Digitalization and network capability as enablers of business model innovation and sustainability performance: The moderating effect of environmental dynamism

Abstract

In the face of relentless global competition and regulatory pressures, the imperative for firms to digitally transform has become critical. This is particularly salient for Chinese manufacturing firms as they strive for sustainability, a multidimensional construct comprising both economic and environmental performance. Leveraging dynamic capabilities theory, this study aims to unravel the intricate interplay between digitalization, network capability, business model innovation (BMI), and environmental dynamism in shaping a firm's sustainability performance. Our research is driven by a compelling question: How do digitalization and network capabilities impact firms' sustainability performance, and what roles do BMI and environmental dynamism play in this relationship? To answer this question, we employed a robust survey-based methodology encompassing 1,600 Chinese manufacturing firms, yielding 255 completed and validated responses. The findings reveal that network capability mediates the influence of digitalization on two types of BMI—novelty-centered and efficiency-centered. Further, these forms of BMI act as mediators between digitalization and network capability, and the two dimensions of sustainability: economic and environmental performance. Notably, environmental dynamism serves as a double-edged sword. It negatively moderates the impact of digitalization on efficiency-centered BMI, but positively moderates the influence of network capability on the same. Our study offers nuanced theoretical and practical implications. It extends dynamic capabilities theory by elucidating how digital and network capabilities can be leveraged for sustainable outcomes via business model innovation. Moreover, the research provides managerial insights, particularly for Chinese manufacturing firms, on navigating the complex landscape of digital transformation toward sustainability. Considering these insights, we recommend that firms prioritize network capabilities and strategically innovate their business models to harness the full potential of digital transformation. Simultaneously, organizations should be cognizant of the environmental dynamism within which they operate, as it can both hinder and enable their journey toward sustainability.

Keywords

Digital transformation; digitalization; dynamic capabilities theory (DCT); business model innovation

(BMI); network capability; environmental dynamism; sustainability performance

Introduction

In recent years, advancements in digital technologies such as the Internet of Things (IoT), cloud computing, big data analytics, artificial intelligence (AI), 3D printing, virtual reality (VR), augmented reality (AR), and industrial robotics have proliferated at an unprecedented rate (Li et al., 2020; Sjödin et al., 2021; Weking et al., 2020). These innovations have exerted a transformative impact on virtually every facet of society and commerce, catalyzing significant shifts in traditional business models on a global scale (Weking et al., 2020; Yu et al., 2019).

Faced with intensified global competition and the disruptive potential of these technologies, organizations are proactively harnessing digital tools to expedite their digital transformation initiatives, aiming to secure a sustainable competitive advantage (Vial, 2019). Despite its promise, digital transformation is inherently complex and fraught with challenges, requiring organizations to maintain agility in response to an ever-changing landscape (Sousa-Zomer et al., 2020).

Further complicating matters, this era of digital transformation coincides with a host of macro-level challenges, such as global financial crises, climate change, pandemic outbreaks, and economic volatility. These external pressures not only intensify the dynamic nature of the environment but also add layers of complexity to digital transformation efforts (Sousa-Zomer et al., 2020). However, a critical gap exists in the understanding of organizational leaders on how to navigate this intricate and fluctuating environment effectively. To optimize the positive results and efficacy of digital transformation initiatives, it becomes imperative to elucidate the underlying mechanisms that govern the process of digital change.

Dynamic capabilities, which are the ability to constantly sense, seize, and reconfigure resources to address rapidly changing environments (Teece et al., 1997), are recognized to "faithfully reflect and guide the organization's digital transformation processes" (Soluk & Kammerlander, 2021, p. 678). *Dynamic capabilities theory* (DCT) (Teece et al., 1997) provides an appropriate theoretical foundation to explain key attributes of digital transformation particularly in such a dynamic business environment. Scholars have explored how to build dynamic capabilities for digital transformation to enable strategic change in organizations (Vial, 2019; von Briel et al., 2019). For example, Warner and Wäger (2019) identified digital sensing, digital seizing, and digital transformation capabilities to pursue a digital transformation, whereas Sousa-Zomer et al. (2020) proposed the micro-foundations related to individual, process and structure to build the blocks of digital transformation capability. Nevertheless, the efforts of the previous studies are not designed to be comprehensive. Digital transformation as a multidisciplinary endeavor involves changes in the process-, organization-, and business-domain level (Hanelt et al., 2021; Parviainen et al., 2017; Verhoef et al., 2021). The dynamic capabilities for digital transformation should be multifaced and interrelated to trigger major business improvements (Tim et al., 2018; Warner & Wäger, 2019).

Our study first highlights *digitalization* as one critical element of dynamic capabilities which supports the precursory phase of digital transformation at the process level (Verhoef et al., 2021). Digitalization is the application of digital technologies to improve current business processes (Thomas & Carsten Lund, 2020; Verhoef et al., 2021; Vial, 2019). Organizations apply IoT to connect industrial assets with business processes (Ghosh et al., 2022), big data analytics to support proactive decision-making (Shamim et al., 2019), and cloud based enterprise resource planning to integrate the business processes on cloud platforms (Gupta et al., 2020). Digital technologies enable organizations to flexibly access information, sense opportunities and unexpected threats, and integrate digital resources such as data and information to seize opportunities or neutralize threats (Cenamor et al., 2019; Li et al., 2022). Scholars have widely recognized that digitalization is the starting point of digital transformation (Soluk & Kammerlander, 2021; Verhoef et al., 2021). However, most empirical studies focus on how firm performance is influenced by digitalization (e.g., Li et al., 2022; Sousa-Zomer et al., 2020), neglecting the mediation path and its broad range of performance outcomes.

Digital transformation goes beyond the application of digital technologies in question (Wessel et al., 2021). Digitalization cannot occur without the foundation of strong organizational capabilities (Li et al., 2018; Teece, 2018; Tim et al., 2018), especially those for managing boundary-spanning practices required for the networked economy (Pouloudi et al., 2016; Schneider & Kokshagina, 2021; Tan et al., 2020). Scholars have noted that the application of digital technologies leads to organizational changes in networking (Cenamor et al., 2019; Pagani & Pardo, 2017). *Network capability*, an organization's ability to develop and leverage relationships with network partners to achieve resource integration, has been proposed (Walter et al., 2006) as an indicator of dynamic capability for digital transformation at the organization level. Whereas digitalization is driven by digital technology resources (Huang et al., 2012), network capability relies on organizational norms (Chi et al., 2010). Digitalization enables organizations to sense potential collaborative opportunities by collecting information extensively using digital technologies (Cenamor et al., 2019; Li et al., 2022). Based on their digital infrastructure, organizations can further establish and manage networks with their potential business partners to integrate resources and heterogeneous capabilities (Cenamor et al., 2019; Goduscheit & Faullant, 2018; Schneider & Kokshagina, 2021). The relationship between digitalization and network capability and their resulting organizational influence need to be further investigated theoretically and empirically.

In today's digital environment, business model innovation (BMI) has been recognized as one source of sustainable competitive advantages for the organization (Yu et al., 2019). BMI is regarded as the ability to recombine and reconfigure information, knowledge, competencies, and resources to transform products, services, and transactions (Mezger, 2014). Our study highlights BMI as the third critical element supporting digital transformation at the business domain level. BMI comprises new ways of creating, capturing, and delivering value through boundary-spanning transactions (Casadesus-Masanell & Zhu, 2013; Zott & Amit, 2007); a critical distinction between digital transformation and IT-enabled organizational transformation is considered to be the BMI that results from the former (Verhoef et al., 2021; Wessel et al., 2021). Following Zott and Amit (2007), our study classifies BMI into novelty- and efficiency-centered types. The former involves creating new ways to conduct business and realize product differentiation, whereas the latter helps organizations achieve transaction efficiency and reduce transaction costs (Zhang et al., 2021). Thomas and Carsten Lund (2020) argued that digitalization should be aligned with the business model design to enhance competitiveness. However, few studies explain how digitalization triggers BMI in the current dynamic business environment. Based on DCT, digitalization and network capability enhance the firm's capabilities to acquire and integrate resources from its business partners. The digital and organizational resources can then be recombined and reconfigured for novelty- and efficiency-centered BMI to deliver value proposition and creation. This study will further provide empirical evidence to validate their interrelationships.

Moreover, the research on digital transformation has focused mainly on how the process affects forms of finance-related business performance, such as operational performance (Buer et al., 2021; Gillani et al., 2020), organizational performance (Nwankpa & Datta, 2017; Sousa-Zomer et al., 2020),, and competitive performance (Mikalef et al., 2020), although a recent study encouraged scholars to explore the wide-ranging negative and positive effects on industry and society (Vial, 2019). Whereas a firm itself tends to focus on economic profits, stakeholders like governments and the general public are often more concerned about whether the firm's business practices have adverse effects on the nature environment in which they live (Pan et al., 2021); and the outcome is often a perceived tension between the two seemingly disparate goals. Recent years have witnessed increasingly devasting consequences from climate change, environmental pollution, and natural disasters, all of which have profoundly affected the economy and societies globally (Pan et al., 2021; Son et al., 2021; Weilnhammer et al., 2021). Because global companies' business operations are regarded as the key causes of environmental problems (e.g., high energy consumption, carbon emissions, waste), scholars have proposed the use of digital technologies in businesses to achieve environmental sustainability (Elliot, 2011; Hanelt et al., 2017; Li et al., 2020). Previous studies have not sufficiently addressed this proposition, especially in terms of how environmental performance could be affected during the company's digital transformation process (Dubey et al., 2019; Li et al., 2020). As two of the three dimensions of sustainability based on *triple bottom line principles*, economic and environmental performance should be emphasized in information systems research (Gupta et al., 2020; Klein et al., 2021).[1] Such research should investigate how digital transformation leads to improved economic and environmental performance.

Our study also investigates how the effects of digitalization and network capability on BMI may vary (e.g., manifest contingency effects) with the rapidly changing business environment. Such changes are reflected in *environmental dynamism*, which is the rate and volume of changes in firms' business environments (Dess & Beard, 1984; Li & Liu, 2014). The dynamic environment is characterized by high-speed innovation, significant technological progress, customer preference change, and

[1] The *triple bottom line of sustainability* comprises (1) economic, (2) environmental, and (3) social performance (Dubey et al., 2019; Gupta et al., 2020; Klein et al., 2021). *Social sustainability* is the influence of firms on the social welfare of relevant stakeholders, such as human rights, labor rights, work conditions, health services, and human equality (Dubey et al., 2019; Shet & Pereira, 2021); its focus on broad societal concerns can make it difficult to measure and monitor (Shet & Pereira, 2021; Sudusinghe & Seuring, 2022). Some scholars have emphasized that economic and environmental performance are closely connected with social sustainability , our study focuses primarily on the economic and environmental dimensions of sustainability performance.

unpredictable regulations (Azadegan et al., 2013; Li & Liu, 2014). COVID-19 pandemic and geopolitical factors have collectively galvanized the dynamism of today's business environment (Pan & Zhang, 2020). Highly dynamic environments not only make it difficult for firms to prepare for changes but also pose challenges to their capacity to maintain efficiency (Azadegan et al., 2013; Mikalef et al., 2021a; Mikalef et al., 2021b)—further emphasizing the importance of dynamic capabilities. Our study extends previous research by empirically examining how environmental dynamism influences the relationships among digitalization, network capability, and novelty- and efficiency-centered BMI (Chen et al., 2014; Mikalef et al., 2021a; Mikalef et al., 2021b). DCT highlights organizations' abilities to adapt to rapidly changing environments (Teece & Pisano, 1994), and the enhancement of organizational capabilities, including digitalization and network capability, should match external environmental conditions. Complex technological adoptions, organizational factors, and external environmental conditions interact to influence the progress of digital transformation (Gillani et al., 2020).

