extent environmental turbulence (ENVT) and organizational factors moderate the DC–BMI relationship. In doing so, we address criticisms related to research gaps in terms of boundary conditions (Schilke, Hu, & Helfat, 2018) and thus follow Baía and Ferreira's (2019) claim that 'for future research, the inclusion of both organization specific and environmental moderators seems pertinent and necessary' (p. 18).

Finally, we respond to prevailing criticism that 'extant literature has not addressed the link between dynamic capability and the different types of innovation, and how different types of innovation may influence the organizational performance' (Zhou, Zhou, Feng, & Jiang, 2019, p. 733), and finally advance the ongoing debate on the role and consequences of DCs. While we generally acknowledge the indirect effect of DCs and propose BMI as a potential intermediate outcome of organizational performance, we argue, consistent with the position of prior research (e.g., Baía & Ferreira, 2019; Helfat & Peteraf, 2009), that it is critical to first understand the direct DCs effect on potential intermediate outcomes before testing the BMI mediating mechanism on the DC–performance relationship. Thus, in this study, we explicitly focus on the DC–BMI relationship.

Theoretical background and hypotheses development

In recent years, the concept of BMI has received increasing attention in academia and practice. BMI, understood as the 'new competitive advantage' (Bashir & Verma, 2017), enables a firm to align with the changing environment and even disrupt market conditions by developing new business areas (Saebi, Lien, & Foss, 2017). However, despite the research progress on the important role of BMI, knowledge on how incumbents from traditional industries approach BMI in the digital age is scarce (Rachinger et al., 2019; Warner & Wäger, 2019; Witschel et al., 2019). In this context, scholars recently highlight the relevance of DCs as an enabler of BMI in times of digitalization (Teece, 2018a; Warner & Wäger, 2019; Witschel et al., 2019). Nevertheless, Loon, Otaye-Ebede and Stewart (2020) recently state, 'While capabilities are essential for BMI, they are nonetheless "intermediate explanations" and do not themselves per se instructively inform academics and practitioners in how business models are innovated' (p. 703). This critique is consistent with the general view in DCs research, that there is limited understanding on the underlying mechanisms on how DCs are build, expressed and transformed within firms (Fallon-Byrne & Harney, 2017; Felin et al., 2012; Schilke, Hu, & Helfat, 2018). Also, Wilden, Devinney, and Dowling (2016) note that empirical research to date has focused primarily on two foci, either the microfoundations of DCs and their outcome effects, or factors that determine the use of DCs (e.g., structure, culture, environmental context). They criticize this isolated view as oversimplified, neglecting the interdependencies of different system elements and levels of analysis and thus constraining theoretical and empirical progress in DC research. Consequently, 'the effects of DCs (…) need to be investigated using a configurational mindset, that is, including both internal and external factors' (Wilden et al., 2016, p. 1001). These gaps in the literature need to be resolved, as scholars argue that a microfoundational approach may unpack the black-box how firms build DCs for BMI (Loon, Otaye-Ebede, & Stewart, 2020), explain performance heterogeneity among firms (Felin et al., 2012) and provide practical insights into how firms create sustainable advantage (Barney & Felin, 2013).

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Therefore, we go beyond the widespread abstract and generic view of DCs and focus specifically on microfoundations of DCs that relate to managerial and organizational processes, activities and structures, and explain how DCs manifest in BMI practice (Loon, Otaye-Ebede, & Stewart, 2020; Witschel et al., 2019). This is an important issue because recent studies show that opposed to non-digital context, the identification, development and implementation of BMs in digital context require different subcapabilities and processes (Warner & Wäger, 2019; Witschel et al., 2019). However, while these authors provide valuable insights into the role of DCs for BMI and suggest a set of microfoundations relevant to competing in the digital economy, the effect of these capabilities remain unexplored. We therefore build on these qualitative studies and examine the degree of strength of DCs as one factor that positively influences BMI of German manufacturers on their road to digitalization.

Second, to gain a deeper understanding of the DC–BMI relationship, we further consider contextual factors that may influence the formation of DCs as well as their potential outcome effects (Wilden et al., 2016). Consistent with current research, we posit that the effects of DCs are moderated by context-specific factors (Baía & Ferreira, 2019; Schilke, Hu, & Helfat, 2018). Thereby, research on DC and BMI found similar organizational and environmental moderators (Foss & Saebi, 2017; Schilke, Hu, & Helfat, 2018). Regarding organizational factors, scholars indicate that strategic factors matter for both, BMI and DCs (Bereznoi, 2015; Teece, 2018a) and are particularly relevant in the digital context (Kane, Palmer, Phillips, Kiron, & Buckley, 2015). Moreover, leadership (Foss & Stieglitz, 2015; Teece, 2007) and firm's culture with entrepreneurial attributes (Karimi & Walter, 2016; Leih, Linden, & Teece, 2015; Witschel et al., 2019) and the design of organizational structure (Teece, 2018a; Witschel et al., 2019) are further potential factors moderating the DC–BMI relationship. However, the role of organizational factors underlying the DC–BMI relationship is neither sufficiently discussed nor empirically validated, even though it is of high practical relevance which conditions are advantageous to address the challenges of digitalization and successfully transform a BM (Kane, Palmer, Phillips, Kiron, & Buckley, 2016; Witschel et al., 2019). Therefore, we follow recent calls (Foss & Saebi, 2017; Teece, 2018a; Witschel et al., 2019) and focus specifically on the moderating role of these factors. We also consider potential effects of ENVT, whose importance as an external moderator is well-recognized (Schilke, Hu, & Helfat, 2018). This also applies for BMI research, as the competitiveness of BMs needs to be reassessed, particularly in turbulent environments (Leih, Linden, & Teece, 2015). Although all firms face the challenges of digitalization, they may be affected differently. Environmental dynamics such as regulatory changes or new technologies may not affect all companies equally, which therefore face varying degrees of turbulence in their business environment. Therefore, we examine the role of ENVT and, similar to Wilden and Gudergan (2015), consider aspects associated with changes in technology, market, regulation, competition and competitive intensity.

Figure 1 illustrates our research framework.

DCs for BMI and their microfoundations

Overall, there is growing consensus in current research that strong DCs are essential for BMI (e.g., Achtenhagen, Melin, & Naldi, 2013; Leih, Linden, & Teece, 2015; Schoemaker, Heaton, & Teece, 2018; Witschel et al., 2019). Following Teece (2018a), the speed and degree of firm's alignment to changing environments are determined by the strength of DCs. Thus, a firm with limited DCs may recognize business opportunities but be unable to innovate its BM due to a lack of seizing and transforming capabilities. Firms with strong DCs have therefore a broader range of potential BMs that can lead to radical shifts (Teece, 2018a). DCs also determine the speed of BMI, as strong sensing capabilities enable a firm to recognize business opportunities early, seize them quickly and transform the organization accordingly (Teece, 2018a). Hence, firms with strong DCs can change their BMs before rivals do and may even shape their surrounding in their favor (Schoemaker, Heaton, & Teece, 2018). Therefore, we hypothesize:

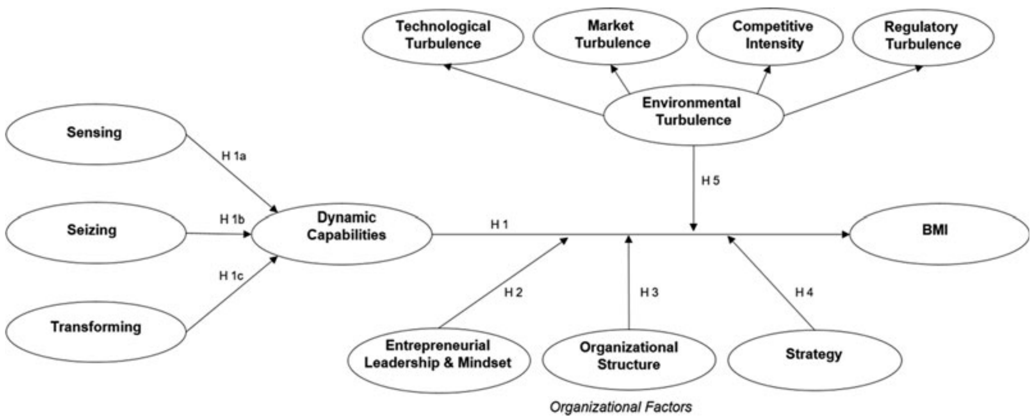

Figure 1. Research framework.

Hypothesis 1: The strength of DCs has a positive effect on BMI.

Since DCs are defined by the three dimensions, sensing, seizing and transforming (Teece, 2007), we apply this disaggregated view to discuss in more detail the link between each dimension and BMI. We focus specifically on the microfoundations that are relevant in the digital age and which we call hereafter as subcapabilities (Warner & Wäger, 2019; Witschel et al., 2019).

First, we argue that the capability to sense new business opportunities is a crucial initial step for BMI, as strong sensing capabilities enable monitoring the external environment and identifying relevant opportunities and threats. This allows a firm to assess the durability of its BM and determine the need for change (Schoemaker, Heaton, & Teece, 2018; Teece, 2014). As high market dynamics with short technology and innovation cycles prevail in the digital age, deep market understanding and early recognition of trends are important subcapabilities of sensing (Day & Schoemaker, 2016; Warner & Wäger, 2019; Witschel et al., 2019). Sensing also involves a deep understanding of customer requirements (Teece, 2018a; Warner & Wäger, 2019; Witschel et al., 2019). Particularly concerning digital solutions, interactively experimenting with customers is relevant to identify latent needs (Day & Schoemaker, 2016; Witschel et al., 2019). Since most digital BMs are customer-centric, firms must also design the value proposition and revenue model to ensure long-term success (Teece, 2010, 2018a; Witschel et al., 2019). Similarly, open innovation is increasingly important to identify digital business opportunities (Warner & Wäger, 2019; Westerman et al., 2014; Witschel et al., 2019). Accordingly, seeking dialog with stakeholders outside the firm and involving them in a suitable form is an important subcapability of sensing (Inigo, Albareda, & Ritala, 2017; Witschel et al., 2019). Therefore, we propose:

Hypothesis 1a: The degree of sensing capabilities has a positive effect on BMI.

