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The key role of digital ambidextrous capabilities in cross-boundary innovation: Moderating effects of technological diversification and environmental turbulence

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ABSTRACT

Although the importance of digital technology in fostering cross-boundary innovation (CBI) has attracted increasing attention from scholars and practitioners, research gaps persist concerning how firms' capabilities in leveraging digital technologies influence CBI and the boundary conditions that either facilitate or impede its effectiveness. Based on firm capability theory, this study distinguishes firms' digital ambidextrous capabilities to achieve different digital goals from an organisational ambidexterity perspective. Using fixed effects and interaction effects models to analyse data from 730 publicly listed Chinese firms, this investigation explores the roles of digital exploratory capability (DERC) and digital exploitative capability (DEIC) in enhancing CBI. The results indicate that DERC and DEIC substantially foster CBI. Technological diversification acts as a positive moderator in the relationship between DERC and CBI, whilst exhibiting an inverted U-shaped moderation between DEIC and CBI. Furthermore, environmental turbulence moderates the relationship between DERC and CBI in an inverted U-shape and positively moderates the relationship between DEIC and CBI. Additionally, SOEs are more reliant on DEIC for CBI and less susceptible to environmental turbulence. This study provides new managerial insights for firms to establish and leverage digital ambidextrous capabilities to achieve CBI.

Inspec: D10; D20

1. Introduction

The rapid development of digital technology enables innovation activities to industry boundaries. Cross-boundary innovation (CBI), which is based on cross-boundary resources and opportunities and is realised through cross-disciplinary technological integration, has become an pivotal means for firms to expand their markets and achieve technological leapfrogging. Internet firms, represented by Microsoft, Alibaba and Tencent, continuously foray into new domains by leveraging digital technology, compelling traditional industry firms to resturcture their original innovation systems or boundaries. In cross-boundary contexts, digital technology allows resources and strengths in different fields to be shared and complemented, whilst focusing on the cross-disciplinary integration of multimodule technologies (Bach et al., 2021). Therefore, as CBI transcends the boundaries of existing technological fields, it introduces cross-field technological components and stimuli, as well as reassembles and forms technological achievements belonging to

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0923-4748/© 2025 Elsevier B.V. All rights reserved, including those for text and data mining, AI training, and similar technologies.

multiple fields—a key means of technological breakthrough for firms (Lyu et al., 2022). However, this innovative model also entails greater complexity and uncertainty, with high costs and model ambiguity issues limiting the cross-boundary development of businesses (Caccamo et al., 2023).

In the field of strategic management, firm capability theory states that the core logic of a firm's response to the complexity and uncertainty of its innovation activities lies in its ability to build risk-resistant capability (Chatterjee et al., 2023a, 2023b; Eisenhardt and Martin, 2000). These capabilities provide the necessary environment for technological innovation and assist firms in optimising resource utilisation, consequently reducing innovation costs whilst facilitating the adoption of more efficient and effective CBI models (Zhang et al., 2023a, 2023b). CBI is the process through which firms interact and coordinate with diverse innovation entities in the context of digital technology (Zhang et al., 2023a, 2023b). The variability and generativity of digital technologies, which serve as a basis for cross-disciplinary technology combinations and explorations, require firms to possess capabilities for effective and flexible digital technology utilisation (Pitelis et al., 2023). These digital capabilities constitute the channels through which firms search, communicate, exchange and interact with resources across boundaries, providing them with effective means to sense and seize cross-boundary opportunities, as well as respond to threats (Annarelli et al., 2021; Pereira et al., 2023). In recent years, researchers have emphasised the special nature of digital technologies to support CBI from the perspectives of digital technology and digital ecology (Brea, 2023). These studies highlight that digital technology is not a sufficient condition for achieving CBI; rather, firms' ability to leverage the advantages of digital technology to deal with complex cross-boundary environments is equally important (Caccamo et al., 2023). Therefore, the present study addresses the following research question: 'What role do different digital capabilities play in promoting firms to implement CBI?'

Some studies have investigated the roles of resources, knowledge and relational foundations in CBI from perspectives such as resource recombination (Bertello et al., 2022), knowledge creation (Robertson et al., 2023) and collaborative networks (Papanastassiou et al., 2020). Nevertheless, the mechanism of CBI from the perspective of capabilities, particularly capabilities rooted in digital technologies, still lacks in-depth discussion. In the digital context, CBI is progressively shaping a new paradigm. The complexity of resources and the dynamic nature of competition brought about by digital resources both demand that firms not only create new cross-boundary products and markets but also continuously leverage cross-boundary resources to solidify existing business models and generate stable profits (Karhade and Dong, 2021). Therefore, firms require two different digital capabilities: digital exploratory capability (DERC) and digital exploitative capability (DEIC). On the one hand, DERC enables firms to experiment, learn and develop new opportunities in uncharted domains. It is used to conduct in-depth analyses of the core patterns of multidomain technologies, extract cross-boundary technology commonalities accurately and algorithmically drive the dynamic adaptation of heterogeneous resources, thereby activating the endogenous drivers of CBI (Karhade and Dong, 2021). On the other hand, DEIC enables firms to optimise, refine and maximise the resources available in their current field. It can integrate multidisciplinary technologies efficiently, break down industry barriers, enhance synergies, promote cross-boundary knowledge flow, and reorganisation and ultimately activate CBI opportunities (Pereira et al., 2023). The digital ambidextrous capabilities composed of DERC and DEIC reflect firms' strategies for navigating complex cross-boundary environments, forming a comprehensive digital capability framework that integrates both "internal cultivation" and "external assistance" (Robertson et al., 2023). However, constrained by tensions in structures, processes and capabilities, addressing the contradiction between exploration and exploitation in digital ambidextrous capabilities remains a crucial challenge (Robertson et al., 2023). Therefore, this study endeavours to clarify the impact mechanism of digital ambidextrous capabilities on CBI.

Exploring how firms leverage capability advantages, firm capability theory emphasises that external environmental characteristics and internal resource foundations jointly influence the dynamic changes firms face and their responsive decisions (Ilmudeen et al., 2021). From the perspective of environmental characteristics, firms depend on their external environments to acquire innovative resources (Stonig et al., 2022). Apart from representing the pace of environment renewal, driving dynamic changes in the recipients and content of cross-boundary cooperation, as well as in the needs of consumers, environmental turbulence also poses additional challenges to the innovation process (Li, 2022). From the resource-based view, the significance of digital technology in the cross-boundary process lies in enabling flexible modifications and adjustments to technological modules, and the resulting coupling of different technological components provides an effective approach (Ceipek et al., 2019). Technological diversification determines the scope and integrity of technological adjustments and couplings for firms, thereby providing greater decision-making latitude for firms to respond to dynamic changes (Choi and Lee, 2022). However, previous studies on the moderating role of environmental turbulence and technological diversification have yielded conflicting conclusions, such as positive, negative and inverted 'U' shapes (Li, 2022; Klimczak et al., 2023). These contradictions essentially hinge on whether firms can align their capabilities and innovation models with the contextual demands. Thus, exploring the contextual effects of environmental turbulence and technological diversification through an ambidextrous lens may help reconcile these discrepancies.

Firm capability framework is a critical topic in the innovation management research (Ilmudeen et al., 2021). Addressing gaps in existing research, the present study analyses how firms can achieve successful CBI through the lens of firm capability theory. Specifically, this paper focuses on the influencing mechanisms of DERC and DEIC on CBI, as well as explores the different moderating effects of environmental turbulence and technological diversification in this process. The findings of this work enrich the antecedent research on CBI from the perspective of firm capability theory, thus providing a new novel framework for firms to achieve CBI based on digital ambidextrous capabilities.