These tensions and opportunities lead to two research questions in our study:

RQ1. How do digitalization and network capability influence novelty- and efficiency-centered BMI, thereby leading to improved economic and environmental performance?

RQ2. How does the contingency of environmental dynamism moderate the effects of digitalization and network capability on novelty- and efficiency-centered BMI?

To address our research questions, we develop and empirically validate a research model through an analysis of survey data gathered from Chinese manufacturing firms. These firms are confronting escalating demands to innovate, while simultaneously striving for enhanced sustainability performance (Chan et al., 2016; Li et al., 2020). Our study contributes to digital transformation research in several noteworthy ways.

First, we introduce economic and environmental performance as dependent variables to evaluate the multidimensional aspects of sustainability. Our findings offer a nuanced comprehension of both the adverse and beneficial impacts of digital transformation on these dimensions of sustainability. *Second*, our results elucidate the interrelated pathways through which various levels of transformation—digitalization at the process level, network capability at the organizational level, and BMI at the business domain level—synergistically influence sustainability performance. Moreover, we explore the moderating role of environmental dynamism, providing a more comprehensive understanding of the mediating and moderating variables that contribute to the complexity of successful digital transformation. *Third*, we employ DCT as a theoretical lens to interpret digital transformation. We extend the scope of DCT by investigating the interactions among various dynamic capabilities, thereby enriching the theoretical framework. Our findings also offer pragmatic insights for manufacturing firms, particularly those operating in contexts like China, by elucidating strategies to attain sustained competitive advantage through effective digital transformation.

Theoretical and Conceptual Foundation

Dynamic capabilities theory

The resource-based view of firms regards organizations as collections of valuable, rare, imperfectly imitable, and irreplaceable resources that support the achievement of competitive advantage (Barney, 1991). Scholars have argued that this view should be extended to explain how such resources contribute to long-term and sustainable competitive advantages in a dynamic environment (Huang et al., 2012; Teece & Pisano, 1994). DCT was proposed primarily to address how firms can survive under rapidly changing business conditions (Li & Liu, 2014; Teece et al., 1997). Teece and Pisano (1994) defined *dynamic capabilities* as an organization's abilities to adjust, integrate, and reconfigure its internal and external resources and its abilities to adapt to ever-changing environments. Subsequent studies have divided dynamic capabilities into three dimensions: sensing, seizing, and transformation (Teece, 2007). The *sensing capability* helps organizations capture environmental signals. The *seizing capability* enables timely decision-making to seize emerging opportunities and neutralize threats. The *transformation capability* concerns the adjustment of organizational structures and processes to adapt to environmental changes and maintain competitiveness.

DCT explains that when superior dynamic capabilities are appropriately combined and integrated, they help organizations obtain sustainable competitive advantage (Teece & Pisano, 1994; Teece, 2007; Teece et al., 1997). Dealing with changes and achieving competitive advantage are major challenges in the context of manufacturing in emerging markets. Such conditions characterize the highly dynamic context familiar to Chinese manufacturers because they deal with fierce competition— both domestic and global—and struggle to achieve the upgrades and transformations necessary for innovation-intensive and high-quality development (Jiao et al., 2019; Long & Liao, 2021; Yuan et al., 2021). In this context, Ludwig and Pemberton (2011) used DCT to explain why it is difficult to change traditional manufacturing processes on short notice and that a firm's dynamic capabilities can help it change manufacturing processes by adapting current routines and determining how processes can be permanently changed in the future. The study by Ludwig and Pemberton (2011) focused on the Russian steel industry, but other studies have demonstrated that DCT can provide apt explanations of the efficacy Chinese manufacturers' dynamic capabilities in dealing with fierce competition and rapidly changing business conditions.[2]

We indicate that in Chinese dynamic manufacturing context, digitalization, network capability, and BMI represent three critical dynamic capabilities that support digital transformation at the process level, organization level, and business domain level, respectively. Digitalization and network capability help organizations acquire resources and information to sense opportunities and integrate capabilities of their functional departments and business partners to seize opportunities, which enable BMI to transform resources and capabilities, leading to improved economic and environmental performance. Next, we explain the foundational concepts we leverage with respect to digitalization, network capability, and BMI.

Digitization, digitalization, and digital transformation

Digitization, digitalization, and digital transformation are regarded as the three phases of digital transformation (Verhoef et al., 2021). *Digitization* is the conversion of information from analog form to a digital representation based on bits and bytes (Teubner & Stockhinger, 2020). *Digitalization* refers to the increasing use and general institutionalization of digitized data and digital technologies (Buer et al., 2021; Ghobakhloo, 2020). That is, digitization emphasizes technological elements, whereas digitalization is the interaction of digital technologies with social and institutional processes (Teubner & Stockhinger, 2020). Driven by advanced technologies (Ghobakhloo, 2020), digitalization enables the transformation of existing business processes. Soluk and Kammerlander (2021) defined *digital transformation* as an organization's use of digital technologies to improve its strategies, processes,

[2] These contexts include the following: leveraging stakeholder alliances (Cui & Jiao, 2011), enhancing complex product system innovations (Su & Liu, 2012), infusing sustainability into supply chain management (Hong et al., 2018), dealing with business and nonbusiness partners in collaborative innovation (Jiao et al., 2019), promoting international diversification and innovation (Wu et al., 2016), and responding to economic incentives and tax credits to produce innovative eco-friendly products (Long & Liao, 2021).

capabilities, products, services, and even stakeholder relations.[3]

Although scholars have recognized firms' adoption of digital technologies to transform business models (Li et al., 2020; Sjödin et al., 2021; Weking et al., 2020), the relationship between digitalization and BMI has not been demonstrated empirically.[4] Most studies have focused on broad economic performance, and only a few have explored the environmental performance of digitalization.[5] Overall, empirical evidence of the effect of digitalization on environmental performance remains limited. Our study partially addresses the need to validate how digitalization leads to improved economic and environmental performance through BMI.

Network capability

The sustainable development of an organization is supported not only by its internal resources but also by its external resources, that is, those obtained from various relationships in its partnering network (Yang et al., 2018). Chi et al. (2010) described this network as a system in which organizations interact with one another, making it a platform for the collaborative development of resources and capabilities. Mu and Benedetto (2012) defined *network capability* as an organization's ability to leverage existing external connections and establish new ones—an ability that enables the flexible allocation of resources that support the development of competitive advantage in a dynamic environment.[6] Network capability involves formal or informal relationships in which organizations exchange resources and capabilities with external partners (Yang et al., 2018).

Whereas some studies have emphasized the ability of organizations to strengthen relationships with external partners, others have explained network capability from a more comprehensive perspective.

[3] Soluk and Kammerlander (2021) divided digital transformation into three stages: (1) process digitalization, (2) product and service digitalization, and (3) business model digitalization.

[4] By contrast, previous studies have empirically validated the role of digitalization in promoting organizations' operational performance (Buer et al., 2021; Gillani et al., 2020), supply chain performance (Paolucci et al., 2021; Yang et al., 2021), firm performance (Sousa-Zomer et al., 2020), and organizational performance (Nwankpa & Datta, 2017). In addition, digital technologies have been found to be beneficial to operating-cost reduction and service-quality improvement (Cenamor et al., 2019; Cenamor et al., 2017), and digitalization helps organizations train employees and monitor performance by establishing automated security and monitoring procedures, thus improving operational efficiency (Bag et al., 2021).

[5] For example, Li et al. (2020) investigated the impact of digital technology adoption on economic and environmental performance. Bag et al. (2021) explored the advantages of renewable energy technology, recycling technology, and other clean production methods in promoting the development of green products and reducing the negative influence of production activities on the environment; they argued that the application of intelligent manufacturing technologies enables firms to achieve sustainable-development goals in terms of environmental quality, economic prosperity, and social equity.

[6] Mu and Benedetto (2012) pinpointed three critical components necessary to enhance an organization's network capabilities: discovering suitable network partners, effectively managing these network relationships, and strategically leveraging these associations for mutual benefit.

Walter et al. (2006) argued that network capability should comprise relational skills, coordination, partner knowledge, and internal communication from both internal and external perspectives: The external information, knowledge, and resources organizations acquire need to be transferred to internal departments and employees (Walter et al., 2006). Partanen et al. (2020) maintained that internal communication and partner knowledge, proposed by Walter et al. (2006), are innovative, distinguishing network capability from alliance management capability and relational capability. Our study follows Walter's conceptualization of network capability.

Previous studies have demonstrated the positive influence of network capability on economic performance. Chi et al. (2010) suggested that firms rely on their partnering networks to access external resources and enable competitive actions, thus improving competitive performance. Parida et al. (2016) found that network capability can positively influence sales growth. Scholars have also proposed that network capability affects innovation performance and new-product performance (Mu, 2014; Najafi-Tavani et al., 2018). Walter et al. (2006) emphasized that organizations with excellent network capabilities are more likely to stimulate innovation than those with poor capabilities. Firms' network capabilities can help them rapidly identify opportunities and paths for launching new services and achieving efficient commercialization. Parida et al. (2017) analyzed how network capability contributes to organizational innovativeness and influences customer, sales, and innovation performance. In one of the few studies that have addressed sustainability performance as an outcome of network capability, Amara and Chen (2020) found that network capability fosters eco-innovation capability and sustainability performance.

Business model innovation (BMI)

Teece (2010) defined a *business model* as an architecture composed of the mechanisms of value creation, delivery, and capture. Saebi et al. (2017) further described a business model as an organization's market segmentation and value proposition, the structure of the value chain, value capture mechanisms, and the organic connections between these elements. *BMI* refers to the discovery of new value propositions to generate new sources of profit (Zott & Amit, 2007). Scholars have argued that BMI consists of an organization's new methods of creating and obtaining value for stakeholders by modifying or improving at least one element of its business model (Casadesus-Masanell & Zhu, 2013).

Efficiency, novelty, lock-in, and complementarity are the four types of BMI (Amit & Zott, 2001). Following Zott and Amit (2007), we investigate novelty- and efficiency-centered designs, which are a firm's fundamental alternatives for creating value and which facilitate the building and testing of a parsimonious theory. Novelty-centered BMI aims to create new transaction types using a new method of communication among transaction participants and fostering product differentiation, whereas efficiency-centered BMI seeks to help organizations achieve transaction efficiency and reduce transaction costs (Zott & Amit, 2007). Scholars have also emphasized that novelty- and efficiency-centered BMI serve as the firm's business strategies for achieving sustainable competitive advantage through product differentiation and price leadership, respectively (Teece, 2010; Zhang et al., 2021; Zott & Amit, 2007).

BMI lays the foundation for sustainable business success (Casadesus-Masanell & Zhu, 2013). Scholars have demonstrated that BMI has a positive influence on firm growth (Wei et al., 2014) and firm performance (Latifi et al., 2021; Zott & Amit, 2007). Both novelty- and efficiency-centered BMI have positive effects on economic performance, but there is limited empirical evidence concerning the relationship between BMI and environmental performance. Klein et al. (2021) noted that businesses prefer to integrate sustainability concerns into their products, services, and processes, and they investigated how a commitment to sustainability influences firms' BMI efforts. However, whether BMI can result in improved environmental performance requires further investigation.

Extant research has explored both internal and external factors affecting BMI. *Internal factors* include company size, entrepreneurship, culture, strategy, human resources, and organizational capabilities, whereas *external factors* include technologies, markets, competition, and policies (Klein et al., 2021; Saebi et al., 2017; Teece, 2010). Scholars have considered the effects of new technologies on BMI in the digital economy. Digital technologies (e.g., AI, cloud computing, big data) can give rise to a variety of novel business models (Guo et al., 2020). Weking et al. (2020) conducted case studies to explain how firms foster BMI by leveraging cyber-physical systems, IoT, and smart factories. Sjödin et al. (2021) showed how AI capabilities enable BMI, and Li (2020) identified emerging trends in the use of digital technologies to facilitate BMI in creative industries. Although extensive research has pointed out the key role of digitalization in BMI, there is still a lack of empirical validation concerning whether and how digitalization leads to novelty- and efficiency-centered BMI.