Second, sensing capabilities are required but not sufficient for BMI because the firm also has to seize the identified opportunities (Schoemaker, Heaton, & Teece, 2018). This involves subcapabilities such as the identification, efficient deployment and allocation of relevant resources and competencies that enable the implementation of innovation activities to create and capture value from the most promising business opportunity (Leih, Linden, & Teece, 2015). Another key subcapability for the development and refinement of BMs represents the organization of the development team, as interdisciplinary knowledge needs to be brought together and bundled (Mezger, 2014). This is a very important feature particularly in a digital context (Teece, 2018a; Witschel et al., 2019). The capability to develop new BMs in an agile and iterative manner is also highly relevant in the digital context (Mezger, 2014; Warner & Wäger, 2019; Witschel et al., 2019). To ensure that a new digital solution optimally satisfies customer needs, continuously testing products and services with end users and directly incorporating their feedback is also critical to success (Amit & Han, 2017; Witschel et al., 2019). Finally, data and IT security issues are critical to competitiveness. Similarly, the sustainable establishment of platforms plays a key role. Thus, firms must effectively implement these IT-based activities (Oswald & Kleinemeier, 2017; Porter & Heppelmann, 2015; Witschel et al., 2019). Therefore, we propose:

Hypothesis 1b: The degree of seizing capabilities has a positive effect on BMI.

Third, transforming capabilities are required to adapt, renew and reshape a firm's resource base or even its entire ecosystems to take full advantage of BMI (Schoemaker, Heaton, & Teece, 2018). They enable a firm to transform elements of its organization and culture to address new opportunities identified in the sensing and seizing process (Teece, 2018a). They are also required to address rigidities within a firm (Leih, Linden, & Teece, 2015), which is especially relevant for manufacturing firms, as they often develop strong resource rigidity over time. For instance, investments in highly specialized manufacturing assets usually imply the goal of high efficiency, which leads to rigidity (Teece, 2018a), and in turn negatively affects a firm's ability to align its BM with environmental changes (Teece, 2018a). Therefore, organizational measures and activities are required to ensure a sustainable organization (Day & Schoemaker, 2016; Inigo, Albareda, & Ritala, 2017; Warner & Wäger, 2019; Witschel et al., 2019). The allocation and development of key competencies are further important subcapabilities of transforming. Digitalization requires many new competencies related to the use and application of digital technologies, which has to be built and developed (Oswald & Kleinemeier, 2017; Warner & Wäger, 2019; Witschel et al., 2019). Equally relevant is fostering internal information and knowledge-exchange to create transparency and change awareness among employees (Song, Lee, & Khanna, 2016; Witschel et al., 2019). Moreover, collaboration with external partners and building ecosystems is important (Day & Schoemaker, 2016; Schoemaker, Heaton, & Teece, 2018; Warner & Wäger, 2019; Witschel et al., 2019). The ability to build relationships with strategic partners who have complementary resources and competencies is critical for successful BM scaling (Mezger, 2014; Rice, Liao, Martin, & Galvin, 2012; Witschel et al., 2019). We hypothesize:

Hypothesis 1c: The degree of transforming capabilities has a positive effect on BMI.

Role of organizational factors

Moderating effect of entrepreneurial leadership and mindset

Prior research has recognized the important role of leadership and cultural factors for BMI (Chesbrough, 2007; Foss & Stieglitz, 2015). This is particularly important for BMI in the digital age, as digitalization implies a high degree of disruption and ongoing process of strategic renewal (Kane et al., 2015; Schoemaker, Heaton, & Teece, 2018; Vial, 2019; Warner & Wäger, 2019; Witschel et al., 2019). Indeed, BMI is different in the digital age, as the speed and complexity of environmental change require greater commitment and involvement from top management (Kane et al., 2015; Witschel et al., 2019). Regarding this, scholars (Karimi & Walter, 2016; Schoemaker, Heaton, & Teece, 2018; Witschel et al., 2019) highlight the role of entrepreneurial leadership and a 'culture that favors rapid response and the nurturing of specialized knowledge to be successful' (Teece, 2000, p. 42). Teece (2014) assumes that entrepreneurial leadership is positively associated with sensing, while Witschel et al. (2019) view it as fundamental also for seizing. Thus entrepreneurial leadership and culture determine the 'encouragement to experiment,' 'failure and learning culture,' 'willingness to invest in new ideas' and 'willingness to

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take risks and cannibalize' (Karimi & Walter, 2016; Schoemaker, Heaton, & Teece, 2018; Witschel et al., 2019), which we summarize as entrepreneurial leadership and mindset (ELMS).

It is generally accepted that, a 'discovery-driven' approach that focuses on experimentation and learning is preferable to BMI (Achtenhagen, Melin, & Naldi, 2013; Bereznoi, 2015; McGrath, 2010; Sosna, Trevinyo-Rodríguez, & Velamuri, 2010; Teece, 2018b). These activities are also positively associated with DCs (Schoemaker, Heaton, & Teece, 2018) and especially relevant for sensing and seizing (Mezger, 2014). In their concept of strategic agility, Doz and Kosonen (2010) emphasize experimentation as a leadership task, which helps to challenge the current BM and prototype new business ideas. Similarly, Teece (2010) indicates the need to experiment with BM and learn from competitors. Thus, we argue that a culture that encourages experimentation and learning creates positive conditions for the DC–BMI relationship.

However, experimenting with new ideas is costly and requires an adequate provision of funding (Achtenhagen, Melin, & Naldi, 2013; Kane et al., 2015). There are many examples of companies that fell short of their expectations because they focused their investments only on technology while neglecting organizational factors (Kane et al., 2015).

Overcoming risk aversion and willingness to break existing business patterns or even cannibalize the core business are further recognized entrepreneurial traits positively associated with innovativeness (Pérez-Luño, Wiklund, & Cabrera, 2011; Schoemaker, Heaton, & Teece, 2018). It is argued that in digitally matured firms, risk-taking has become a cultural norm. It is therefore a key leadership task to transform the cultural mindset toward entrepreneurship and make it less risk-averse (Kane et al., 2015; Leih, Linden, & Teece, 2015).

Accordingly, we argue that ELMS promotes cultural conditions that positively affect the DC–BMI relationship. ELMS promotes sensing and seizing, which leads to more creativity and innovation. Moreover, the future orientation and openness of an entrepreneurial culture stimulates flexibility and experimentation, reduces transformation barriers and thus fosters BMI (Teece, 2018b). Therefore, we hypothesize:

Hypothesis 2: The degree of ELMS positively moderates the DC–BMI relationship.

Moderating effect of organizational structure

In current literature, the question whether an organic or mechanistic organizational structure is more favorable for DCs remains unclear (Wilden, Devinney, & Dowling, 2016). On the one hand, it is argued that a highly organic structure is beneficial for DCs to enhance firm's success (Teece, 2000; Wilden et al., 2013). According to Teece (2000), an organization that has a decentralized, non-bureaucratic decision-making structure or even the ability to self-govern is highly flexible and can respond to external changes with a faster decision-making process. In particular, this type of structure can facilitate sensing and seizing activities. Conversely, others highlight the advantages of a mechanistic structure associated with centralized decision-making, high formalization and tight control of information flow. For example, different control mechanisms can foster innovation (Cardinal, 2001), but also 'enable efficient information processing, knowledge development and sharing, coordination and integration, and more generally, collective action' (Felin et al., 2012, p. 1364). Similarly, it can support BM stability and operational efficiency, but can also lead to rigidity and hinder BMI (Saebi, 2015). Since we assume that a mechanistic structure impedes transforming capabilities, we expect that an organic structure, implying decentralized decision-making, low formalization and high integration (Burns & Stalker, 1961), will strengthen the DC–BMI relationship.

Scholars found that decentralization of decision-making positively affects DCs (Leih, Linden, & Teece, 2015; Schoemaker, Heaton, & Teece, 2018; Teece, 2007; Wilden et al., 2013). One example is the leading hearing aid manufacturer Oticon, whose restructuring from a mechanistic to an organic structure led to a revival of innovative and entrepreneurial capabilities (Leih, Linden, & Teece, 2015). The new structure, characterized by low hierarchies, high degree of

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self-organization and project orientation, facilitated the capabilities of sensing and seizing (Leih, Linden, & Teece, 2015). Also, this structure combined with DCs, enhances firm's responsiveness and adaptability required in turbulent environments (Andersen & Nielsen, 2009; Rindova & Kotha, 2001). Thus, we derive that a decentralized structure facilitates the DC–BMI relationship.

There are opposed views whether formalization constrains communication and knowledge exchange (Pertusa-Ortega, Zaragoza-Sáez, & Claver-Cortés, 2010), which represents a key microfoundation of DCs. High formalization includes established work routines and limited decision-making autonomy (Agarwal, 1993), which can impede essential elements of an entrepreneurial culture, for example, experimentation, risk-taking or exploration (Burns & Stalker, 1961; Menguc & Auh, 2010). Van der Panne, van Beers, and Kleinknecht (2003) found that a formalized structure counteracts the trial-error-approach that is important for BMI. Also, formalization is associated with a high level of bureaucracy (Menguc & Auh, 2010), which fosters rigidity and impedes creativity (Hartline, Maxham, & McKee, 2000). Contrary, less formalization fosters the use of new information and opportunities, leading to more effective seizing capabilities (Deshpande & Zaltman, 1982; Wilden et al., 2013). Therefore, we assume that low formalization will strengthen the DC–BMI relationship, as it stimulates idea generation, provides a setting to exploit these and increases flexibility during the transformation process.

Moreover, a decentralized structure requires high coordination and communication to align different departments and share best practices. Regarding this, scholars highlight the value of internal cooperation and knowledge-exchange for DCs (Achtenhagen, Melin, & Naldi, 2013; Leih, Linden, & Teece, 2015; Witschel et al., 2019). High integration enhances sensing by fostering creativity and diverse perspectives among employees. Also, seizing and transforming activities require high levels of internal communication and collaboration (Achtenhagen, Melin, & Naldi, 2013; Leih, Linden, & Teece, 2015). Thus, we assume that a high integration degree is favorable for the DC–BMI relationship.

Considering all aspects together, we hypothesize:

> Hypothesis 3: A highly organic organizational structure positively moderates the DC–BMI relationship.

