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RESEARCH ARTICLE

The Impact of Digital Innovation Network Embeddedness on New Product Development Performance of Manufacturing Enterprises*

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Abstract

In the digital economy era, many manufacturing enterprises are leveraging digital service enterprises to enhance their digital innovation processes. This paper introduces the concept of "digital innovation network embeddedness" to describe this trend. Unlike traditional strategic resources, which are constrained by high-value, relatively static, restricted flow, and exclusivity, digital resources demonstrate superior fluidity, non-rivalrous access, and high value-driven interdependencies. To bridge this theoretical gap, this study examines the distinctive attributes of digital resources through the dual lenses of resource orchestration theory and dynamic capability theory. Specifically, it proposes big data capability as a mediating mechanism and organizational structure flexibility as a critical moderating factor. Developing this integrated research framework aims to elucidate the underlying mechanisms through which digital innovation network embeddedness dynamically shapes new product development (NPD) performance. Ultimately, this study seeks to advance theoretical understanding and provide actionable insights for digitally empowered manufacturing enterprises to enhance their NPD outcomes. The framework is tested using data from 559 manufacturing enterprises located in South China. There are three findings. (1) An inverted U-shaped relationship exists between digital innovation network structure and NPD performance, and between relationship embeddedness and NPD performance, respectively. (2) Big data capability mediates the relationship between moderate levels of digital innovation network embeddedness and NPD performance. However, at high levels of digital innovation network embeddedness, big data capability does not significantly mediate the relationship between digital innovation network structure/relationship embeddedness and NPD performance, respectively. (3) Organizational structure flexibility positively moderates the relationship between digital innovation network relationship embeddedness, big data capability, and NPD performance. Moreover, while mediated moderation occurred, the direct moderation effect on digital innovation network embeddedness is nonsignificant. The conclusions of this study provide insights for manufacturing enterprises seeking to enhance NPD performance within the context of digital innovation network embeddedness.

Keywords embeddedness digital innovation network structure; embeddedness digital innovation network relationship; big data capability; organizational structure flexibility; new product development (NPD) performance

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1 Introduction

The continuous development of new products that meet consumer demands is a critical source of competitive advantage for manufacturing enterprises (Schilke, 2014). In the knowledge economy era, enterprises are embedded in innovation networks formed through collaborative relationships with customers, suppliers, distributors, universities, and research institutions. This embeddedness facilitates access to complementary resources, technological knowledge, and market information, enhancing new product development (NPD) performance (Mazzola et al., 2015; Ying et al., 2018). With the advent of the digital economy, digital technologies such as cloud computing, the Internet of Things (IoT), big data, artificial intelligence (AI), and mobile internet are rapidly advancing and deeply integrating into various manufacturing sectors. These advancements deconstruct and reconstruct traditional product forms, development and manufacturing processes, and value realization pathways within the digital space (Dabić et al., 2023). However, due to constraints such as insufficient digital infrastructure, difficulty in shifting to digital thinking, and a lack of digital capabilities (Deperi et al., 2022), traditional NPD approaches in manufacturing enterprises are inadequate in addressing the challenges posed by digitalization (Xiao et al., 2020). Consequently, many manufacturing enterprises seek to leverage digital service enterprises to drive the digital transformation of their NPD processes (L. Li et al., 2018). Digital service enterprises are enterprises that utilize extensive digital resources (e.g., data, software, and algorithms) to provide digital products and services (e.g., platforms, software, and systems) to clients (Giustiziero et al., 2023). These enterprises include digital-native enterprises founded on digital technologies, such as Tencent and Alibaba; information technology service providers like Yonyou, Kingdee, and SiE; as well as digital pioneers within traditional industries, such as Midea Group's Midea Cloud and Zongsen Group's Humi Network (CMM). As collaboration between manufacturing enterprises and digital service enterprises strengthens, the structure of existing innovation networks evolves, and their boundaries expand. This process incorporates manufacturing enterprises into a complex innovation network interconnected by numerous digital service enterprises, a phenomenon that this study defines as digital innovation network embeddedness.

Extensive empirical evidence suggests that digital innovation network embeddedness significantly influences the NPD process of manufacturing enterprises. For example, Schneider Electric, at the early stage of its digital transformation, recognized the critical role of digital search. By collaborating with digital service providers such as Telvent and MiningLamp Technology, it gained access to digital technologies and knowledge, achieving remarkable success in product and service innovation (Wang et al., 2023). Similarly, Suofeiya Home Collection successfully transitioned its product development from standardized production operations to mass customization and eventually to smart manufacturing by partnering with software companies like Oracle and large e-commerce platforms (Xie et al., 2023). In contrast, the industrial design company LKK Design Group initially attempted a self-reliant approach to digital transformation between 2014 and 2017 but made little progress. However, starting in 2018, by leveraging digital service providers such as DingTalk and Alibaba Cloud, LKK Design Group successfully restructured its entire product development process, from concept to delivery, through digitalization (Chen & Wang, 2021). Despite these successes,

many manufacturing enterprises have invested substantial resources in collaborating with digital service enterprises but have failed to achieve the expected outcomes. According to the 2023 China Enterprise Digital Transformation Index, jointly released by Accenture and the China Industrial Control Systems Cyber Emergency Response Team (CICS-CERT) (a research academy under the Ministry of Industry and Information Technology (MIIT)), only 9% of enterprises were categorized as digital transformation leaders in 2023. Fewer than 30% recognized the need for sustained deepening of digital transformation efforts. These findings highlight the necessity of clarifying the mechanisms through which digital innovation network embeddedness influences NPD performance. Understanding this process can guide manufacturing enterprises in navigating their digital transformation journeys.

Innovation networks function as intricate resource allocation mechanisms between external markets and enterprises' internal operations, with their core role being to facilitate the flow of innovation-related elements and resources (Freeman, 1991; Rycroft & Kash, 2004). From the perspective of the Resource-Based View (RBV), embedding within an innovation network enables enterprises to access resources that are valuable, rare, imperfectly imitable, and non-substitutable (VRIN resources), thereby enhancing NPD performance (Bonner & Walker Jr., 2004; Echols & Tsai, 2005). However, while existing studies have explored the blessing effect of VRIN resources on NPD, few have examined the relationship between resource base and NPD performance from the perspective of resource–native attributes (Lu et al., 2021). RBV assumes that strategic resources possess high value, are relatively static, have limited mobility, and exhibit proprietary characteristics (Barney, 1991). In the context of the digital economy, data resources—characterized by homogeneity, self-growth, and re-programmability (Y. Liu et al., 2020)—have emerged as pivotal production factors alongside digital technologies and knowledge. The latter, distinguished by their generalizability (Zhang, 2022), play a critical role in fostering innovation-driven development (Cuthbertson & Furseth, 2022). These digital production factors demonstrate greater fluidity and non-exclusivity (Chen et al., 2020). Unlike traditional strategic resources that inherently hold high value, digital production factors exhibit high-value dependency, meaning that their maximum value can only be realized when effectively integrated with specific business scenarios (X. Zhang et al., 2023). This shift in resource attributes challenges the explanatory power of traditional innovation network embeddedness theories based on the blessing logic in understanding the relationship between digital innovation network embeddedness and NPD performance.

Furthermore, while prior studies have primarily focused on the blessing aspect of resources, some research highlights the potential curse effects of resources. Early investigations into the resource curse primarily examined national economic development, revealing that resource-rich countries tend to allocate attention and investments toward resource extraction and trade, leading to stagnation in domestic innovation-driven sectors (Badeeb et al., 2017). Subsequent studies extended this logic to organizational research, exploring how excessive resources might hinder corporate innovation. For instance, Yuan et al. (2015) found that strong political connections mitigate market competition pressures, reducing enterprises' motivation for technological innovation and resulting in a curse effect of political resources. Similarly, Li et al. (2017) discovered that excessive network embeddedness can lead to exclusivity, inertia, and opportunistic behaviors, ultimately constraining enterprises' productivity. The

resource curse logic is built upon the traditional characteristics of strategic resources—high value, exclusivity, and limited mobility—which create opportunities for resource holders to engage in rent-seeking behavior, thus diminishing innovation incentives (Yuan et al., 2015). However, the unique attributes of digital production factors may not induce such rent-seeking behavior. Instead, they pose new challenges for innovation. For instance, the vast volume of data resources may require excessive investment in technical infrastructure (e.g., data collection, storage, and analysis), incurring substantial costs (Cappa et al., 2021). The heavy reliance on digital production factors also presents significant technical and managerial challenges in transforming raw data into actionable knowledge (Braganza et al., 2017). If data resources fail to be effectively integrated with business contexts, enterprises may suffer from "information obesity" (InfoObesity)—a state of data overload that undermines decision-making efficiency (Cappa et al., 2021). This phenomenon raises a critical question: Could excessive embeddedness in digital innovation networks lead manufacturing enterprises to amass an unsustainable volume of digital production factors, ultimately triggering a resource curse effect? To date, existing literature has not adequately addressed this issue.

Building on these distinctions in resource attributes, this study applies resource orchestration theory to construct a conceptual model of the relationship between digital innovation network embeddedness and NPD performance. By examining the blessing and curse effects of digital production factors, this study aims to clarify the underlying mechanisms that influence the impact of digital innovation network embeddedness on NPD performance in manufacturing enterprises. The findings contribute to the theoretical discourse on digital product innovation from an innovation network perspective and offer practical insights for manufacturing enterprises seeking to enhance digital product development.

2 Theoretical Framework and Research Hypotheses

2.1 Theoretical Framework

The evolution of the RBV can be broadly categorized into three stages: the traditional RBV, the dynamic RBV, and the resource-action view (L. Zhang et al., 2023). The traditional RBV asserts that an enterprise's competitive advantage stems from possessing VRIN resources (Barney, 1991). However, this perspective primarily focuses on static resource stock and does not adequately address how enterprises manage resources under uncertain conditions. To address this limitation, the dynamic RBV, represented by the concept of dynamic capabilities, emphasizes how enterprises acquire and utilize resources in dynamic environments (Teece, 2007). This approach shifts the focus from resource possession to resource reconfiguration, enabling enterprises to adapt to changing market conditions. Subsequently, to develop a more comprehensive and practical framework for resource management, Sirmon et al. (2007) integrate the process perspective of resource management with the synergistic perspective of asset orchestration, leading to resource orchestration theory. This theory aims to open the "black box" of how resources influence enterprise performance. Resource orchestration theory proposes that resource management consists of three interconnected processes (Sirmon et al., 2007, 2011). (1) The construction of resource portfolios refers to the process of building a resource pool, whereby enterprises acquire and accumulate valuable resources

while divesting non-essential ones to establish a resource base necessary for development. This represents the logical starting point for value creation through resource management. (2) The bundling of resources into capabilities constitutes the resource conversion process, emphasizing that enterprises should leverage their resources to develop specific competencies in order to enable value creation. (3) The utilization of capabilities for value creation embodies the value realization process, underscoring that organizational capabilities serve as a critical precondition for gaining competitive advantage. These three processes collectively form the resource–capability–performance logic, which provides the theoretical foundation for investigating how digital innovation network embeddedness affects NPD performance.

Within the resource–capability–performance logic chain, the dynamic capability theory explores resource allocation mechanisms from a process perspective, offering strong explanatory power regarding how resources are transformed into performance outcomes. Dynamic capabilities, distinct from ordinary capabilities, comprise three dimensions: sensing, seizing, and reconfiguration (Teece, 2007). Sensing and seizing reflect an enterprise's ability to identify market opportunities and threats and to respond effectively. In the traditional industrial economy, manufacturing enterprises rely on environmental scanning to develop market insights, identify opportunities and threats, and make corresponding strategic decisions. However, based on limited information and managerial experience, cognitive biases often constrain this decision-making process, making it challenging to navigate technological disruptions and rapidly changing market demands (Hodgkinson & Healey, 2011). In the digital economy era, integrating intelligent digital technologies has transformed traditional methods of market insight generation. The diverse experiences, consultations, and information that traditional market insights rely upon can now be systematically stored, analyzed, and disseminated digitally. Big data, with its vast, multi-source, and multidimensional nature, has become the foundation for enterprises to perceive and seize opportunities in the digital era (Zhou et al., 2023). However, enterprises' ability to convert massive datasets into valuable insights and actionable knowledge depends heavily on their big data capabilities (Correani et al., 2020). Big data capability refers to an enterprise's ability to identify, acquire, store, and analyze large volumes of data to generate insights that support decision-making and operations, thereby reducing business uncertainty (Lin & Kunnathur, 2019). It serves as a key enabler of opportunity sensing and opportunity seizing in the digital age. Enterprises with strong big data capabilities can transform resources into useful new product insights, such as personalized consumer preferences and digital product prototypes, thereby driving NPD (Dubey et al., 2024; Mikalef et al., 2019). Following the resource orchestration theory framework, this study posits that enterprises should develop strong big data capabilities to fully leverage digital innovation network resources, thereby enhancing NPD performance. Thus, big data capability is likely to mediate between digital innovation network embeddedness and NPD performance.

In addition, the transformational reconfiguration dimension of dynamic capabilities reflects an enterprise's ability to continuously innovate and adapt its existing management paradigms and routines (Teece, 2007). The unique characteristics of digital resources significantly differentiate how enterprises acquire, store, and utilize digital resources compared to traditional resources (Kwon et al., 2014). This shift presents new challenges

for organizational management, particularly in organizational structure design and human resource allocation. On the one hand, digital resources are highly structured and encoded in binary format (0/1), fundamentally differing from traditional resources regarding acquisition and utilization (Y. Liu et al., 2020). Manufacturing enterprises often need to reconfigure their organizational structure, personnel systems, and business processes to effectively harness digital resources, such as establishing big data departments and data resource management teams. On the other hand, data and digital technologies should be seamlessly integrated into business operations to create value, requiring close collaboration between digital technology teams and business units (X. Zhang et al., 2023). Enterprises that lack the organizational flexibility to coordinate and restructure effectively may struggle to align digital resources with business needs. This misalignment can sometimes lead to the "digital efficiency paradox," where digital transformation investments fail to deliver expected performance gains (Z. Liu et al., 2020). Therefore, organizational structure flexibility is a key manifestation of transformational reconfiguration capability in the digital economy, representing an enterprise's ability to adapt its organizational structure in response to changes in the external environment or strategic objectives (Brozovic, 2018; Miroshnychenko et al., 2021).