Research Model and Hypotheses

Figure 1 presents our conceptual model, which we operationalize in hypothesis form. From the DCT perspective, digitalization helps organizations sense potential collaborative opportunities by collecting information extensively using digital technologies (Cenamor et al., 2019; Li et al., 2022).Based on its digital infrastructure, an organization can further establish and manage networks with its potential business partners to integrate heterogeneous resources (Goduscheit & Faullant, 2018; Schneider & Kokshagina, 2021). Thus, digitalization triggers organizational changes in networking. Digitalization can contribute to BMI through sensing and seizing opportunities driven by digital resources (e.g., data, software and hardware) (Li et al., 2022), whereas network capability promotes BMI through sensing and seizing opportunities driven by organizational resources (e.g., management, expertise, and norms) (Cenamor et al., 2019; Chen et al., 2021). We thus propose the direct effects of digitalization on BMI, network capability on BMI, and the mediating effect of network capability. BMI enables reconfiguration of resources and capabilities integrated through digitalization and network capability to transform value proposition and creation to main competitiveness (Teece, 2018), and thus we propose the effects of BMI on performance and the mediating effects of BMI . Environmental dynamism as the contextual factor is incorporated into the model as a moderating variable. In the remainder of this section, we explain the operationalization of our model through testable hypotheses.

[Insert Figure 1 here]

Digitalization and network capability as enablers of BMI

A firm that embraces *digitalization* relies on the use of digital technologies to connect its business processes across intra- and inter-organizational boundaries (Li et al., 2020; Yang et al., 2021), whereas a firm's *network capability* reflects how it manages the boundaries within its business networks (Amara & Chen, 2020; Parida et al., 2017). Firms with excellent digitalization capability can sense opportunities to collaborate with potential business partners (Cenamor et al., 2019). Our study argues that digitalization provides a technological infrastructure to connect these business partners to establish firms' networks (Cenamor et al., 2019; Chi et al., 2010; Pagani & Pardo, 2017). The functional departments and external partners can be connected efficiently through the application of digital technologies. Such digital connections can increase information transparency within the network (Battleson et al., 2016), which improve the efficiency of communication and coordination and promote mutual understanding among business partners (Pagani & Pardo, 2017). Cenamor et al. (2019) proposed that digital-technology-enabled platforms facilitate intra- and interorganizational interactions and help firms manage their networks. In addition, digitalization enable firms to integrate new, heterogeneous resources across organizational boundaries and strengthen network connections (Cenamor et al., 2019). Lyytinen et al. (2016) proposed that digital technology adoption accelerates network integration. Thus, we hypothesize that:

H1. Digitalization has a positive influence on a firm's network capability.

Digitalization improves firms' resource acquisition and integration capabilities (Sousa-Zomer et al., 2020; von Briel et al., 2019; Yu et al., 2019). Digital technologies provide organizations with better access to external information and resources that can improve their capabilities to sense market changes and uncertainties (Li et al., 2020), and both the integration of diverse and heterogeneous resources and the establishment of data assets through digitalization strengthen the organizations' seizing capability to promote new-product development (Durmusoglu & Kawakami, 2021). Moreover, firms can easily involve consumers in product development processes through digitalization when creating new products and services in line with market demands (Guo et al., 2020; Lyytinen et al., 2016). Francesco et al. (2022) demonstrated that big-data-analytics capabilities support effective marketing actions, such as new-product launches, by capturing and analyzing customers' needs and behavior patterns and can thus help optimize product customization. With digital technologies, firms can upgrade production lines to provide new combinations of products and services (Buer et al., 2021). Our study assumes that digitalization will help firms overcome geographical barriers and physical constraints, thereby facilitating connections with new business partners to generate collaborative and innovative solutions. For example, cloud-based technologies make it easy to share knowledge among decentralized supply chain partners to enable innovation and continuous change (Gupta et al., 2020). Thus, we predict:

H2a. Digitalization has a positive influence on a firm's novelty-centered BMI.

Digitalization influences efficiency-centered BMI in several respects. First, digitalization, such as adopting automation technologies and robotics, enables standardized and large-scale production processes that will improve production efficiency (Buer et al., 2021; Ghobakhloo, 2020). The transformation of production processes in modern manufacturing firms relies mostly on the application of digital technologies (Buer et al., 2021). Second, digitalization can improve communication efficiency with business partners (Li et al., 2020). The application of digital technologies facilitates real-time information exchange and thus increase transparency while reducing transaction costs (Yang et al., 2021). Improved information-gathering and information-processing capabilities also promote quick decision-making and transaction efficiency (Li et al., 2020). Third, digital technologies open boundaries so firms can interact with more business partners and promote the free mobility and efficient integration of heterogeneous resources (Pagani & Pardo, 2017). Broekhuizen et al. (2021) pointed out that digitalization enables firms to establish digital-related dynamic capabilities and to integrate internal and external resources to support efficiency-centered innovation. In summary, we hypothesize:

H2b. Digitalization has a positive influence on a firm's efficiency-centered BMI.

We also propose that network capability can effectively promote novelty-centered BMI by integrating and leveraging resources and capabilities from business partners. First, an extensive partnering network and a strong network capability can broaden a firm's sources of information and resources, which helps the firm rapidly identify market opportunities and introduce new businesses (Zhu et al., 2019). Firms obtain information and knowledge through their networks to deepen their understanding of the business environment (Guo et al., 2021) and to innovate their business models to adjust to ever-changing conditions (Zhang et al., 2021). Second, network capability enables companies to obtain heterogeneous external capabilities, develop new resource combinations and cooperative relationships, drive new-product development, and provide resources and support for novelty-centered BMI (Chen et al., 2021; Mu, 2014; Najafi-Tavani et al., 2018); Zhang et al. (2021). Zhang et al. (2021) demonstrated that exploration across organizational boundaries contributes to knowledge integration and generation and promotes the overall evolution of a product class and technology. Third, firms with strong network capabilities can reduce the uncertainty in the process of novelty-centered BMI through sufficient information and knowledge sharing (von Delft et al., 2019). Therefore, we predict:

H3a. Network capability has a positive influence on a firm's novelty-centered BMI.

Similarly, our study explains the positive effect of network capability on efficiency-centered BMI.

Networks provide flexible communication channels for all types of information and resources (To et al., 2019). Companies in networks can exchange and share resources more easily by establishing external connections, and they can obtain at lower costs the knowledge and capabilities required to promote efficiency-centered BMI (Zhang et al., 2021). The establishment of partnering networks also reduces firms' dependence on certain scarce proprietary resources, thus mitigating opportunistic behaviors, promoting cost reduction, and improving transactional efficiency (Chi et al., 2010). Yu et al. (2019) showed that communication and mutual understanding between partners reduce the risks of information asymmetry. Moreover, good network relationships can provide the focal firm with a cushion (i.e., alternative sources) that reduces the risk of vendor lock-in, subsequently preventing unexpected supply chain disruptions and lowering the average costs of production (Riccardo et al., 2021). Therefore, firms with strong network capabilities can reduce transaction costs and improve transaction efficiency, providing favorable conditions for efficiency-centered BMI (Zott & Amit, 2007). Thus, we hypothesize the following:

H3b. Network capability has a positive influence on a firm's efficiency-centered BMI.

Our study further proposes that network capability mediates the effects of digitalization on novelty- and efficiency-centered BMI. Generally, the use of digital technologies can help firms establish collaborative platforms (Li et al., 2020), which serve as resource pools that enable network participants to innovate (Wang & Hu, 2020). However, not all external resources are equally accessible to all firms (Nwankpa & Datta, 2017). The firm needs to absorb and integrate valuable heterogeneous organizational resources from its business partners by developing network capability (Chen et al., 2021). Network capability can promote cooperation among business partners and the "wisdom of the crowd" (Chen et al., 2021) and enhance the quality of resources gathered through digital technologies, which subsequently promote innovation activities (Chen et al., 2021). Digitalization provides a technological architecture that enables network partners to exchange information and discover new business opportunities and network capability can help partners promote product innovation and improve transaction efficiency (Cenamor et al., 2019; Chi et al., 2010; Mikalef et al., 2021a). Firms without adequate network capabilities cannot fully use external resources of their business partners to conduct novelty- and efficiency-centered BMI (Chen et al., 2021; Mu, 2014). Our study emphasizes the role of network capability in high-quality and high-efficiency decision-making, which cannot be replaced by digitalization (Cenamor et al., 2019; Chi et al., 2010). In summary, digitalization should influence BMI activities through network capability. Thus, we hypothesize the following:

H4. A firm's network capability positively mediates the effects of digitalization on (a) novelty-centered BMI and (b) efficiency-centered BMI.

Influence of BMI on sustainability performance

This study claims that novelty-centered BMI can help firms achieve unique forms of competitive advantage, thereby leading to improved economic performance. Novelty-centered BMI aims to connect new trading partners or reconnect existing trading partners in innovative ways (Amit & Zott, 2001). Firms focusing on novelty-centered BMI can reconfigure heterogeneous knowledge and resources from partners to create new values or profit (Pati et al., 2018). Guo et al. (2020) pointed out that by supporting the development of novel products, services, or both, innovative business model designs can help companies leap into new markets. Novelty-centered BMI also motivates firms to continuously learn and accumulate specialized knowledge from their partners (Pati et al., 2018), rapidly replace scarce assets and resources, establish high switching costs for buyers, and set up invisible entry barriers for competitors (Zott & Amit, 2007). If in fact novelty-centered BMI has these positive aspects, they should enable firms to gain potential first-mover advantages, thus improving their economic performance. Scholars have also found that successful novel business models tend to entice imitations (Teece, 2010). In this case, firms conducting novelty-centered BMI can develop an excellent reputation and corporate/brand image in the market, which will help them expand their market share and increase their pricing power. In summary, novelty-centered BMI can strengthen a firm's unique competitive advantage, consequently enhancing the firm's economic performance. Thus, we hypothesize:

H5a. Novelty-centered BMI is positively related to a firm's economic performance.

We also propose that novelty-centered BMI can improve environmental performance. Again, in the last few decades, environmental sustainability has become increasingly important to both organizations and consumers (Elliot, 2011). This concern has led to a downstream demand for responsible production and environmentally friendly products and services (Loeser et al., 2017). Firms that engage in novelty-centered BMI can better understand downstream customers' demand for such products and services and develop innovative eco-friendly products and services to bolster a green image (Klein et al., 2021) and improve their environmental performance. Extensive collaboration with various partners, such as universities and research institutions, can be beneficial to sustainability-related innovation (Sudusinghe & Seuring, 2022). Furthermore, as firms get better at leveraging knowledge partners and delivering novelty-centered BMI for environmental performance, they can better introduce, encourage, and integrate such environmental thinking when they connect with new trading partners (Amit & Zott, 2001). In summary, with the help of knowledgeable partners, firms tend to obtain and absorb environmental management knowledge to improve green production and engage in green-product development. Therefore, the following hypothesis is consistent with prior research:

H5b. Novelty-centered BMI is positively related to a firm's environmental performance.