Moderating effect of strategy

Research has also highlighted the role of strategy for DCs and BMI (Foss & Saebi, 2017; Leih, Linden, & Teece, 2015; Teece, 2014). Generally, there is consensus in literature that strategy and BMI need to be aligned (Kane et al., 2016; Teece, 2018a; Witschel et al., 2019). However, the role of strategy in the DC–BMI relationship is not clearly defined. Strategy is considered as an antecedent of DCs and of BMI, but also as a moderator of this relationship (Foss & Saebi, 2018; Schilke, Hu, & Helfat, 2018). This depends on which strategic aspects are observed in the respective studies. While a strategic shift is considered as a trigger of BMI, different strategy types are regarded as potential moderators (Foss & Saebi, 2018). In this work, we refer to research findings that show that digital mature firms have a clear communicated and embedded vision and a digital strategy to guide digitalization (Bereznoi, 2015; Kane et al., 2015) and thus expect that strategy affects the strength of DCs on BMI (Witschel et al., 2019). More recently, Witschel et al. (2019) also found evidence for the moderating impact of strategic issues, which are crucial for DCs. While strategy can provide guidance for sensing, a firm's vision guides seizing and transforming. Similarly, Teece (2014) highlights the interaction between the DC-dimensions and Rumlet's elements of strategy. Thereby, sensing relates to diagnosis while seizing and transforming interacts with guiding policy and coherent action (Teece, 2014). Hence, we hypothesize:

> Hypothesis 4: A clear and organizational embedded vision and digital strategy positively moderates the DC–BMI relationship.

Role of ENVT

The core idea that DCs are helpful to address rapidly changing environments (Teece, Pisano, & Shuen, 1997) and the organization's ability to influence its environment (Teece, 2007) let assume that the strength of DCs is especially relevant in turbulent environments. Many scholars followed this view, which is why ENVT is the most frequently used moderator in literature (Schilke, Hu, & Helfat, 2018; Wilden, Devinney, & Dowling, 2016). According to Teece (2018a), the strength of DCs determines the speed and degree of firm's BM alignment with environment changes. For this reason, we argue that DCs positively affect BMI. Both speed and degree of alignment seem to be especially crucial in a highly turbulent environment. In this regard, strong sensing is required to detect changes before rivals do and to understand their implications on the firm and competition (Schoemaker, Heaton, & Teece, 2018). Also, strong seizing and transforming capabilities enable a firm to change its BMs adequately and timely. This way firms can differentiate and stay competitive (Wilden et al., 2013; Zahra, 1993). There is evidence that firms with strong DCs are faster in the BMI process, which may lead to a first-mover advantage (Wilden et al., 2013) and is particularly important for platform-based BMs (Schoemaker, Heaton, & Teece, 2018). Moreover, a highly turbulent environment requires more fundamental organizational changes and thus an even higher need for transforming capabilities to address this turbulence and to soften rigidities. In contrast, firms operating in a stable environment or in a monopoly position have fewer needs for BMI than firms facing strong competition, new technology or regulatory shifts (Auh & Menguc, 2005; Wilden et al., 2013). We hence conclude that strong DCs seem to be especially required in turbulent environments and hypothesize:

> Hypothesis 5: The degree of environmental turbulence positively moderates the DC–BMI relationship.

Methods

Data collection and sample

For our sample, we focused on the German manufacturing industry for several reasons. First, Germany as a global manufacturing leader and the most important pillar of economic strength is embracing the emerging Industry 4.0. Second, the digitalization trend is forcing the industry's players as traditional hardware natives to combine their physical products with digital services in order to create hybrid solutions for customers (Brenk et al., 2019). Third, due to their long history and good reputation, companies are more rigid on the path to digitalization, as their success has positively reinforced their trust in conventional ways of working. Fourth, with digitalization, a paradigm shift is coming. The focus of strategic considerations will shift from a supply chain to an ecosystem view focusing on digital technologies, platforms and data-driven BMs (Demchenko, De Laat, & Membrey, 2014). Accordingly, deeper BMI insights are especially important for German manufacturing firms.

Standard & Poor's Capital IQ platform was used as a single-source to identify firms classified to the manufacturing industry applying the Standard Industry Classification codes 20–39. Using different platforms (e.g., XING, LinkedIn, firms' websites), we searched for key informants and finally sent personalized emails with a link to our online survey. To increase the response rate, we offered the questionnaire in German or English, assured confidentiality and anonymity and incentivized respondents to participate by offering the study results. During data collection, we continuously tracked response behavior and termination rate. This allowed making minor adjustments to improve the response rate. Finally, 123 of the 2061 contacted firms completed the questionnaire, resulting in a response rate of 5.97%. To address typically data collection issues, for example, missing data, outliers and suspicious response patterns (Hair, Hult, Ringle, & Sarstedt, 2014), we checked the data and assessed their plausibility and correctness. Thereby, we removed one observation due to straight lining issues, where the respondent only selected

Table 1. Descriptive results of the respondents and sample

Factors	Sample ($N = 119$)	Percentage
Respondent's position		
CEO/Executive	35	29.4
CDO/CIO	2	1.7
(Senior) Vice President	4	3.4
Director	11	9.2
Head of Digital Business/Innovation	10	8.4
Head of Department	11	9.2
Manager	43	36.1
Not specified	3	2.5
Respondent's job tenure (in years)		
1–4	65	54.6
5–10	41	34.4
11–15	5	4.2
>15	6	5.0
Not specified	2	1.7
Firm age (in years)		
<10	3	2.5
10–20	7	5.9
20–40	18	15.1
40–60	20	16.8
60–80	28	23.5
80–100	16	13.4
100–120	5	4.2
>120	22	18.5
Sales revenue (in Mio. Euro)		
<1	1	0.8
1–49	30	25.2
50–250	47	39.5
250–500	16	13.4
500–10,000	11	9.2
>10,000	14	11.8

'1 strongly disagree.' Besides, since only observations covering more than 97% of the indicators were included, we deleted three observations due to missing data. The remaining missing data points were replaced by the mean value of the respective indicator. Thereby, we met the criteria for mean value replacement of a maximum of 5% missing values per indicator in any case (Hair et al., 2014). This procedure resulted in a final sample size of 119 firms. For descriptive statistics of the sample and respondents, see Table 1.

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Structural modeling

For hypothesis testing we used PLS-SEM, which is increasingly used in management research (Hair, Sarstedt, Ringle, & Gudergan, 2018). Besides, consistent with prior studies (e.g., Karimi & Walter, 2016; Wilden et al., 2013) and recommended by leading scholars in the area of PLS-SEM (Ringle, Wende, & Becker, 2015), we applied SmartPLS software.

We selected PLS-SEM for several reasons, which makes PLS-SEM appropriate to test our hypotheses. First, compared to covariance-based SEM (CB-SEM), the soft-modeling approach PLS-SEM is less suited for well-established theories, but more appropriate in exploratory research, where the objective is theory development (Hair et al., 2014). Due to scarce theoretical and empirical knowledge on the proposed relationships, this study is categorized as preliminary exploratory. To the best of our knowledge, the relationship between DC, BMI, organizational factors and ENVT has not been empirically tested. Second, it allows including unobservable variables, which need to be measured indirectly by indicator variables (Fornell & Larcker, 1981). In this study, the DC construct includes the capability to sense, seize and transform, which cannot be observed directly and hence need to be measured by several indicators. This also applies to the organizational factors and partly for the BM construct and ENVT. Third, reflective, formative and single-item constructs can be used directly by applying PLS-SEM, whereas the common factor approach CB-SEM is limited to the use of formative measurements and would require modifications of the construct specification (Hair et al., 2014; Henseler, Ringle, & Sinkovics, 2009). This is an important feature, as we used all three kinds of measurement constructs. Fourth, PLS-SEM results are robust for potential non-normal distributed data with excess kurtosis and skewness (Ringle, Götz, Wetzels, & Wilson, 2009). Finally, PLS-SEM leads to higher statistical power than the alternative CB-SEM when testing a complex model with a relatively small sample size as in our study (Hair et al., 2014; Reinartz, Haenlein, & Henseler, 2009).

Measures

Given that the research area of this study is relatively new and only a limited number of empirical studies have examined the DC–BMI relationship, we had to develop new measurement constructs or at least partially adapt existing ones (see Appendix 1). For this, we first created a pool of indicators for each construct based on an extensive literature review, clustered them and defined the measurement scales in an iterative process. Finally, we partly adapted the indicators to set them into the context of digitalization. Feedback loops with external and independent researcher and a pilot study among graduate management students helped to optimize and validate our questionnaire design and minimize item ambiguity. This procedure, along with assuring respondent confidentiality helped to address common method bias concerns (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). All constructs, except the control variables, were measured applying a 7-point Likert scale, ranging from 1 'strongly disagree' to 7 'strongly agree'. Table 2 shows the measurement scales with related test statistics.

Dynamic capabilities

Following Wilden et al. (2013), we measured DCs as a type II multi-dimensional second-order index (reflective-formative type). We measured the higher-order component (HOC) of the DC construct formatively by the three lower-order components (LOCs) sensing, seizing and transforming, which were measured reflectively. For scale development, we compiled items drawn from various studies, whereby we mainly refer to Witschel et al. (2019), since their work examines the relevant microfoundations for BMI in the digital age and thus fits to our research context. We measured sensing using four items: collaboration with external partners and customers in the ideation phase (Makkonen, Pohjola, Olkkonen, & Koponen, 2014; Wilden et al., 2013; Witschel et al., 2019), use of established processes for customer integration (Fainshmidt & Frazier, 2017;

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Table 2. Validated measurement constructs