When a manufacturing enterprise is embedded in a digital innovation network, high organizational structure flexibility may play a crucial role in accelerating digital resource acquisition and enhancing the alignment of digital resources with business operations (Bag et al., 2021). Following the logic of resource orchestration theory, this study posits that organizational structure flexibility may act as a catalyst in unlocking the potential value of digital innovation network embeddedness. Specifically, organizational structure flexibility moderates the impact of digital innovation network embeddedness on NPD performance.

In summary, this study applies resource orchestration theory as its theoretical foundation. It integrates insights from dynamic capability theory to examine the relationships between digital innovation network embeddedness, big data capability, and NPD performance. Additionally, it explores the moderating role of organizational structure flexibility. The overall research framework is illustrated in Figure 1.

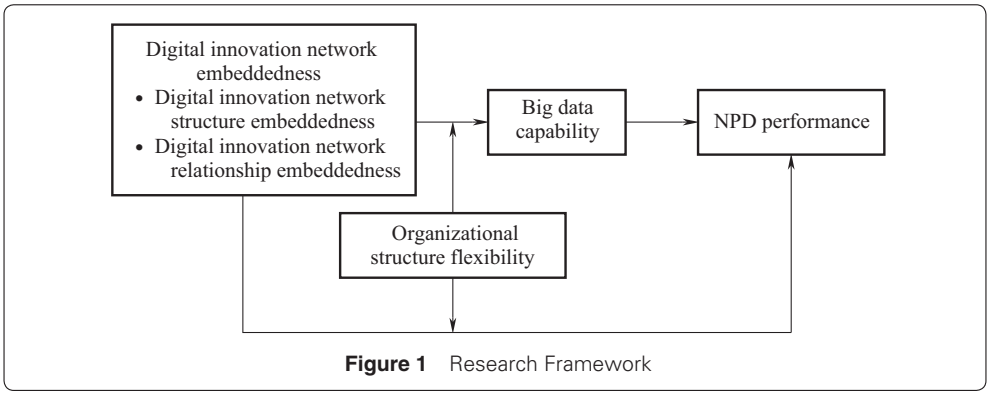

Figure 1 Research Framework

2.2 Digital Innovation Network Embeddedness and NPD Performance

Building on the previous analysis, this paper defines the digital innovation network as the relatively stable set of formal and informal relationships gradually formed through extensive collaboration between manufacturing enterprises and various digital development entities. These entities primarily include digital service enterprises, as well as digital technology-related colleges or departments within universities, digital research institutions, and service organizations. This network serves to foster digital innovation within enterprises. Drawing on the classic network embeddedness theory (Granovetter, 1985), this paper categorizes digital innovation network embeddedness into two dimensions: digital innovation network structure embeddedness and digital innovation network relationship embeddedness. The former reflects the positional characteristics of the focal enterprise within the digital innovation network. In contrast, the latter reflects the quality of relationships between the focal enterprise and its digital innovation partners.

2.2.1 Digital Innovation Network Structure Embeddedness and NPD Performance

As manufacturing enterprises connect with an increasing number of digital development entities, they become embedded in traditional and digital innovation networks. This dual embeddedness enables enterprises to acquire traditional strategic resources from traditional innovation networks and digital resources from digital innovation networks. Based on the resource orchestration theory and its logic of resource restructuring to enhance performance, this paper posits that under the condition of moderate digital innovation network structure embeddedness, as the degree of structure embeddedness increases, the focal enterprise gradually strengthens its influence as a key node for digital resource exchange within the network. This enables the enterprise to acquire multidimensional big data resources, accumulate diverse digital technologies, continuously update data resources, and advance the construction of virtual innovation organizations, thereby enhancing NPD performance.

First, digital innovation networks contain vast and highly fluid data resources, but individual network participants often hold fragmented data, which may limit its utility. As manufacturing enterprises deepen their structure embeddedness in the digital innovation network, they connect with many digital innovation entities—such as digital platform enterprises, digital technology service providers, and leading digital manufacturing enterprises. This enables them to aggregate fragmented data into multidimensional datasets, enhancing the value of data resources (Elia et al., 2020). For example, in the NPD process, enterprises can acquire increasingly multidimensional consumer data, including basic demographic information, consumption habits, and customer feedback. The greater the number of data dimensions, the more effective enterprises become in leveraging big data analytics to develop detailed consumer profiles, allowing them to create new products tailored to consumers' personalized needs (Mariani & Fosso Wamba, 2020). Second, the digital innovation network structure embeddedness provides manufacturing enterprises with more opportunities to access diverse digital technologies, which in turn supports the digitalization of NPD. Technologies such as cloud computing and big data analytics enable enterprises to uncover hidden consumer preferences within massive datasets, thereby assisting managers in making data-driven

strategic decisions and reducing uncertainty in product innovation (Mikalef et al., 2019). Moreover, AI technologies, through intelligent simulation, real-time monitoring, precise execution, and iterative learning, enhance the efficiency of NPD and manufacturing (Haenlein & Kaplan, 2019). Third, due to the self-evolving nature of digital technologies (i.e., continuous self-updating and self-iteration), manufacturing enterprises embedded in digital innovation networks can continuously update their digital resources through this self-growth process (Zhang et al., 2021). During this iterative evolution, the command logic of digital technologies has become increasingly sophisticated, and software versions are continuously upgraded, helping enterprises accumulate new data resources that provide higher-level technological support for NPD performance. For instance, Noblelift collaborates closely with digital technology service provider Shanghai Moze Intelligent Technology Co., Ltd. and research institutions such as Shanghai Jiao Tong University and Zhejiang University. They advance smart warehousing equipment, software, and hardware through continuous technological iteration, enabling digital product innovation (Jiang et al., 2023). Finally, the digital connections between nodes in a digital innovation network create opportunities for manufacturing enterprises to establish virtual innovation organizations (Vuchkovski et al., 2023). With the support of such virtual innovation organizations, manufacturing enterprises can develop new products with greater agility and flexibility. For example, Aomate, a small and medium-sized manufacturing enterprise, has leveraged its membership in the China Machine Tool & Tool Builders' Association (CMTBA) and collaborated with digital service enterprises such as Ningbo Jianing Information Technology Limited Company and Eossoft to jointly develop intelligent manufacturing solutions (Lou et al., 2023).

However, due to the high-value dependency on digital resources (X. Zhang et al., 2023), manufacturing enterprises with excessive digital innovation network structure embeddedness may face the digital resource curse. This occurs when excessive investments in digital infrastructure and the weakened position of product innovation departments significantly crowd out resources for product innovation, ultimately hindering NPD. First, NPD in manufacturing enterprises involves multiple business units and processes, each of which relies on different digital systems (Wang et al., 2023). To support their operational needs, various business units collaborate with external digital technology service providers, introducing digital technologies and systems that enhance the enterprise's level of digital innovation network structure embeddedness and improve operational efficiency. However, excessive structure embeddedness can lead to the over-introduction of digital systems. Since different digital systems are developed by various service providers using distinct source codes, they may not be interoperable, creating information silos and data islands within the enterprise. This prevents enterprises from fully leveraging digital resources and leads to data waste (Shan et al., 2021). In response to "data islands," enterprises should allocate substantial resources to strengthen their digital infrastructure, such as storage hardware and software, servers, and network equipment, to transform big data into "big information" and realize its potential value (Lin & Kunnathur, 2019). The larger the data resources, the greater the demand for advanced storage, computing power, and algorithm processing. These infrastructure investments consume a significant portion of the enterprise's R&D budget. Furthermore, digital infrastructure often exhibits strong asset specificity, making sharing

costs with NPD activities difficult. As a result, excessive digital innovation network structure embeddedness leads to an over-allocation of resources to digital infrastructure, crowding out investments that could otherwise be directed toward NPD (Guo et al., 2023). Second, the higher the degree of structure embeddedness, the more central the enterprise's status in the digital innovation network. This can cause management to emphasize IT or digital technology R&D departments more, granting them a stronger position relative to product innovation departments. Consequently, digital innovation departments may enjoy preferential access to limited R&D resources, further constraining investments in NPD (Luo et al., 2018). Based on the above analysis, this study proposes the following hypothesis:

H1a: There is an inverted U-shaped relationship between digital innovation network structure embeddedness and NPD performance.

2.2.2 Digital Innovation Network Relationship Embeddedness and NPD Performance

Traditional network embedding theory primarily examines the impact of relationship embeddedness from a trust-based perspective. It suggests that high levels of relationship embeddedness foster trust among network participants (McFadyen & Cannella Jr., 2004), facilitating the exchange of specialized, exclusive resources and proprietary, tacit knowledge. This, in turn, reduces transaction costs associated with acquiring valuable resources and expertise (Yan et al., 2019). Additionally, some studies explore the relationship embeddedness from the perspective of opportunism, positing that it mitigates information asymmetry and curbs free-riding behavior in collaborations (Boxu et al., 2022). However, in digital innovation networks, digital technologies and knowledge tend to be highly standardized and widely accessible (Zhang, 2022). Tacit knowledge is significantly codified, and digital resources are non-exclusive (Faraj et al., 2016; Wei et al., 2021), allowing enterprises to access data resources without establishing strong relational ties with partners. Moreover, in digital innovation networks, the high-speed, low-latency exchange of information via "digital connections" weakens—if not wholly overturns—the assumption of information asymmetry (Chen et al., 2022). Therefore, explaining the relationship between digital innovation network relationship embeddedness and NPD performance using traditional mechanisms may be theoretically insufficient.

From the perspective of digital innovation practices in manufacturing enterprises, enterprises face two key challenges when leveraging digital technologies to enable NPD: transitioning from traditional product development thinking to a digital innovation mindset (Wang, 2022), and integrating general digital technologies with specific NPD applications (Ciarli et al., 2021; X. Zhang et al., 2023). Moderate digital innovation network relationship embeddedness can effectively help enterprises overcome these challenges. First, transitioning to a digital innovation mindset requires changes in cognitive structures and mental models (Furr & Eisenhardt, 2021). Higher levels of digital innovation network relationship embeddedness indicate more frequent and deeper interactions between focal enterprises and digital innovation partners. These interactions facilitate intellectual exchanges and expose enterprises to extensive digital technology knowledge and experience, enhancing their understanding of digitalization. This, in turn, reshapes their cognitive structures and

mental models, encouraging enterprises to actively adopt digital technologies in NPD actively, thereby improving NPD performance. Second, unlike traditional innovation networks, which primarily emphasize the transactional attributes of collaboration, digital innovation networks require the deep integration of general digital technologies with enterprises' specific NPD application scenarios to generate positive outcomes. As a result, cooperation among digital innovation partners is more about value co-creation (Shi et al., 2023). Digital enterprises cannot achieve their goals merely by delivering standardized digital products or solutions to manufacturing enterprises. Instead, they should engage in deep collaboration to facilitate the actual implementation of digital technologies within manufacturing enterprises (Björkdahl, 2020). For example, during the construction of a digital factory at the leading printed circuit board maker Shennan Circuits Co., Ltd. (SCC), the prominent industrial software provider SiE Consulting stationed a specialized implementation team on-site for more than a year, only then achieving preliminary success. Consequently, high-level digital innovation network relationship embeddedness signifies that, through value co-creation, partners can drive deeper integration between digital technologies and the focal firm's NPD process, ultimately boosting NPD performance.

However, an excessively high level of digital innovation network relationship embeddedness may also negatively impact an enterprise's innovation performance. On the one hand, excessive relationship embeddedness increases the costs of information filtering, thereby crowding out resources allocated to innovation (Boxu et al., 2022). On the other hand, overly tight collaborative relationships can lead to knowledge homogenization, locking enterprises into specific technological trajectories and hindering innovation (McFadyen & Cannella Jr., 2004). In the context of digital innovation network embeddedness, the information filtering mechanisms enabled by digital technology significantly reduce enterprises' information processing costs. Moreover, the homogeneity and generalizability of data resources and digital technologies reduce the explanatory power of these mechanisms for the connection between excessive digital innovation network relationship embeddedness and NPD performance.

Empirical observations suggest that the negative impact of excessive digital innovation network relationship embeddedness on NPD performance in manufacturing enterprises primarily manifests through two mechanisms. First, excessive digital innovation network relationship embeddedness gives manufacturing enterprises an overabundance of external emotional resources, such as trust and mutual assistance commitments. Since managers have bounded rationality, an excessive supply of trust-based support may lead to overconfidence, causing them to overestimate their knowledge and capabilities while underestimating innovation risks (Molina-Morales & Martínez-Fernández, 2009). Consequently, they may overemphasize the role of digital technology in NPD, overstate their ability to control digital technology R&D, and make irrational decisions—such as allocating excessive R&D resources to digital technology—ultimately impairing NPD performance. Second, under excessive digital innovation network relationship embeddedness, digital thinking permeates manufacturing enterprises, rapidly advancing managerial digital mindsets. As a result, managers may not be content with simply integrating digital technology into existing business activities (such as NPD) to drive growth within the current business model. Instead, they may begin exploring ways to leverage mature digital technology systems to generate additional

profits, such as transitioning toward digital servitization (Li et al., 2022).

Gebauer et al. (2020) indicate that digital solutions are highly customized, and their development requires substantial R&D investment. Consequently, as enterprises shift their business models, they may divert significant R&D resources from NPD, thereby hindering innovation. Based on the above analysis, this study proposes the following hypothesis:

H1b: There is an inverted U-shaped relationship between digital innovation network relationship embeddedness and NPD performance.