2. Theoretical background and hypothesis

2.1. Digital ambidextrous capabilities

The extensive integration of digital technology into various processes enables firms to manage, assess and leverage vast digital assets, transforming the competitive landscape from single-industry rivalry to cross-boundary competition (Eisenhardt and Martin, 2000; Teece et al., 1997). The intricate web of internal and external resources, combined with the ever-changing dynamics of competition, demands the extensive integration of manageable digital assets—specifically those capable of seamlessly linking these resources—to enhance operational effectiveness and foster value generation. This process ultimately positions digital capabilities as a critical organizational competence (Fernandez-Vidal et al., 2022). Digital capabilities relate to enhancing and refining a firm's business tactics and operational frameworks, encompassing different phases of the value chain and fostering efficiency in value acquisition, generation and dissemination within the organisation (Plekhanov et al., 2023).

In the field of innovation studies, scholars have explored the impact of digital capabilities on innovation. However, digital capabilities are often viewed as a one-dimensional variable or meticulously categorised based on their practical applications. For example, Chen, Tang (2024) divided digital capabilities into digital diffusion and digital collaborative capabilities from a supply chain perspective. Anwar et al. (2024) focused on the area of business models, distinguishing between digital knowledge sharing, digital business and digital platform capabilities. However, these categorisations were either too general or focused on a particular dimension or application area of digital technology, leading to various views on the impacts of digital capabilities. Supporters believe these capabilities aid firms in optimising the use of surplus resources, boosting research and development (R&D) and expanding technological applications (Ghosh et al., 2022), whilst critics point out that the process of applying capabilities to the practical innovation process hinders firms from achieving successful innovation (Li et al., 2023). Indeed, the disparity between these two viewpoints stems from the clash between novelty and efficiency. In this regard, the organisational ambidexterity perspective could shed light on this paradox.

From the organisational ambidexterity perspective, ambidextrous capabilities represent two distinct sets of resources and mechanisms enabling firms to address complex environments and achieve innovation (O'Reilly, Tushman, 2008). DERC denotes firms' ability to effectively address intricate issues through profound knowledge and proficiency in digital, algorithmic or programming languages, thus isolating crucial components and patterns from intricate digital data (Wu et al., 2021). In the process, CBI is reflected in the firm through the deconstruction and reshaping of the algorithm, resulting in a new algorithmic model that adapts to the new cross-boundary needs and scenarios (Wu et al., 2021). For example, automobile manufacturers reconstruct production scheduling models by fusing genetic algorithms and simulated annealing algorithms to enhance the global optimality and stability of scheduling schemes. DEIC denotes firms' ability to skillfully leverage digital technology for task simplification and enhanced efficiency through the acquisition and proficiency of diverse digital instruments and platforms (Mishra et al., 2022). A case in point is healthcare firms using big data and artificial intelligence (AI) technologies, combined with medical knowledge, to continuously enhance medical diagnosis and treatment options. On the one hand, firms require DEIC to enhance processes and empower products, thereby improving the current input–output ratio (Mele et al., 2024). On the other hand, DERC is required to disrupt established technological trajectories by creating innovative products, application scenarios and business models (Hund et al., 2021). DERC and DEIC have distinct needs for resources, goals for innovation and approaches to risk, determining whether firms can successfully utilise digital technology to enhance the efficiency of value innovation or generate novel value (Mann et al., 2022). Consequently, examining the effect mechanism of CBI through the lens of digital ambidextrous capabilities is essential.

2.2. Cross-boundary innovation (CBI)

Boundaries, defined as the limits between firms and their external environments, delineate the range of resources that can be used directly by firms, whilst simultaneously constraining the scope within which they can operate (Castellani et al., 2022). Whilst technological boundaries act as a 'moat' to maintain competitive advantage, they also impede business expansion (Moorthy and Polley, 2010). In recent years, the advent of digital technologies has transformed this scenario, markedly enhancing the efficacy of information dissemination and the scope of collaboration, whilst also facilitating rapid communication and coordination across disparate technological domains (Bach et al., 2021). The sharing and rapid flow of information facilitate the integration and optimisation of data-driven technologies across domains, enabling greater customisation and flexibility in cross-boundary technology integration and driving the development of CBI (Plekhanov et al., 2023). For example, the combination of 5 G communication technology and autonomous driving technology has enaled autonomous driving possible—an innovation that has rapidly propelled the development of smart cities, intelligent transport and other related fields. Consequently, CBI is a process through which firms transcend the boundaries of their original technologies, emphasizing how firms integrate knowledge, methodologies, or tools from diverse technological domains to develop novel technical solutions that disrupt existing paradigms, ultimately connecting the value propositions of their native domain with those of new fields to create emergent value (Meissner et al., 2021).

Owing to the complex and layered characteristics of boundaries, existing studies on CBI mainly focus on personal elements (e.g. cognitive distance and organisational identity), organisational features (e.g. firm traits and product attributes) and environmental factors (e.g. network architecture and technological evolution), emphasising how firms' resources, knowledge and relational foundation drive CBI (Bertello et al., 2022; Pershina et al., 2019). Nevertheless, these studies have paid limited attention to the capabilities required for executing CBI. In the digital context, scholars mostly emphasise how digital technology assists firms in CBI to achieve value creation, mostly highlighting the evolution of organisational structures and the transformation of the innovation paradigm

(Bertello et al., 2022). Most of them also underscore the role of digital technology; however, there is a lack of attention to how digital ambidextrous capabilities work for CBI.

Based on firm capability theory, digital ambidextrous capabilities rooted in digital technology serve as the foundation for firms to flexibly perceive and respond to cross-boundary opportunities and challenges in the 'digital ocean', mapping out effective paths for achieving CBI (Amoroso et al., 2023). At the level of innovation objectives, digital ambidextrous capabilities enable firms to identify potential connections between different domains, anticipate market and technology trends and provide strong support for CBI decisions that are flexible and responsive to environmental changes. At the innovation execution level, digital ambidextrous capabilities help firms to choose appropriate digital resource acquisition and allocation modes, and facilitate the rapid cross-boundary application and seamless connection of technologies between different domains to meet increasingly complex environmental needs (Kreuzer et al., 2022). Therefore, it is vital to explore the ways in which firms can improve CBI's efficiency via digital ambidextrous capabilities.

2.3. Digital ambidextrous capabilities and CBI

Firm capability theory argues that firms must build and reshape their internal and external resources to adapt to the ever-changing needs of customers and evolving competitive tactics. Digital ambidextrous capabilities reflect firms' efficiency in addressing the two distinct problems of 'exploration' and 'exploitation' using digital technologies, both of which are beneficial for firms to achieve CBI (Papanastassiou et al., 2020). DERC helps firms identify more cross-boundary opportunities. First, DERC helps firms break inherent technological paths, thereby uncovering the potential value of cross-boundary resources (Huang et al., 2022). Firms possessing elevated DERC levels have the capability to seek out and gather innovative technologies that complement each other in cross-boundary independent fields, integrate these synergistic technologies—customised for varied requirements—into current offerings, and generate novel attributes or products to realise CBI (Chatterjee et al., 2020). For example, BMW and Immersion successfully transferred the aircraft anticollision braking system (ABS) to the automotive iDrive operating system. Second, DERC encourages firms to ocate and procure diverse external data sources, thereby facilitating advanced data analysis. Firms are capable of precisely utilising data to forecast upcoming market patterns and consumer requirements through DERC, seek cross-boundary technologies to adapt to market shifts and enhance market flexibility via CBI (Zhang et al., 2022). Finally, having stronger DERC enables firms to validate ideas and concepts via rapid prototyping and iterative and refinement. Consequently, firms can leverage DERC to rapidly create prototypes, as well as conduct continuous experimentation and modification. This ability assists firms in continuously experimenting with various cross-boundary technologies and in reshaping and merging cross-boundary resources, thus leading to the creation of novel CBI models (Zhang et al., 2022). Therefore, we propose that firms with higher DERC demonstrate superior CBI performance, as presented in the following hypothesis:

H1a. *DERC has a positive effect on CBI.*

DEIC facilitates the enhancement of firms' CBI efficiency, enabling them to rapidly adapt to dynamic cross-boundary demands. First, DEIC helps firms integrate cross-boundary resources more economically, thus broadening the scope of current knowledge and technology through cross-boundary knowledge searches(Zapadka et al., 2022). Firms with high DEIC are able to transcend current technological barriers and leverage digital technologies from other areas to optimise existing technology paths. In this way, firms can achieve granular management of their technology utilisation, thus changing the nature and value of their original input resources to achieve CBI. Second, DEIC helps firms decompose complex nested production processes into loosely coupled systems using digital technology, thereby forming a more standardised and transparent modular architecture (Wei et al., 2021). This architecture not only helps firms effectively identify weaknesses in existing products and processes but also targets the acquisition of cross-boundary technologies with specific functionality. In turn, this allows firms to use these cross-boundary technologies to reorganise and improve the processes, features and functionality of their products within their boundaries, resulting in continuous CBI iterations based on customer feedback (Stonig et al., 2022). Finally, DEIC offers enhanced paths for firms to engage with entities across boundaries at various stages and form lasting connections via immediate data exchange. In particular, DEIC accelerates precise data sharing between firms and cross-boundary entities, reduces technology transaction costs, improves the efficiency of existing technology utilisation and expands the control scope of existing product functions through CBI (Meissner et al., 2021). Therefore, we propose that firms with higher DEIC demonstrate superior CBI performance, as presented in the following hypothesis:

H1b. *DEIC has a positive effect on CBI.*

2.4. Moderating role of technological diversification

In firm capability theory, a firm's technological foundation, as an important component of internal resources, is the key internal support enabling them to continuously seek and leverage opportunities amidst rapidly changing external environments (Radosevic, 2022). CBI involves technologies and resources across multiple domains. The diverse technological foundation influences how effectively firms can transfer and integrate technology across boundaries, providing essential technical support and resource assurance for achieving CBI through digital ambidextrous capabilities (Kim et al., 2013, Kodama, 1986).

However, existing research offers divergent perspectives on the effects of technological diversification. On the one hand, technological diversification enriches firms' technological foundation, mitigating the risks of innovation by mechanisms, such as interactive coupling effects between resources and 'dynamic increasing returns' (Martynov, 2021). On the other hand, technological diversification can lead to resource dispersion within firms, accompanied by a dual effect of increasing marginal costs and decreasing marginal returns, thereby imposing challenges in attention allocation and cost pressures for firms (Yoo & Lee, 2023). The conflict view stems from differences in the application scenarios of diverse technologies. Accordingly, technological diversification has varying effects on the relationship between digital ambidextrous capabilities and CBI.

The knowledge foundation and flexibility enhancement brought about by technological diversification enable firms to better leverage the advantages of DERC to achieve CBI (Machado et al., 2022). First, a high level of technological diversification can reduce the technological and cognitive distance between firms and cross-boundary domains, enabling firms to acquire broader diverse knowledge and information (Lee, 2023). Lower technological and cognitive distance enables firms to search for more extensive, novel and heterogeneous cross-boundary technological resources through DERC, as well as to integrate and encode new knowledge and information from different fields. This benefit helps firms achieve diversity in building their CBI technology repositories (Liu et al., 2023).

Second, a high level of technological diversification enables firms to have a stronger tolerance for heterogeneous knowledge across technological domains, enabling more efficient management of knowledge exchange challenges (Bockelmann et al., 2024). The inclusion of heterogeneous knowledge can reduce the technological lock-in effect in firms, thus enabling them to fully understand specialised knowledge from cross-boundary fields and better explore the complementary advantages of cross-domain technologies. This enables firms to leverage DERC to foster the integration and collaborative application of diverse technologies, resulting in accelerated CBI development.

Finally, a high level of technological diversification will inspire firms to explore new technological trajectories. Multiple technology paths exist within technologically diversified firms, leading to concurrent focus on different theories, methodologies and processes across domains (Yoo and Lee, 2023). Such novel knowledge empowers firms integrate and re-engineer cross-boundary emerging technologies and knowledge into existing products and processes through DERC, resulting in new functionalities or products that enable CBI (Kim et al., 2013). Therefore, the impact of DERC on CBI is likely to be stronger in the presence of high technological diversification, as presented in the following hypothesis:

H2a. *Technological diversification positively moderates the relationship between DERC and CBI.*

As firms achieve CBI through DEIC—a process of gradual and sustained returns—they need to balance the technological advantages and cost risks posed by technological diversification. Therefore, technological diversification has a nonlinear impact on firms' abilty to achieve CBI through DEIC. Specifically, under a condition of low technological diversification, a firm's technological foundation is relatively weak, the scope of cross-boundary search is limited and the cost of transferring resources across boundaries is substantial (Martynov, 2021). These limitations not only hinder firms from expanding their access to cross-boundary technological resources but also reduce the speed and timeliness of knowledge acquisition for CBI and increase the risk of firms achieving CBI through DEIC (Zhu et al., 2024). When technological diversification is moderate, diverse technological extensions enrich the firm's knowledge base, enabling firms to deploy R&D personnel and equipment from different fields (Kretschmer & Symeou, 2024). An enriched knowledge base makes it more effective for firms to leverage their DEIC to identify suitable cross-boundary technology connections and integration points, which can strengthen collaborations with other cross-boundary entities. Effective cross-boundary links will improve the efficiency of cross-boundary technology exchanges for firms, helping them realise economies of scale and increasing CBI efficiency (Bockelmann et al., 2024).

Under high technological diversification, resource dispersion and coordination complexity hinder firms to rely on DEIC to achieve CBI. From the resource dispersion perspective, a high level of technological diversification will disperse firms' resources, making them vulnerable to excessive redundant knowledge and information interference during cross-boundary searches (Liu et al., 2023). The resulting information overload will reduce firms' focus on achieving CBI through DEIC and the precision of allocating cross-boundary resources (Andreasson et al., 2024). From the perspective of coordination complexity, the expansion of technological variety escalates the intricacies and challenges involved in managing technology within firms. Such management pressure makes it more necessary for firms to digitally transform existing technologies through DEIC with the aim of modular integration and improved organisation of their internal resources. At this time, CBI—through DEIC—will further increase firms' management and coordination costs (Kolagar et al., 2022). Accordingly, the following hypothesis is proposed:

H2b. *Technological diversification with an inverted U-shape moderates the relationship between DEIC and CBI. Specifically, technological diversification positively (negatively) moderates the relationship between DEIC and CBI when technological diversification is low (exceeds a certain level).*

2.5. Moderating role of environmental turbulence

How to cope with changing external environments and maintain competitiveness is central to firm capability theory, emphasising that the focus of firm capabilities is not limited to itself but on the development of optimal capabilities in varying environments (Meyer, 1982). Environmental turbulence, a typical feature that firms must face in a digital era, not only reflects the extent and unpredictability of market and technology demands faced by firms but also determines the opportunities and threats in the external environment (Zhang et al., 2023a, 2023b).

CBI is the process by which firms create value through cross-boundary collaboration. Environmental turbulence determines the objects and methods of firms' cross-boundary cooperation, providing a platform for firms to obtain valuable cross-boundary resources and information through digital ambidextrous capabilities (Duan et al., 2021). Environmental turbulence stimulates firms to continuously innovate to satisfy market needs (Hamsal et al., 2023), thus increasing opportunities for firms whilst also bringing greater unpredictability and risks. In turn, these may lead to suboptimal decision-making and, consequently, affect firms' competitiveness and market performance (Rajala and Hautala-Kankaanpaeae, 2023). This dual effect stem from how firms deploy diverse capabilities to respond to environmental changes and navigate paths for maintaining competitiveness amid volatility (Dayioglu et al., 2024). Therefore, environmental turbulence has a differential impact on the relationship between digital ambidextrous capabilities and CBI.

Due to the high novelty and risk associated with CBI achieved through DERC, firms must evaluate the feasibility of such an innovation model amid turbulent environments. Therefore, environmental turbulence has a nonlinear impact on how firms achieve CBI through DERC. Under low environmental turbulence, higher technological maturity raises the innovation threshold for firms, whilst stable and saturated market demand decelerates innovation commercialisation (Acikgoz et al., 2024). Relatively closed and stable environments constrain communication and collaboration amongst firms, hampering accessing new technological knowledge and resources across industry domains (Cenamor et al., 2019). These restrictions hinder firms from breaking through existing frameworks and achieving CBI through DERC.