Efficiency-centered BMI can improve transaction efficiency and reduce transaction costs for firms and their partners. Low cost is always associated with pricing advantages, and it not only encourages existing customers to increase their purchase quantities but also attracts new customers and trading partners (Zott & Amit, 2007). In our context, firms implementing efficiency-centered BMI can continuously expand transaction scales and increase their market share and sales, ultimately improving their economic performance (Latifi et al., 2021; Wei et al., 2014). Previous studies have shown that efficiency-centered BMI enables firms to simplify coordination and communication procedures and mechanisms with their business partners (Zhang et al., 2021; Zott & Amit, 2007). Thus, a smooth trading experience will strengthen a firm's customer retention and loyalty, and the firm's partners, such as suppliers and logistics providers, will in turn become more willing to collaborate for the purpose of value co-creation (Sudusinghe & Seuring, 2022). Moreover, efficiency-centered BMI improves transparency and reduces uncertainty and information asymmetry (Wei et al., 2014). Firms that cannot respond to uncertainty and risks effectively tend to suffer from higher risks of recovery costs and loss of profit (Syed et al., 2020). Thus, we predict:

H6a. Efficiency-centered BMI is positively related to a firm's economic performance.

Environmental performance involves resource saving, energy consumption reduction, and environmental protection (Zhu & Sarkis, 2004). Efficiency-centered BMI can promote environmental performance by improving resource utilization efficiency and simplifying trading procedures (Zott & Amit, 2007). When implementing efficiency-centered BMI, firms generally reallocate or reconfigure available resources to avoid redundancy, eliminate unnecessary trading procedures to save resources and energy, and improve trading transparency to reduce waste of resources, rework, and errors (Zhang et al., 2021), thereby improving environmental performance. Efficiency-centered BMI also enables firms to rapidly gather and process information that helps them deal with the increasing uncertainty and complexity of environmental management activities (Klein et al., 2021). In summary, to comply with sustainable-development strategies, firms introduce efficiency-centered BMI to implement energy-saving and environmentally friendly processes and reduce waste and pollution, hence improving their environmental performance. Thus, we hypothesize the following:

H6b. Efficiency-centered BMI is positively related to a firm's environmental performance.

Mediating effect of BMI

Based on DCT, digitalization and network capability enable organizations to gather and aggregate information, knowledge, competencies, and resources for identifying opportunities and challenges by connecting organizations with business partners and seizing the opportunities or neutralize threats through investment in digital resources and organizational resources , whereas novelty- and efficiency-centered BMI enable organizations to recombine and reconfigure internal and external resources that enable them to transform and adjust to changes (Teece, 2018). As a result, the effects of digitalization and network capability on the two dimensions of sustainability performance are mediated by novelty- and efficiency-centered BMI.

Digitalization allows firms to access external information and resources from their business partners and to establish links with their external business environments by leveraging digital technologies (Li et al., 2020). Similarly, network capability enables firms to acquire resources from their network partners through social or relational mechanisms (Chi et al., 2010). Adequate and diverse information and resources enhance firms' sensing capabilities, which enable them to rapidly pick up signals from the environment and identify business opportunities and challenges (Mikalef et al., 2021). For example, firms can obtain the best insights into customer demand through big-data-analytics techniques (Shamim et al., 2019). The fourth Industrial Revolution (i.e., Industry 4.0) has introduced technologies such as virtual reality, augmented reality, and digital twins that can detect or monitor bottlenecks in the production process, enable predictive maintenance, and minimize production-line downtime (Frank et al., 2019; Mourtzis, 2020). External partners in a firm's network can also inspire the firm with new knowledge and ideas about the business (Chi et al., 2010).

However, identifying opportunities and gathering resources offer limited capabilities that directly support the continuous improvement of sustainability performance. To deal with potential business changes, firms should implement novelty- and efficiency-centered BMI to dynamically reconfigure resources acquired through digitalization and network capability. BMI requires firms' transformation capabilities to periodically reposition themselves for the purpose of addressing new opportunities and threats (Teece, 2018). Mezger (2014) proposed a capability-based conceptualization of BMI and showed that new business models are designed based on bundles of valuable competencies and resources. Teece (2018) argued that the refinement and transformation of business models are high-order capabilities that support the adjustment and recombination of low-order capabilities and resources. BMI serves to orchestrate and connect organizational elements based on a core value proposition to provide sustainable competitive advantage (Teece, 2010; Zott & Amit, 2007). Novelty-centered BMI enables firms to innovate for new value propositions, new ways of conducting transactions, and new links with business partners, whereas efficiency-centered BMI focuses on improving transaction efficiency and reducing transaction costs (Zott & Amit, 2007). In summary, with the support of distinct BMI types, firms maximize the sustained values of resources obtained using digital technologies and network-partner collaborations. Thus,

H7. Novelty-centered BMI positively mediates the effect of digitalization on a firm's (a) economic performance and (b) environmental performance.

H8. Efficiency-centered BMI positively mediates the effect of digitalization on a firm's (a) economic performance and (b) environmental performance.

H9. Novelty-centered BMI positively mediates the effect of network capability on a firm's (a) economic performance and (b) environmental performance.

H10. Efficiency-centered BMI positively mediates the effect of network capability on a firm's (a) economic performance and (b) environmental performance.

Moderating effect of environmental dynamism

Environmental dynamism can be defined as a high rate and large volume of changes in a firm's business environment (Azadegan et al., 2013; Dess & Beard, 1984). In a highly unstable and unpredictable environment, product life cycles tend to be shortened, and existing production processes can easily compromise a firm's competitiveness (Azadegan et al., 2013; Chan et al., 2016). Therefore, a dynamic environment drives firms to constantly introduce new products, services, or processes to respond to changing market demand and intensified market competition (Chan et al., 2016). Our study proposes that the implementation of novelty-centered BMI to cope with the ever-changing environment involves two basic requirements: the speed and heterogeneity of resource acquisition. The effect of digitalization on novelty-centered BMI can be strengthened by rapid information gathering and processing and timely acquisition of heterogeneous resources (Guo et al., 2021; Li, 2020). Digital technologies enable real-time connectivity to support quick decision-making (Gillani et al., 2020) and standardize digitalized resources to gather heterogeneous resources (Thomas & Carsten Lund, 2020). Hence, the firm can efficiently and rapidly utilize heterogeneous resources to generate novel ideas and respond to high environmental uncertainties. Moreover, the new markets and business opportunities in a dynamic environment are fleeting if not promptly grasped (Yuan et al., 2021). Firms have to enhance the perception of rapid changes (Mikalef et al., 2020) in customer needs and technological breakthroughs (Li & Liu, 2014). We extend this connection to propose that novelty-centered BMI relies strongly on digitalization to quickly sense and seize opportunities in the presence of environmental dynamism.

On the other hand, environmental dynamism is highly related to organizational pressure, causal ambiguity, and exchange hazards (Yuan et al., 2021), which lead to high transaction costs and low transaction efficiency. The exploratory use of emerging digital technologies motivates firms to introduce novel solutions (Wei et al., 2014), but it can also increase the complexity of business operations (Paolucci et al., 2021), particularly when technologies are premature in their development or have not been well integrated in the operations of the firm. In a dynamic environment, the efficiency of business operations and transactions can be seriously harmed by the inappropriate use of digital technologies (Rana et al., 2021; Son et al., 2021). In contrast to novelty-centered BMI, efficiency-centered BMI favors a more stable organizational environment and disciplined decision-making (Yuan et al., 2021). Rana et al. (2021) emphasized the technology, privacy, and security risks associated with digitalization. The presence of these risks implies that the positive effects of digitalization on efficiency-centered BMI can be weakened by the increased complexity and risks caused by environmental dynamism. Thus, we hypothesize:

H11a. Environmental dynamism positively moderates the relationship between a firm's digitalization and novelty-centered BMI.

H11b. Environmental dynamism negatively moderates the relationship between a firm's digitalization and efficiency-centered BMI.

Environmental dynamism requires firms to make decisions and take actions in a timely and flexible manner. Both novelty- and efficiency-centered BMI drive firms to transform their methods of conducting transactions with business partners (Zott & Amit, 2007). When firms engage in novelty- and efficiency-centered BMI in highly unstable environments, business partners are required to accept and adjust to frequent changes in the business models (Pati et al., 2018). Firms also need to respond to a variety of new or existing partners from different domains (Mikalef et al., 2021). Network capability can increase the flexibility of relationships with such partners (Parida et al., 2016). Firms with strong network capabilities can efficiently coordinate and communicate with business partners to reconfigure competencies and resources and escape unfavorable path dependencies collaboratively (Cenamor et al., 2019; Chen et al., 2021). In addition, strong network capabilities can help firms ensure the quality of resources acquired from business partners, contributing to both novelty- and efficiency-centered BMI in an unpredictable environment (Chi et al., 2010). Despite the potential risks related to environmental dynamism, firms can leverage communication and coordination mechanisms, relational skills, and partner knowledge to govern business partners and prevent the negative effects on BMI (Chen et al., 2021). Our study thus proposes that environmental dynamism can strengthen the effects of network capability on novelty- and efficiency-centered BMI. Thus, we predict:

H12a. Environmental dynamism positively moderates the relationship between a firm's network capability and novelty-centered BMI.

H12b. Environmental dynamism positively moderates the relationship between a firm's network capability and efficiency-centered BMI.

Research Methodology

Sampling and data collection

Our study focused on large manufacturing firms in China, a burgeoning economy marked by swift economic expansion and robust productivity (Chen et al., 2014; Yang et al., 2021). In alignment with national initiatives like "Made in China 2025," the Chinese government has been actively encouraging digital transformation as a pathway to high-quality development (Wang & Hu, 2020). Specifically within the manufacturing industry, firms are increasingly adopting digital solutions as a strategic response to intense global competition and the disruptions precipitated by the COVID-19 pandemic (Pan & Zhang, 2020). Additionally, driven by mounting concerns over rapid resource depletion and environmental degradation, these Chinese manufacturing entities are taking deliberate steps toward environmental conservation and resource efficiency to achieve sustainable development (Chan et al., 2016; Li et al., 2020).

Given this intricate, volatile, and dynamic environment, the Chinese manufacturing landscape offers an ideal research context for examining the interplay between digital transformation and sustainability performance through the lens of DCT (Yuan et al., 2021). To empirically validate our research model, which posits that digitalization enhances sustainability performance, we gathered data from Chinese manufacturing firms using an online survey methodology.

The potential sampling pool was determined based on the Yellow Pages of China Telecom (Jacobs et al., 2016), which contains information on Chinese manufacturing companies' names and contacts. To improve the quality and efficiency of data collection, we collaborated with a national information technology company to contact the manufacturing companies directly. Data collection was conducted from October 2021 to December 2021. An email linked to the survey was sent to potential respondents, inviting them to participate (Dillman, 2007). We explained that this study had received Institutional Review Board approval from the lead author's institution and that the data collected would be used with absolute confidentiality and only for academic research purposes (Yang et al., 2021). We also offered to share a report of the findings at the end of the study. The questionnaire contained two attention-check questions. Followed-up messages and calls were used to remind participants to respond. These measures helped ensure the quality and reliability of the data. A total of 1,681 questionnaires were distributed, and 255 valid responses were returned.

Table 1a–d provides a comprehensive summary of the respondent companies, categorizing them based on industry, sales volume, workforce size, and geographical regions. Our survey targeted middle- and top-level managers, such as CEOs, general managers, and departmental managers in areas like production, product management, marketing, and procurement. These individuals possess in-depth knowledge of their companies' business operations, product lines, core production processes, and key performance indicators (Jacobs et al., 2016).

The survey demographics reveal that 36.5% (93 respondents) held top-management positions, whereas the remaining 63.5% (162 respondents) were from middle management. As for their tenure, 8.7% had been in their roles for 1–3 years, 52.9% for 4–6 years, and 38.4% for seven years or longer.

Regarding industry subsectors, the participating firms were predominantly situated in electronics and electrical manufacturing (26.3%), equipment manufacturing (21.2%), and metal, mechanical, and engineering (20.4%). Only a minimal proportion (0.8%) came from the toy, arts, and crafts subsector. This distribution closely mirrors the concentration of manufacturing sectors in China (Flynn et al., 2010; Yang et al., 2021).