2.3 The Mediating Effect of Big Data Capability

Big data capability refers to an enterprise's ability to identify, acquire, store, and analyze big data to generate insightful information or knowledge that supports managerial decision-making and operational processes and ultimately reduces business uncertainty (Lin & Kunnathur, 2019). It is a critical manifestation of enterprises' dynamic capabilities in sensing and seizing opportunities in the digital era.

2.3.1 Digital Innovation Network Embeddedness and Big Data Capability

Extant research on the factors influencing big data capability primarily examines three dimensions: technology, organization, and environment (Ma et al., 2023). Following the resource orchestration theory's "resource–capability" logic, this study posits that an appropriate level of digital innovation network embeddedness can strengthen enterprises' data resource foundations across these three dimensions, thereby enhancing big data capability. First, secure, novel, and company-compatible digital technologies are essential for building big data capability (Maroufkhani et al., 2020). Structure embeddedness provides focal enterprises with diverse channels to access cutting-edge and diversified digital technologies (Fürstenau et al., 2019), while relationship embeddedness facilitates in-depth interactions between focal enterprises and digital partners regarding big data resource acquisition, big data analysis, and processing (Kraus et al., 2019). Combining abundant digital technology sources and deep technological understanding significantly enhances big data capability. Second, top management support and organizational readiness are prerequisites for enterprises to build big data capability (Wamba et al., 2017). As structure embeddedness deepens, collaboration with an increasing number of digital entities broadens senior management's "digital vision" and strengthens their commitment to developing big data capability. Relationship embeddedness fosters strategic alignment between focal enterprises and their digital partners (Yan et al., 2019), making enterprises more likely to be influenced by digital partners that regard data as a core resource and "data empowerment" as a key value. Consequently, enterprises are more inclined to prioritize big data capability development and prepare accordingly. Third, external pressures and support are crucial in shaping enterprises' big data capability. Regarding structure embeddedness, as focal enterprises collaborate with more digital entities, they experience growing competitive pressures and challenges in the digital economy, prompting them to actively develop big data capabilities to remain competitive (Obal, 2017). Regarding relationship embeddedness, close connections with digital partners provide enterprises with

additional resources and technical support necessary for building big data capabilities, further facilitating their development (Gangwar, 2018).

When a focal enterprise's level of digital innovation network embeddedness reaches a certain threshold, further increasing its embeddedness may hinder the continued enhancement of its big data capability. First, from a technological perspective, as mentioned earlier, excessive structure embeddedness can lead to data islands (Shan et al., 2021), reducing the compatibility between digital technologies (Maroufkhani et al., 2020) and impeding the sustained improvement of big data capability. Meanwhile, excessive relationship embeddedness may result in the homogenization of digital production factors between the focal firm and its digital partners, locking the enterprise into a specific digital technology trajectory (Kolade et al., 2022). This rigidity prevents the enterprise from leveraging diverse digital technologies and data resources flexibly, negatively affecting its big data capability. Second, from an organizational perspective, both excessive structure and relationship embeddedness can lead top managers of the focal firm to become overconfident in their ability to obtain substantial social support through the digital innovation network (Molina-Morales & Martínez-Fernández, 2009). This overconfidence can result in the Dunning-Kruger effect—where individuals, trapped in an illusion of self-perceived superiority, fail to recognize their shortcomings and misjudge risks (Kruger & Dunning, 1999). Consequently, managers may blindly or excessively invest in higher-order big data capabilities without fully understanding potential risks, ultimately restricting further improvement. Third, from an environmental perspective, excessive structure embeddedness creates highly complex business interconnections between the focal firm and its digital partners. In such cases, if the enterprise attempts to implement innovation-driven changes in certain business processes to enhance its big data capability, it may encounter substantial internal and external coordination difficulties. This change process could even face resistance or passive opposition from certain business units or partners (Shipilov & Gawer, 2020). Furthermore, excessive relationship embeddedness may lead managers to over-perceive external pressures, resulting in irrational adoption of digital technologies and misallocation of resources, ultimately reducing operational efficiency (Firk et al., 2021) and hindering the continuous enhancement of big data capability. Based on the above analysis, this study proposes the following hypotheses:

H2a: There is an inverted U-shaped relationship between digital innovation network structure embeddedness and big data capability.

H2b: There is an inverted U-shaped relationship between digital innovation network relationship embeddedness and big data capability.

2.3.2 Big Data Capability and NPD Performance

The resource orchestration theory suggests that one of the primary mechanisms for value creation through capabilities is enabling managers to make scientific decisions by enhancing their opportunity sensing and seizing capabilities (Sirmon et al., 2007, 2011). This study posits that the stronger an enterprise's big data capability, the more effectively it can help manufacturing enterprises rapidly identify and extensively collect vast amounts of data relevant to various stages of NPD. This allows enterprises to build large-scale, comprehensive, and efficiently managed raw data repositories, analyze data using their big data capabilities

to extract market insights, and track market trends (Lin & Kunnathur, 2019). As a result, big data capabilities provide decision-making support for managers, helping them make accurate judgments in NPD and reducing uncertainties associated with innovation. First, in the new product design stage, the innovation team can analyze de-identified customer consumption data and online reviews to construct detailed consumer profiles and generate predictive insights into customer purchasing behaviors. This helps the enterprise anticipate market trends more accurately (Mariani & Fosso Wamba, 2020; Mikalef et al., 2019). A precise understanding of consumer preferences significantly enhances the directionality of new product ideation, shortens the product design cycle, and improves NPD efficiency. Second, during the NPD and testing phase, enterprises can rapidly obtain prototype usage data and user feedback from lead users. By leveraging big data analytics, enterprises can identify design flaws and functional shortcomings, enabling targeted product optimization (Dong & Yang, 2020) and ensuring product quality improvements. Finally, in the new product market launch stage, big data analytics-driven consumer profiling allows enterprises to precisely target specific consumer segments, ensuring effective product positioning and launch strategies. Moreover, enterprises can use big data techniques to evaluate product distributors' qualifications, select optimal business partners (Dubey et al., 2024), and ultimately enhance new product sales performance. Based on the above analysis, this study proposes the following hypothesis:

H3: Big data capability is positively correlated with NPD performance.

2.3.3 The Non-Linear Mediating Effect of Big Data Capability on the Relationship between Digital Innovation Network Embeddedness and NPD Performance

Following the resource orchestration theory's "resource acquisition–capability formation–performance enhancement" logic (Sirmon et al., 2007), this study posits that big data capability acts as a mediator in the relationship between digital innovation network embeddedness and NPD performance. First, under moderate structure and relationship embeddedness in a digital innovation network, the pressure from digital partners incentivizes focal enterprises to develop a strong intent to acquire big data resources and build big data capabilities (Obal, 2017). As the breadth and depth of collaboration between focal enterprises and their digital partners expand, enterprises gain access to an increasing variety of novel digital technologies and data resources (Fürstenau et al., 2019). This process deepens managers' understanding of digital production factors, significantly enhancing their support for big data capability development (Wamba et al., 2017). Furthermore, extensive and close connections with digital partners provide focal enterprises with the necessary data resources and digital technology support for constructing big data capabilities (Gangwar, 2018). Consequently, enterprises accelerate their big data capability formation, leveraging vast data resources to derive accurate market insights, support scientific decision-making in NPD, and improve product innovation quality and efficiency (Awan et al., 2021). Once an enterprise's digital innovation network embeddedness surpasses a certain threshold, further deepening its embeddedness may hinder the enhancement of big data capability. Obstacles such as data islands, reduced compatibility among digital technologies, and managerial overconfidence may lead to excessive or misguided investments in digital production factors, ultimately diminishing NPD performance. Based on this analysis, the

following hypotheses are proposed:

H4a: Big data capability plays a nonlinear mediating role in the relationship between digital innovation network structure embeddedness and NPD performance.

H4b: Big data capability plays a nonlinear mediating role in the relationship between digital innovation network relationship embeddedness and NPD performance.

2.4 The Moderating Effect of Organizational Structure Flexibility

Organizational structure flexibility reflects an enterprise's ability to dynamically adjust its organizational structure to respond swiftly to changes in internal and external environments or strategic shifts (Bag et al., 2021; Miroshnychenko et al., 2021). It is a key indicator of an enterprise's transformation and restructuring capabilities. Grounded in dynamic capability theory, resource orchestration activities are embedded in dynamic organizational contexts. Enterprises should continuously adjust their organizational structures to align with resource utilization needs, thereby unlocking the full value of their resources (Teece, 2007). The rise of the digital economy has compressed spatial and temporal gaps in inter-firm collaboration while weakening traditional market entry barriers. As a result, cross-industry competition has become as prevalent as within-industry competition. To adapt to the evolving market landscape of the digital era, enterprises should redefine their boundaries and strike a balance between formal and informal organizational structures (Yang et al., 2021). In this context, organizational structure flexibility emerges as a crucial capability for transformation and restructuring. Within a digital innovation network, a manufacturing enterprise's ability to effectively leverage data resources hinges on its ability to integrate them into its core business processes (Z. Liu et al., 2020). This requires enterprises to reconfigure their organizational structures, personnel systems, and operational workflows to align with digital transformation. Consequently, this study posits that high organizational structure flexibility—characterized by dynamically adapting organizational structures—enhances enterprises' ability to integrate digital resources effectively and, in turn, amplifies the benefits of digital innovation network embeddedness.

2.4.1 The Moderating Effect of Organizational Structure Flexibility in the Relationship between Digital Innovation Network Embeddedness and NPD Performance

First, when a focal firm incorporates externally acquired digital resources into its NPD process, high structural flexibility enables it to reorganize existing R&D teams or establish new project teams at minimal cost and with minimal disruption to other strategic initiatives. This adaptability allows enterprises to tailor their organizational structures to the specific demands of different types and stages of product innovation, ultimately improving NPD performance. Additionally, high structural flexibility enhances an enterprise's cross-organizational penetration capabilities, facilitating the formation of closely coordinated virtual innovation networks with its digital partners (Vuchkovski, 2023). This further empowers NPD efforts. As a result, enterprises with high organizational structure flexibility demonstrate significantly enhanced NPD performance when exposed to moderate digital innovation network structure embeddedness. Under excessive structure embeddedness, the

curse effect of digital innovation network structure embeddedness on NPD may also be amplified by high structural flexibility. On the one hand, compared to enterprises with low structural flexibility, those with high structural flexibility possess greater resource allocation agility (Bock et al., 2012). When investing in advanced digital infrastructure, these enterprises can allocate more substantial R&D resources, accelerating the deployment of complementary digital hardware and software. This increased investment in digital infrastructure may come at the cost of resources that could have been allocated to NPD. On the other hand, highly flexible enterprises can dynamically redirect R&D resources toward IT and digital service development—areas that tend to receive greater managerial attention—thereby exacerbating resource constraints for NPD. This further intensifies the crowding-out effect, ultimately reducing NPD performance.

Second, under moderate digital innovation network relationship embeddedness, enterprises with high structural flexibility benefit from enhanced human resource adaptability. This enables focal enterprises to establish well-matched organizational structures for cross-organizational value co-creation with highly trusted partners (Bock et al., 2012; Brozovic, 2018). Consequently, digital technologies can be more seamlessly integrated into NPD processes, significantly improving innovation performance. In other words, high structural flexibility further strengthens the blessing effect of moderate digital innovation network relationship embeddedness on NPD performance. Under excessive relationship embeddedness, the curse effect of digital innovation network relationship embeddedness on NPD performance may be further intensified by high structural flexibility. Excessive trust within partnerships may lead to managerial overconfidence, causing decision-makers to underestimate the risks associated with digital innovation (Molina-Morales & Martínez-Fernández, 2009). Overemphasis on the role of digital technologies in product development may result in inflated expectations regarding enterprises' control over digital technology development. This, in turn, drives excessive investments in digital technologies at the expense of NPD. Since enterprises with high organizational structure flexibility can rapidly allocate resources to support managerial decisions, they may unintentionally facilitate the misallocation of resources toward digital technology initiatives, further constraining investments in NPD. Based on this analysis, the following hypotheses are proposed:

H5a: Organizational structure flexibility positively moderates the relationship between digital innovation network structure embeddedness and NPD performance. When organizational structure flexibility is high, the inverted U-shaped curve of this relationship becomes steeper.

H5b: Organizational structure flexibility positively moderates the relationship between digital innovation network relationship embeddedness and NPD performance. When organizational structure flexibility is high, the inverted U-shaped curve of this relationship becomes steeper.

2.4.2 The Moderating Effect of Organizational Structure Flexibility in the Relationship between Digital Innovation Network Embeddedness and Big Data Capability

First, high organizational structure flexibility enables enterprises to achieve a more flexible

and dynamic "organizational structure–strategy" fit (Parthasarthy & Sethi, 1992). Under moderate digital innovation network structure embeddedness, the focal firm may propose a big data capability building strategy due to the increasing demand for big data processing (Suoniemi et al., 2020). At this point, a firm with high structural flexibility can dynamically adjust its organizational structure or establish strategic departments (such as a Big Data Business Unit) to facilitate the smooth implementation of the big data capability building strategy. In addition, enterprises with high structural flexibility possess resource reconfiguration capabilities (Bock et al., 2012). These capabilities can provide sufficient resource support for big data capability building, thereby strengthening the impact of digital innovation network structure embeddedness on enterprises' big data capabilities. Under excessive structure embeddedness, the focal firm may become more inclined to outsource data processing services to meet the growing demand for big data processing due to the advantages gained from structure embeddedness. High organizational structure flexibility can significantly accelerate the implementation of this strategy, thereby reinforcing the negative impact of excessive digital innovation network structure embeddedness on big data capabilities.