Construct	Indicator	Item	Mean	SD	1st order loading	2nd order loading	AVE	CR	α
DCs (2nd order construct, repeated items see below)									
Sensing	In my company…						.71	.91	.86
	we use an open innovation approach to generate new ideas by collaborating with external partners from both in- and outside our industry (e.g., professional associations, research communities).	SEN1	3.71	1.81	.77***	.72***			
	we use established processes to integrate our customers in the idea generation process.	SEN2	3.54	1.76	.87***	.75***			
	we use systematic processes to identify new trends and market dynamics in time.	SEN3	3.38	1.60	.87***	.77***			
	we specify and evaluate our benefit promise and conceptualize our revenue mechanism.	SEN4	3.80	1.74	.84***	.78***			
Seizing	In my company…						.56	.83	.72
	we integrate our customers in the development process and change our practices if customer feedback gives a reason for change.	SEI1	4.97	1.56	.44***	.38***			
	we apply agile methods (e.g., scrum) in the development of new business ideas free from bureaucracy.	SEI2	3.44	1.82	.81***	.73***			
	we systematically allocate key resources and competencies for the development of new business activities and cooperate with external partners if appropriate (e.g., IT-developer).	SEI3	3.97	1.58	.83***	.78***			
	we develop a sustainable platform architecture and the implementation of adequate IT security measures.	SEI4	4.16	1.83	.83***	.76***			
Transforming	In my company…						.54	.82	.71
	we encourage internal communication as well as the exchange of information and best practices within the entire organization.	TRA1	4.73	1.38	.50***	.42***			

	we substantially transform and restructure our organization to ensure a sustainable and digital alignment (e.g., acquisitions, institutionalization of Data Analytics/Digital Transformation departments).	TRA2	3.73	1.67	.79***	.58***			
	we scale our BM by using intra- and cross-industry cooperation or accelerator programs.	TRA4	2.92	1.54	.76***	.69***			
	we ensure a sustainable allocation and development of digital key competencies.	TRA5	4.06	1.53	.84***	.76***			
ENVT							.58	.84	.75
	within our industry, technology is changing rapidly leading to new product/service opportunities.	TEC1	3.67	1.83	.85***				
	within our industry, customers' product preferences are changing rapidly over time.	MAR1	3.42	1.62	.86***				
	we are witnessing demand for our products/services from customers who have never bought from us before.	MAR2	3.75	1.60	.66***				
	our main competitors have changed.	COM2	3.57	1.74	.64***				
ELMS							.72	.91	.87
	Top management shows a high willingness to invest and sponsor new business ideas.	LMS1	4.76	1.66	.87***				
	We are willing to develop and commercialize fundamental new business ideas even if they are likely to cannibalize our core business.	LMS2	4.03	1.70	.85***				
	Employees are encouraged to generate new ideas and experiment with them.	LMS3	4.47	1.56	.86***				
	Employees' failures are associated positively as learning opportunity.	LMS4	4.38	1.62	.81***				
Structure (2nd order construct, repeated items see below)									
Decentralization							.78	.88	.72
	Most decisions, even small matters, are made by the top management.	STR1	4.60	1.65	.89***	.75***			
	Management favors superior decision making with minimum consultation and involvement of subordinates.	STR2	4.76	1.36	.88***	.73***			

(*Continued*)

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Table 2. (*Continued.*)

Construct	Indicator	Item	Mean	SD	1st order loading	2nd order loading	AVE	CR	α
Formalization							.81	.89	.76
	We emphasize to follow formal written procedures whatever situation arises.	STR3	4.63	1.34	.91***	.78***			
	We emphasize that employees adhere to formal job descriptions.	STR4	5.26	1.38	.89***	.70***			
Integration	Employees of different departments are encouraged to collaborate and communicate closely.	STR5	4.74	1.51	SIM	.46***			
Strategy	We have a clear vision in line with our corporate strategy that is communicated and embedded in the entire organization.	STG1	4.40	1.59	SIM				
	We have a digital strategy as part of the corporate strategy.	STG2	3.84	1.88	SIM				

Significance levels (p-values): $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Wilden et al., 2013; Witschel et al., 2019), systematic processes for timely trend and market recognition (Makkonen et al., 2014; Witschel et al., 2019) and specification and evaluation of benefit promise and conceptualization of revenue mechanism (Witschel et al., 2019). For seizing, we also used four items: customer integration in the development process (Fainshmidt & Frazier, 2017; Wilden et al., 2013; Witschel et al., 2019), application of agile methods for developing new business ideas (Kurtmollaiev, Pedersen, Fjuk, & Kvale, 2018; Witschel et al., 2019), allocation of key resources and competencies (Makkonen et al., 2014; Witschel et al., 2019) and implementation of sustainable IT platform architecture and IT security measures (Witschel et al., 2019). Transforming includes: degree of internal communication, information exchange and best practices (Makkonen et al., 2014; Witschel et al., 2019), degree of transformation and restructuring to ensure sustainable and digital alignment (Fainshmidt & Frazier, 2017; Wilden et al., 2013; Witschel et al., 2019), use of intra and cross-industry cooperation or accelerator programs to scale new BMs (Witschel et al., 2019) and allocation and development of key digital competencies (Witschel et al., 2019).

Environmental turbulence

We measured ENVT through four dimensions. Thereof technological and market turbulence, and competitive intensity are similar to Jaworski and Kohli (1993), Wilden et al. (2013) and Wilden and Gudergan (2015). Regulatory turbulence was added as a further dimension, which is particularly relevant in the digital context (Saebi, 2015; Witschel et al., 2019). We adapted all items from other studies and explicitly referred to the context of digitalization. We assessed technological turbulence by asking for the speed of technological change leading to new product and service opportunities (Jaworski & Kohli, 1993; Wilden & Gudergan, 2015). The items for market turbulence cover the speed of changing customers' product preferences (Jaworski & Kohli, 1993; Schrauder, Kock, Baccarella, & Voigt, 2018; Wilden & Gudergan, 2015) and the degree to which firms witness demand from new customers (Jaworski & Kohli, 1993; Wilden & Gudergan, 2015). Competitive intensity considers the general degree of competition and the change of main competitors (Jaworski & Kohli, 1993; Wilden et al., 2013; Wilden & Gudergan, 2015). Finally, regulatory turbulence takes the impact of regulatory uncertainties into account.

Organizational factors

To measure organizational structure, we used a multi-dimensional second-order index (reflective-formative-type). Decentralization includes two items: the extent of decision-making by top management (Dedahanov, Rhee, & Yoon, 2017; Deshpande & Zaltman, 1982; Hage & Aiken, 1967; Jaworski & Kohli, 1993) and the degree of involvement and consultation of subordinates in decision-making (Dedahanov, Rhee, & Yoon, 2017; Jaworski & Kohli, 1993; Khandwalla, 1977; Slevin & Covin, 1990). Formalization includes two items measuring the extent to which formal procedures and adherence to formal job descriptions are emphasized (Dedahanov, Rhee, & Yoon, 2017; Deshpande & Zaltman, 1982; Jansen, van den Bosch, & Volberda, 2006). Integration includes one item addressing the extent of collaboration and communication across departments (Dedahanov, Rhee, & Yoon, 2017; Germain, 1996).

For ELMS, we used a reflective construct with four items: willingness to invest in new ideas (Witschel et al., 2019), willingness to take risks (Karimi & Walter, 2016), degree to which employees are encouraged to experiment with new ideas (Karimi & Walter, 2016; Witschel et al., 2019) and the presence of a failure and learning culture (Cannon & Edmondson, 2005).

Finally, we measured strategic factors as a reflective measurement construct, including communication and embeddedness of a clear vision and corporate strategy, and the existence of a digital strategy as a part of a corporate strategy (Kane et al., 2015; Witschel et al., 2019).

Business model innovation

As there is no generally accepted measurement construct for BMI (Foss & Saebi, 2017) and only a few validated scales exist (i.e., Clauss, 2017; Spieth & Schneider, 2016), we developed a new

Table 3. Cluster analysis BMI

(a) Cluster analysis (final cluster centers)		
	Cluster	
	1 'BM adaptors' ($n = 64$)	2 'BM innovators' ($n = 55$)
New value proposition	2.93	5.02
New structure of value delivery	2.41	4.89
New value capture	2.02	4.57

(b) Cluster analysis (ANOVA)						
	Cluster		Error		*F*	Sig.
	Mean square	*df*	Mean square	*df*		
New value proposition	129.103	1	1.045	117	123.587	.000
New structure of value delivery	181.448	1	.952	117	190.647	.000
New value capture	193.432	1	.941	117	205.467	.000

Note: The *F*-tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not correct for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

construct by adapting and recombining existing ones. Thereby, we used the nine building blocks of a BM (Osterwalder & Pigneur, 2010) and allocated them to the dimensions value proposition, value delivery and value capture (Clauss, 2017; Osterwalder & Pigneur, 2010; Saebi, Lien, & Foss, 2017). In the next step, we defined a measurement scale for BMI, drawing on previous studies (Achtenhagen, Melin, & Naldi, 2013; Spieth & Schneider, 2016; Clauss, 2017; Saebi, Lien, & Foss, 2017; Schrauder et al., 2018).

The extent of novelty of the three BM-dimensions is determined by asking if each BM element is new to the firm. Novelty of value proposition (NVP) includes four items asking for the extent to which products/services, addressed customer and market segments, relationships and distribution channels are new. Three items including the novelty of key activities, resources and partners measured the novelty of value delivery (NVD). Novelty of value capture (NVC) assesses if the underlying cost structure and the revenue mechanism are new to the firm. Thereby we explicitly asked whether the elements have changed in the context of digitalization. This way, we minimized the risk of including other drivers for change.

To define the scope of BMI, which considers how many BM elements are affected by digital-driven changes, we applied a cluster analysis (Saebi, Lien, & Foss, 2017). First, we determined the novelty of each BM dimension by calculating the average novelty of the BM elements in each dimension. The novelty scores of each dimension ranged from '1 – BM dimension is not new at all' to '7 – BM dimension is completely new.' Second, we ran a cluster analysis on the novelty scores of the three BM-dimensions: NVP, NVD and NVC. Here, we used statistic software IBM SPSS using *K*-means clustering. This allows classifying each firm into one cluster based on the extent of their BM novelty (see Table 3). Both clusters are significantly different from each other on a 1% level and contain a comparable number of firms with 64 in cluster 1 and 55 in cluster 2. Firms that fall into cluster 2 have high novelty scores for each dimension with centroid points of 5.02 for NVP, 4.89 for NVD and 4.57 for NVC, and are classified as business model innovators. Firms that fall into cluster 1 adapted their BM in the digital context and hence have relatively low centroid points of 2.93 for NVP, 2.41 for NVD and 2.02 for NVC. These firms we classified as business model adaptors (BMAs). In order to include these results in the PLS-SEM, we built a dummy

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variable for BMI of each firm with 1 = BMIs and 0 = BMAs (Saebi, Lien, & Foss, 2017). This serves as single-item construct for BMI, the endogenous variable of our model.

Control variables

Following prior studies (Huergo & Jaumandreu, 2004; Roger, 2004), we controlled for firm's size and age. Similar to Wilden et al. (2013), we measured firm's age by asking the foundation year. For firm's size, we ask for number of employees and sales revenue. Due to missing data related to number of employees, we were only able to use sales revenue as an indicator for size.