When environmental turbulence is moderate, it raises the frequency of the collision and fusion of cross-boundary knowledge, giving rise to new technological knowledge and paradigms, whilst shortening the technology life cycle (Acikgoz et al., 2024). The emergence of new technological knowledge helps firms efficiently explore diverse combinations of cross-boundary technologies through DERC, enabling them to break through existing technological bottlenecks and discover new technological application scenarios (Boadu et al., 2023). The rapid replacement of knowledge strengthens firms' cross-boundary search for emerging knowledge and technologies through DERC, and prompts them to seek new development opportunities and growth points in these fields. This process helps firms achieve CBI, enabling them to 'overtake on the curve' (Bodlaj and Cater, 2019).

Meanwhile, under high environmental turbulence, decision-making pressure and opportunism will diminish firms' propensity to achieve CBI through DERC. From the perspective of decision-making pressure, high environmental turbulence leads to significant uncertainty in technological development. The resulting innovation ambiguity increases the risk of firms achieving CBI through DERC, prompting firms to make more conservative decisions within existing information boundaries to maintain stability (Chatterjee et al., 2023a, 2023b). From the opportunism perspective, intense external competition under high environmental turbulence increases the threat of opportunism faced by firms in the process of CBI. This threat, in turn, will cause firms to shift their innovation focus from external to internal, prioritizing in-house knowledge development and technological innovation capabilities, and ultimately reducing the motivation to achieve CBI through DERC (Gemici and Zehir, 2023). Accordingly, the following hypothesis is proposed:

H3a. *Environmental turbulence with an inverted U-shape moderates the relationship between DERC and CBI. Specifically, environmental turbulence positively (negatively) moderates the relationship between DERC and CBI when environmental turbulence is low (exceeds a certain level).*

In a turbulent environment, the limited availability of resources and market uncertainty not only drive firms to be more meticulous but also encourages them to collect information and collect information. Consequently, environmental turbulence will motivate firms to achieve CBI through DEIC. First, turbulent external environments are accompanied by a cyclical turnover of information between firms and the rapid diffusion of knowledge and technology, resulting in higher technological spillovers (Hamsal et al., 2023). In turn, technological spillover effects assist firms in learning cross-boundary technologies or knowledge through DEIC, imitating or replicating solutions from CBI. This will help firms leverage the market perception advantages of leading firms to maintain market stability (Ferreira et al., 2024).

Second, environmental turbulence is accompanied by rapid changes in market demand and competitors, rapid depreciation of technology and market knowledge. With their existing knowledge and technology, firms will struggle to respond adequately to changes and challenges in the marketplace, and their reliance on old pathways will limit their flexibility in innovation (Bodlaj and Cater, 2019). To maintain competitiveness in rapidly changing environments, firms are likely to adopt a more proactive approach to leveraging their DEIC across boundaries. This process involves the continuous expansion of their knowledge base, the introduction and integration of cross-boundary technologies to update outdated technological approaches and practices, the optimisation of the functionality of existing products and the expansion across boundaries. Consequently, firms can offer diverse products and services through CBI to meet complex and ever-changing market demands (Gemici and Zehir, 2023).

Finally, environmental turbulence implies that firms' relevant technological development is highly uncertain, requiring firms to bear higher risks in innovation (Derayati, 2024). Uncertainty prompts firms to actively seek out cross-boundary partners through DEIC, diversify their investments in technological innovation and establish technological linkages and dependencies with different cross-boundary entities through digital connections. Firms may also establish cross-boundary ecosystems or multi-party cooperation networks in the process of CBI, thus sharing the risks of innovation (Li, 2022). Therefore, the impact of DEIC on CBI is expected to be stronger in the presence of high environmental turbulence, as proposed in the following hypothesis:

H3b. *Environmental turbulence positively moderates the relationship between DEIC and CBI.*

3. Methodology

3.1. Sample selection and data collection

As global market competition intensifies and market demand diversifies, traditional manufacturing firms face several challenges, such as rising costs and declining efficiency, under the wave of digitisation (Yoo and Lee, 2023). In the context of evolving market environments and technological advancements, traditional manufacturing firms must continuously adapt by leveraging digital technologies to facilitate their transformation and upgrading. Consequently, this leads to the emergence of several novel industrial configurations and business paradigms. To adapt and thrive, traditional manufacturing firms must transcend the limits of their initial technological boundaries. They must achieve this by engaging in profound CBI and cross-boundary integration with information technology, biotechnology, new material technology and other relevant domains. Such integration allows them to share resources and complement each other's strengths in cross-boundary areas, thereby optimising and upgrading the production processes (Opazo-Basáez et al., 2022). Therefore, CBI often occurs between manufacturing firms in different industries, and studies in the manufacturing industry have better explanatory power and reference value for CBI-related research issues.

Considering the starting and ending time of the data and the timeliness of the data, this paper took the A-share listed firms in Shanghai and Shenzhen in China's manufacturing industry from 2012–2023 as the research sample. First, China is an emerging economy with a substantial manufacturing industry comprising diverse disciplines and a complete industrial system. Thus, its development achievements and typical cross-boundary success cases offer significant inspiration and serve as a valuable reference point for firms in other countries and regions worldwide.

Second, China possesses a huge amount of manufacturing data, which not only covers all aspects from raw material procurement to product manufacturing but also includes information on product sales and market feedback, thus providing a favourable environment for analysing firms' digital ambidextrous capabilities (Li et al., 2023). In addition, the digital transformation of China's manufacturing industry continues to advance, and its data collection, processing and analysis capabilities are constantly improving. Thus, the data quality and reliability of China's manufacturing industry are effectively assured, encompassing a wide range of scenarios with high generalisability.

To avoid the effects of extreme and exceptional values, the present paper screened the samples based on the following criteria (Yoo and Lee, 2023): (1) excluding samples of financial listed firms; (2) excluding ST, PT and *ST listed firms; (3) excluding samples with gearing ratios greater than 100 %; (4) excluding samples with missing data; and (5) applying a 1 % winsorization to the continuous variables. Finally, 7171 observations involving 730 nonfinancial listed firms were obtained. In this study, data were primarily processed and preprocessed using Python, and correlation analysis and multiple regression analysis were performed using Stata16. The basic and financial data of the firms came from the China Stock Market and Accounting Research (CSMAR) database, the patent data of the firms came from the China Research Data Service Platform (CNRDS) and the industry data mainly came from the China Statistical Yearbook.

3.2. Measurement

Dependent variable: CBI emphasises how firms recombine technologies and knowledge from different domains, resulting in technological innovations spanning multiple domains. The IPC patent classification numbers that appear in patent documents are categorised based on the different technological fields covered by the patent and can reflect the technological fields to which the patent belongs (Duan et al., 2021; Moorthy and Polley, 2010). Thus, if a patent contains two or more broad categories of IPC classification numbers, it means that the innovation involves knowledge and technology from multiple technological fields, reflecting the characteristics of CBI involving the intersection and integration of technological fields. Consequently, the current paper adopted the total number of invention patents and utility model patents granted to firms each year that contain IPC codes from at least two broad categories. Then, CBI was measured by the natural logarithm of the numbers.

Independent variable: Digital ambidextrous capabilities can be measured in two dimensions. DERC emphasises how firms explore digital frontier technologies and launch innovative digital products, services and technologies to pursue differentiated competitive advantages or tap into new markets. As 'technological innovation' refers to firms' acquisition and transformation of new technologies or the use of their resources to create related technologies, this study follows prior research by using digital technology keyword frequency as a proxy variable for DERC (Liu et al., 2023). DEIC emphasises how firms apply mature digital end-terminal technologies to improve technological paradigms for enhanced operational efficiency. Notably, 'digital process' refers to the systematic optimisation of production processes to improve output levels, refine product varieties and enhance process efficiency, and 'digital business' refers to the restructuring of user business interaction and division of labour collaboration methods. Thus, this study references literature to use digital process and digital business keyword frequencies as DEIC measures (Tang et al. 2023).