Second, under the condition of moderate digital innovation network relationship embeddedness, enterprises with high organizational structure flexibility, which possess an agile "organizational structure–strategy" fit capability (Parthasarthy & Sethi, 1992), can more rapidly establish an organizational structure aligned with the big data capability building strategy (e.g., establishing a Big Data Business Unit or enhancing technical talent development in big data capability building). This accelerates the implementation and execution of the strategy. In contrast, enterprises with low structural flexibility find it challenging to adjust their organizational structure agilely to support the big data capability building strategy, thereby limiting their ability to empower big data capabilities. However, the embeddedness of excessive digital innovation network relationships may lead to resource and technology homogenization among enterprises. In this case, high structural flexibility could further intensify overinvestment in homogeneous data resources and digital technologies, locking the enterprise into a specific digital technology trajectory (Kolade et al., 2022). This reduces the enterprise's sensitivity to other data resources and digital technology, amplifying the negative impact of excessive digital innovation network relationship embeddedness on big data capabilities. Based on this, the following hypotheses are proposed:

H6a: Organizational structure flexibility positively moderates the relationship between digital innovation network structure embeddedness and big data capability. When organizational structure flexibility is high, the inverted U-shaped relationship becomes steeper.

H6b: Organizational structure flexibility positively moderates the relationship between digital innovation network relationship embeddedness and big data capability. When organizational structure flexibility is high, the inverted U-shaped relationship becomes steeper.

2.4.3 The Mediated Moderation Effect of Organizational Structure Flexibility in the Relationship between Digital Innovation Network Embeddedness and NPD Performance

In building big data capabilities through digital innovation networks, manufacturing

enterprises often need to adjust their organizational structure, such as establishing a Big Data Business Unit to identify, acquire, and manage digital resources. Enterprises with high organizational structure flexibility can adapt their structure efficiently to acquire digital resources that align with business development needs, thereby enhancing the impact of digital innovation network embeddedness on big data capabilities. As revealed in *H4a* and *H4b*, moderate digital innovation network embeddedness can enhance big data capabilities. In contrast, excessive embeddedness can suppress big data capabilities, resulting in the blessing effect and curse effect on NPD performance. Therefore, this study posits that organizational structure flexibility plays a moderating role between digital innovation network embeddedness and big data capabilities, indirectly influencing NPD performance. Specifically, when enterprises possess more dynamic structural adjustment capabilities and flexible human resource allocation, the marginal effect of digital innovation network embeddedness on big data capabilities will be strengthened. Consequently, the blessing and curse mechanisms of digital innovation network embeddedness on NPD performance will also be amplified. Based on the above analysis, the following hypotheses are further proposed:

H7a: The moderating effect of organizational structure flexibility on the inverted U-shaped relationship between digital innovation network structure embeddedness and NPD performance is mediated by big data capability, indicating the presence of a moderated mediation effect.

H7b: The moderating effect of organizational structure flexibility on the inverted U-shaped relationship between digital innovation network relationship embeddedness and NPD performance is mediated by big data capability, indicating the presence of a moderated mediation effect.

3 Research Design

3.1 Variable Measurement

This study primarily adopts well-established measurement scales from domestic and international research. For certain novel variables or those lacking mature scales due to insufficient empirical studies—such as digital innovation network embeddedness—measurement items are redesigned based on theoretical analysis and practical insights. The measurement of digital innovation network embeddedness is adapted from the mature scale proposed by Y. Li et al. (2018), with modifications to fit the context of this study. It is divided into structure and relationship embeddedness, comprising four and six items, respectively. The former focuses on capturing embedded enterprises' overall network structure and structural centrality. At the same time, the latter emphasizes the strength of interactive relationships between enterprises and their digital partners. NPD performance is measured using the six-item scale developed by Kawakami et al. (2015). Big data capability is assessed using the 16-item scale developed by Lin and Kunnathur (2019), which comprehensively evaluates an enterprise's ability to identify, collect, store, and analyze big data. The five-item scale developed by Bag et al. (2021) measures organizational structure flexibility. All items are rated on a seven-point Likert scale, where 1 represents "strongly disagree" and 7 represents "strongly agree." This study follows the approach of Yu et al. (2020) for control variables including firm size, firm age, ownership

type, industry type, and industry chain position as control variables.[1] The variables used in this study are listed in Table 1.

Table 1 Definition of Key Variables

Category	Variable	Symbol	Definition
Independent variable	Digital innovation network structure embeddedness	*DISE*	Each measurement item for this variable is rated on a seven-point Likert scale: 1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = agree, 7 = strongly agree. The arithmetic mean of all item scores is calculated to represent the variable level.
	Digital innovation network relationship embeddedness	*DIRE*	
Moderator	Organizational structure flexibility	*OSF*	
Mediator	Big data capability	*BBC*	
Dependent variable	NPD performance	*NPDP*	
Control variable	Firm size (dummy variable)	*Size*	1 = large enterprise, 0 = SME
	Firm age	*Age*	1(⩽ 5 years), 2 (> 5 to ⩽ 10 years), 3 (> 10 to ⩽ 15 years), 4 (> 15 years)
	Ownership type	*PRN*	Three categories include state-owned enterprises, private enterprises, and other types of enterprises
	State-owned enterprise (dummy variable)	*SOE*	1 = state-owned enterprise, 0 = non-state-owned enterprise
	Private enterprise (dummy variable)	*PE*	1 = private enterprise, 0 = non-private enterprise
	Industry type (dummy variable)	*IT*	1 = strategic emerging industry, 0 = traditional industry
	Industry chain position (dummy variable)	*ICP*	1 = midstream and downstream enterprise, 0 = upstream enterprise

[1] The classification of enterprise-scale follows the Measures for the Classification of Large, Medium, Small, and Micro Enterprises in Statistics (2017) [统计上大中小微型企业划分办法(2017)] issued by the National Bureau of Statistics of China. Industrial enterprises with 1,000 or more employees and annual revenue of 400 million yuan or above are classified as large enterprises. Non-large enterprises that meet the criteria of 20 or more employees and annual revenue of 3 million yuan or above are classified as small and medium enterprises (SMEs). The survey includes two questions to assess enterprise scale: (1) What is the number of employees? (fewer than 20, between 20 (inclusive) and 1,000, 1,000 or more); (2) What was the total revenue of the previous year? (less than 3 million yuan, between 3 million (inclusive) and 400 million yuan, 400 million yuan or more). The ownership type is based on the classification of business registration by the State Administration for Industry and Commerce of the People's Republic of China (SAIC). The survey includes the question: "What is the ownership structure of your company?" with the options "state-owned enterprise," "private enterprise," and "other types of enterprises." The industry type is categorized according to the Classification of Strategic Emerging Industries (2018) (National Bureau of Statistics Order No. 23). Industries that drive major technological breakthroughs and meet critical development needs, playing a leading role in long-term economic and social development, are classified as strategic emerging industries. Other industries are classified as traditional industries. The survey includes the question: "What is your company's industry type?" with options "strategic emerging industry" and "traditional industry." The position within the industrial chain is divided into upstream enterprises and midstream and downstream enterprises. Upstream enterprises primarily focus on raw material production and component supply, while midstream and downstream enterprises mainly manufacture products. The survey question "What is your company's position in the industrial chain?" offers two options "upstream" and "midstream and downstream." The data is self-reported by the respondents.

3.2 Data Collection

This study focuses on manufacturing enterprises in South China and collects data through a survey questionnaire.[2] The formal survey was conducted between April and June 2022. Before the survey, the research team collaborated with a wide range of manufacturing enterprises, government agencies, and industry associations, establishing a survey network covering over 2,000 manufacturing enterprises to ensure smooth data collection. To ensure data quality, both pre-survey controls and post-survey controls were implemented. Pre-survey controls ensured respondents had sufficient knowledge of their enterprises' digital transformation efforts. Only mid-to-senior managers with at least two years of work experience in the enterprise were allowed to complete the survey to minimize response bias. Post-survey controls included manual screening of responses after data collection. Invalid responses—including those with obvious response patterns, missing values, or from respondents who do not meet the experience criteria—were removed. The survey was conducted electronically, and 596 responses were collected. After eliminating invalid responses, 559 valid samples were retained for analysis. As shown in Table 2, the distribution of valid sample enterprises in terms of size, age, ownership type, industry type, and industry chain position is diverse, with no extreme biases. This indicates that the sample is representative. Descriptive statistics for the key variables can be found in Table A1 of the Appendix.

Table 2 Composition of the Valid Sample ($N = 559$)

Variable	Category	*n*	Percentage
Size	Large enterprise	219	39.177%
	SME	340	60.823%
Age	⩽ 5 years	102	18.247%
	> 5 to ⩽ 10 years	190	33.989%
	> 10 to ⩽ 15 years	172	30.769%
	> 15 years	95	16.995%
PRN	State-owned enterprise	161	28.802%
	Private enterprise	318	56.887%
	Other types of enterprises	80	14.311%
IT	Strategic emerging industry	300	53.667%
	Traditional industry	259	46.333%
ICP	Midstream and downstream enterprise	382	68.336%
	Upstream enterprise	177	31.664%

[2] South China is home to a large concentration of leading domestic digital services providers, such as Huawei, Tencent, and Alibaba Cloud Industrial Internet Headquarters, as well as numerous top digital service enterprises across various industries, including ROOTCLOUD, Midea Cloud, SiE, and Aofei Data. This makes it significantly easier for manufacturing enterprises in South China to embed themselves in the digital innovation network. Amid the booming digital economy, manufacturing enterprises in South China are accelerating their digital transformation in NPD. According to data from the Guangdong Provincial People's Government's website, as of June 2022, over 22,500 large-scale manufacturing enterprises in Guangdong Province had undergone digital transformation, driving more than 650,000 SMEs to adopt cloud-based data solutions. Therefore, selecting manufacturing enterprises from South China as the research sample is appropriate for the context of this study.

4 Empirical Tests and Results Analysis

4.1 Reliability and Validity Testing

Before testing the research hypotheses, the reliability and validity of the collected data are analyzed. For reliability testing, this study selects Cronbach's alpha coefficient (α) and composite reliability (CR) value as evaluation criteria. The results are shown in Table 3, where all subscales' Cronbach's α and CR values are above 0.807. This exceeds the threshold value of 0.7, indicating that the variables measured in this study demonstrate good reliability.

Table 3 Measurement Items and Reliability and Validity Analysis (N = 559)

Variable	Measurement items	Loading	Cronbach's α	CR	AVE
DISE	The company holds a certain degree of influence within the digital partner network[a].	0.840	0.882	0.883	0.653
	Upstream and downstream enterprises frequently obtain industry and market-related data and information through the company.	0.819			
	Upstream and downstream enterprises often establish connections with digital-native enterprises through the company.	0.789			
	A high proportion of our closely collaborating digital-native partners possess key digital technologies and data resources.	0.784			
DIRE	The company and its digital partners can fulfill their commitments.	0.760	0.898	0.898	0.595
	The company and its digital partners communicate with honesty and transparency.	0.755			
	The company and its digital partners can provide each other with the necessary technology and information.	0.787			
	The company trusts its digital partners and prioritizes building long-term partnerships.	0.809			
	The company and its digital partners support each other and help solve each other's problems.	0.764			
	The company and its digital partners frequently remind each other of potential changes and challenges.	0.753			
OSF	The company can speedily change the organizational structure to respond to changing business conditions.	0.747	0.807	0.807	0.457
	The company can cost-effectively change the organizational structure to respond to changing business conditions.	0.686			
	The company can change the organizational structure without negatively impacting product or service quality.	0.691			
	Current organization structure enables us to adapt to changing business conditions.	0.637			
	The company is more flexible than our competitors in changing our organizational structure.	0.611			

(*To be continued*)

(*Continued*)

Variable	Measurement items	Loading	Cronbach's α	CR	AVE
BBC	The company is able to identify sources of big data that meet our needs.	0.724	0.943	0.943	0.510
	The company is able to collect big data that meets our needs.	0.690			
	The company is able to store large volumes of data.	0.752			
	The company is able to process big data with a fast speed.	0.730			
	The company adopts state-of-the-art technologies to process big data.	0.708			
	The company constantly updates our computing equipment to process big data.	0.659			
	The company constantly updates our IT architecture to process big data.	0.761			
	The company constantly updates our IT infrastructure to process big data.	0.743			
	The company is good at data analytics, which is mainly data mining and statistical analysis.	0.722			
	The company is good at text analytics that deals with unstructured textual format data.	0.666			
	The company is good at web analytics that deals with websites.	0.729			
	The company is good at mobile analytics that deals with mobile computing.	0.738			
	The company relies on big data to identify new business opportunities.	0.732			
	The company relies on big data to develop new products.	0.709			
	The company relies on big data to enhance our innovativeness.	0.680			
	The company relies on big data to formulate our business strategy.	0.677			
NPDP	Compared to major competitors, the company's NPD projects are more proficient at the discovery stage (idea creation, expanding the idea into a full product concept, and business and market opportunity analyses).	0.720	0.878	0.878	0.547

(*To be continued*)

(*Continued*)

Variable	Measurement items	Loading	Cronbach's α	CR	AVE
NPDP	Compared to major competitors, the company's NPD projects are more proficient at the development stage (technical development, determining the final product design, cost reduction and quality control, and product testing).	0.674			
	Compared to major competitors, the company's NPD projects are more proficient at the commercialization stage (launching the product in the marketplace, product life cycle management).	0.736			
	The company's new product sales revenue is higher than major competitors.	0.766			
	The company's new product market share is higher than major competitors.	0.791			
	Overall, the company's new products demonstrate significantly stronger competitiveness than major competitors.	0.745			

Note. [a] A digital partner refers to an enterprise that provides customers with digital products and services (such as platforms, software, and systems) through extensive digital resources (such as data, software, and algorithms). This includes digital-native enterprises established based on digital technologies from the outset, such as Tencent and Alibaba, and IT service providers like Yonyou, Kingdee, and SiE. Additionally, it includes traditional enterprises that have taken the lead in digital transformation, such as Midea Group, which incubated Midea Cloud, and Zonsen Group, which launched CMM.