Assessment of measurement constructs

Assessment of the DC measurement construct

As we conceptualized DCs as a reflective-formative construct (Wetzels, Odekerken-Schröder, & van Oppen, 2009; Wilden et al., 2013), we applied different quality criteria (Hair et al., 2018). For the reflective LOCs of DCs, we examined internal consistency reliability, convergent validity and discriminant validity. In our original model, the first problem rose by the latent variable transforming, whose average variance extracted (AVE) was below the required threshold of .5. We found that TRA3 with a loading of .44 was the reason for this. Hence, based on the recommended outer-loadings relevance test for the transforming construct (Hair et al., 2014), we removed TRA3 to attain a higher and significant value for AVE. Besides, we kept all other indicators with lower loadings, considering that the minimum requirements for indicator validity and AVE were met. Furthermore, the Fornell–Larcker criterion, testing discriminant validity, is met for all LOCs of DCs, also in relation to all other final constructs of the path model (Table 4). Regarding the cross-loadings, the results show that discriminant validity has been fulfilled, as the value of each factor was higher than the value of the latent variable. Similarly the factor loading values of each factor to its latent variable show that all values were above the threshold of .7. Notably, discriminant validity between the LOCs and HOC does not need to be established, as the HOC is measured formatively (Hair et al., 2018). Consequently, all test statistics for LOCs meet the requirements for reflective measurements.

To specify the HOC, we choose the repeated indicators approach used by Wilden et al. (2013). Compared to the reflective LOCs, we conceptualized DCs using a formative composite model high-order index, which is supported by various evidence regarding expert validity (Wilden & Gudergan, 2015). To test for common method bias we applied multicollinearity testing, which is the appropriate method for PLS-SEM (Kock, 2015; Ringle, Wende, & Becker, 2015). As shown in Table 5, the variance inflation factors (VIFs) are all below the suggested threshold of 5 (Hair, Risher, Sarstedt, & Ringle, 2019) or ideally 3.3 (Kock, 2015) and all weights are positive and significant at a 1% level (Figure 2).

Consequently, our DC measurement construct fulfills all evaluation criteria and provides a reliable basis for further analysis.

Assessment of moderating factors

For the reflective measurement construct of ELMS, factor loading and AVE are above .5, the composite reliability (.91) and Cronbach's alpha (.87) exceeding .7. Thus, this construct fulfills the criteria of internal consistency reliability and convergent validity. In contrast, strategy could not be measured as a two-item reflective measure, as Cronbach's alpha of .65 is below .7. Thus, we tested the moderating effect of both strategy indicators using single-item measures. Furthermore, the second-order reflective-formative measure of organizational structure was assessed using the same criteria as for DCs. Both values for the reflective LOCs, internal consistency reliability and convergent validity, exceed the required threshold. The VIFs for the HOC are also below 5 and statistically significant (Table 6). Also, we can assume expert validity. Moreover,

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Table 4. Correlations and Fornell–Larcker criterion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) BMI	SIM															
(2) Age	.09	SIM														
(3) Size	.11	.23	SIM													
(4) DEC	.08	−.16	−.27	.88												
(5) DCs	.65	.12	.24	.04	FOM											
(6) ENVT	.51	.04	.16	.03	.49	.76										
(7) FOR	−.09	−.08	−.32	.43	−.13	−.12	.90									
(8) INT	.23	−.01	−.20	.29	.22	.10	.20	SIM								
(9) ELMS	.48	.00	−.12	.30	.54	.42	.17	.50	.85							
(10) REG	.22	−.06	.07	−.01	.07	.28	−.30	−.03	.05	SIM						
(11) SEI	.63	.06	.18	.11	.92	.48	−.06	.27	.53	.03	.75					
(12) SEN	.47	.18	.29	−.08	.89	.34	−.26	.06	.34	.08	.72	.84				
(13) STG1	.34	.09	−.05	.22	.45	.20	.14	.43	.55	.04	.40	.33	SIM			
(14) STG2	.43	.12	.11	.05	.55	.34	.02	.20	.57	−.03	.47	.39	.48	SIM		
(15) STR	.03	−.13	−.36	.84	.00	−.03	.82	.46	.36	−.18	.08	−.18	.28	.08	FOM	
(16) TRA	.64	.07	.15	.11	.86	.49	.02	.29	.60	.06	.74	.61	.48	.61	.13	.74

SIM, single-item measurement; FOM, formative measurement; BMI, business model innovation; DEC, decentralization; DCs, dynamic capabilities; ENVT, environmental turbulence; FOR, formalization; INT, integration; ELMS, entrepreneurial leadership and mindset; REG, regulatory; SEI, seizing; SEN, sensing; STG1, strategy 1; STG2, strategy 2; STR, structure; TRA, transforming.
Note: Values on the diagonal: the square root of AVE for reflective measurement constructs (this value must be greater that all correlations of the respective indicators to fulfill the Fornell–Larcker criterion).

Table 5. Quality criteria formative measurement DC

Construct/item	No. of items	VIF	Weights
Sensing	4	2.154	.44***
Seizing	4	2.943	.36***
Transforming	4	2.242	.32***

***Significant at .01 (two-tailed).

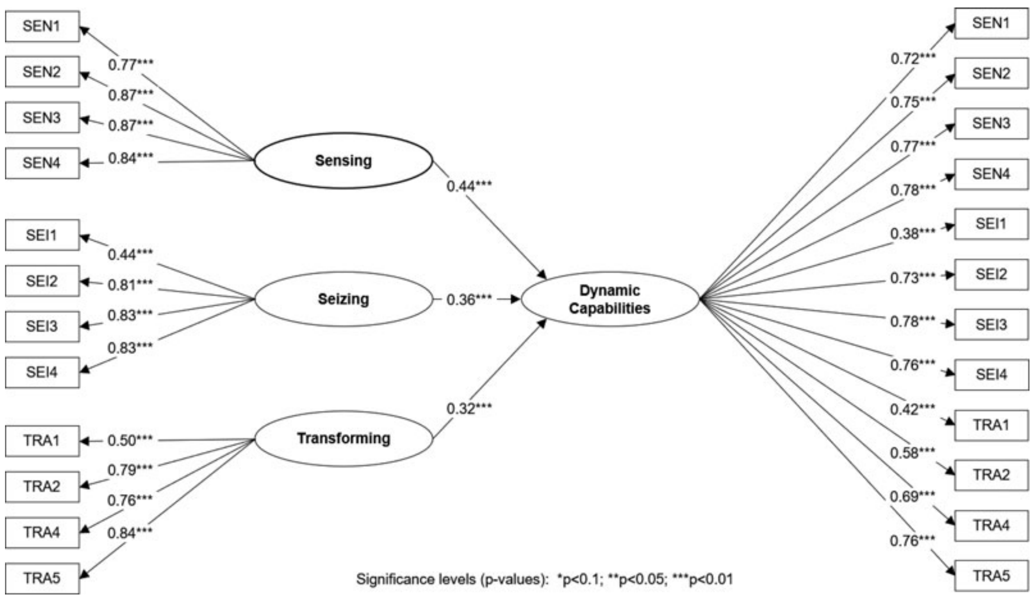

Figure 2. Validation of the DC measurement construct.

we note that an advanced measurement combining different organizational factors to test the impact of organizational alignment was not possible due to the construct's insufficient validity and reliability. Hence, we tested the moderating effect of each organizational factor separately.

Table 6. Quality criteria formative measurement organizational structure

Construct/item	No. of items	VIF	Weights
Decentralization	2	1.87	.44***
Informalization	2	1.44	.36***
Integration	1	1.83	1.00***

***Significant at .01 (two-tailed).

Next, we assessed ENVT. Originally, we planned to measure the degree of ENVT from the view of competition, market, technology and regulation. Since we included only six indicators for ENVT, we applied a six-item reflective measurement. Using an HOC, with each perspective as LOCs is not practical in our case due to the limited number of items measuring ENVT. Following the same validation procedure as for the LOCs of DCs, we excluded the items of

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competition and regulation, considering their low loadings and unsatisfied AVE of the latent variable representing ENVT. The final ENVT construct includes the change in technology, market and competition, while regulatory uncertainty (REG1) and overall competitive intensity (COM1) were studied separately. The final construct of ENVT fulfills all relevant validation criteria.

Finally, we assessed the discriminant validity of all reflective measurement constructs, using the Fornell–Larcker criterion. As Table 4 illustrates, discriminant validity is given. We also found that the constructs are sufficiently low correlated, except for the correlations between the DC-dimensions. However, as it is in their nature to relate closely to each other (Teece, 2007), the measurement is still appropriate. Hence, we assume that our constructs are independent and suitable for deeper analysis.

Results

Analysis of the DC–BMI relationship and moderating effects

To test our hypotheses, we assessed the path coefficients, their statistical significance and effect sizes for each model. Besides, we compared the explanatory power (R^2) and predictive power (Q^2) of the respective model. Thereby, we used SmartPLS applying PLS algorithm, the bootstrapping procedure and blindfolding to calculate Q^2.[1]

In model 1, we examined the DC–BMI relationship (Table 7). Here, the adjusted R^2 of BMI is substantial (.41). The result supports hypothesis 1, showing a positive direct effect of DCs on BMI ($\beta = .66$; $p < .01$). The results also support our hypotheses 1a–c, showing significant ($p < .01$) and positive indirect effects of all DC-dimensions. Thereby, sensing has the highest indirect effect ($\beta = .27$) on BMI, while seizing ($\beta = .24$) and transforming ($\beta = .22$) have slightly lower effects.

Furthermore, we measured the moderating effects of ENVT and organizational factors on the DC–BMI relationship. As our variables are non-categorical, we used the product term approach, which is superior for continuous moderating variables used in our study (Henseler & Fassott, 2010). Thereby we applied the two-stage approach to model the interaction term. This is suggested if the moderator or, as in our case, the exogenous variable DCs, is measured formatively (Hair et al., 2014). We conducted separated analyses for each moderator using the full sample and built a final model based on these results. Thereby we assessed two main criteria: the moderating effects by testing whether the moderators' path coefficients, which is also called interaction term, are statistically significant, and the strength of moderating effects using the effect size f^2. Thus, we compared the R^2 value of the base model with the R^2 value of each model that includes the respective moderating effect. Effect sizes of .35 represent large effects, while effect sizes of .15 and .02 represent medium and small effects.

We found that the DC–BMI relationship varies positively with the degree of ELMS (model 2). The moderating effect of .11 is positive, significant and hence supports hypothesis 2. Yet, due to $f^2 = .03$, the moderating effect is low. In model 3, we examined the moderating effect of an organic structure. Here the interaction effect ($\beta = .05$) and the direct effect ($\beta = .03$) are positive, but not significant. Since we found no evidence for moderating effects, we rejected hypothesis 3. Besides, we examined the effect of strategy on the DC–BMI relationship (model 4). While the direct effect of STG1 ($\beta = .08$) is positive but insignificant, its moderating effect is significant ($\beta = .10$; $p < .1$). Yet, due to $f^2 = .02$ the effect is small. In contrast, we found no significant results for STG2 (Appendix 2, model 7).