Moderator variable: Referring to Wang and Chen (2010), firm sales, as a barometer of business operations, is highly sensitive to environmental changes. When turbulence exists in the external environment, such as changes in market demand, the resulting intensification of the competitive situation, adjustment of policies and regulations, and so on, will have a direct impact on firm sales. Therefore, we used the level of firm sales to measure the degree of environmental turbulence to the firm. We regressed firms' sales outcomes on time using a 5-year moving window (using year's t to t-4), obtaining the standard errors of the regression coefficients for that year. An industry-unadjusted standardised index was then calculated by dividing the standard error by the average turnover of the firm over the last five years. Finally, the median sales figure for the industry as a whole was determined for the same period. Next, the industry-unadjusted standardised index for each firm was divided by the median industry sales, thus providing the firm's industry-adjusted environmental dynamics index. The higher this index, the more volatile the environment.

The core measure of technological diversity is a measure of the breadth (how many fields are covered) and balance (whether the fields are evenly represented) of the distribution of technology. As technological diversification requires firms to have the ability to innovate in different technological fields, the Herfindahl–Hirschman index (HHI), as a diversity index, provides a good assessment of firms' diversity in technological fields. The index calculates the sum of squares of each component within a given metric. Thus, by leveraging the amplification effect of squared terms, additivity and normalisation properties, it reflects whether the metric is concentrated in a few components or dispersed across many components, thereby indicating the concentration or diversity of the metric (Choi and Lee, 2022). Therefore, referring to the study by Miller (2006), the HHI is used in the current study to measure technological diversification in terms of broad categories of technologies in which firms are involved, as well as the technological fields in which firms are involved. The calculation was based on the three-digit international patent number (IPC-3) involved in the firm's patents. The technological diversification index was calculated as follows:

$$TD = 1 - \sum_{i}^{N} \left(\frac{P_i}{P} \right)^2, \tag{1}$$

where P_i denotes the number of patents of the firm that contain IPC number i, whilst P denotes the number of all IPC numbers in the patents filed by the firm. The larger the *TD*, the greater the dispersion of the firm's technology amongst technological fields and the more diversified the firm's technology is.

Control variables: To account for differences in firms' other properties, the current study controlled for several variables (Lee, 2023). Firm age (AGE): the natural logarithm of the length of years from the date of a firm's establishment to the year of statistics. Firm size (SIZE): the natural logarithm of a firm's total assets. Leverage ratio (LEV): the ratio of the total liabilities to the total capital. Dual role of the board chairman (DUAL): if the CEO also served as the chairman of the board of directors, it was set as 1, otherwise it was set to 0. Proportion of independent directors (PID): the ratio of the number of external independent directors to the total number of directors. Shareholding concentration (OC): the natural logarithm of the square sum of the shareholding ratios of the top ten shareholders. Growth of the firm (GR): the current year's operating income/previous year's operating income minus 1. Institutional investments (INST): the total number of institutional investor's shareholdings divided by the outstanding share capital. Research and development (RD): the natural logarithm of the firm's R&D expenditures plus 1. Return on assets (ROA): the ratio of the firm's net profit to its total assets. The current paper also defined individual(id), year and city, as dummy variables to control macroeconomic performance.

3.3. Measurement model

Considering the unobservable heterogeneity of data types, different firms and regional economic environments, the endogeneity problem caused by omitted variables must be minimised. To combine the influences of multiple dimensions, this paper chose to perform the regression with a multidimensional fixed-effects model, controlling for individual, time and regional fixed effects simultaneously, thus providing a more comprehensive understanding of the relationship between the variables (Dai et al., 2018). To further address the endogeneity problem caused by reciprocal causation, the dependent variable is regressed with a one-period lag. Thus, this paper empirically examined the impact of digital ambidextrous capabilities on CBI using Eq. (2) and the moderating role of environmental turbulence and technological diversification using Eqs. (3) and (4), as shown below:

$$CBI_{i,t+1} = \alpha + \beta_1 \times DAC_{i,t}\gamma \times C_{i,t} + \varepsilon_{i,t}\,, \tag{2}$$

$$CBI_{i,t+1} = \alpha + \beta_1 \times DAC_{i,t} + \beta_2 \times TD_{i,t} + \beta_3 \times TD_{i,t} \times DAC_{i,t} + \beta_4 \times TD_{i,t} \times TD_{i,t} \times DAC_{i,t} + \gamma \times C_{i,t} + \varepsilon_{i,t}, \tag{3}$$

$$CBI_{i,t+1} = \alpha + \beta_1 \times DAC_{i,t} + \beta_2 \times ET_{i,t} + \beta_3 \times ET_{i,t} \times DAC_{i,t} + \beta_4 \times ET_{i,t} \times ET_{i,t} \times DAC_{i,t} + \gamma \times C_{i,t} + \varepsilon_{i,t} \tag{4}$$

where *CBI* represents cross-boundary innovation; *DAC* is digital ambidextrous capabilities, replaced by DERC and DEIC, respectively; *TD* denotes technological diversification; *ET* denotes environmental turbulence; *C* represents all the control variables; and ε is the model's random error term. The validation framework is as follows. First, the relationship between digital ambidextrous capabilities and CBI was tested. Then, the moderating effect of environmental turbulence and technological diversification on the above relationship (the variables have been centred before constructing the interaction term) was also tested. Finally, the robustness and endogeneity tests were conducted.

4. Results

4.1. Descriptive statistics and correlations

Table A.3 presents the descriptive statistical results of the main variables. The results reveal that the mean of DERC is 0.637 (range: 0–51) whilst that of DEIC is 2.619 (range: 0–99), indicating significant differences in digital ambidextrous capabilities across firms. Furthermore, the mean value of TD is 0.338 (range: 0–0.844) whilst that of ET is 0.038 (range: 0–0.424), indicating significant differences in technological diversification and environmental turbulence faced by different firms. The mean of CBI for firms is 3.502 (range: 0–9.249), suggesting that the decision mechanism of CBI warrants further analysis.

The results of the correlation analysis are reported in Table A.4, with a maximum correlation coefficient of 0.501. The variance inflation factor (VIF) test was conducted on all the variables entered into the model. The results show a maximum VIF value of 2.12 for each variable, which is well below the threshold (<5) (Lee, 2023). In summary, the data in this paper do not exhibit severe multicollinearity issues and are thus suitable for further regression analyses.

4.2. Hypotheses testing

The relationship between digital ambidextrous capabilities and CBI is shown in Table A.5. Model 1 only includes control variables. The results of Model 2 indicate that the regression coefficient of DERC on CBI is significantly positive ($\beta = 0.022$, $p < 0.01$). This finding suggests that, to explore the potential value of cross-boundary resources, firms with stronger DERC are more likely to use digital technologies to search for and acquire new knowledge and resources externally, thus achieving CBI. The regression coefficient of DEIC on CBI is significantly positive (β=0.011, $p < 0.01$), suggesting that firms with stronger DEIC are more likely to use digital technologies to expand their existing knowledge, technologies and paradigms through refinement, selection and implementation, thus achieving CBI. Hence, hypotheses H1a and H1b are confirmed.

In incorporating interaction terms into the model to test H2 and H3, we refer to Table A.5. In Model 3, the regression coefficient of the interaction term between TD and DERC ($\beta = 0.043, p < 0.01$) is significantly positive. In Model 4, the regression coefficient of the interaction term between TD and DEIC ($\beta = 0.144$, $p < 0.01$) is significantly positive, whilst that of the square term of TD and the interaction term with DEIC ($\beta = -0.085$, $p < 0.01$) is significantly negative. Thus, H2a and H2b are validated. The results reveal that firms' technological diversification contributes to CBI through the use of DERC and DEIC. However, excessive technological diversification will reduce firms' efficiency in promoting CBI through DEIC.