The validity test is conducted from three aspects: content validity, convergent validity, and discriminant validity. In terms of content validity, most of the measurement items in this study are derived from established scales published in authoritative domestic and international journals, ensuring good content validity. Regarding convergent validity, this study employs confirmatory factor analysis (CFA) and calculates the AVE to assess the validity. The CFA results show that the four-variable, five-factor model proposed in this study achieves the best fit (χ^2/df = 1.705; CFI = 0.961; TLI = 0.958; IFI = 0.961; RMSEA = 0.036),[3] as shown in Table 3. The factor loading of all items exceeds 0.5, except for the AVE value of organizational structure flexibility, which is 0.457, slightly below the threshold of 0.5. However, the AVE values for all other variables are above 0.5, indicating good convergent

[3] The χ^2/df (Chi-square to degrees of freedom ratio) is a statistical measure that directly tests the similarity between the sample covariance matrix and the estimated variance matrix. A value closer to 1 indicates a better model fit. CFI (Comparative Fit Index) measures the consistency between the model and the original data. A CFI value greater than 0.9 is considered a good fit. TLI (Tucker-Lewis Index) is another comparative fit index. A TLI value greater than 0.9 is also considered a good fit. IFI (Incremental Fit Index) assesses the incremental fit of the model. A value above 0.9 indicates a good fit. RMSEA (Root Mean Square Error of Approximation) measures the error of approximation. An RMSEA value less than 0.05 indicates a good fit.

validity. Regarding discriminant validity, a competitive model approach is used for CFA analysis. The results in Table 4 suggest that the four-variable, five-factor model (Model A) proposed in this study achieves the best fit compared to the other two models. Moreover, by comparing the square root of the AVE values with the Pearson correlation coefficients between variables, the square root of each variable's AVE value is found to be greater than the correlation coefficients between variables (see Table A2 in the Appendix for details), confirming good discriminant validity. In summary, the content validity, convergent validity, and discriminant validity of this study are all satisfactory.

Table 4 Confirmatory Factor Analysis: Discriminant Validity Test (N = 559)

Model	Factor	χ^2/df	CFI	TLI	IFI	RMSEA
Model A	5 Factors: *DISE; DIRE; BBC; OSF; NPDP*	1.705	0.961	0.958	0.961	0.036
Model B	4 Factors: *DISE + DIRE; BBC; OSF; NPDP*	2.403	0.921	0.916	0.921	0.050
Model C	1 Factor: *DISE + DIRE + BBC + OSF + NPDP*	8.299	0.586	0.561	0.587	0.114

4.2 Common Method Variance

Since the data are collected through self-reported surveys from middle and senior managers, there is a potential risk of common method variance (CMV). First, Harman's single-factor test is conducted to assess CMV. The results show that five factors with eigenvalues greater than one are extracted, with the largest single factor accounting for 32.97% of the variance below the 40% threshold, indicating that CMV is not a serious concern. Second, the study adopts the Controlling for Unmeasured Single Method-Latent Factor Approach recommended by Xiong et al. (2012) to control for CMV. Specifically, (1) Model M1 is the original confirmatory factor analysis model proposed in this study, (2) Model M2 includes a latent method factor, and (3) when comparing the fit indices of M1 and M2, ΔCFI = 0.013, ΔTLI = 0.012, ΔNFI = 0.016, and ΔRMSEA = 0.006. The changes in all fit indices are less than 0.02, indicating that adding the method factor does not significantly improve the model fit. This suggests that CMV is well-controlled in this study.

4.3 Descriptive Statistical Analysis and Correlation Analysis

A descriptive statistical analysis is conducted on each variable. The results show that the data distribution is reasonable (see Table A1 in the Appendix for details). The correlation analysis results indicate that most of the core variables are significantly correlated at the 0.01 level, except for the correlation between big data capability and organizational structure flexibility, which is not significant (see Table A2 in the Appendix for details). This implies that there may be no direct relationship between organizational structure flexibility and big data capability, and further examination is needed to clarify their relationship. Multiple regression analysis will be conducted in the following section to obtain more robust analytical results

and test the proposed hypotheses.

4.4 Test of Direct Effects

This study adopts the three-step test method proposed by Haans et al. (2016) to examine the hypothesized inverted U-shaped relationship. First, the independent variable data is standardized (i.e., converting the original data to have a mean of 0 and a standard deviation of 1. Then, the squared term of the independent variable is constructed. Hierarchical regression analysis is then conducted to test the relationship. Second, the standardized regression results derive from the corresponding quadratic curve equation. The first derivative of the curve equation is then calculated to obtain the slope equation of the curve's tangent line. By computing the slope when the independent variable takes its minimum and maximum values within the standardized range, the direction of the slope is analyzed. Third, based on the hierarchical regression results and the tangent line slope equation, the curve's stationary point (i.e., the point where the slope is zero) is calculated. The stationary point is then checked to determine whether it fell within the standardized range of the independent variable. According to Haans et al. (2016), an inverted U-shaped relationship exists when the following three conditions are met: (1) The regression coefficient of the quadratic term of the independent variable is negative and significant. (2) The slope of the tangent line is positive when the independent variable is at its minimum value within the range and negative when at its maximum value. (3) The stationary point of the curve falls within the range of the independent variable. The hierarchical regression analysis results are shown in Table 5.

First, in Model 2 and Model 6, the quadratic term of digital innovation network structure embeddedness shows a negative and significant effect on big data capability (β = –0.129, $p < 0.001$) and NPD performance (β = –0.087, $p < 0.001$). Similarly, Model 3 and Model 8 show that the quadratic term of digital innovation network relationship embeddedness also has a negative and significant effect on big data capability (β = –0.136, $p < 0.001$) and NPD performance (β = –0.111, $p < 0.001$). This satisfies Condition (1). Second, to verify whether the results meet Condition (2), the slope of the tangent line equation is calculated, as shown in Table 6. After standardization, the range of *DISE* (digital innovation network structure embeddedness) is [–2.726, 2.038]. When *DISE* is at its minimum value, the slopes of Path 1 and Path 2 (*S*) are positive, while at the maximum value, the slopes are negative. Similarly, the range of *DIRE* (digital innovation network relationship embeddedness) is [–3.054, 1.880]. When *DIRE* is at its minimum value, the slopes of Path 3 and Path 4 (*S*) are positive, while at the maximum value, the slopes are negative. This satisfies Condition (2). Finally, the stationary points of the curve equations, shown in Table 6, all fall within the range of the independent variable, meeting Condition (3). In conclusion, Hypotheses *H1a*, *H1b*, *H2a*, and *H2b* are supported by empirical data. To provide a more intuitive representation of the functional relationships of the four paths, the corresponding function graphs are plotted (see Figure A1 and Figure A2 in the Appendix for details). Moreover, Model 5 demonstrates a significant positive relationship between big data capability and NPD performance (β = 0.411, $p < 0.001$), supporting *H3*.

Table 5 Results of Hierarchical Regression Analysis (N = 559)

Variable	*BBC*			*NPDP*					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
Size	0.210 (0.114)	0.140 (0.103)	0.077 (0.101)	0.257* (0.112)	0.171 (0.103)	0.205 (0.107)	0.158 (0.101)	0.134 (0.101)	0.114 (0.098)
Age	0.007 (0.056)	0.024 (0.051)	0.058 (0.050)	0.055 (0.056)	0.052 (0.051)	0.067 (0.053)	0.059 (0.050)	0.101* (0.050)	0.085 (0.049)
SOE	–0.260 (0.133)	–0.246* (0.121)	–0.204 (0.118)	–0.338* (0.132)	–0.231 (0.121)	–0.327** (0.125)	–0.244* (0.119)	–0.284* (0.118)	–0.231* (0.115)
PE	–0.061 (0.122)	–0.103 (0.111)	–0.117 (0.108)	0.090 (0.121)	0.115 (0.110)	0.058 (0.115)	0.093 (0.109)	0.033 (0.108)	0.064 (0.105)
IT	0.353*** (0.084)	0.302*** (0.076)	0.261** (0.075)	0.186* (0.083)	0.041 (0.077)	0.147 (0.079)	0.045 (0.076)	0.096 (0.075)	0.029 (0.073)
ICP	–0.064 (0.089)	–0.116 (0.081)	–0.036 (0.079)	0.116 (0.088)	0.142 (0.080)	0.078 (0.084)	0.117 (0.079)	0.137 (0.079)	0.147 (0.077)
DISE		0.321*** (0.040)				0.248*** (0.042)	0.140** (0.042)		
$DISE^2$		–0.129*** (0.029)				–0.087** (0.031)	–0.044 (0.029)		
DIRE			0.341*** (0.041)					0.341*** (0.041)	0.252*** (0.042)

(*To be continued*)

(*Continued*)

Variable	*BBC*			*NPDP*					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
$DIRE^2$			–0.136*** (0.027)					–0.111*** (0.027)	–0.076** (0.027)
BBC					0.411*** (0.038)		0.337*** (0.042)		0.260*** (0.041)
Constant	–0.136 (0.175)	0.061 (0.160)	–0.028 (0.155)	–0.369 (0.173)	–0.314 (0.158)	–0.229 (0.166)	–0.249 (0.157)	–0.272 (0.155)	–0.264 (0.150)
R^2	0.062	0.232	0.271	0.082	0.240	0.176	0.263	0.267	0.316
F	6.131***	20.791***	25.503***	8.204***	24.893***	14.680***	21.811***	25.011***	28.180***
ΔR^2		0.170	0.208		0.158	0.094	0.087	0.185	0.049
ΔF		60.790***	78.458***		114.874***	31.397***	65.161***	69.340***	39.514***
VIF	1.009 ⩽ VIF ⩽ 2.172								

Note. The regression coefficients in the table are unstandardized values. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$ (two-tailed test).

Table 6 Curve Equations, Slope Equations, and Stationary Point Analysis

Path	Curve equation	Slope equation of the curve	Stationary point
1. DISE→BBC	$BBC = -0.129DISE^2 + 0.321DISE + 0.061$	$S = -0.258DISE + 0.321$	$DISE = 1.244$
2. *DISE→NPDP*	$NPDP = -0.087DISE^2 + 0.248DISE - 0.229$	$S = -0.174DISE + 0.248$	$DISE = 1.425$
3. DIRE→BBC	$BBC = -0.136DIRE^2 + 0.341DIRE - 0.028$	$S = -0.272DIRE + 0.341$	$DIRE = 1.254$
4. *DIRE→NPDP*	$NPDP = -0.111DIRE^2 + 0.341DIRE - 0.272$	$S = -0.222DIRE + 0.341$	$DIRE = 1.536$

Note. The slope equation is derived by taking the first derivative of the curve equation concerning the independent variable. The stationary point refers to the value of the independent variable when the slope equation S equals zero.

4.5 Test for Nonlinear Mediation Effect

First, this study adopts the "three-step method" to examine nonlinear mediation effects. As shown in Table 5, both the quadratic and linear terms of digital innovation network structure embeddedness and digital innovation network relationship embeddedness have significant effects on big data capability and NPD performance. Additionally, big data capability significantly affects NPD performance. When the quadratic and linear terms of digital innovation network structure embeddedness and big data capability are included in the model (see Model 7), the regression coefficient of big data capability on NPD performance is significant ($\beta = 0.337$, $p < 0.001$). Similarly, when the quadratic and linear terms of digital innovation network relationship embeddedness and big data capability are included in the model (see Model 9), the regression coefficient of big data capability on NPD performance remains significant ($\beta = 0.260$, $p < 0.001$). Furthermore, using the Medcurve macro program developed by Hayes and Preacher (2010) with 5,000 bootstrap samples, the results indicate that when digital innovation network structure embeddedness takes three typical values ($M - 1SD$; M; $M + 1SD$), the nonlinear mediation effects of digital innovation network structure embeddedness on NPD performance through big data capability are 0.196, 0.108, and 0.021, respectively. The confidence intervals (CIs) are [0.134, 0.272], [0.074, 0.154], and [–0.030, 0.073], respectively. The fact that the first two CIs do not include zero suggests a nonlinear mediation effect. At the same time, the effect becomes insignificant when the digital innovation network structure embeddedness is too high (as the CI contains zero). Similarly, when digital innovation network relationship embeddedness takes three typical values (M – 1SD; M; $M + 1SD$), the nonlinear mediation effects through big data capability are 0.159, 0.089, and 0.018, respectively, with CIs of [0.101, 0.230], [0.055, 0.131), and [–0.017, 0.060), respectively. The first two CIs do not include zero, confirming the existence of the nonlinear mediation effect. However, the effect becomes insignificant when digital innovation network relationship embeddedness is too high. In summary, *H4a* and *H4b* are supported by empirical data.

4.6 Test for Moderating Effect

According to Lin and Feng (2022), to test for the potential moderating effect in an inverted U-shaped relationship, the significance of the quadratic interaction term coefficient β_4 in the equation: $Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 XZ + \beta_4 X^2 Z + \beta_5 Z$ (where Z is the moderating variable

and XZ and X^2Z are the interaction terms between the linear and quadratic terms of the independent variable and the moderator) needs to be examined. A significant β_4 indicates a moderating effect: If β_4 is positive, the curve becomes flatter; if negative, the curve becomes steeper. Following this criterion, the results in Table 7 reveal the following: Model 10 shows that the interaction term between the quadratic term of digital innovation network structure embeddedness and organizational structure flexibility is not significant ($\beta = -0.045$, $p > 0.05$), indicating that organizational structure flexibility does not moderate the relationship between digital innovation network structure embeddedness and NPD performance. Thus, *H5a* is not supported. Model 11 shows a significant interaction between the quadratic term of digital innovation network relationship embeddedness and organizational structure flexibility ($\beta = -0.082$, $p < 0.05$). When organizational structure flexibility is high ($M + 1SD$), the quadratic coefficient is –0.201, which is significantly larger in absolute value than when organizational structure flexibility is low ($M-1SD$), where the quadratic coefficient is –0.037. This indicates that organizational structure flexibility positively moderates the relationship between digital innovation network relationship embeddedness and NPD performance. Under high organizational structure flexibility, the curve becomes steeper. Hence, *H5b* is supported. Model 12 shows that the interaction term between the quadratic term of digital innovation network structure embeddedness and organizational structure flexibility has no significant correlation with big data capability ($\beta = -0.033$, $p > 0.05$), indicating that organizational structure flexibility does not moderate the relationship between digital innovation network structure embeddedness and big data capability. Thus, *H6a* is not supported. Model 13 shows a significant interaction between the quadratic term of digital innovation network relationship embeddedness and organizational structure flexibility ($\beta = -0.080$, $p < 0.05$). When organizational structure flexibility is high ($M + 1SD$), the quadratic coefficient is –0.183, which is significantly larger in absolute value than when organizational structure flexibility is low ($M-1SD$), where the quadratic coefficient is –0.023. This suggests that organizational structure flexibility positively moderates the relationship between digital innovation network relationship embeddedness and big data capability. Under high organizational structure flexibility, the curve becomes steeper. Hence, *H6b* is supported.