Lastly, we test the moderating effect of ENVT (model 5) and found a highly significant direct effect on BMI ($\beta = .26$), whereas the moderating effect is positive ($\beta = .04$), but insignificant. As

[1]We used following settings for analyses: PLS algorithm: path weighting scheme, maximum iterations of 1,000, stop criterion of 7 and mean value replacement of missing values; the bootstrapping procedure: 5,000 subsamples and 116 bootstrap cases, basic bootstrapping, two-tailed significance test and the described settings for PLS algorithm; blindfolding: omission distance of 5, other settings as described before. These are standard settings applied for all models of this work and recommended by Hair et al. (2014).

Table 7. Main results DC–BMI relationships and moderating effects

	Model 1 (base model)	Model 2 (ELMS)	Model 3 (STR)	Model 4 (STG1)	Model 5 (ENVT)	Model 6 (ELMS as moderator & ENVT as antecedent)
Path coefficients						
Control variables						
Revenue → BMI	−.05	.02	−.03	−.04	−.06	−.01
Age → BMI	.02	.01	.01	.01	.02	.02
Main variables						
DCs → BMI	.66***	.53***	.66***	.63***	.54***	.46***
ELMS → BMI		.24***				.17**
DCs × ELMS → BMI		.11**				.10*
STR → BMI			.03			
DCs × STR → BMI			.05			
STG1 → BMI				.08		
DCs × STG1 → BMI				.10*		
ENVT → BMI					.26***	.22***
DCs × ENVT → BMI					.04	
R^2 (BMI)	.42	.46	.42	.43	.48	.49
Adjusted R^2 (BMI)	.41	.43	.40	.41	.45	.47
f^2 (direct effect moder. var.)		.06	.00	.01	.10	.03
f^2 (moderating effect)		.03	.00	.02	.00	.02
Q^2 (BMI)	.39	.42	.37	.39	.43	.45
q^2 effect size		.05	−.03	.00	.07	.11
Specific indirect effects						
SEN → DCs → BMI	.27***	.22***	.27***	.26***	.22***	.19***
SEI → DCs → BMI	.24***	.20***	.24***	.23***	.20***	.17***
TRA → DCs → BMI	.22***	.18***	.22***	.22**	.18***	.16***

BMI, business model innovation; DCs, dynamic capabilities; ENVT, environmental turbulence; ELMS, entrepreneurial leadership and mindset; SEI, seizing; SEN, sensing; STG1, strategy 1; STR, structure; TRA, transforming.
Significance levels (p-values): *p < .1; **p < .05; ***p < .01.

the direct effect on BMI is considered small (f^2 = .10), our results do not support hypothesis 5. Also, we tested the moderating effects of COM1 (model 11) and REG (model 12). The results show insignificant values for the moderating effect. Yet, REG shows a direct effect (β = .18) on BMI with a small effect size (f^2 = .06). In contrast, COM1 has no significant direct effect on BMI.

Based on our main results, we built model 6 (see Figure 3), which includes the effects of ELMS and ENVT. We developed the model as a combination of models 2 and 5 due to their significant results, effect sizes and high explanatory power of the respective models. Thus, model 6 has the highest explanatory power for BMI (adj. R^2 = .47) and shows significant path coefficients for ELMS and ENVT on BMI. Moreover, the results suggest that ELMS positively moderates the DC–BMI relationship with a small effect size (f^2 =.02). Remarkably, none of the control variables showed significance in all models.

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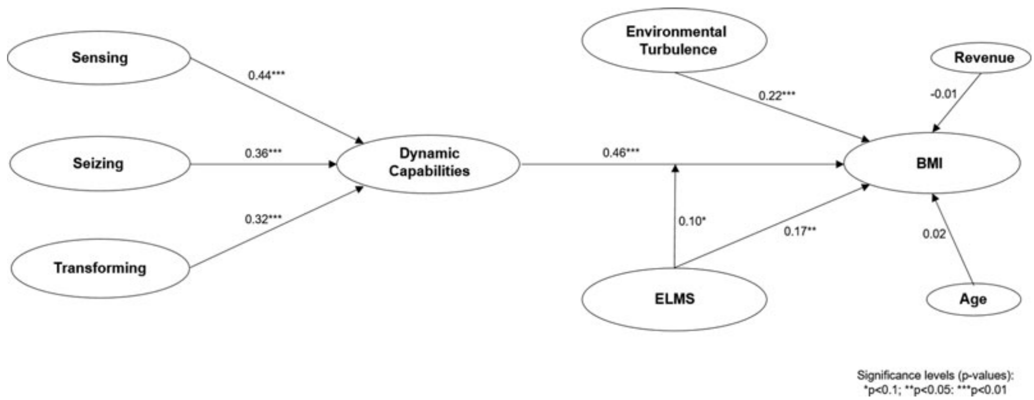

Figure 3. Results model 6.

Finally, to examine each models' predictive relevance, we determined Stone–Geisser's Q^2 value (Geisser, 1974; Stone, 1974) using the cross-validated redundancy approach as proposed by Hair et al. (2014). Q^2 values >0 indicate sufficient predictive relevance for the respective path model, which is applicable for endogenous single-item constructs (here BMI). All models 1–6 fulfill this criterion for the endogenous variable BMI. To compare the impact of predictive relevance between the different models, we calculated the q^2 effect size. We found that only ELMS in model 2 ($q^2 = .05$) and ENVT in model 5 ($q^2 = .07$), and the combination of these two in model 6 ($q^2 = .11$), have small predictive effects. For any other model, we found no predictive effect compared to the base model.

Additional analysis: the antecedents of DCs and BMI

Since we only found ELMS and STG1 as significant moderators, the question arises, which role the other contextual factors play in the DC–BMI relationship. As research highlights ENVT and STR not only as moderating factors but also as antecedents for DCs and BMI (e.g., Foss & Saebi, 2017; Schilke, Hu, & Helfat, 2018) and our results above support the view of these factors as antecedents, we therefore conducted an additional analysis (Table 8).[2]

First, we studied organizational factors as antecedents of BMI and DCs in one model. We found significant effects of organizational structure neither on BMI nor on DCs. In contrast, strategic factors (models 13 and 14) significantly affect sensing, seizing and transforming. Thereby, transforming (βSTG1 = .49; βSTG2 = .62) is stronger stimulated than seizing (βSTG1 = .40; βSTG2 = .48) and sensing (βSTG1 = .33; βSTG2 = .40). The effect size of the strategic factors on the DC-dimensions is medium ($f^2 > .15$) and even $f^2 > .35$ for STG2 on transforming, suggesting a large effect size. Yet, the direct effects of STG1 and STG2 on BMI are insignificant, which does not support the view that strategic factors are direct antecedents of BMI. As our results suggest that strategy is an antecedent of DCs, we conclude that strategic factors indirectly affect BMI. The significant specific indirect effects of STG1 and STG2 on BMI also indicate this. Although results reveal that ELMS positively moderates the DC–BMI relationship and directly affects BMI, we also found a significant direct effect of ELMS on the DC-dimensions (model 16). Hence, our results suggest a threefold role of ELMS, as a moderator of the DC–BMI relationship and as an

[2]At this point, we concede that our additional analysis is unconventional, and places the risk of post-hoc ergo propter or committing the post-hoc fallacy, as noted by one reviewer. However, we argue, that we have good reasoning for doing the additional analysis, since our prior results indicate that the mentioned factors are antecedents of BMI. Certainly, we could have omitted this kind of analysis at this point, however valuable results would have been lost that would contribute to DC research.

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Table 8. Additional analysis – antecedents of DCs and BMI

	Model 13 (STG1)	Model 14 (STG2)	Model 15 (STR)	Model 16 (ELMS)	Model 17 (ENVT)	Model 18 (COM1)	Model 19 (REG)
Path coefficients							
Control variables							
Revenue → BMI	−.04	−.04	−.04	.00	−.06	−.05	−.06
Age → BMI	.01	.01	.02	.02	.02	.01	.03
Main variables							
DCs → BMI	.63***	.60***	.65***	.56***	.53***	.66***	.65***
ANT → BMI	.05	.10	.03	.17**	.26***	.07	.18***
ANT → SEN	.33***	.40***	−.18*	.33***	.34***	.04	.08
ANT → SEI	.40***	.48***	.08	.53***	.48***	.08	.03
ANT → TRA	.49***	.62***	.13	.60***	.51***	.00	.06
R^2	.42	.43	.42	.44	.47	.43	.46
R^2 adj. (BMI)	.40	.41	.40	.42	.46	.41	.44
R^2 adj. Sen	.10	.15	.02	.10	.11	−.01	.00
R^2 adj. Sei	.15	.22	.00	.27	.23	.00	−.01
R^2 adj. TRA	.23	.38	.01	.35	.25	−.01	.00
f^2 (DCs → BMI)	.51	.42	.69	.34	.39	.70	.72
f^2 (ANT → SEN)	.12	.19	.03	.13	.13	.00	.01
f^2 (ANT → SEI)	.19	.30	.01	.38	.30	.01	.00
f^2 (ANT → TRA)	.31	.63	.02	.56	.35	.00	.00
f^2 (ANT → BMI)	.00	.01	.00	.03	.10	.01	.06
Specific ind. variables							
SEN → DCs → BMI	.26***	.25***	.27***	.23***	.22***	.27***	.27***
SEI → DCs → BMI	.23***	.22***	.24***	.21***	.20***	.24***	.24***
TRA → DCs → BMI	.21***	.20***	.22***	.19***	.18***	.22***	.22***
ANT → SEN → DCs	.14***	.17***	−.07*	.14***	.14***	.02	.03
ANT → SEI → DCs	.15***	.18***	.03	.19***	.18***	.03	.01
ANT → TRA → DCs	.17***	.21***	.05	.20***	.17***	.00	.02
ANT → SEN → DCs → BMI	.09***	.10***	−.05*	.08***	.07***	.01	.02
ANT → SEI → DCs → BMI	.09***	.11***	.02	.11***	.09***	.02	.01
ANT → TRA → DCs → BMI	.10***	.12***	.03	.11***	.09***	.00	.01

ANT, antecedent; BMI, business model innovation; COM1, competitive intensity 1; DCs, dynamic capabilities; ENVT, environmental turbulence; ELMS, entrepreneurial leadership and mindset; REG, regulatory; SEI, seizing; SEN, sensing; STG1, strategy 1; STG2, strategy 2; STR, structure; TRA, transforming.

antecedent of DCs and BMI. All direct and specific indirect effects are significant. Also, the effect of ELMS is particularly strong for transforming and seizing capabilities, while the effect on sensing is smaller but still substantial.