In terms of company size, based on the number of employees, the sample covered a spectrum of small (<300 employees), medium (300–1000 employees), and large (>1000 employees) enterprises. Specifically, the proportions were 33.3%, 45.9%, and 20.8%, respectively, aligning well with the overall composition of manufacturing firms in China (Wei et al., 2014).

Geographically, the firms were located across major Chinese economic zones, including the Circum-Bohai Sea Economic Zone (encompassing cities such as Beijing, Tianjin, Hebei, Liaoning, Shandong, and Shanxi), the Pan-Pearl River Delta Economic Zone (e.g., Guangdong, Guangxi, Fujian, Jiangxi, Hunan, Sichuan, Yunnan, and Guizhou), and the Yangtze River Delta Economic Zone (e.g., Shanghai, Zhejiang, Jiangsu, and Anhui). Some were also situated in other areas, including Gansu and Chongqing. These zones are the primary industrial hubs of China, covering a broad range of eastern, central, and western cities. Consequently, as corroborated by Table 1d, our sample of respondent companies aptly represents the distribution of China's key economic zones (Yang et al., 2021).

[Insert Table 1a–d here]

Construct measures

The measurement scales for digitalization, network capability, novelty-centered BMI, efficiency-centered BMI, economic performance, and environmental performance were adapted from well-established scales, as detailed in Appendix A. We first developed an English version of the questions with a 7-point Likert-type scale. A back-translation procedure was carried out by two bilingual researchers to ensure conceptual equivalence between the versions (Douglas & Craig, 2007). Subsequently, a pilot study was conducted among 15 practitioners. It gave the researchers the opportunity to further improve the wording and readability of the items, which can enhance content validity (MacKenzie et al., 2011). We summarize the measurements of the key constructs in the following sections.

Digitalization. Digitalization is the adoption of advanced technologies (e.g., cloud service, the IoT, big data analytics, smart manufacturing, and automation) to digitalize business processes aspects (Nasiri et al., 2020). Five reflective measures were adapted to measure digitalization in manufacturing firms (Bharadwaj et al., 2013; Henseler & Chin, 2010; Nasiri et al., 2020). We asked the respondents to indicate, on a 1–7 Likert-type scale, the degree to which their firms adopt digital technologies to (1) connect business processes, (2) collect data from various sources, (3) exchange information, (4) manage customer interfaces, and (5) digitalize everything that can be digitalized. The responses of 1 to 7 represent "extremely low" to "extremely high," accordingly.

Network capability: Walter et al. (2006), define network capability as an integrated construct comprising four key components: coordination, relational skills, partner knowledge, and internal communication. Enhancement in any of these components subsequently fortifies a firm's overall network capability. In line with the frameworks proposed by Parida et al. (2016) and Walter et al. (2006), we conceptualized network capability as a second-order reflective–formative construct.

For the component of *coordination*, we employed three metrics aimed at quantifying the boundary-spanning activities that facilitate a firm's interaction with various stakeholders such as customers, suppliers, and business partners (Walter et al., 2006). In assessing relational *skills*, we utilized three items that gauge the social competencies essential for initiating and sustaining interpersonal relationships with partners (Baron & Markman, 2003). Partner knowledge, or the vital information firms should possess for proactively managing business relationships, was measured through three items (Walter et al., 2006). Finally, internal communication was evaluated via three items that capture the extent to which managerial and non-managerial staff assimilate and disseminate pertinent information about external partners across organizational departments (Walter et al., 2006).

Survey participants were instructed to indicate their level of agreement with various statements related to these components, utilizing a 1–7 Likert-type scale. Specifically, they were asked, "To what extent do the statements apply to your organization in terms of the form, care, and use of relationships with partners (customers, suppliers, technology partners, multipliers)?" (Walter et al., 2006, p. 561). Here, a score of "1" denoted "not applicable at all," whereas a score of "7" signified "to a great extent."

Novelty- and efficiency-centered BMI. This study constructs metrics for evaluating both novelty- and efficiency-centered BMI, drawing upon the foundational work by Wei et al. (2014) and Zott and Amit (2007). Respondents were directed to assess statements related to their organization's business model themes using a 1–7 Likert-type scale, where "1" indicated "not at all," and "7" signified "to a great extent."

For novelty-centered BMI, we utilized a seven-item scale designed to capture various aspects of innovation within business models. The items include: (1) The incorporation of new amalgamations of products, services, and information; (2) The introduction of unique incentives in transactional engagements; (3) Innovative methods for linking participants in transactions; (4) The creation of untapped revenue streams; (5) The adoption of novel business strategies and methods; (6) The implementation of new operational processes, routines, and norms; and (7) A general sense of novelty pervading the company's business model.

Efficiency-centered BMI was measured using a seven-item scale, highlighting transactional elements specifically designed to reduce costs, accelerate speed, and enhance overall efficiency (Zott & Amit, 2007). The scale encompasses: (1) Minimization of transaction costs for business model participants; (2) Simplification of transactions from the user perspective; (3) Reduction in transactional errors; (4) Cost-efficient strategies for marketing, sales, and communication among participants; (5) Transparency in transactions; (6) Provision of informational symmetry among transaction participants, reducing knowledge asymmetry concerning the quality and nature of goods exchanged; and (7) Facilitation of swift transactions.

Economic and environmental performance. Measures of economic performance include five items adapted from Flynn et al. (2010). The respondents were asked to evaluate their firm's performance on a 1–7 Likert-type scale in terms of growth in (1) market share, (2) return on investment, (3) return on sales, (4) profit, and (5) sales compared with those of their major competitors. An answer of "1" indicated "worse that competitors" and "7" indicated "better than competitors." Environmental performance was measured using five items based on Zhu and Sarkis (2004). The respondents were required to indicate, on a 1–7 Likert-type scale, the degree of (1) decrease of energy consumption, (2) improvement of the firm's environmental situation, (3) reduction of solid wastes, (4) reduction of wastewater, and (5) reduction of air emission in firms' production and operation activities. An answer of "1" indicated "not at all," and "7" indicated "great extent." We operationalized both constructs as reflective latent variables.

Environmental dynamism. The four reflective items of environmental dynamism were adapted from Azadegan et al. (2013), Dess and Beard (1984), and Li et al. (2020). The respondents were asked to evaluate the changes in (1) consumer demographics, (2) government regulations, (3) their production/service provision modes, and (4) the rate of innovation. A 1–7 Likert-type scale was used, with "1" representing "extremely low" and "7" representing "extremely high."

Control variables. This study included two control variables to limit the influence of confounding effects, reduce endogeneity issues, and enhance internal validity. Firm size is considered an influence on performance outcomes because larger organizations tend to enjoy a wide range of capabilities and resources (Zhu & Sarkis, 2004). Our study measured firm size using an ordinal variable based on the number of employees` (Mikalef et al., 2021a; Mikalef et al., 2021b) into small (less than 300 employees), medium (300–1000 employees) and large (more than 1000 employees) according to the recommendations of National Bureau of Statistics of China. Firm ownership structure was the second control variable, as suggested by Chen et al. (2014). We measured it with one coded variable, with "1" for privately owned and "0" for not privately owned. In China, privately owned enterprises are usually more proactive in innovation and commercial activities than non-privately-owned firms (Chen et al., 2014).

Data Analysis and Results

This study used partial least squares structural equation modeling (PLS-SEM) to analyze the survey data. PLS-SEM is a variance-based technique that uses the total data variance to estimate model parameters (Hair et al., 2019). Following Ringle et al. (2012), Lowry and Gaskin (2014), and Hair et al. (2019), we used PLS-SEM for three reasons.

First, this study's objective was to clarify how network capability and digital transformation relate to firms' sustainability performance from both explanation and prediction perspectives. The *explanation* *perspective* indicates that the research model should explain the variance of dependent variables and be evaluated with measures of explanatory power (e.g., R^2 and the statistical significance of coefficients), whereas the *prediction perspective* focuses on predictive power measured by statistical criteria, such as the cross-validated redundancy measure Q^2 (Shmueli & Koppius, 2011). PLS-SEM can contribute to theory extension and development and offers a means of assessing the model's practical relevance for managerial consideration (Hair et al., 2019; Ringle et al., 2012), which is highly relevant to our study.

Second, our study established a hierarchical latent variable model with formative relationships. Network capability was operationalized as a formative higher-order construct that consisted of reflectively measured first-order constructs, such as relational skills, coordination, partner knowledge, and internal communication (Walter et al., 2006). PLS-SEM is the preferred method for analyzing reflective–formative type II models (Becker et al., 2012; Lowry & Gaskin, 2014; Ringle et al., 2012). Our research model included 12 latent constructs, 47 indicators, and 21 structural model relationships, and PLS-SEM is a powerful means of handling model complexity with fewer restrictions than with covariance-based structural equation modeling (Hair et al., 2019; Lowry & Gaskin, 2014; Ringle et al., 2012). The structural relationships among the constructs in our model can be assessed using main path analysis, mediation analysis, and moderation analysis. PLS-SEM can generate a high degree of statistical power, which is suitable for examining mediation and moderation effects.

Our third reason for choosing PLS-SEM was related to the sample. The 255 responses in our study satisfied the commonly suggested *10-times rule* proposed by Hair et al. (2019) and the minimum sample size estimated by the gamma-exponential method and the inverse square root method (Kock & Hadaya, 2018). We also conducted a Kolmogorov–Smirnov test to analyze the normality of the sample data. Because the results indicated a non-normal distribution, PLS-SEM was a more robust choice than CB-SEM.

Establishing the factorial validity and reliability of reflective constructs

SmartPLS 3.2.8 software was used to analyze the survey data. The measurement model was first evaluated to determine the factorial validity and reliability of the survey instruments. The hypothesized relationships in the structural model were then examined through a bias-corrected and accelerated bootstrapping procedure with 255 cases and 5,000 subsamples.

Appendix B, Table B1 shows the measurement-assessment results of all the first-order reflective constructs. Reliability was confirmed using factor loadings, Cronbach's α, and composite reliability (CR). As Appendix A shows, the values of all the factor loadings for each construct were greater than 0.50 and significant at the 0.001 level. The Cronbach's α values were between 0.65 and 0.85, and internal consistency reliability was thus ensured (Nunnally, 1978). Moreover, the CR values for all the constructs were larger than 0.800, indicating satisfactory construct reliability. The average variance extracted (AVE) values were used to measure each construct's convergent validity. AVE values higher than 0.50 indicated that more than 50% of the variance in measurement items was explained by the corresponding construct (Hair et al., 2019).

Discriminant validity was evaluated based on the heterotrait–monotrait (HTMT) ratio of the correlations. Table B1 shows that all the HTMT values were lower than the 0.85 threshold suggested by Henseler et al. (2015). We also assessed discriminant validity by determining whether the Fornell–Larcker criterion (Fornell & Larcker, 1981) was satisfied. The AVE values of all the constructs were greater than their squared correlations with other constructs. Appendix B, Table B2 summarizes all the items' cross loadings. Each item's loading on its corresponding construct was higher than its cross loadings on other constructs. The discriminant validity of the reflectively measured constructs was therefore confirmed.

Establishing the factorial validity of second-order formative constructs

Network capability was modeled as a second-order formative construct with four reflective first-order constructs (Walter et al., 2006). Following Becker et al. (2012), we estimated the parameters in the reflective–formative-type model by combining the repeated indicator approach and the two-stage approach. First, the first-order constructs—including coordination, internal communication, relational skills, and partner knowledge—were reflectively measured and linked to network capability, which was formatively measured using all 12 first-order construct indicators. Because the reliability and validity of the first-order constructs were confirmed, we then assessed the formative second-order construct in terms of indicator weights, significance of weights, and low multicollinearity of indicators, which was assessed with variance inflation factors (VIFs) lower than 3 (Becker et al., 2012; Hair et al., 2019). The results presented in Table 2 indicated that the reflective–formative model for network capability passed all the thresholds of acceptability and thus represented a valid second-order construct.