In Model 5, the regression coefficient of the interaction term between ET and DERC (β=0.045, $p < 0.01$) is significantly positive, whilst that of the square term of ET and the interaction term with DERC ($\beta = -0.001, p < 0.05$) is significantly negative. Furthermore, in Model 6, the regression coefficient of the interaction term between ET and DEIC ($\beta = 0.014, p < 0.01$) is significantly positive. Thus, H3a and H3b are validated. The results reveal that environmental turbulence contributes to firms' efforts in using DERC and DEIC to achieve CBI. However, excessive environmental turbulence may lead them to perceive greater uncertainty risks, thereby weakening firms' tendency to use DERC for CBI.

4.3. Robustness test

We improved the robustness of our findings by substituting measures of variables. Referring to Dai et al. (2018), monitoring patent changes and trends within a specific technology field can approximate the environmental turbulence indicator. Here, we regressed the number of patent applications in the industry on time using a 5-year moving window (using year t to t-4), obtaining the standard errors of the regression coefficients for that year. The new standardisation factor was derived from the ratio of the standard errors to the average number of patents filed in the industry. Referring to Carnabuci and Operti (2013), the Teachman entropy index was used to measure firms' technological diversification. The formula is as follows:

$$TD = \sum_{i=1}^{n} p_i \ln\left(\frac{1}{p_i}\right), \tag{6}$$

where p_i=P_i/P, in which i denotes a technology category of the firm; n denotes all technology categories covered by the firm's patents; P_i denotes the number of patents containing technology category i in all the patents of the firm; and P denotes the total number of patents owned by the firm. The significance of some of the regression results changes, but the basic results remain robust.

Although we used a multidimensional fixed-effects model and a one-period lag of the dependent variable in the above regressions to mitigate the endogeneity problem, we argue that the endogeneity problem must still be further addressed. Thus, we drew on the higher-order joint fixed effects approach of Moser and Voena (2012) to test the model by controlling for 'time * city' effects, which was consistent with the findings of the study.

Due to differences in institutional background and governance models between state-owned and non-state-owned firms (Li, 2022), we divided the sample into groups of state-owned firms and non-state-owned firms to further examine the impact of firm ownership type on the research results. The results are shown in the appendix. Interestingly, the positive effect of the digital ambidextrous capabilities of state-owned firms on CBI remains significant, but the significance and coefficient of DERC both decrease significantly. Furthermore, whilst technological diversification still significantly moderates the relationship between digital ambidextrous capabilities and CBI, the moderating effect of environmental turbulence is not significant. It can be inferred that state-owned firms are closely related to government macro-control, which means that they tend to continuously improve internal efficiency by leveraging DEIC, thus facilitating the strict selection of cross-boundary firms and fields through an inside-out CBI model (Hamsal et al., 2023).

In comparison, the regression results of non-state-owned firms are basically consistent with the results of the entire sample regression. However, it is interesting that they are more susceptible to environmental turbulence impacts. It can be inferred that non-state-owned firms are more proactive in breaking through difficulties through CBI and have stronger perceptions of environmental turbulence. Thus, they have a greater need to utilise their diverse capabilities to build ecological advantage through CBI amidst turbulent environments.

5. Discussion and conclusions

The importance of CBI has led many scholars to conduct relevant research from many perspectives, such as knowledge, resources and relationships (Bertello et al., 2022; Ghosh et al., 2022). Nevertheless, a research gap from the perspective of capabilities remains. To uncover more key factors that are conducive to CBI in business, the present study used firm capability theory to develop a comprehensive conceptual framework that examines the relationships between firms' digital ambidextrous capabilities and CBI, after which the respective hypotheses were tested empirically.

First, DERC and DEIC both have positive impacts on CBI. Digital ambidextrous capabilities not only serve as a bridge for firms to establish efficient cross-boundary communication but also as a foundation for cross-boundary resource exchange and interaction. DERC facilitates more in-depth data analysis and processing, enabling firms to effectively explore potential CBI opportunities within complex cross-boundary scenarios and concepts via rapid prototype creation and refinement (Chatterjee et al., 2020). Meanwhile, DEIC helps firms to fully exploit digital technology to improve the standardisation and modularisation of their production processes, as well as to access cross-boundary technologies faster and more accurately to enrich the functionality and application scope of firms' existing technology fields (Wei et al., 2021). In turn, this helps firms respond accurately to the dynamic cross-boundary demands and produce innovative achievements.

Second, technological diversification positively moderates the relationship between DERC and CBI, whilst exhibiting an inverse U-shaped moderation effect on the DEIC-CBI relationship. Although technological diversification is more conducive to firms achieving cross-boundary breakthroughs through DERC, it has limited positive effects on firms achieving cross-boundary expansion through DEIC. The primary reason for this discrepancy is that, whilst technological diversification constitutes a pivotal resource base for firms to leverage digital ambidextrous capabilities for CBI, when the degree of technological diversification is elevated, the simple application of digital technologies alone is incapable of providing adequate support for sustained CBI. Firms with strong DEIC can better analyze cross-boundary technologies and leverage their diverse technology base to better serve CBI (Martynov, 2021).

Third, environmental turbulence exhibits an inverse U-shaped moderation effect on the relationship between DERC and CBI, whilst it positively moderates the relationship between DEIC and CBI. Continued cross-boundary expansion by firms through DEIC increases firms' stability in the face of external environmental turbulence. However, excessive environmental turbulence makes it difficult for firms to predict trends in technological change and raises the risk of cross-boundary exploration, which in turn reduces their incentives to expand across boundaries through DERC (Gemici and Zehir, 2023).

5.1. Implication for theory

This paper provides theoretical insights into firm capability theory in the following three ways:

First, we advance research on CBI from a capability perspective by addressing to the growing demand for new theories on innovation in the digital era. Grounded in the capability-building perspective, firm capability theory emphasises that firms should develop corresponding adaptive capabilities as technological paradigms and market demands change to support their innovative development and maintain their competitive advantages (Zhang et al., 2022). From diverse angles, prior studies have explored how resources, knowledge, and relational foundations impact CBI, while consistently highlighting digital technology's critical role in this process. However, the new capabilities based on digital technology remain conceptualized at the conceptual level (Annarelli et al., 2021). This paper starts from the perspective of firms' ability to achieve different innovation goals through digital technology. In particular, it answers how firms achieve CBI through digital ambidextrous capabilities. This finding reveals the mechanism of the role of digital ambidextrous capabilities in CBI, thus expanding the research scope of firm capability theory in the field of CBI.

Second, our study identifies technological diversification as a boundary condition for the impact of digital ambidextrous capabilities on CBI from an internal perspective. Drawing on the resource-matching perspective, firm capability theory emphasises the necessity for firms to continuously adapt their resource allocation and utilization to maximise the utility of their capabilities in creating value and gaining competitive advantage (Choi and Lee, 2022). This means that firms should not only possess the capabilities to cope with dynamic change but also the resources to maximise these capabilities. As the integration of digital resources and technologies renders a firm's technological base increasingly significant (Ilmudeen et al., 2021), the present paper examines the differential moderating effect of firms' technological diversification on the relationship between digital ambidextrous capabilities and CBI. In particular, it integrates a number of different conclusions derived from previous studies on technological diversification from a dual perspective (Kim et al., 2013; Machado et al., 2022), emphasising the manner in which firms with different technological bases can build digital ambidextrous capabilities in ways that allow for the efficient realisation of CBI.

Third, our study identifies environmental turbulence as a boundary condition for the impact of digital ambidextrous capabilities on CBI from an external perspective. Firm capability theory rooted in the environmental matching perspective posits that dynamic, complex and uncertain environments require firms to continuously adapt their capabilities to align with external demands and respond promptly (Dosi et al., 2022). Although the dynamics and complexity of the environment are increasingly affecting firms in digital contexts, our understanding of how these factors shape internal innovation processes remains limited (Zapadka et al., 2022). Therefore, the present paper explores the differential moderating effect of environmental turbulence on the relationship between digital ambidextrous capabilities and CBI. The current work also integrates the conflicting conclusions drawn by previous studies on environmental turbulence from a dual perspective (Dayioglu et al., 2024; Hamsal et al., 2023) and emphasises how environmental characteristics can motivate firms with digital ambidextrous capabilities to achieve CBI.