Second, we tested the role of ENVT as antecedent of DCs and BMI. As mentioned, we identified direct effects of ENVT and REG on BMI, whereas we found no significant influence of COM1. Besides the direct effects on BMI, we also studied the potential direct impact of

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environmental factors on DCs by building models 17–19, in which these factors act as antecedents of DCs and BMI. The direct effects of ENVT and REG on BMI did not change substantially. Regarding their effects on DCs, we found a highly significant direct impact of ENVT on sensing ($\beta = .34$), seizing ($\beta = .48$) and transforming ($\beta = .51$). This finding supports our hypothesis 5 that DCs are especially required in a turbulent environment. Thereby, seizing ($f^2 = .30$) and transforming ($f^2 = .35$) are stronger stimulated by ENVT than sensing ($f^2 = .13$). These direct effects are transferred to BMI, which account for the positive indirect effects of ENVT on BMI. As shown in 'specified indirect effects,' those indirect effects on BMI are significant ($p < .01$). In contrast, we cannot identify any significant direct impact of COM1 and REG on DCs, nor an indirect effect on BMI. The control variables show no significance.

Discussion

Relationship of DCs and BMI in the digital context

Our results confirm that DCs are an enabler of BMI (Achtenhagen, Melin, & Naldi, 2013; Foss & Saebi, 2017; Leih, Linden, & Teece, 2015; Teece, 2018a; Witschel et al., 2019). Furthermore, we found that the DC-dimensions are not only unequally pronounced (Teece, 2018a; Witschel et al., 2019), but also differ slightly regarding their effects on BMI. Although the dimensions are highly correlated, we found that sensing has the largest specific indirect effect on BMI, slightly lower effects for seizing and the lowest for transforming. From a processed view, sensing is 'of utmost importance' (Protogerou, Caloghirou, & Lioukas, 2012, p. 620), as this ability is considered as a starting point for BMI (Teece, 2018a) and a fundamental component of sustainable competitive advantage (Teece, 2007). Applied to our context, without strong sensing capabilities there is no systematic and early detection of new digital opportunities, and thus no appropriate response in form of seizing and transforming.

Moreover, we used and refined a newly developed conceptualization of DCs based on Witschel et al. (2019), which is also similar to traditional ones of, for example, Wilden et al. (2013). In our analysis, we were able to empirically validate this conceptualization that takes aspects of digitalization into account. Besides, our conceptualization is a combination of general and specific subcapabilities for digitalization. General subcapabilities are usually already established in an organization and need to be adapted in the digital context. However, specific subcapabilities emerged in the context of digitalization and became crucial for BMI (Witschel et al., 2019). In particular, our results confirm the findings of Witschel et al. (2019), highlighting the role of internal and external cooperation as an important microfoundation for all DC-dimensions. This is also consistent with earlier findings indicating an increasing relevance of internal and external collaboration in turbulent environments (Helfat, Finkelstein, Mitchell, Peteraf, Singh, & Winter, 2007), such as in the context of digitalization (Day & Schoemaker, 2016; Witschel et al., 2019).

Surprisingly, the control variables had no significant impact in our models, contradicting the assumption that these factors are boundary conditions of BMI (Foss & Saebi, 2017; Karimi & Walter, 2016) and influence the DC-effects (Schilke, Hu, & Helfat, 2018; Wilden et al., 2013). The digitalization context may provide an explanation, as the nature and impact of digitalization is so profound that it affects firms of all size, age and industries. Consequently, responding to digitalization becomes a strategic imperative, according to the much-quoted motto 'digitalize or drown' (Schreckling & Steiger, 2017).

Role of organizational factors on the DC–BMI relationship

The result shows a strong interrelationship of ELMS and strategy with both main constructs DCs and BMI. Thereby, we conceptualized and validated a measurement construct that is similar to previous studies (Karimi & Walter, 2016; Schoemaker, Heaton, & Teece, 2018) and show that ELMS moderates the DC–BMI relationship. Consistent with Karimi and Walter (2016), ELMS also has a significant direct effect on BMI, but also acts as an antecedent of the DC-dimensions. Surprisingly, ELMS has the largest impact on transforming, with lower but still significant effects on seizing and sensing. This is in contrast to prior work suggesting that entrepreneurial leadership is especially relevant for sensing, while a managerial leadership style is positively associated with seizing and transforming (Teece, 2007, 2014; Witschel et al., 2019). One explanation for this could be that our ELMS definition differs slightly from the one of entrepreneurial and managerial leadership style used in the mentioned studies, as we consider not only leadership style, but also organizational culture. Nevertheless, we found that ELMS, associated with openness to change and risk-taking, is crucial for the transformation process, in which an organization often undergoes fundamental changes. Consequently, since we found a threefold role of ELMS as an antecedent of DCs and BMI and as a moderator of the DC–BMI relationship, we conclude that ELMS is a beneficial condition for doing business in the digital age as it encourages firms to transform their BM. Hence, the high relevance of ELMS supports the assumption that top management involvement is important for BMI (Foss & Stieglitz, 2015; Kane et al., 2015).

Moreover, we cannot confirm that an organic structure is positively associated with BMI and moderates DCs (Teece, 2000, 2007; Wilden et al., 2013). Indeed, we found no evidence that organizational structure affects the DC–BMI relationship, nor other construct. One explanation could be that neither extreme of the continuum between organic and mechanistic structure favors the DC–BMI relationship, but rather a mixture of both may be more beneficial. Thus, the relationship could be non-linear.

Concerning the strategic factors, we found no direct effect of strategy on BMI, but a significant, yet weak moderating effect of STG1 on the DC–BMI relationship. Hence, our findings provide limited evidence for the moderating role of strategic factors as suggested by Witschel et al. (2019). In contrast, our results reveal that STG1 and STG2 act as antecedents of DCs and thus have indirect effects on BMI. This finding is consistent with Kane et al. (2015) and Bereznoi (2015) and contributes to the understanding on how strategy affects BMI and empirically validates the importance of a clear and embedded vision combined with a digital strategy. Likewise, we show that strategy is highly important for all DC-dimensions, with the largest effect on transforming. This is similar to Teece (2014) and suggests that strategy provides the necessary guidance for sensing and seizing, while being particularly important for transforming. Thus, our results highlight the importance of strategic factors for the strength of DCs and BMI (Teece, 2018a).

Role of environmental factors in the DC–BMI relationship

Against the prevalent view (Schilke, Hu, & Helfat, 2018; Wilden et al., 2013; Witschel et al., 2019), we found no evidence for a moderating effect of ENVT on the DC–BMI relationship. Instead, we show that ENVT is an antecedent of DCs and BMI. Specifically, high ENVT positively influences DCs and thus indirectly affects BMI. Notably, the impact is greater on seizing and transforming than on sensing. This lets us assume that firms constantly need a moderate level of sensing, while seizing and transforming are mainly stimulated in a turbulent environment. Constant sensing is essential for identifying threats and opportunities in the context of digitalization and is thus a prerequisite of seizing and transforming. Besides, we found evidence that ENVT is an antecedent of BMI, reflecting the common understanding in literature and business practice that firms change or even radically innovate their BMs in highly dynamic environments (Sauer, Dopfer, Schmeiss, & Gassmann, 2016). Similar to ENVT, regulatory turbulence acts as an antecedent of BMI.

Managerial implications

Our conceptualization of DCs from a microfoundational view gives practitioners insights which subcapabilities are required to build strong DCs and how they influence BMI in the context of digitalization. Moreover, the significant weights of the DC-dimensions indicate that a firm must develop all DCs at the same time to innovate its BM, whereas sensing seems to be especially relevant. Thus, we provide guidance for management concerning their investments in DCs. Since a key concern for business practice is, which organizational conditions are beneficial to foster BMI and respond adequately to the major changes associated with digitalization, we shed light on this question. We thereby found evidence, that leadership and mindset should be entrepreneurial. Although, culture and leadership cannot be changed overnight, top management can exemplify these characteristics and initiate the organizational change toward an entrepreneurial mindset. Likewise, we create awareness for the importance of a clear vision and aligned corporate and digital strategy. Our findings implicate that both strategic aspects are antecedents of DCs and thus positively influence their strength. They seem to provide guidance to employees in the context of substantial change that digitalization entails. Finally, the role of ENVT as an antecedent of DCs underlines the high relevance for firms to build strong DCs in the context of digitalization. Furthermore, our results indicate the high relevance of BMI in the digital context, highlighting the need to constantly asses the appropriateness of the current BM.

Limitations and avenues for future research

Our analysis is not without limitations. First, we acknowledge limitations concerning the used data. Although we applied measures to minimize potential biases in data collection, we cannot completely exclude bias. We also used a relatively small sample. However, this is common in surveys involving top management (Wilden et al., 2013). Second, insignificant results of control variables, for example, firm size, may be caused by missing data related to employee numbers. Measuring revenue expressed as a logarithm of its absolute value (Wilden et al., 2013) would improve the results. Similarly, our insignificant results for organizational structure may be affected by the newly developed construct, involving aspects that are especially relevant in the digital context. Third, to achieve a more holistic view and minimize lower response rate, we used a lean survey design with single-item constructs to measure contextual factors, which is in contrast to related in-depth studies (Jaworski & Kohli, 1993; Karimi & Walter, 2016; Wilden et al., 2013). Using multi-item constructs, research could reveal additional insights related to the specific impact of different types of ENVT. Similarly, a more nuanced investigation of organizational factors is required to examine which organization design is beneficial for the DC–BMI relationship. Also examining to which extent these factors need to be congruent deserves more attention (Kane et al., 2016; Witschel et al., 2019). Fourth, in our analysis we solely focused on moderation effects, which is one of the most growing research areas (Schilke, Hu, & Helfat, 2018). Nevertheless, in line with other scholars (e.g., Baía & Ferreira, 2019; Schilke, Hu, & Helfat, 2018; Wilden et al., 2013) we encourage future work to examine causal mechanisms (i.e., mediators), which are still hardly explored. As a starting point, it would be interesting to study the role of entrepreneurial orientation or strategic factors (e.g., Ciampi, Demi, Magrini, Marzi, and Papa, 2021) as mediators of the DC–BMI relationship. Similarly, future research could investigate the mediating role of DCs in enhancing firm performance. Fifth, although our results deliver valuable insights regarding the DC–BMI relationship in the digitalization context, we have neither an indication on the success of BMI nor the effect on firm performance. Investigating performance implications of DCs and extending the ongoing debate by introducing BMI as an intermediate outcome is important, since this would reduce 'the relative scarcity of empirical research on the performance implications of dynamic capabilities, particularly on the mediating mechanisms of dynamic capabilities effects' (Zhou et al., 2019, p. 742). Moreover, examining this relationship by considering contingency effects would be another fruitful research area (Baía & Ferreira, 2019; Wilden et al., 2013). Sixth, we acknowledge the limitation regarding the use of a single-item construct for measuring BMI. Since this work did not involve a differentiated discussion of the results in terms of adaptors and innovators, we call to replicate this study and address this weakness. Similarly, the use of a more complex BMI scale would allow a more detailed analysis from a microfoundational perspective and improve understanding of DC effectiveness. Finally, we encourage scholars to build on this study and further deepen the understanding of the microfoundations of DCs that enable BMI in the digital context. For example, as our results indicate a high importance of relational capabilities, for example, cooperation with internal and external stakeholder or engagement in ecosystems, further studies could examine their optimal design, specific role and impact. Likewise, examining other industries, geographical areas or different firm characteristics would enhance the understanding of the role of DCs and their underlying microfoundations in different contextualization.