Table 7 Regression Results of the Moderating Effect of Organizational Structure Flexibility ($N = 559$)

Variable	*NPDP*		*BBC*		*NPDP*	
	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)
Size	0.191 (0.101)	0.080 (0.096)	0.134 (0.103)	0.035 (0.101)	0.149 (0.095)	0.072 (0.093)
Age	0.046 (0.050)	0.096* (0.047)	0.024 (0.051)	0.071 (0.050)	0.038 (0.048)	0.080 (0.046)
SOE	–0.321** (0.118)	–0.269* (0.110)	–0.257* (0.121)	–0.208 (0.117)	–0.240* (0.108)	–0.222* (0.107)
PE	0.033 (0.108)	0.030 (0.101)	–0.105 (0.111)	–0.109 (0.107)	0.066 (0.091)	0.054 (0.098)

(*To be continued*)

(*Continued*)

Variable	*NPDP*		*BBC*		*NPDP*	
	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)
IT	0.116 (0.075)	0.082 (0.070)	0.299*** (0.076)	0.267*** (0.074)	0.022 (0.069)	0.022 (0.069)
ICP	0.048 (0.079)	0.122 (0.074)	–0.104 (0.081)	–0.021 (0.079)	0.081 (0.082)	0.127 (0.072)
DISE	0.197*** (0.040)		0.314*** (0.041)		0.099* (0.041)	
$DISE^2$	–0.109*** (0.029)		–0.131*** (0.029)		–0.068* (0.028)	
DIRE		0.226*** (0.040)		0.307*** (0.043)		0.158*** (0.041)
$DIRE^2$		–0.119*** (0.028)		–0.103** (0.030)		–0.096** (0.027)
OSF	0.320*** (0.048)	0.343*** (0.044)	0.047 (0.049)	0.082 (0.047)	0.305** (0.053)	0.325*** (0.043)
DISE×*OSF*	0.154*** (0.039)		0.069 (0.040)		0.132** (0.038)	
$DISE^2$×*OSF*	–0.045 (0.030)		–0.033 (0.030)		–0.035 (0.028)	
DIRE×*OSF*		0.156*** (0.040)		0.093* (0.046)		0.135** (0.042)
$DIRE^2$×*OSF*		–0.082* (0.033)		–0.080* (0.035)		–0.064* (0.032)
BBC					0.315** (0.046)	0.224*** (0.039)
Constant	–0.117 (0.158)	–0.221 (0.146)	0.055 (0.161)	–0.087 (0.155)	–0.134 (0.147)	–0.202 (0.142)
R^2	0.277	0.371	0.241	0.291	0.352	0.407
F	19.021***	29.391***	15.819***	20.396***	24.724***	31.221***
ΔR^2	0.101	0.105	0.009	0.020	0.075	0.035
ΔF	25.391***	30.380***	2.197	5.214**	63.536***	32.650***
VIF			1.030 ⩽ VIF ⩽ 2.205			

Note. The regression coefficients presented in the table are unstandardized values. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$ (two-tailed test).

This study presents the results using function graphs to provide a more intuitive representation of the moderating effect of organizational structure flexibility in the corresponding relationships. Specifically, organizational structure flexibility at $M–1SD$ is treated as low, while $M + 1SD$ is considered high. The corresponding function graphs are plotted (see Figure A3 and Figure A4 in the Appendix for details). The graph clearly shows that the curve under high organizational structure flexibility is significantly steeper, further supporting *H5b* and *H6b*.

Finally, this study adopts the stepwise testing method proposed by Ye & Wen (2013) to examine the mediated moderation effects. This method includes three steps. First, regress the dependent variable, NPD performance, on the independent variable, digital innovation network structure embeddedness (*DISE/DIRE*), the square of the independent variable ($DISE^2$/$DIRE^2$), the moderating variable, organizational structure flexibility (*OSF*), the interaction terms (*DISE* × *OSF* / *DIRE* × *OSF*) and ($DISE^2$ × *OSF* / $DIRE^2$ × *OSF*). The criterion for passing this step is that the coefficient of $DISE^2$ × *OSF* / $DIRE^2$ × *OSF* is significant. Second, regress the mediating variable, big data capability (*BBC*), on the independent variable, digital innovation network structure embeddedness (*DISE/DIRE*), the square of the independent variable ($DISE^2$/$DIRE^2$), the moderating variable organizational structure flexibility (*OSF*), the interaction terms (*DISE* × *OSF* / *DIRE* × *OSF*) and ($DISE^2$ × *OSF* / $DIRE^2$ × *OSF*). The criterion for passing this step is that the coefficient of $DISE^2$ × *OSF* / $DIRE^2$ × *OSF* is significant. Third, regress the dependent variable, NPD performance, on the independent variable, digital innovation network structure embeddedness (*DISE/DIRE*), the square of the independent variable ($DISE^2$/$DIRE^2$), the moderating variable organizational structure flexibility (*OSF*), the interaction terms (*DISE* × *OSF* / *DIRE* × *OSF*) and ($DISE^2$ × *OSF* / $DIRE^2$ × *OSF*), and the mediating variable big data capability (*BBC*). The criterion for passing this step is that the coefficient of *BBC* is significant. The mediated moderation effect is considered significant when all three steps are satisfied. The analysis results are shown in Table 7: Models 10, 12, and 14 are used to test *H7a*. Model 10 indicates that organizational structure flexibility does not moderate the relationship between digital innovation network structure embeddedness and NPD performance ($\beta = -0.045$, $p > 0.05$), failing to meet the criterion of Step (1). Therefore, *H7a* is not supported by empirical data. Models 11, 13, and 15 are used to test *H7b*. Model 11 shows that in Step (1), the coefficient of $DIRE^2$ × *OSF* is –0.082 and $p < 0.05$, meeting the criterion of Step (1). Model 13 shows that in Step (2), the coefficient of $DIRE^2$ × *OSF* is –0.080 and $p < 0.05$, meeting the criterion of Step (2). Model 15 shows that in Step (3), the coefficient of *BBC* is 0.224 and $p < 0.001$, meeting the criterion of Step (3). Therefore, *H7b* is supported by empirical data.

5 Conclusions and Discussions

5.1 Research Findings

This study constructs a research framework based on resource orchestration theory and dynamic capability theory to clarify how digital innovation network embeddedness affects NPD performance in manufacturing enterprises. The framework identifies digital innovation network embeddedness as the independent variable, NPD performance as the dependent variable, big data capability as the mediating variable, and organizational structure flexibility as the moderating variable. The proposed framework is tested using survey data from 559 manufacturing enterprises in South China, leading to the following conclusions.

First, both moderate digital innovation network structure embeddedness and relationship embeddedness can enhance NPD performance in manufacturing enterprises. However, excessive digital innovation network embeddedness can trigger a curse effect, negatively impacting NPD performance. This finding extends the view of Li et al. (2017), who argue

that excessive network embeddedness induces a resource curse effect, thereby limiting organizational productivity improvement. It demonstrates that digital innovation network embeddedness exhibits the same "too much of a good thing" characteristic as traditional innovation networks. Moderate embeddedness helps manufacturing enterprises access multidimensional big data resources (Elia et al., 2020), accelerate the shift from traditional product development thinking to digital innovation thinking (Wang, 2022), and promote the deep integration of digital technologies with NPD scenarios (Ciarli et al., 2021). For example, the leading construction machinery manufacturer, San, strategically partnered with IBM and SAP during its digital transformation phase, significantly accelerating the acquisition of digital resources and facilitating the deep integration of digital technology into NPD processes (Cheng et al., 2023). However, big data resources are characterized by massive volume, low-value density, and high-value dependence. The method of filtering out useless digital resources and converting big data into valuable information involves significant resource allocation. Therefore, excessive digital innovation network embeddedness may lead to a crowding-out effect on NPD investment, thereby hindering NPD performance improvement.

Second, big data capability mediates the relationship between moderate digital innovation network embeddedness and NPD performance. This finding supports the "resource–capability–performance" logic of the resource orchestration theory (Sirmon et al., 2007) in the context of digital innovation network embeddedness. Manufacturing enterprises should build big data capability to drive NPD through digital innovation network embeddedness. The digital transformation of Haier is a practical example. In its early stage of transformation, Haier collaborated with digital service providers to aggregate vast amounts of high-quality external data resources and established a "data carrier platform." Subsequently, by leveraging these resources, Haier focused on developing big data capability, supported by big data analytics and AI technologies, to derive insights into user needs and improve NPD performance (Li & Sun, 2021). However, under high-level digital innovation network embeddedness, big data capability ceases to mediate between digital innovation network embeddedness and NPD performance. As shown in Table 6, after standardization, the stationary points for the inverted U-shaped impact of digital innovation network structure embeddedness and relationship embeddedness on big data capability are 1.244 and 1.254, respectively. Meanwhile, the stationary points for the inverted U-shaped impact on NPD performance are 1.425 and 1.536, respectively. In other words, as the level of digital innovation network structure embeddedness increases, the negative impact on big data capability emerges earlier. At this point, further enhancing the digital innovation network embeddedness will negatively affect big data capability yet still contribute to improving NPD performance. This leads to the insignificant mediating effect of big data capability between digital innovation network embeddedness and NPD performance. From the perspective of the underlying mechanism, the primary reason why excessive digital innovation network embeddedness leads to a decline in NPD performance is that excessive embeddedness creates a crowding-out effect on NPD investments, which falls within the scope of internal conflicts. Strengthening communication between the digital and product innovation departments can help alleviate this issue. However, the main reason excessive digital innovation network

embeddedness leads to a decline in big data capability is that the cooperation with data processing service providers stimulates the outsourcing intention for data processing needs. This, in turn, weakens the enterprise's strategic inclination to build big data capability independently. Compared to internal conflicts, this type of external conflict is more challenging to resolve, causing the negative impact on big data capability to occur earlier as the level of digital innovation network embeddedness increases.

Third, organizational structure flexibility moderates the impact of digital innovation network relationship embeddedness on NPD performance mediated by big data capability. However, this moderating effect is absent for digital innovation network structure embeddedness on NPD performance. This finding aligns with Bag et al. (2021)'s proposition that structural flexibility empowers enterprises to dynamically reconfigure their organizational architecture, thereby accelerating the implementation of innovation activities and maximizing the value of resource input. This is exemplified in Haier's digital transformation. Through embedding itself in digital innovation network and leveraging network resources, Haier has built a flexible and resilient organizational structure, enabling efficient digital resource flow and high-performance resource allocation (Li & Sun, 2021). In contrast, the moderating effect of organizational structure flexibility is insignificant in the embeddedness of the digital innovation network structure, affecting big data capability and NPD performance. This is because structure embeddedness reflects the enterprise's position within the digital innovation network. Enterprises with high structure embeddedness occupy advantageous positions in the digital innovation network, aligning their strategies with digital partners (Yan et al., 2019). In this situation, although enterprises with low organizational structure flexibility face more incredible difficulty in adjusting their structure to meet the demands of digital product development, under the strong leadership of enterprise managers, enterprises will still strive to make adaptive structural adjustments to drive digital product development and strengthen their positional advantage within the digital innovation network. In other words, network structure embeddedness enhances managers' commitment to digital transformation, thereby masking the differences in outcomes caused by variations in organizational structure flexibility. As a result, organizational structure flexibility does not exert a moderating effect in the process of digital innovation network structure embeddedness influencing NPD performance.

5.2 Theoretical Contributions

The theoretical contributions of this study are reflected in the following three aspects. First, this paper introduces the new concept of digital innovation network embeddedness, which captures the phenomenon of manufacturing enterprises forming network connections through extensive collaboration with digital service enterprises, thereby enriching and expanding existing innovation network research. The essence of an innovation network lies in a complex resource allocation mechanism between the external market and the internal organization (Freeman, 1991; Rycroft & Kash, 2004). RBV assumes that traditional strategic resources possess high value, relative stability, imperfect mobility, and exclusivity (Barney, 1991). In contrast, digital resources are characterized by high liquidity, non-exclusivity

(Chen et al., 2020), and high-value dependence (X. Zhang et al., 2023). These differences in resource attributes may result in digital innovation network embeddedness functioning through a different mechanism compared to traditional innovation network embeddedness. However, current research in this area remains limited. By examining the mechanism of digital innovation network embeddedness from the perspective of resource attributes, this study provides an initial exploration of this topic. Future research can further investigate how changes in resource attributes lead to shifts in the structural and relational characteristics of digital innovation network embeddedness, thereby influencing the logic of building competitive advantage. This will help expand the theoretical scope of digital innovation network embeddedness.

Second, drawing on the resource orchestration theory and following the "resource–capability–performance" theoretical logic, this paper conducts an in-depth investigation into how digital innovation network embeddedness influences NPD performance. This study expands the theoretical boundary of extant research on innovation network embeddedness and extends the applicability of resource orchestration theory in the digital economy. Chen et al. (2022) point out that there are significant differences between the digital and traditional economies. Therefore, it is necessary to re-examine whether the logic of existing theories remains applicable in light of the changes brought about by the digital economy. This paper argues that the digital economy's primary transformation is the shift in the source of competitive advantage for manufacturing enterprises, from traditional strategic resources to digital production factors (Cuthbertson & Furseth, 2022). Therefore, by examining the differences between digital and traditional production factors, this study provides a deeper understanding of how digital innovation network embeddedness affects NPD performance. In doing so, this paper responds to the academic call for re-examining existing theoretical perspectives in the context of digital transformation.