5.2. Implications for practice

The conclusions of this study provide a reference for how firms can leverage digital ambidextrous capabilities to drive CBI. When engaging in CBI, firms should fully leverage their digital infrastructure and tools to prioritize the development of digital ambidextrous capabilities and utilise digital technologies to achieve diverse objectives. On the one hand, firms ought to thoroughly explore the potential of digital technologies by establishing dedicated innovation labs focused on industry-specific adaptability research for cutting-edge fields, such as AI, blockchain and the metaverse. Firms should also implement rapid user demand validation mechanisms through minimum viable product (MVP) testing to explore additional cross-boundary scenarios. On the other hand, firms must maximise the integrative and optimising potential of digital technologies. By leveraging digital platforms, they can facilitate agile and extensive cross-domain collaboration, harnessing digital tools and cross-boundary resources to upgrade core products/services and expand market reach (Cepa and Schildt, 2023).

Second, our results highlight the technological context in which firms innovate across boundaries. In particular, we find that firms require the appropriate digital ambidextrous capabilities and technological resources to be successful. Firms should appropriately increase the level of technological diversification to fully utilise their knowledge base and reduce technological and cognitive distance. Doing so allows firms to maximise digital technologies to improve the effectiveness and accuracy of cross-boundary resource exchanges and explore synergies among different cross-boundary technologies. As the degree of technological diversification increases, firms should establish technology synergy platforms (e.g. API interface libraries) to promote cross-boundary technology reuse and enhance utilisation efficiency. Moreover, to sustain their competitive advantages, firms with higher degrees of technology diversification should appropriately divest low-synergy technologies, reduce management costs through technology licensing or eco-alliances and pay more attention to achieving more innovative and differentiated CBI through digital technologies (Knudsen et al., 2021). For example, through technological diversification, Huawei has gradually expanded across its previous boundaries into consumer electronics, cloud computing, smart cars and other fields, achieving a globalised layout of its business.

Finally, to maximise the benefits of developing their digital ambidextrous capabilities, firms should also consider the external environment in which CBI can be achieved. Firms in turbulent environments can fully discover the dynamically evolving resources and opportunities in such environments, as well as utilise digital technology to identify new development opportunities and growth points. Doing so helps firms create multi-layered and diversified products and services, enabling them to meet the complex and changing demands of the market. Moreover, firms facing higher levels of environmental turbulence should make extensive use of digital technologies to search for information, prioritise investments in modular digital systems (e.g. microservices architectures), enable rapid reconfiguration of existing technologies to adapt to change and build extensive collaborative networks to maintain stability (Knudsen et al., 2021). For example, Amazon, one of the world's largest e-commerce platforms, faces fierce market competition and changing consumer demands. Thus, it makes full use of its automated warehousing systems, intelligent logistics networks and other digital technologies, whilst constantly expanding into new business areas to enrich its product line with innovative products, such as the Kindle e-book reader and Alexa smart speakers.

5.3. Limitations and future research

First, regarding research methodology, this study validates the relationship between digital ambidextrous capabilities and CBI based on secondary data obtained from a large sample. The conclusions reached using this approach may be interesting and fruitful. However, this method may not fully capture the complex and dynamic relationships between digital capabilities and CBI (Chatterjee et al., 2020). As such, future research could employ in-depth interviews to explore the process mechanisms and historical evolutionary trajectories of CBI achieved through digital capabilities.

Second, concerning research scenarios, this paper examines the internal and external contexts of firms achieving CBI through digital ambidextrous capabilities from the dual perspectives of environmental turbulence and technological diversification. Considering that CBI covers the entire process of firms' production and operation, there are many other factors that play important roles in this process, such as cultural distance and institutional environment (Duan et al., 2021). Thus, future research could further explore how these different internal and external environmental factors influence the mechanisms, processes, structures and outcomes of CBI.

Additionally, this paper is based on firms' viewpoints to analyse how they utilise their digital ambidextrous capabilities to achieve CBI. In the future, we can look at the microfunctions of digital technologies, segment different digital capabilities and, with the help of methods such as response surface analysis or qualitative comparative analysis (QCA), explore the multidimensional triggers that stimulate a firm's CBI and the interactions between them.

CRediT authorship contribution statement

Xiaobin Feng: Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Bowen Xiao:** Writing – original draft, Methodology, Data curation, Conceptualization. **Hanzhong Zheng:** Software, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

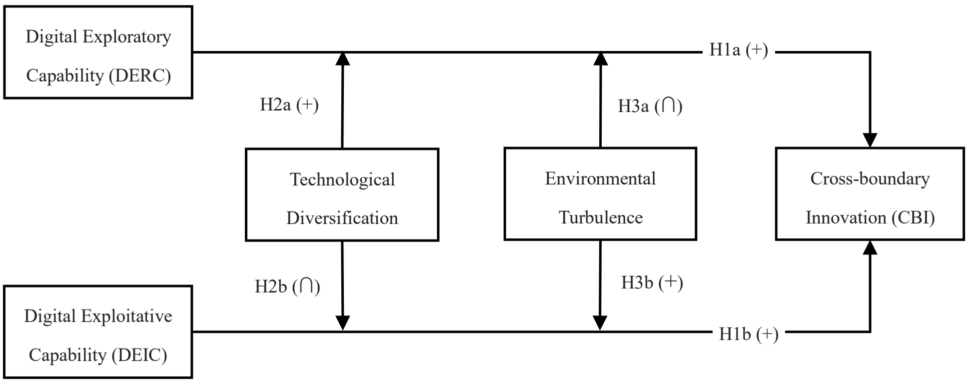

Figure A.1. Research model

Table A.1
Measurement of digital Ambidextrous capabilities

	Measurement item
Digital Exploratory Capability	**Digital technology word:** digital twin, meta-universe, avatar, 3D printing, 5 G, technology, mobile internet, mobile internet, industrial internet, digital technology, nanocomputing, smart planning, smart optimization, smart wear
Digital Exploitative Capability	**Digital process word:** intelligent manufacturing, intelligent customer service, intelligent marketing, digital marketing, unmanned retail, unmanned factory, mobile payment, third-party payment, NFC payment, human-computer interaction, social network
	Digital business word: smart agriculture, smart transport, smart healthcare, smart home, smart investment, smart culture and tourism, smart environmental protection, smart grid, smart energy, internet healthcare, internet finance, digital finance, fintech, fintech, quantitative finance, open banking, netflix, internet+

Table A.2
Variable definitions

Variable Type	Variable	Label	Operationalization
Dependent Variables	Digital exploratory capability	DERC	Digital technology innovation word frequency
	Digital exploitative capability	DEIC	Digital process innovation and digital business innovation word frequency
Independent Variable	Cross-boundary innovation	CBI	Natural logarithm of total number of cross-boundary patents
Moderator Variables	Technological diversification	TD	Herfindahl index of technology patents
	Environmental turbulence	ET	Standard error of regression of sales level on year divided by sales mean
Control Variables	Firm age	AGE	Natural logarithm of years since inception
	Firm size	SIZE	Natural logarithm of total assets
	Leverage ratio	LEV	Total liabilities as a percentage of total capital
	Dual role of the board chairman	DUAL	Set to 1 if the CEO is also the chairman of the board of directors, otherwise 0.
	Proportion of independent directors	PID	Ratio of the number of outside independent directors to the total number of directors.
	Shareholding concentration	OC	Natural logarithm of the sum of the squares of the shareholdings of the top ten shareholders
	Growth of the firm	GR	Ratio of current year's operating income to previous year's operating income - 1
	Institutional investments	INST	Total number of shares held by institutional investors divided by outstanding share capital
	Research and development	RD	Natural logarithm of R&D expenditures plus 1
	Return on assets	ROA	Ratio of net profit to total assets