[Insert Table 2 here]

Testing for nonresponse bias

Following a widely applied approach (Armstrong & Overton, 1977), we tested for potential nonresponse bias by comparing early and late responses. The 255 responses were categorized into two groups according to response time (127 early responses collected before November 13, 2021; 128 late responses collected after this time). We performed a *t*-test between the groups on firm size (measured by the number of employees) and firm ownership type. The results indicated no significant differences in firm size ($t = -0.036$, $p = 301$) or type of ownership ($t = 1.003$, $p = 0.317$) between the two groups. Thus, nonresponse bias was not an issue of concern.

Controlling for and testing common method bias

Common method bias was controlled through a priori procedural methods and tested using ex post statistical methods. For the procedural methods, the measurement scale of each construct was separated from the others in the questionnaire. We selected knowledgeable top- and middle-level managers with rich management experience and ensured complete confidentiality to encourage honest responses (Podsakoff et al., 2003). We conducted Harman's one-factor test with the nonrotation and extraction method based on an eigenvalue greater than 1. The results indicated that the extracted first factor accounted for 35.845% of the total variance. We also created a latent common method factor to estimate all the items in the PLS analysis and, at the same time, estimated each item on its theoretical construct (Lindell & Whitney, 2001; Mikalef et al., 2021a; Mikalef et al., 2021b). The results indicated no notable differences between the estimated path model relationships with the common method factor and those without it. Therefore, common method bias was not a critical concern for our PLS analysis.

Structural model analysis of the main effects

The direct effects were first evaluated based on the PLS model depicted in Figure 2, and Table 3 summarizes the details. The coefficients for DT→NC, DT→NBMI, and DT→EBMI were 0.568 ($t = 9.678$, $p = 0.000$), 0.436 ($t = 5.216$, $p = 0.000$), and 0.264 ($t = 3.631$, $p = 0.000$), respectively. Therefore, the effects of digitalization on network capability, novelty-centered BMI, and efficiency-centered BMI were positive and significant, supporting H1, H2a, and H2b. In support of H3a and H3b, network capability was positively and significantly related to novelty-centered BMI (β = 0.423, t = 5.676, p = 0.000) and efficiency-centered BMI (β = 5.595, t = 9.684, p = 0.000). Novelty-centered BMI exhibited a positive and significant relationship with economic performance (β = 0.444, t = 5.936, p = 0.000) and environmental performance (β = 0.327, t = 3.992, p = 0.000), supporting H5a and H5b. The results also indicated that efficiency-centered BMI positively and significantly influenced economic performance (β = 0.330, t = 4.701, p = 0.000) and environmental performance (β = 0.445, t = 5.643, p = 0.000), supporting H6a and H6b. Additionally, the effect of firm nature on novelty centered-BMI was positive (β = 0.124, t = 2.684, p = 0.007), which indicated that privately owned Chinese companies facing fierce competition pursued novelty-centered BMI (Zhu et al., 2019) more actively than did their non-privately-owned counterparts.

[Insert Figure 2 here]

[Insert Table 3 here]

We also evaluated the structural model's explanatory power using the coefficient of determination (R^2). R^2 values of 0.25, 0.50, and 0.75 indicated weak, moderate, and strong in-sample predictive power, respectively (Hair et al., 2019). As Figure 2 shows, the R^2 value of network capability, 0.323, implied that the model explained 32.3% of the variance for network capability, representing weak-to-moderate predictive power. The model explained 59.2% of the variance for novelty-centered BMI, 59.7% for efficiency-centered BMI, 56.7% for economic performance, and 50.7% for environmental performance. Therefore, the model has moderate-to-strong predictive power for BMI and sustainability performance.

We further evaluated the model using the f^2 effect size. The effect size ranged from small to medium to large when the f^2 values were higher than 0.02, 0.15, and 0.35, respectively. Table 3 indicates that the effect size for each hypothesized path ranged from 0.105 to 0.593, indicating medium-to-high effect sizes.

Finally, we calculated the cross-validated redundancy measure Q^2 for each endogenous latent variable based on a blindfolding procedure. The value of Q^2 for network capability was 0.193, which was higher than 0 but lower than 0.25, indicating small-to-medium predictive relevance (Hair et al., 2019). The values of Q^2 for novelty-centered BMI (0.277), efficiency-centered BMI (0.280), economic performance (0.318), and environmental performance (0.281) were higher than 0.25 but lower than 0.50, demonstrating medium-to-large predictive accuracy (Hair et al., 2019).

Structural model mediation effects of BMI

Next, we tested the mediation hypotheses based on a bootstrap test of the indirect effects (cf. Flynn et al., 2010; Vance et al., 2015; cf. Zhao et al., 2010) in the structural model shown in Figure 3. The results are summarized in Table 4 and Appendix B, Table B3. The direct effects of digitalization on network capability ($\beta = 0.566$, $t = 9.606$, $p = 0.000$), novelty-centered BMI ($\beta = 0.436$, $t = 5.365$, $p = 0.000$), and efficiency-centered BMI ($\beta = 0.266$, $t = 3.744$, $p = 0.000$) were all positive and significant. The indirect path coefficients for DT→NC→NBMI and DT→NC→EBMI were 0.240 with a t-value of 4.484 and 0.336 with a t-value of 6.128, which meant that network capability partially mediated the effects of digitalization on novelty- and efficiency-centered BMI. Thus, H4a and H4b were supported. The direct effect of digitalization on economic performance ($\beta = -0.045$, $t = 0.593$, $p = 0.553$) and environmental performance ($\beta = 0.031$, $t = 0.448$, $p = 0.654$) were not significant, whereas the coefficients for indirect paths, including DT→NBMI→ECOP ($\beta = 0.189$, $t = 3.428$, $p = 0.001$), DT→NBMI→ENVP ($\beta = 0.113$, $t = 2.328$, $p = 0.020$), DT→EBMI→ECOP ($\beta = 0.075$, $t = 2.893$, $p = 0.004$), and DT→EBMI→ENVP ($\beta = 0.092$, $t = 2.748$, $p = 0.006$), were all significantly positive. Therefore, novelty- and efficiency-centered BMI fully mediated the effect of digitalization on economic and environmental performance, supporting H7a, H7b, H8a, and H8b.

Similarly, the direct effect of network capability on economic performance ($\beta = 0.112$, $t = 1.139$, $p = 0.255$) and its direct effect on environmental performance ($\beta = 0.179$, $t = 1.822$, $p = 0.068$) were nonsignificant, and the indirect path coefficients for NC→NBMI→ECOP, NC→NBMI→ENVP, NC→EBMI→ECOP, and NC→EBMI→ENVP were 0.183 ($t = 3.913$, $p = 0.000$), 0.109 ($t = 2.622$, $p = 0.009$), 0.167 ($t = 2.766$, $p = 0.006$), and 0.205 ($t = 2.950$, $p = 0.003$), respectively. Thus, H9a, H9b, H10a, and H10b were supported, indicating that novelty- and efficiency-centered BMI fully mediated the effect of network capability on economic and environmental performance.

We analyzed other indirect paths, which are summarized in Table 4. The coefficients for indirect paths, including DT→NC→NBMI→ECOP ($\beta = 0.104$, $t = 3.483$, $p = 0.000$), DT→NC→NBMI→ENVP ($\beta = 0.062$, $t = 2.392$, $p = 0.017$), DT→NC→EBMI→ECOP ($\beta = 0.095$, t

= 2.495, p = 0.013), and DT→NC→EBMI→ENVP (β = 0.116, t = 2.700, p = 0.007), were all significantly positive. Table B3 summarizes the direct effects, indirect effects, and total effects, providing a full picture of how digitalization leads to enhanced economic and environmental performance.

[Insert Table 4 here]

Structural model moderation effects of environmental dynamism

We then generated interaction terms to validate the moderating effects of environmental dynamism and added them to the structural model shown in Figure 2. Figure 4 summarizes the structural model results for testing moderating effects. The product indicator approach was used to build product terms between the indicators of digitalization and those of environmental dynamism. All the indicators were mean centered to avoid multicollinearity, as suggested by Henseler and Fassott (2010). The interaction term (DT × EDYN) was measured with the product terms and linked to NBMI and EBMI in the structural model. The coefficients for the path from the interaction term of digitalization and environmental dynamism to novelty- and efficiency-centered BMI were −0.125 (t = 1.553, p = 0.120) and −0.164 (t = 3.028, p = 0.002), supporting H11b only.

[Insert Figure 4 here]

Because network capability was modeled as a formative construct, we used a two-stage method to establish the interaction term, which we then linked to novelty- and efficiency-centered BMI. Following Chin et al. (2003) and Henseler and Chin (2010); Henseler and Fassott (2010), in the first stage, we ran the PLS path model to obtain the latent variable scores for network capability and environmental dynamism. In the second stage, we calculated the interaction term (NC × EDYN) using the product of the latent variable scores and then added it to the main effect model. The results indicated that the coefficient for the path linking the interaction term between environmental dynamism and network capability with novelty-centered BMI was nonsignificant (β = 0.047, t = 0.851, p = 0.395), thus H12a was unsupported. The interaction term had a significantly positive influence only on efficiency-centered BMI (β = 0.105, t = 2.568, p = 0.010), supporting H12b. Table 5 summarizes the results for the moderating effects.

[Insert Table 5 here]

Discussion

As we navigate the transformative landscape shaped by the global pandemic, the urgency of digital transformation has never been more palpable. Digital transformation is not merely a technological shift but an intricate, multidimensional endeavor that reconfigures organizational processes, interorganizational relationships, and business models, thereby exerting a profound influence on an organization's performance as well as the broader ecosystem. However, this transformation raises compelling questions about its various outcomes—both positive and negative—specifically in the context of sustainability. Drawing upon the robust framework of DCT, our study delves into the intricate mechanisms through which digitalization—the strategic application of digital technologies—enhances firms' sustainability performance.

We argue that BMI serves as a pivotal mediator, and environmental dynamism acts as a nuanced moderator in this equation. We consider both economic and environmental aspects as integral subdimensions of sustainability. Our empirical focus rests on Chinese manufacturing firms, an industry facing immense challenges including stringent government policies and intense global competition, making them compelling subjects for the exploration of digital transformation strategies. Our robust survey-based methodology aimed for expansive reach and generalizability, targeting 1,600 firms, and garnering 255 completed, validated responses. Through this inquiry, we offer valuable theoretical and practical insights, contributing to a more refined understanding of the path towards digital transformation and sustainable development. In the remainder of this section, we discuss these particulars, as well as the limitations and future research directions of this research.

Contributions to research and theory

Our study helps explain the phenomenon of digital transformation by investigating the interrelationships among digitalization, network capability, and BMI. Digital transformation is far more than the adoption of digital technologies in changing business processes (Wessel et al., 2021): it also includes the changes in the organization and business domain level (Hanelt et al., 2021; Parviainen et al., 2017; Verhoef et al., 2021). Based on DCT, our study proposes digitalization, network capabilities and BMI as three critical dynamic capabilities to support digital transformation in the process, organization, and business domain level, respectively. Digitalization as the precursory phase of digital transformation triggers organizational changes in networking relationships and business model transformation. The results confirm the positive effects of digitalization on network capability and BMI and the mediating effect of network capability on the association between digitalization and BMI. Following Li et al. (2018), Töytäri et al. (2018), and Cenamor et al. (2019), our study suggests that digitalization should be complemented by network capability development. Digitalization enables the organization to sense and seizing the business opportunities by integrating digital resources, whereas network capability can help the organization acquire and integrate organizational resources from its business partners to promote transformation. The findings therefore provide theoretical and empirical evidence of how digitalization contributes to business model transformation (Li et al., 2020; Weking et al., 2020) and advance the understanding of how successful digital transformation occurs.