Third, while this paper focuses on the blessing mechanism of digital innovation network embeddedness, it also delves into the curse effect, addressing the lack of research on the adverse impacts of digital resources in the existing literature. In the digital economy era, big data, digital technologies (such as AI, big data analytics, cloud computing, blockchain, and the IoT), and other digital resources are playing an increasingly crucial role in the long-term development of enterprises. As a result, scholars have extensively explored the positive impact of digital resources on firm growth. However, insufficient attention has been given to the digital resource curse effect. Through extensive observation of digital transformation practices in manufacturing enterprises, the authors found that excessive digital resources can lead to overinvestment in supporting digital hardware and software infrastructure, thereby reducing the status of product innovation departments and crowding out investment in NPD. This phenomenon ultimately traps manufacturing enterprises in the digital resource curse dilemma. Following this logic, this paper conducts an in-depth analysis of the negative impact of digital resources on NPD performance, supported by large-scale survey data for empirical verification. The findings contribute to a deeper understanding of the value of digital resources and the mechanism through which they exert influence.

5.3 Managerial Implications

This study provides the following practical implications for manufacturing enterprises aiming to enhance NPD performance through digital innovation network embeddedness. First, the findings reveal that moderate digital innovation network embeddedness positively contributes to NPD performance. Therefore, manufacturing enterprises should actively seize opportunities to strengthen collaboration with digital service enterprises. This can be achieved through joint R&D initiatives with digital technology service providers or strategic alliances with digital platform enterprises. By enhancing network structure embeddedness through diversified partnerships and strengthening network relationship embeddedness through close cooperation with digital partners, enterprises can access rich, multidimensional data resources and diverse digital technologies to empower NPD. However, it is essential to recognize that continuously developing new products that meet customer needs is the core source of competitive advantage for manufacturing enterprises. Digital innovation network embeddedness serves as a means rather than an end. When the level of embeddedness reaches a certain point, enterprises should be cautious of potential adverse effects from over-embeddedness, such as excessive investment in digital technologies or blind confidence in risky ventures. These actions could result in the over-occupation of R&D resources, ultimately crowding out investments in NPD.

Second, manufacturing enterprises should also recognize the critical role of big data capability and organizational structure flexibility while enhancing digital innovation network embeddedness. Specifically, managers should focus on introducing and developing big data-related technologies and integrating them into the enterprise's existing technical system. At the same time, efforts should be made to build a data-driven talent team by nurturing and hiring high-level professionals proficient in technology development and application. Moreover, enhancing big data capability requires management to make rational and clear judgments based on the enterprise's actual situation while adopting a dialectical approach to absorbing successful external experiences. In addition, organizational structure flexibility acts as a "catalyst" for maximizing the value of digital innovation network embeddedness. Enterprise managers should establish a flat, networked, and flexible organizational structure, foster an efficient internal communication mechanism with seamless horizontal and vertical collaboration, and enable the free flow of data resources within the organization. This will allow the enterprise to unlock digital resources' potential value fully.

5.4 Limitations and Future Research Directions

First, this study focuses solely on the impact of digital innovation network embeddedness on NPD performance in manufacturing enterprises. Following a similar theoretical logic, digital innovation network embeddedness may also significantly affect other production and operational aspects, such as technological innovation, market innovation, and business model innovation, as well as different types of enterprises, such as agricultural or service enterprises. Future research could further explore these directions to deepen the understanding of the mechanism through which digital innovation network embeddedness functions. Second, this study empirically tested the relationship between variables using cross-sectional data.

However, the process by which manufacturing enterprises leverage digital innovation network embeddedness to empower NPD is complex and dynamic. The current study's findings cannot fully capture the dynamic process mechanism of how digital innovation network embeddedness influences NPD performance. Future research could adopt a longitudinal case study design to track the digital innovation network embeddedness process and its impact on typical enterprises, thereby gaining deeper insights into the underlying mechanisms. Third, as China transitions from a manufacturing powerhouse to a manufacturing innovation leader, the transformation and upgrading of Chinese manufacturing enterprises exhibit a parallel development pattern of industrialization, informatization, digitalization, and intelligence. Whether the conclusions drawn from the Chinese manufacturing enterprise sample can be applied to other countries and regions remains to be further validated. Future research could expand the sample scope to collect data from manufacturing enterprises in different countries or regions to examine whether the impact mechanism of digital innovation network embeddedness varies under different institutional or cultural contexts. Future studies could further introduce other variables to explore the potential mechanisms within this "black box."

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References

Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technological Forecasting and Social Change, 168*, 120766.

Badeeb, R. A., Lean, H. H., & Clark, J. (2017). The evolution of the natural resource curse thesis: A critical literature survey. *Resources Policy, 51*, 123–134.

Bag, S., Pretorius, J. H., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change, 163*, 120420.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, (1), 99–120.

Björkdahl, J. (2020). Strategies for digitalization in manufacturing firms. *California Management Review*, (4), 17–36.

Bock, A. J., Opsahl, T., George, G., & Gann, D. M. (2012). The effects of culture and structure on strategic flexibility during business model innovation. *Journal of Management Studies*, (2), 279–305.

Bonner, J. M., & Walker Jr., O. C. (2004). Selecting influential business-to-business customers in new product development: Relational embeddedness and knowledge heterogeneity considerations. *Journal of Product Innovation Management*, (3), 155–169.

Boxu, Y., Xingguang, L., & Kou, K. (2022). Research on the influence of network embeddedness on innovation performance: Evidence from China's listed firms. *Journal of Innovation & Knowledge*, (3), 100210.

Braganza, A., Brooks, L., Nepelski, D., Maged, A., & Russ, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research, 70*, 328–337.

Brozovic, D. (2018). Strategic flexibility: A review of the literature. *International Journal of Management Reviews*, (1), 3–31.

Cappa, F., Oriani, R., Peruffo, E., & McCarthy, I. (2021). Big data for creating and capturing value in the digitalized environment: Unpacking the effects of volume, variety, and veracity on firm performance.

Journal of Product Innovation Management, (1), 49–67.

Chen, D., Wang, L., & Chen, A. (2020). Digitalization and strategic management theory: Review, challenges, and prospects. *Journal of Management World*, (5), 220–236, 20 (陈冬梅, 王俐珍, 陈安霓 (2020). 数字化与战略管理理论——回顾、挑战与展望. 管理世界, (5), 220–236, 20).

Chen, W., & Wang, J. (2021). Platform-dependent upgrade: Digital transformation strategy of complementors in platform-based ecosystem. *Journal of Management World*, (10), 195–214 (陈威如, 王节祥 (2021). 依附式升级: 平台生态系统中参与者的数字化转型战略. 管理世界, (10), 195–214).

Chen, X., Li, Y., Song, L., & Wang, Y. (2022). Theoretical framework and research prospect of digital economy. *Journal of Management World*, (2), 208–224, 13–16 (陈晓红, 李杨扬, 宋丽洁, 汪阳洁 (2022). 数字经济理论体系与研究展望. 管理世界, (2), 208–224, 13–16).

Cheng, Q., Guo, B., Zhang, Y., & Zhao, X. (2023). The dynamic process mechanism of the competition of intelligent manufacturing technology standards of latecomer firms: A longitudinal case study based on Sany Heavy Industry. *Journal of Management World*, (4), 119–140, 191 (成琼文, 郭波武, 张延平, 赵晓鸽 (2023). 后发企业智能制造技术标准竞争的动态过程机制——基于三一重工的纵向案例研究. 管理世界, (4), 119–140, 191).

Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, (7), 104289.

Correani, A., De Massis, A., Frattini, F., Petruzzelli, A. M., & Natalicchio, A. (2020). Implementing a digital strategy: Learning from the experience of three digital transformation projects. *California Management Review*, (4), 37–56.

Cuthbertson, R. W., & Furseth, P. I. (2022). Digital services and competitive advantage: Strengthening the links between RB, KBV, and innovation. *Journal of Business Research*, *152*, 168–176.

Dabić, M., Obradović Posinković, T., Vlačić, B., & Gonçalves, R. (2023). A configurational approach to new product development performance: The role of open innovation, digital transformation and absorptive capacity. *Technological Forecasting and Social Change*, *194*, 122720.

Deperi, J., Bertrand, O., Meschi, P.-X., & Nesta, L. (2022). An organizational learning approach to digital and non-digital firm acquisition behavior. *European Management Journal*, (6), 873–882.

Dong, J. Q., & Yang, C.-H. (2020). Business value of big data analytics: A systems-theoretic approach and empirical test. *Information & Management*, (1), 103124.

Dubey, R., Bryde, D. J., Graham, G., Foropon, C., Kumari, S., & Gupta, O. (2024). The role of alliance management, big data analytics and information visibility on new-product development capability. *Annals of Operations Research*, *333*, 743–767.

Echols, A., & Tsai, W. (2005). Niche and performance: The moderating role of network embeddedness. *Strategic Management Journal*, (3), 219–238.

Elia, G., Polimeno, G., Solazzo, G., & Passiante, G. (2020). A multi-dimension framework for value creation through big data. *Industrial Marketing Management*, *90*, 617–632.

Faraj, S., von Krogh, G., Monteiro, E., & Lakhani, K. R. (2016). Special section introduction—Online community as space for knowledge flows. *Information Systems Research*, (4), 668–684.

Firk, S., Hanelt, A., Oehmichen, J., & Wolff, M. (2021). Chief digital officers: An analysis of the presence of a centralized digital transformation role. *Journal of Management Studies*, (7), 1800–1831.

Freeman, C. (1991). Networks of innovators: A synthesis of research issues. *Research Policy*, (5), 499–514.

Furr, N. R., & Eisenhardt, K. M. (2021). Strategy and uncertainty: Resource-based view, strategy-creation view, and the hybrid between them. *Journal of Management*, (7), 1915–1935.

Fürstenau, D., Baiyere, A., & Kliewer, N. (2019). A dynamic model of embeddedness in digital infrastructures. *Information Systems Research*, (4), 1319–1342.

Gangwar, H. (2018). Understanding the determinants of big data adoption in India: An analysis of the manufacturing and services sectors. *Information Resources Management Journal*, (4), 1–22.

Gebauer, H., Fleisch, E., Lamprecht, C., & Wortmann, F. (2020). Growth paths for overcoming the digitalization paradox. *Business Horizons*, (3), 313–323.

Giustiziero, G., Kretschmer, T., Somaya, D., & Wu, B. (2023). Hyperspecialization and hyperscaling: A resource-

based theory of the digital firm. *Strategic Management Journal*, (6), 1391–1424.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Journal of Sociology*, (3), 481–510.

Guo, X., Li, M., Wang, Y., & Mardani, A. (2023). Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. *Journal of Business Research*, *163*, 113868.

Haans, R. F., Pieters, C., & He, Z. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, (7), 1177–1195.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, (4), 5–14.

Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research*, (4), 627–660.

Hodgkinson, G. P., & Healey, M. P. (2011). Psychological foundations of dynamic capabilities: Reflexion and reflection in strategic management. *Strategic Management Journal*, (13), 1500–1516.

Jiang, Z., Wang, J., & Li, J. (2023). The process of manufacturers' leapfrog servitization transformation based on digital technology: A case study of Noblelift. *Journal of Industrial Engineering and Engineering Management*, (3), 212–223 (姜中霜, 王节祥, 李靖华 (2023). 制造商依托数字技术推进跨越式服务化转型的过程: 基于诺力股份的案例研究. 管理工程学报, (3), 212–223).

Kawakami, T., Barczak, G., & Durmuşoğlu, S. S. (2015). Information technology tools in new product development: The impact of complementary resources. *Journal of Product Innovation Management*, (4), 622–635.

Kolade, O., Odumuyiwa, V., Abolfathi, S., Schröder, P., Wakunuma, K., Akanmu, I., Whitehead, T., Tijani, B., & Oyinlola, M. (2022). Technology acceptance and readiness of stakeholders for transitioning to a circular plastic economy in Africa. *Technological Forecasting and Social Change*, *183*, 121954.

Kraus, S., Palmer, C., Kailer, N., & Kallinger, F. L. (2019). Digital entrepreneurship: A research agenda on new business models for the twenty-first century. *International Journal of Entrepreneurial Behavior & Research*, (2), 353–375.

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*, (6), 1121–1134.

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, (3), 387–394.

Li, D., Fan, L., & Yang, Z. (2017). Can network embedded enterprises rest easy? Research based on the listed manufacturing enterprises in China. *Nankai Business Review*, (1), 67–82 (李德辉, 范黎波, 杨震宁 (2017). 企业网络嵌入可以高枕无忧吗——基于中国上市制造业企业的考察. 南开管理评论, (1), 67–82).

Li, L., Su, F., & Mao, J. (2018). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal*, (6), 1129–1157.

Li, S., & Sun, L. (2021). How to solve the manufacturing uncertainty risk by data driven? A case study based on Haier. *R&D Management*, (6), 5–17 (李少帅, 孙丽文 (2021). 数据驱动如何化解制造业不确定性风险?——基于海尔的案例研究. 研究与发展管理, (6), 5–17).

Li, S., Luo, J., & Hu, W. (2022). From value transaction to value co-creation: Research on the value transformation process of innovative enterprises. *Journal of Management World*, (3), 125–145 (李树文, 罗瑾琏, 胡文安 (2022). 从价值交易走向价值共创: 创新型企业的价值转型过程研究. 管理世界, (3), 125–145).

Li, Y., Gao, N., Yi, Q., & Tan, R. (2018). Research on the relationship between innovation network embeddedness and innovation performance of high-tech enterprise R&D personnel. *Journal of Management Science*, (2), 3–19 (李永周, 高楠鑫, 易倩, 谭蓉 (2018). 创新网络嵌入与高技术企业研发人员创新绩效关系研究. 管理科学, (2), 3–19).

Lin, C., & Kunnathur, A. (2019). Strategic orientations, developmental culture, and big data capability. *Journal of Business Research*, *105*, 49–60.