Conclusion

To refer to the title of our work, we conclude: when sailing in stormy waters, such as the age of digitalization, it is vital for firms to direct their sails through DCs and BMI. Or as Ella Wheeler Wilcox (1916), a famous American author and poet, would say: 'One ship drives east and other drives west by the same winds that blow. It's the set of the sails and not the gales that determines the way they go.'

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Appendix A

Table A1. Scales and sources

Construct	Indicator	Item	Sources/adapted from
DCs			
	In my company…		
Sensing	we use an open innovation approach to generate new ideas by collaborating with external partners from both in- and outside our industry (e.g., professional associations, research communities).	SEN1	Makkonen et al. (2014); Wilden et al. (2013); Witschel et al. (2019)
	we use established processes to integrate our customers in the idea generation process.	SEN2	Fainshmidt and Frazier (2017); Wilden et al. (2013); Witschel et al. (2019)
	we use systematic processes to identify new trends and market dynamics in time.	SEN3	Makkonen et al. (2014); Witschel et al. (2019)
	we specify and evaluate our benefit promise and conceptualize our revenue mechanism.	SEN4	Witschel et al. (2019)
Seizing	we integrate our customers in the development process and change our practices if customer feedback gives a reason for change.	SEI1	Fainshmidt and Frazier (2017); Wilden et al. (2013); Witschel et al. (2019)
	we apply agile methods (e.g., scrum) in the development of new business ideas free from bureaucracy.	SEI2	Kurtmollaiev et al. (2018); Witschel et al. (2019)
	we systematically allocate key resources and competencies for the development of new business activities and cooperate with external partners if appropriate (e.g., IT-developer).	SEI3	Makkonen et al. (2014); Witschel et al. (2019)
	we develop a sustainable platform architecture and the implementation of adequate IT security measures.	SEI4	Witschel et al. (2019)
Transforming	we encourage internal communication as well as the exchange of information and best practices within the entire organization.	TRA1	Makkonen et al. (2014); Witschel et al. (2019)
	we substantially transform and restructure our organization to ensure a sustainable and digital alignment (e.g., acquisitions, institutionalization of Data Analytics/ Digital Transformation departments).	TRA2	Fainshmidt and Frazier (2017); Wilden et al. (2013); Witschel et al. (2019)
	we scale our BM by using intra- and cross-industry cooperation or accelerator programs.	TRA4	Witschel et al. (2019)
	we ensure a sustainable allocation and development of digital key competencies.	TRA5	
ENVT	In the context of digital transformation…		
Technological	within our industry, technology is changing rapidly leading to new product/service opportunities.	TEC1	Jaworski and Kohli (1993); Wilden and Gudergan (2015)
Market		MAR1	

(*Continued*)

Table A1. (*Continued.*)

Construct	Indicator	Item	Sources/adapted from
	within our industry, customers' product preferences are changing rapidly over time.		Jaworski and Kohli (1993); Wilden and Gudergan (2015); Schrauder et al. (2018)
	we are witnessing demand for our products/ services from customers who have never bought from us before.	MAR2	Jaworski and Kohli (1993); Wilden and Gudergan (2015)
Competition	our main competitors have changed.	COM2	Jaworski and Kohli (1993); Wilden et al. (2013); Wilden and Gudergan (2015)
Regulatory	our business is significantly affected by regulatory uncertainties	REG1	Newly developed
ELMS			
	Top management shows a high willingness to invest and sponsor new business ideas.	LMS1	Witschel et al. (2019)
	We are willing to develop and commercialize fundamental new business ideas even if they are likely to cannibalize our core business.	LMS2	Karimi and Walter (2016)
	Employees are encouraged to generate new ideas and experiment with them.	LMS3	Karimi and Walter (2016); Witschel et al. (2019)
	Employees' failures are associated positively as learning opportunity.	LMS4	Cannon and Edmondson (2005); van Dyck et al. (2005)
Structure			
Decentralization	Most decisions, even small matters, are made by the top management.	STR1	Dedahanov, Rhee and Yoon (2017); Deshpande and Zaltman (1982); Hage and Aiken (1967); Jaworski and Kohli (1993)
	Management favors superior decision making with minimum consultation and involvement of subordinates.	STR2	Dedahanov, Rhee and Yoon (2017); Jaworski and Kohli (1993); Khandwalla (1977); Slevin and Covin (1990)
Formalization	We emphasize to follow formal written procedures whatever situation arises.	STR3	Dedahanov, Rhee and Yoon (2017); Deshpande and Zaltman (1982); Jansen, van den Bosch and Volberda (2006)
	We emphasize that employees adhere to formal job descriptions.	STR4	
Integration	Employees of different departments are encouraged to collaborate and communicate closely.	STR5	Dedahanov, Rhee and Yoon (2017); Germain (1996)
Strategy	We have a clear vision in line with our corporate strategy that is communicated and embedded in the entire organization.	STG1	Newly developed
	We have a digital strategy as part of the corporate strategy.	STG2	Kane et al. (2015); Witschel et al. (2019)
BMI			
Value proposition	We introduced new bundles of products and services to our customers.	BM1	Achtenhagen, Melin, and Naldi (2013); Jaworski and Kohli (1993); Clauss (2017); Saebi, Lien, and Foss (2017); Schrauder et al. (2018); Spieth and Schneider (2016)

(*Continued*)

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Table A1. (*Continued.*)

Construct	Indicator	Item	Sources/adapted from
	We use new distribution channels for our products and services.	BM2	Clauss (2017, p. 395); Schrauder et al. (2018); Spieth and Schneider (2016)
	We established new ways of interaction with our customers (e.g., co-creation, automated customer service).	BM3	Clauss (2017); Schrauder et al. (2018)
	We are addressing new customers/unserved market segments.	BM4	Achtenhagen, Melin, and Naldi (2013); Clauss (2017); Saebi, Lien, and Foss (2017); Spieth and Schneider (2016)
Structure of delivery	The key activities of our BM have changed.	BM5	Achtenhagen, Melin, and Naldi (2013); Clauss (2017); Saebi, Lien, and Foss (2017); Spieth and Schneider (2016); Schrauder et al. (2018)
	We use new key resources (physical, intellectual, financial or human).	BM6	Clauss (2017); Schrauder et al. (2018); Spieth and Schneider (2016)
	We cooperate with our key partners in a new way (e.g., strategic alliances, coopetition, start-up cooperation, etc.).	BM7	Achtenhagen, Melin, and Naldi (2013); Clauss (2017); Spieth and Schneider (2016); Schrauder et al. (2018)
Value capture	Our underlying cost structure is new.	BM8	Achtenhagen, Melin, and Naldi (2013); Clauss (2017); Saebi, Lien, and Foss (2017); Spieth and Schneider (2016)
	The logic we generate revenue is new (e.g., pricing structure, pay-as-you-use, freemium, leasing).	BM9	Achtenhagen, Melin, and Naldi (2013); Clauss (2017); Spieth and Schneider (2016); Schrauder et al. (2018)

Table A2. DC–BMI relationship and moderators (models 7–12)

	Model 1 (base model)	Model 7 (STG2)	Model 8 (DEC)	Model 9 (FOR)	Model 10 (INT)	Model 11 (COM1)	Model 12 (REG)
Path coefficients							
Control variables							
Revenue → BMI	−.05	−.04	−.03	−.05	−.03	−.04	−.06
Age → BMI	.02	.01	.02	.02	.01	.02	.03
Main variables							
DCs → BMI	.66***	.60***	.66***	.65***	.64***	.66***	.65***
STG2 → BMI		.10					
DCs × STG2 → BMI		.03					
DEC → BMI			.05				
DCs × DEC → BMI			.06				
FOR → BMI				−.06			
DCs × FOR → BMI				.05			
INT → BMI					.09		
DCs × COM1 → BMI					.02		

(*Continued*)

Table A2. (*Continued.*)

	Model 1 (base model)	Model 7 (STG2)	Model 8 (DEC)	Model 9 (FOR)	Model 10 (INT)	Model 11 (COM1)	Model 12 (REG)
COM1 → BMI						.06	
DCs × COM1 → BMI						−.08	
REG → BMI							.18***
DCs × REG → BMI							−.02
R^2	.42	.43	.43	.43	.43	.43	.46
Adjusted R^2	.41	.41	.40	.40	.40	.41	.43
f^2(direct effect moder. var.)		.01	.00	.00	.01	.01	.06
f^2 (moderating effect)		.00	.01	.00	.00	.01	.00
Q^2 (BMI)	.39	.39	.38	.38	.39	.37	.41
q^2 effect size		.00	−.02	−.02	.00	−.03	.03
Specific indirect effects							
SEN → DCs → BMI	.27***	.25***	.27***	.27***	.26***	.27***	.27***
SEI → DCs → BMI	.24***	.22***	.24***	.24***	.23***	.24***	.24***
TRA → DCs → BMI	.22***	.21***	.22***	.22***	.22***	.22***	.22***

BMI, business model innovation; COM1, competitive intensity; DEC, decentralization; DCs, dynamic capabilities; FOR, formalization; INT, integration; REG, regulatory; SEI, seizing; SEN, sensing; STG2, strategy 2; TRA, transforming.
Significance levels (*p*-values): $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

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