To provide a nuanced understanding of the differential influence of digital transformation from the sustainability perspective, our research model introduces economic and environmental performance as dependent variables. Previous studies have extensively discussed the influence of digital technologies on operational performance (Buer et al., 2021; Gillani et al., 2020), organizational performance (Nwankpa & Datta, 2017; Sousa-Zomer et al., 2020), and competitive performance (Mikalef et al., 2020)—all of which are reflected in the economic dimension of sustainability performance. Our study extends existing research on digital transformation by including the environmental dimension of sustainability performance (Dubey et al., 2019; Hanelt et al., 2017; Nayal et al., 2022). Following Vial's (2019) suggestions, our study establishes links between digitalization and two dimensions of sustainability performance to elaborate the wider-ranging outcomes of digital transformation. We analyze and validate the mediating effects of network capability and BMI to reveals the paths through which digitalization leads to better economic and environmental performance (Soluk & Kammerlander, 2021; Wessel et al., 2021). Our results demonstrate that digitalization leads to novelty- and efficiency-centered BMI through network capability and that novelty- and efficiency-centered BMI mediate the effects of digitalization and network capability on economic and environmental performance. The results indicate that digital transformation has the potential not only to increase an organization's economic profits but also to mitigate the negative influence of its manufacturing and operating activities on the natural environment. The paths of DT→NC→NBMI/EBMI→ECOP/ENVP provide unprecedented insights into the ways how digitalization can lead to desired sustainability-related outcomes on the firm level.

By investigating the moderating role of environmental dynamism, this study also specifies the boundary conditions under which digitalization and network capability lead to novelty- and efficiency-centered BMI. The results show that environmental dynamism negatively moderates the effect of digitalization on efficiency-centered BMI but positively moderates the relationship between network capability and efficiency-centered BMI. This means that in a highly dynamic environment, like that of Chinese manufacturing, the use of digital technologies can further increase the complexity of business operations and carry additional transaction risks (Paolucci et al., 2021; Rana et al., 2021; Yuan et al., 2021) that may impede efficiency-centered BMI—yet bolster novelty-centered BMI. However, network capability can enable firms to deal with a dynamic environment and improve transaction efficiency in a flexible and reliable manner through social and relational mechanisms, such as communication and coordination (Cenamor et al., 2019). Environmental dynamism does not strengthen the effects of digitalization and network capability on novelty-centered BMI, indicating that novelty-centered innovation in both stable and dynamic environments relies on digitalization and network capability. Thus, our study reveals the distinct effects of digitalization (a technology-driven approach) and of network capability (an organizational factor) on BMI in different environmental conditions. These findings are consistent with those of Gillani et al. (2020), which strongly urge future studies to take a more comprehensive perspective such as the Technology-Organization-Environment (TOE) framework when investigating the critical success factors of digital transformation. As a result, our study adds valuable evidence to the existing conceptualization of digital transformation as a multidisciplinary process.

Our study uses DCT to illuminate the role of digital transformation in Chinese manufacturing firms, which is characterized by high-speed development and rapidly changing environment. DCT highlights the organization can maintain sustainable competitiveness by improving dynamic capabilities of opportunity-sensing, opportunity-seizing, and transformation to manage the dynamic environment (Li & Liu, 2014; Teece, 2007). From the perspective of DCT, digitalization, network capability, and BMI can be regarded as manufacturers' dynamic capabilities, which cannot be easily imitated, to enable digital transformation and achieve significant, sustained competitive advantage. Many scholars have used DCT to conceptualize digitalization (Soluk & Kammerlander, 2021), network capability (Chen et al., 2021), and BMI (Teece, 2018). Our study strengthens this research stream by identifying digitalization and network capability as keys to help the firm sense business opportunities and challenges and seize opportunities through integration of digital resources and organizational resources (Chi et al., 2010; Mikalef et al., 2021a; Mikalef et al., 2021b; Warner & Wäger, 2019). Novelty- and efficiency-centered BMI are dynamic capabilities that enable firms to reconfigure resources and competencies in ways that transform value creation and delivery (Mezger, 2014). Our study distinguishes the three dynamic capabilities and reveals the mediating role of network capability and BMI and the moderating role of environmental dynamism. These findings extend DCT by empirically validating the interplay among these dynamic capabilities and clarifying how the relationships vary with environmental conditions.

Implications for practice and management

In recent years, the COVID-19 outbreak and extreme weather events have had profoundly negative effects on the natural environment and have attracted widespread public attention (Pan & Zhang, 2020; Weilnhammer et al., 2021). China-based global manufacturing firms are under tremendous pressure to improve their economic and environmental performance and to maintain sustainable development using digital technologies (Pan et al., 2021). In highly dynamic environments, firms are encouraged to seize opportunities to promote sustainable business model transformation in the digital economy (Hanelt et al., 2017; Pan et al., 2021). Our study indicates that for these firms, digitalization leads to improved economic and environmental performance through novelty- and efficiency-centered BMI. Manufacturing firms need to leverage digital technologies to create new ways of conducting economic exchange as well as to reduce transaction costs and improve transaction efficiency, consequently promoting sustained returns. The findings thus offer practitioners insights into the integration of digital technology use and business model design in the pursuit of sustainable development.

Our study suggests that if a firm's digital transformation relies only on technologies, it is likely to have a high chance of failure. Although our study is conducted based on survey data collected from the Chinese manufacturing industry, a recent McKinsey survey from "1,793 participants representing the full range of regions, industries, company sizes, functional specialties, and tenures," shows that the success rate of digital transformation is less than 30% (McKinsey, 2018). The result is a warning to all managers whose organizations aspire to engage in digital transformation. For the endeavor to succeed, firms need to consider all aspects of technological, organizational, and environmental factors. They must focus on intra- and interorganizational relationship management in the transformation process and take full advantage of internal and external network partnerships to establish reliable connections and ensure the acquisition of high-quality resources. Network capabilities, including effective communication and coordination, relational skills, and partner knowledge, play essential roles in a successful digital transformation.

In a highly dynamic global manufacturing environment, digital technology use has a dark side. Our findings suggest that environmental dynamism weakens the effect of digitalization on efficiency-centered BMI, at least for Chinese manufacturing firms. Such firms emphasize operational excellence and endeavor to become price leaders by lowering transactional costs (Zhang et al., 2021). They must effectively manage the complexity and risks related to digitalization, which impede transaction efficiency; moreover, to collaborate with business partners flexibly and reliably in view of efficiency-centered BMI, they must put more emphasis on network capability development.

Conclusions

Our study leveraged DCT to investigate the influence of digitalization and network capability on the economic and environmental performance of firms and proposed a mediating role of BMI and a moderating role of environmental dynamism. Based on survey data collected from Chinese manufacturing industry, our empirical results indicate that the effects of digitalization on novelty- and efficiency-centered BMI are mediated by network capability and that both novelty- and efficiency-centered BMI mediate the effects of digitalization and network capability on economic and environmental performance. Environmental dynamism also negatively moderates the relationship between digitalization and efficiency-centered BMI; however, it positively moderates the effect of network capability on efficiency-centered BMI. The findings reveal the potential broad downstream effects of digitalization on sustainability in today's dynamic business environment.

However, our study has several limitations that need to be addressed in future research. First, we collected self-reported data from the Chinese manufacturing industry to test the hypothesized relationships. Although we made earnest efforts to ensure the data's quality, we suggest that future studies triangulate data sources to avoid potential biases and improve the reliability of their results. To further establish causality and rule out other forms of endogeneity bias, future research could employ additional techniques such as longitudinal surveys, qualitative case studies, and econometric studies using panel data.

Second, digital transformation has become a global trend across different sectors (McKinsey, 2018). This study addresses a single-sector, single-country context. To complement our study, which examined the technology-intensive and operations-oriented Chinese manufacturing industry (Chen et al., 2014), future research could explore digital transformation in the construction industry, which is labor-intensive and project oriented (Ernstsen Sidsel et al., 2021). We also encourage researchers to expand the context to other settings with distinct cultural norms and institutional environments, because extensive technology-related research has long shown substantial national- and individual-level culture differences in technology use and attitudes, across many different dimensions (e.g., Lowry et al., 2011; Srite & Karahanna, 2006). Such differences are likely in the digital transformation space because they have also been demonstrated in multiple innovation, creativity, and organizational risk contexts (e.g., Weber & Hsee, 1998; Westwood & Low, 2003). For example, future research could compare the differences in digital transformation between firms in western countries and those in China, or test whether the research model can be supported in other Asian countries with an equivalent level of environment dynamism.

Finally, sustainability research highlights the need to balance—as a *triple bottom line*—economic, environmental, and social goals (Gupta et al., 2020; Klein et al., 2021). Our study focuses on the two goals to which companies devote the most attention: economic and environmental performance (Elliot, 2011; Hanelt et al., 2017; Li et al., 2020). However, social goals and performance, as the third dimension of sustainability, should also be addressed. Formally, *social performance* is defined as a company's social accountability to itself, its stakeholders, and the public (Dubey et al., 2019; Gupta et al., 2020). We encourage researchers to build on our model and the work of Dubey et al. (2019) and Gupta et al. (2020) to further consider the social aspects of sustainability performance in different contexts and explore the different influencing factors for the three dimensions of sustainability performance. Future studies could scrutinize the bidirectional and interactive relationships between social performance (e.g., corporate social responsibility) and economic performance (e.g., profitability), along with their isolated effects.

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Digitalization and network capability as enablers of business model innovation and sustainability performance: The moderating effect of environmental dynamism

Appendix A. Construct Measures

Construct	Subconstruct	Items		Factor loadings	*t*-values
Digital transformation (DT) (Nasiri et al., 2020)	n/a	DT1	We aim to digitalize everything that can be digitized	0.775	26.899
		DT2	We aim to create stronger networking between the different business processes with digital technologies	0.774	25.025
		DT3	We aim at achieving information exchange with digital technologies.	0.777	27.663
		DT4	We aim to enhance an efficient customer interface with digital technologies.	0.749	21.930
		DT5	We collect massive volumes of data from different sources.	0.767	23.847
Business model innovation (BMI) (Wei et al., 2014; Zott & Amit, 2007)	Novelty centered BMI	NBMI1	The business model offers new combinations of products, services, and information.	0.694	19.342
		NBMI2	Incentives offered to participants in transactions are novel.	0.681	18.693
		NBMI3	The business model links participants to transactions in novel ways.	0.775	26.037
		NBMI4	The business model creates new sources of revenues.	0.682	15.598
		NBMI5	The business model adopts new ideas and methods to conduct business.	0.719	17.401
		NBMI6	The business model adopts new operational processes, routines, and norms to conduct business.	0.703	19.231
		NBMI7	Overall, the company's business model is novel.	0.725	19.314
	Efficiency centered BMI	EBMI1	Transaction costs for participants in the business model are reduced.	0.705	20.254
		EBMI2	Transactions are simple from the user's point of view.	0.736	24.056
		EBMI3	The business model enables a low number of errors in the execution of transactions.	0.701	22.494
		EBMI4	Marketing and sales cost, communication costs for participants in the business model are reduced.	0.774	31.715
		EBMI5	Transactions are transparent.	0.665	16.472
		EBMI6	As part of transactions, information is provided to participants to reduce the asymmetric degree of knowledge among them regarding the quality and nature of the goods being exchanged.	0.683	16.927
		EBMI7	The business model enables fast transactions.	0.709	20.106