Table A.3
Descriptive statistics

Variables	Obs	Mean	SD	Min	Max
DERC	7171	0.637	2.250	0.000	51.000
DEIC	7171	2.619	6.253	0.000	99.000
CBI	7171	3.502	1.358	0.000	9.249
TD	7171	0.338	0.196	0.000	0.844
ET	7171	0.038	0.032	0.000	0.424
AGE	7171	2.884	0.330	1.609	3.610
SIZE	7171	22.471	1.194	19.768	26.429
LEV	7171	0.421	0.181	0.034	0.924
DUAL	7171	0.269	0.443	0.000	1.000
PID	7171	0.373	0.053	0.285	0.600
OC	7171	0.047	0.016	0.000	0.202
GR	7171	0.151	0.320	−0.659	4.309
INST	7171	0.411	0.228	0.000	0.886
RD	7171	0.048	0.040	0.000	0.981
ROA	7171	0.040	0.059	−1.057	0.372

Table A.4
Correlation matrix

VARIABLES	DERC	DEIC	CBI	TD	ET	AGE	SIZE	LEV	DUAL	PID	OC	GR	INST	RD	ROA
DERC	1														
DEIC	0.292***	1													
CBI	0.083***	0.142***	1												
TD	0.060***	0.114***	0.501***	1											
ET	0.006	0.011	0.029**	−0.008	1										
AGE	−0.001	0.086***	0.114***	0.155***	−0.071***	1									
SIZE	−0.018	0.044***	0.497***	0.474***	0.025**	0.292***	1								
LEV	−0.030**	0.010	0.259***	0.217***	0.074***	0.229***	0.529***	1							
DUAL	0.063***	0.041***	−0.043***	−0.029**	0.013	−0.111***	−0.143***	−0.106***	1						
PID	0.029**	0.005	0.031***	0.030**	−0.014	0.005	0.003	−0.013	0.120***	1					
OC	0.026**	0.026**	0.065***	0.018	0.034***	0.039***	0.027**	0.156***	−0.004	0.005	1				
GR	0.009	0.033***	−0.004	0.046***	0.429***	−0.061***	0.040***	0.012	0.027**	0.009	−0.047***	1			
INST	−0.082***	−0.030**	0.213***	0.181***	−0.053***	0.154***	0.409***	0.214***	−0.193***	−0.030**	−0.040***	0.011	1		
RD	0.116***	0.142***	0.092***	0.090***	0.024**	−0.077***	−0.185***	−0.253***	0.085***	0.081***	−0.029**	−0.034***	−0.141***	1	
ROA	−0.051***	−0.059***	−0.020*	0.056***	−0.090***	−0.039***	0.030**	−0.323***	0.005	−0.020*	−0.145***	0.224***	0.154***	−0.049***	1

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. T value are in parentheses. Same below

Table A.5
Fixed effects panel data analysis results

	Model1	Model2	Model3	Model4	Model5	Model6
DERC		0.022^{***}	−0.003		0.019^{***}	
		(6.430)	(−0.351)		(3.802)	
DEIC		0.011^{***}		-0.044^{***}		0.007^{***}
		(7.845)		(−3.531)		(3.728)
TD			−0.017	0.015		
			(−0.370)	(0.327)		
ET					0.308^{***}	0.309^{***}
					(10.959)	(11.063)
DERC*TD			0.043^{***}			
			(2.925)			
DEIC*TD				0.144^{***}		
				(3.568)		
DEIC*TD^2				-0.085^{***}		
				(−2.778)		
DERC*ET					0.045^{***}	
					(3.632)	
DEIC*ET						0.014^{***}
						(3.712)
DERC*ET^2					-0.001^{**}	
					(−2.030)	
Controls	YES	YES	YES	YES	YES	YES
Observations	7171	7171	7171	7171	7171	7171
R-squared	0.870	0.872	0.871	0.872	0.874	0.874
id FE	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES
city FE	YES	YES	YES	YES	YES	YES

Table A.6
Regression results with replacement variables

	Model3	Model4	Model5	Model6
DERC	0.027^{***}		0.030^{***}	
	(7.895)		(8.236)	
DEIC		0.016^{***}		0.012^{***}
		(9.554)		(8.798)
TD	0.019	0.016		
	(0.877)	(0.722)		
ET			0.036	0.020
			(0.772)	(0.871)
DERC*TD	0.015^{**}			
	(2.130)			
DEIC*TD		0.006^{**}		
		(2.023)		
DEIC*TD^2		-0.024^{***}		
		(−3.876)		
DERC*ET			0.017^{***}	
			(4.047)	
DEIC*ET				0.003^{***}
				(2.788)
DERC*ET^2			-0.003^{**}	
			(−2.624)	
Controls				
Observations				
R-squared	YES	YES	YES	YES
id FE	7171	7171	7171	7171
year FE	0.871	0.872	0.872	0.871
city FE	YES	YES	YES	YES

Table A.7
Regression results controlling for the interaction effects of time and city

	Model2	Model3	Model4	Model5	Model6
DERC	0.024***	0.001		0.020***	
	(6.908)	(0.101)		(3.950)	
DEIC	0.011***		−0.040***		0.006***
	(7.571)		(−3.165)		(3.144)
TD		−0.033	0.001		
		(−0.682)	(0.012)		
ET				0.291***	0.295***
				(10.252)	(10.444)
DERC*TD		0.038***			
		(2.596)			
DEIC*TD			0.130***		
			(3.230)		
DEIC*TD^2			−0.076**		
			(−2.446)		
DERC*ET				0.048***	
				(3.877)	
DEIC*ET					0.017***
					(4.272)
DERC*ET^2				−0.001**	
				(−2.155)	
Controls	YES	YES	YES	YES	YES
Observations	7171	7171	7171	7171	7171
R-squared	0.895	0.894	0.895	0.896	0.896
id FE	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES
city FE	YES	YES	YES	YES	YES
year * city FE	YES	YES	YES	YES	YES

Table A.8
Regression results of state-owned firms

	Model2	Model3	Model4	Model5	Model6
DERC	0.014**	−0.138***		0.011	
	(1.967)	(−3.355)		(1.104)	
DEIC	0.014***		−0.027		0.014***
	(6.155)		(−0.978)		(4.648)
TD		−0.015	−0.175**		
		(−0.196)	(−2.250)		
ET				0.101**	0.095**
				(2.358)	(2.278)
DERC*TD		0.195***			
		(4.005)			
DEIC*TD			0.264***		
			(3.159)		
DEIC*TD^2			−0.261***		
			(−4.335)		
DERC*ET				0.043	
				(1.375)	
DEIC*ET					0.003
					(0.504)
DERC*ET^2				0.000	
				(0.207)	
Controls	YES	YES	YES	YES	YES
Observations	2644	2644	2644	2644	2644
R-squared	0.909	0.908	0.911	0.907	0.909
id FE	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES
city FE	YES	YES	YES	YES	YES

Table A.9
Regression results for non-state owned firms

	Model2	Model3	Model4	Model5	Model6
DERC	0.026***	−0.024**		0.035***	
	(6.583)	(−2.034)		(5.720)	
DEIC	0.013***		−0.040***		0.007***
	(7.196)		(−2.793)		(2.738)
TD		0.027	0.060		
		(−0.460)	(1.009)		
ET				0.381***	0.373***
				(10.183)	(10.067)
DERC*TD		0.081***			
		(4.888)			
DEIC*TD			0.136***		
			(2.831)		
DEIC*TD^2			−0.076**		
			(−2.024)		
DERC*ET				0.028**	
				(1.975)	
DEIC*ET					0.019***
					(4.036)
DERC*ET^2				−0.002***	
				(−3.064)	
Controls	YES	YES	YES	YES	YES
Observations	4527	4527	4527	4527	4527
R-squared	0.850	0.849	0.850	0.852	0.853
id FE	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES
city FE	YES	YES	YES	YES	YES

Data availability

Data will be made available on request.

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