Network capability (NC) (Acosta et al., 2018; Parida et al., 2017; Walter et al., 2006)	Coordination (COOR)	COOR1	We analyze what we would like and desire to achieve with each partner.	0.750	18.184
		COOR2	We match the use of resources (e.g., personnel, finances) to the individual relationship.	0.781	22.141
		COOR3	We inform ourselves of our partners' goals, potentials and strategies.	0.774	21.385
	Relational skills (RELS)	RELS1	We have the ability to build good personal relationships with business partners.	0.766	18.012
		RELS2	We can deal flexibly with our partners.	0.704	13.162
		RELS3	We almost always solve problems constructively with our partners.	0.876	42.286
	Partner knowledge (PARK)	PARK1	We know our partners' markets.	0.808	23.360
		PARK2	We know our partners' strengths and weaknesses.	0.686	11.781
		PARK3	We know our competitors' potentials and strategies.	0.865	41.466
	Internal communication (ICOM)	ICOM1	In our organization, employees develop informal contacts among themselves	0.736	15.961
		ICOM2	In our organization, communication is often across projects and subject areas.	0.805	23.470
		ICOM3	In our organization, information is often spontaneously exchanged.	0.781	20.232
Environmental dynamism (EDYN) (Azadegan et al., 2013; Dess & Beard, 1984; Li et al., 2020)	n/a	EDYN1	Major changes in consumer demographics.	0.647	9.355
		EDYN2	Frequent and major changes in government regulations.	0.585	6.009
		EDYN3	Major changes in the modes of production and/or service provision.	0.862	28.943
		EDYN4	A high rate of innovation.	0.770	11.937
Economic performance (ECOP) (Flynn et al., 2010)	n/a	ECOP1	Growth in market share.	0.787	32.153
		ECOP2	Growth in return on investment.	0.762	28.278
		ECOP3	Growth in return on sales.	0.787	25.352
		ECOP4	Growth in profit.	0.818	35.716
		ECOP5	Growth in sales.	0.741	20.195
Environmental performance (ENVP) (Zhu & Sarkis, 2004)	n/a	ENVP1	Decrease of energy consumption.	0.744	21.624
		ENVP2	Improvement of the firm's environmental situation.	0.761	23.206
		ENVP3	Reduction of solid wastes.	0.770	26.343
		ENVP4	Reduction of wastewater.	0.815	33.037
		ENVP5	Reduction of air emission.	0.795	26.204

Appendix B. Additional Detailed Support for Analyses

Table B1. Reliability and validity of the first-order Constructs.

Construct	**# of items**	**Cronbach's α**	**CR**	**AVE**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. DT	5	0.827	0.878	0.591	**0.769**									
2. COOR	3	0.654	0.812	0.590	0.506 (0.684)	**0.768**								
3. RELS	3	0.701	0.827	0.616	0.479 (0.590)	0.546 (0.787)	**0.785**							
4. PARK	3	0.697	0.831	0.624	0.443 (0.576)	0.528 (0.784)	0.589 (0.834)	**0.790**						
5. ICOM	3	0.667	0.818	0.600	0.432 (0.580)	0.533 (0.806)	0.568 (0.819)	0.509 (0.744)	**0.775**					
6. NBMI	7	0.837	0.878	0.507	0.684 (0.820)	0.566 (0.759)	0.542 (0.685)	0.560 (0.721)	0.534 (0.716)	**0.712**				
7. EBMI	7	0.837	0.877	0.506	0.595 (0.713)	0.580 (0.779)	0.623 (0.798)	0.616 (0.806)	0.601 (0.806)	0.707 (0.842)	**0.711**			
8. EDYN	5	0.721	0.812	0.524	0.284 (0.318)	0.333 (0.424)	0.246 (0.287)	0.362 (0.448)	0.299 (0.399)	0.363 (0.396)	0.312 (0.339)	**0.724**		
9. ECOP	5	0.839	0.886	0.608	0.512 (0.613)	0.494 (0.658)	0.502 (0.628)	0.552 (0.718)	0.420 (0.559)	0.704 (0.835)	0.660 (0.782)	0.373 (0.417)	**0.780**	
10. ENVP	5	0.836	0.884	0.604	0.509 (0.608)	0.504 (0.676)	0.471 (0.586)	0.538 (0.699)	0.501 (0.670)	0.639 (0.759)	0.674 (0.799)	0.308 (0.368)	0.596 (0.712)	**0.777**

Note: AVE = average variance extracted; COOR = coordination; CR = composite reliability; DT = digital transformation; EBMI = efficiency-centered BMI; ECOP = economic performance; EDYN = environmental dynamism; ENVP = environmental performance; ICOM = internal communication; NBMI = novelty centered BMI; PARK = partner knowledge; RELS = relational skills.

Table B2. Cross loadings.

Items	DT	COOR	RELS	PARK	ICOM	NBMI	EBMI	EDYN	ECOP	ENVP
DT1	**0.775**	0.398	0.391	0.349	0.344	0.546	0.465	0.184	0.390	0.350
DT2	**0.774**	0.393	0.344	0.353	0.346	0.550	0.435	0.240	0.394	0.391
DT3	**0.777**	0.361	0.377	0.374	0.297	0.487	0.460	0.252	0.423	0.403
DT4	**0.749**	0.409	0.368	0.341	0.341	0.540	0.504	0.253	0.356	0.426
DT5	**0.767**	0.382	0.361	0.284	0.330	0.504	0.422	0.158	0.407	0.382
COOR1	0.367	**0.750**	0.445	0.401	0.463	0.429	0.418	0.264	0.335	0.374
COOR2	0.371	**0.781**	0.334	0.360	0.325	0.380	0.428	0.276	0.338	0.388
COOR3	0.424	**0.774**	0.472	0.450	0.437	0.488	0.485	0.231	0.454	0.399
RELS1	0.299	0.421	**0.766**	0.449	0.428	0.389	0.442	0.198	0.353	0.335
RELS2	0.271	0.364	**0.704**	0.421	0.414	0.344	0.443	0.184	0.313	0.276
RELS3	0.497	0.488	**0.876**	0.513	0.494	0.510	0.564	0.204	0.480	0.457
PARK1	0.353	0.399	0.456	**0.808**	0.439	0.436	0.496	0.309	0.370	0.386
PARK2	0.279	0.418	0.430	**0.686**	0.340	0.340	0.413	0.252	0.411	0.372
PARK3	0.405	0.443	0.507	**0.865**	0.422	0.530	0.541	0.297	0.520	0.504
ICOM1	0.307	0.427	0.365	0.340	**0.736**	0.381	0.421	0.194	0.281	0.392
ICOM2	0.360	0.408	0.490	0.369	**0.805**	0.418	0.461	0.213	0.312	0.367
ICOM3	0.334	0.407	0.458	0.472	**0.781**	0.441	0.514	0.288	0.383	0.409
NBMI1	0.544	0.381	0.395	0.430	0.380	**0.694**	0.513	0.256	0.446	0.433
NBMI2	0.446	0.463	0.418	0.346	0.428	**0.681**	0.477	0.257	0.477	0.375
NBMI3	0.550	0.481	0.408	0.452	0.418	**0.775**	0.552	0.329	0.542	0.557
NBMI4	0.478	0.388	0.387	0.434	0.406	**0.682**	0.495	0.249	0.496	0.452
NBMI5	0.452	0.363	0.400	0.325	0.322	**0.719**	0.475	0.249	0.538	0.448
NBMI6	0.458	0.417	0.343	0.382	0.380	**0.703**	0.527	0.183	0.508	0.446
NBMI7	0.475	0.324	0.351	0.416	0.333	**0.725**	0.481	0.276	0.501	0.455
EBMI1	0.409	0.377	0.342	0.402	0.416	0.449	**0.705**	0.229	0.495	0.477
EBMI2	0.404	0.465	0.481	0.479	0.385	0.524	**0.736**	0.290	0.482	0.504
EBMI3	0.466	0.487	0.415	0.449	0.472	0.528	**0.701**	0.147	0.463	0.525
EBMI4	0.443	0.384	0.439	0.396	0.451	0.516	**0.774**	0.225	0.524	0.514
EBMI5	0.413	0.362	0.489	0.477	0.406	0.471	**0.665**	0.237	0.427	0.431
EBMI6	0.379	0.395	0.426	0.448	0.454	0.463	**0.683**	0.205	0.382	0.381
EBMI7	0.443	0.410	0.512	0.428	0.414	0.559	**0.709**	0.220	0.493	0.500
EDYN1	0.112	0.118	0.085	0.193	0.168	0.157	0.152	**0.647**	0.220	0.249
EDYN2	0.064	0.115	0.027	0.100	0.139	0.094	0.061	**0.585**	0.071	0.063
EDYN3	0.285	0.278	0.191	0.291	0.267	0.361	0.309	**0.862**	0.306	0.253
EDYN4	0.238	0.344	0.290	0.360	0.243	0.297	0.253	**0.770**	0.358	0.258
ECOP1	0.454	0.371	0.417	0.444	0.334	0.597	0.527	0.262	**0.787**	0.426
ECOP2	0.405	0.457	0.384	0.477	0.407	0.594	0.534	0.335	**0.762**	0.515
ECOP3	0.366	0.311	0.363	0.410	0.286	0.513	0.481	0.294	**0.787**	0.452
ECOP4	0.386	0.373	0.409	0.407	0.282	0.566	0.509	0.283	**0.818**	0.439
ECOP5	0.376	0.409	0.376	0.407	0.322	0.460	0.516	0.278	**0.741**	0.495
ENVP1	0.409	0.454	0.404	0.458	0.417	0.502	0.570	0.313	0.476	**0.744**
ENVP2	0.361	0.308	0.293	0.397	0.324	0.489	0.465	0.197	0.425	**0.761**
ENVP3	0.331	0.364	0.367	0.424	0.350	0.456	0.507	0.177	0.462	**0.770**
ENVP4	0.381	0.396	0.414	0.439	0.472	0.510	0.538	0.279	0.488	**0.815**
ENVP5	0.483	0.425	0.344	0.369	0.373	0.521	0.529	0.219	0.461	**0.795**

Note: COOR = coordination; DT = digital transformation; EBMI = efficiency-centered BMI; ECOP = economic performance; EDYN = environmental dynamism; ENVP = environmental performance; ICOM = internal communication; NBMI = novelty centered BMI; PARK = partner knowledge; RELS = relational skills.

Table B3. Summary of direct, indirect, and total effects.

	NC	NBMI	EBMI	ECOP	ENVP
DT					
Total effect	0.566*** (9.606)	0.676*** (14.145)	0.602*** (12.091)	0.481*** (7.199)	0.514*** (7.885)
Direct effect	0.566*** (9.606)	0.436*** (5.365)	0.266*** (3.744)	-0.045 (0.593)	0.031 (0.448)
Indirect effect	-	0.240*** (4.484)	0.336*** (6.128)	0.526*** (9.019)	0.483*** (8.890)
NC					
Total effect	-	0.424*** (5.856)	0.594*** (9.777)	0.463*** (5.961)	0.492*** (7.506)
Direct effect	-	0.424*** (5.856)	0.594*** (9.777)	0.112 (1.139)	0.179 (1.822)
Indirect effect	-	-	-	0.351*** (4.782)	0.314*** (4.004)
NBMI					
Total effect	-	-	-	0.433*** (5.015)	0.258** (2.84)
Direct effect	-	-	-	0.433*** (5.015)	0.258** (2.84)
Indirect effect	-	-	-	-	-
EBMI					
Total effect	-	-	-	0.281** (3.180)	0.344** (3.342)
Direct effect	-	-	-	0.281** (3.180)	0.344** (3.342)
Indirect effect	-	-	-	-	-

Note" *** *p* = significant at 0.001; ** *p* = significant at 0.01; * *p* = significant at 0.05; DT = digital transformation; EBMI = efficiency-centered BMI; ECOP = economic performance; ENVP = environmental performance; NBMI = novelty centered BMI; NC = network capability.

References for Appendices

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