Lin, W., & Feng, B. (2022). Curvilinear effect and statistical test method in the management research. *Nankai*

Business Review, (1), 155–166 (林伟鹏, 冯保艺 (2022). 管理学领域的曲线效应及统计检验方法. 南开管理评论, (1), 155–166).

Liu, Y., Dong, J., & Wei, J. (2020). Digital innovation management: theoretical framework and future research. *Journal of Management World*, (7), 198–217, 219 (刘洋, 董久钰, 魏江 (2020). 数字创新管理: 理论框架与未来研究. 管理世界, (7), 198–217, 219).

Liu, Z., Yao, Y., Zhang, G., & Kuang, H. (2020). Firm's digitalization, specific knowledge, and organizational empowerment. *China Industrial Economics*, (9), 156–174 (刘政, 姚雨秀, 张国胜, 匡慧姝 (2020). 企业数字化、专用知识与组织授权. 中国工业经济, (9), 156–174).

Lou, S., Yang, C., Wang, J., & Shi, Y. (2023). How to promote the digital transformation of small & medium manufacturing enterprises? An embedded autonomous process model. *Science of Science and Management of S.& T.*, (6), 168–182 (娄淑珍, 杨淳羽, 王节祥, 施宇 (2023). 中小制造企业如何推进数字化转型: 嵌入性自主视角的案例研究. 科学学与科学技术管理, (6), 168–182).

Lu, R., Zhou, Y., Ding, Y., Zhou, D., & Fen, X. (2021). Enterprise innovation network: Tracing, evolution, and research prospect. *Journal of Management World*, (1), 217–233, 14 (鲁若愚, 周阳, 丁奕文, 周冬梅, 冯旭 (2021). 企业创新网络: 溯源、演化与研究展望. 管理世界, (1), 217–233, 14).

Luo, J., Guan, J., Zhong, J., Zhao, L., & Han, Y. (2018). Choosing in the fog: Research on managers' paradox coping strategies and path in the context of innovation. *Journal of Management World*, (11), 150–167 (罗瑾琏, 管建世, 钟竞, 赵莉, 韩杨 (2018). 迷雾中的抉择: 创新背景下企业管理者悖论应对策略与路径研究. 管理世界, (11), 150–167).

Ma, H., Xiao, B., & Wang, C. (2023). The driving factors and outcomes of big data capabilities: Research based on meta-analysis. *Nankai Business Review*, (2), 143–153, 165 (马鸿佳, 肖彬, 王春蕾 (2023). 大数据能力影响因素及效用: 基于元分析的研究. 南开管理评论, (2), 143–153, 165).

Mariani, M. M., & Fosso Wamba, S. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research*, *121*, 338–352.

Maroufkhani, P., Tseng, M.-L., Iranmanesh, M., Ismail, W. K., & Khalid, H. (2020). Big data analytics adoption: determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, *54*, 102190.

Mazzola, E., Perrone, G., & Kamuriwo, D. S. (2015). Network embeddedness and new product development in the biopharmaceutical industry: The moderating role of open innovation flow. *International Journal of Production Economics*, *160*, 106–119.

McFadyen, M. A., & Cannella Jr., A. A. (2004). Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships. *Academy of Management Journal*, (5), 735–746.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, (2), 272–298.

Miroshnychenko, I., Strobl, A., Matzler, K., & De Massis, A. (2021). Absorptive capacity, strategic flexibility, and business model innovation: Empirical evidence from Italian SMEs. *Journal of Business Research*, *130*, 670–682.

Molina-Morales, F. X., & Martínez-Fernández, M. T. (2009). Too much love in the neighborhood can hurt: How an excess of intensity and trust in relationships may produce negative effects on firms. *Strategic Management Journal*, (9), 1013–1023.

Obal, M. (2017). What drives post-adoption usage? Investigating the negative and positive antecedents of disruptive technology continuous adoption intentions. *Industrial Marketing Management*, *63*, 42–52.

Parthasarthy, R., & Sethi, S. P. (1992). The impact of flexible automation on business strategy and organizational structure. *The Academy of Management Review*, (1), 86–111.

Rycroft, R. W., & Kash, D. E. (2004). Self-organizing innovation networks: Implications for globalization. *Technovation*, (3), 187–197.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic Management Journal*, (2), 179–203.

Shan, Y., Xu, H., Zhou, L., & Zhou, Q. (2021). Digital and intelligent empowerment: How to form organizational

resilience in crisis? An exploratory case study based on Forest Cabin's turning crisis into opportunity. *Journal of Management World*, (3), 84–104, 7 (单宇, 许晖, 周连喜, 周琪 (2021). 数智赋能: 危机情境下组织韧性如何形成?——基于林清轩转危为机的探索性案例研究. 管理世界, (3), 84–104, 7).

Shi, Y., Cui, T., & Kurnia, S. (2023). Value co-creation for digital innovation: An interorganizational boundary-spanning perspective. *Information & Management*, (5), 103817.

Shipilov, A., & Gawer, A. (2020). Integrating research on interorganizational networks and ecosystems. *Academy of Management Annals*, (1), 92–121.

Sirmon, D. G., Hitt, M. A., & Ireland, R. D. (2007). Managing firm resources in dynamic environments to create value: Looking inside the black box. *Academy of Management Review*, (1), 273–292.

Sirmon, D. G., Hitt, M. A., Ireland, R. D., & Gilbert, B. A. (2011). Resource orchestration to create competitive advantage. *Journal of Management*, (5), 1390–1412.

Suoniemi, S., Meyer-Waarden, L., Munzel, A., Zablah, A. R., & Straub, D. (2020). Big data and firm performance: The roles of market-directed capabilities and business strategy. *Information & Management*, (7), 103365.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, (13), 1319–1350.

Vuchkovski, D., Zalaznik, M., Mitręga, M., & Pfajfar, G. (2023). A look at the future of work: The digital transformation of teams from conventional to virtual. *Journal of Business Research*, *163*, 113912.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365.

Wang, G. (2022). Digital reframing: The design thinking of redesigning traditional products into innovative digital products. *Journal of Product Innovation Management*, (1), 95–118.

Wang, Y., Wang, L., & Li, X. (2023). Research on the iterative transformation from digital search to digital ecosystem: A case study of digital transformation based on Schneider Electric. *Journal of Management World*, (8), 91–114 (王永贵, 汪淋淋, 李霞 (2023). 从数字化搜寻到数字化生态的迭代转型研究——基于施耐德电气数字化转型的案例分析. 管理世界, (8), 91–114).

Wei, J., Liu, J. L., & Liu, Y. (2021). New trends and problems of innovation strategy theory in the context of new organizations. *Journal of Management World*, (7), 182–197, 13 (魏江, 刘嘉玲, 刘洋 (2021). 新组织情境下创新战略理论新趋势和新问题. 管理世界, (7), 182–197, 13).

Xiao, J., Hu, Y., & Wu, Y. (2020). Evolving product: A case study of data-driven enterprise and user-interactive innovation. *Journal of Management World*, (3), 183–205 (肖静华, 胡杨颂, 吴瑶 (2020). 成长品: 数据驱动的企业与用户互动创新案例研究. 管理世界, (3), 183–205).

Xie, K., Hu, Y., Liu, Y., & Luo, T. (2023). Data factor driven high-quality digital transformation of enterprise: A longitudinal case study of sogal's intelligent manufacturing. *Management Review*, (2), 328–339 (谢康, 胡杨颂, 刘意, 罗婷予 (2023). 数据要素驱动企业高质量数字化转型——索菲亚智能制造纵向案例研究. 管理评论, (2), 328–339).

Xiong, H., Zhang, J., Ye, B., Zheng, X., & Sun, P. (2012). Common method variance effects and the models of statistical approaches for controlling it. *Advances in Psychological Science*, (5), 757–769 (熊红星, 张璟, 叶宝娟, 郑雪, 孙配贞 (2012). 共同方法变异的影响及其统计控制途径的模型分析. 心理科学进展, (5), 757–769).

Yan, Y., Zhang, J., & Guan, J. (2019). Network embeddedness and innovation: Evidence from the alternative energy field. *IEEE Transactions on Engineering Management*, (3), 769–782.

Yang, Z., Hou, Y., Li, D., & Wu, C. (2021). The balancing effect of open innovation networks in the "dual circulation" of Chinese enterprises: An investigation based on digital empowerment and organizational flexibility. *Journal of Management World*, (11), 184–205, 12 (杨震宁, 侯一凡, 李德辉, 吴晨 (2021). 中国企业"双循环"中开放式创新网络的平衡效应——基于数字赋能与组织柔性的考察. 管理世界, (11), 184–205, 12).

Ye, B., & Wen, Z. (2013). A discussion on testing methods for mediated moderation models: Discrimination and integration. *Acta Psychologica Sinica*, (9), 1050–1060 (叶宝娟, 温忠麟 (2013). 有中介的调节模型检验方法: 甄别和整合. 心理学报, (9), 1050–1060).

Ying, Y., Liu, Y., & Wei, J. (2018). Value appropriation mechanism in open innovation network: Openness dilemma and swimming-with-sharks dilemma. *Journal of Management World*, (2), 144–160, 188 (应瑛, 刘

洋, 魏江 (2018). 开放式创新网络中的价值独占机制: 打开“开放性”和“与狼共舞”悖论. 管理世界, (2), 144–160, 188).

Yu, C., Lin, C., Zhang, Z., & Ye, B. (2020). Specialized knowledge search, management innovation, and enterprise performance: The moderating effect of cognitive appraisal. *Journal of Management World*, (1), 146–166, 240 (余传鹏, 林春培, 张振刚, 叶宝升 (2020). 专业化知识搜寻、管理创新与企业绩效: 认知评价的调节作用. 管理世界, (1), 146–166, 240).

Yuan, J., Hou, Q., & Chen, C. (2015). The curse effect of corporate political resources: An examination based on political connections and corporate technological innovation. *Journal of Management World*, (1), 139–155 (袁建国, 后青松, 程晨 (2015). 企业政治资源的诅咒效应——基于政治关联与企业技术创新的考察. 管理世界, (1), 139–155).

Zhang, L., Hu, B., & Wang, S. (2021). Research on the evolution mechanism and characteristics of digital economy. *Studies in Science of Science*, (3), 406–414 (张路娜, 胡贝贝, 王胜光 (2021). 数字经济演进机理及特征研究. 科学学研究, (3), 406–414).

Zhang, L., Wang, Y., Su, J., Chang, Q., & Zhang, Q. (2023). Resource-based theory: Development context, knowledge framework, and outlook. *Nankai Business Review*, (4), 246–258 (张璐, 王岩, 苏敬勤, 长青, 张强 (2023). 资源基础理论: 发展脉络、知识框架与展望. 南开管理评论, (4), 246–258).

Zhang, W. (2022). The endogenous attributes and industrial organization of digital economy. *Journal of Management World*, (7), 79–90 (张文魁 (2022). 数字经济的内生特性与产业组织. 管理世界, (7), 79–90).

Zhang, X., Song, J., Shi, L., Zhang, F., Wang, W., & Liu, H. (2023). Collaboration for digital manufacturing of high-end equipment in the era of new-generation information technology environment. *Journal of Management World*, (1), 190–204 (张玺, 宋洁, 侍乐媛, 张帆, 王伟豪, 刘皓天 (2023). 新一代信息技术环境下的高端装备数字化制造协同. 管理世界, (1), 190–204).

Zhou, X., Ye, W., & Li, X. (2023). Digit-intellectualized knowledge orchestration and the evolution of organizational dynamic capabilities: A case study of Xiaomi Technology. *Journal of Management World*, (1), 138–157 (周翔, 叶文平, 李新春 (2023). 数智化知识编排与组织动态能力演化——基于小米科技的案例研究. 管理世界, (1), 138–157).

Appendix

Table A1 Descriptive Statistics of Key Variables

Variable	*N*	*M*	*SD*	*Min.*	*25th percentile*	*Median*	*75th percentile*	*Max.*
DISE	559	4.433	1.259	1.000	3.750	4.500	5.250	7.000
DIRE	559	4.611	1.182	1.000	4.000	4.667	5.500	6.830
OSF	559	4.589	0.908	1.600	4.000	4.600	5.200	6.600
BBC	559	4.312	1.060	1.130	3.688	4.438	5.063	6.690
NPDP	559	4.396	1.117	1.170	3.667	4.500	5.333	6.500
Size	559	0.390	0.489	0.000	0.000	0.000	1.000	1.000
Age	559	2.465	0.977	1.000	2.000	2.000	3.000	4.000
SOE	559	0.288	0.453	0.000	0.000	0.000	1.000	1.000
PE	559	0.569	0.496	0.000	0.000	1.000	1.000	1.000
IT	559	0.537	0.499	0.000	0.000	1.000	1.000	1.000
ICP	559	0.680	0.466	0.000	0.000	1.000	1.000	1.000

Table A2 Correlation Analysis between Variables

Variable	*Size*	*Age*	*SOE*	*PE*	*IT*	*ICP*	*DISE*	*DIRE*	*BBC*	*OSF*	*NPDP*
Size											
Age	0.661**										
SOE	–0.009	0.009									
PE	0.018	–0.003	–0.731**								
IT	0.158**	0.086*	–0.075	0.039							
ICP	–0.021	0.013	–0.034	0.044	–0.069						
DISE	0.081	0.048	–0.071	0.082	0.085*	0.048	**0.808**				
DIRE	0.095*	0.026	–0.133**	0.139**	0.133**	0.010	0.648**	**0.771**			
BBC	0.136**	0.089*	–0.109*	0.063	0.203**	–0.042	0.402**	0.454**	**0.714**		
OSF	0.085*	0.106*	–0.097*	0.101*	0.074	0.098*	0.126**	0.168**	0.061	**0.676**	
NPDP	0.177**	0.144**	–0.195**	0.165**	0.127**	0.053	0.321**	0.447**	0.443**	0.317**	**0.740**

Note. ** $p < 0.01$ and * $p < 0.05$. The bold numbers along the diagonal represent the square root of the AVE for each variable.

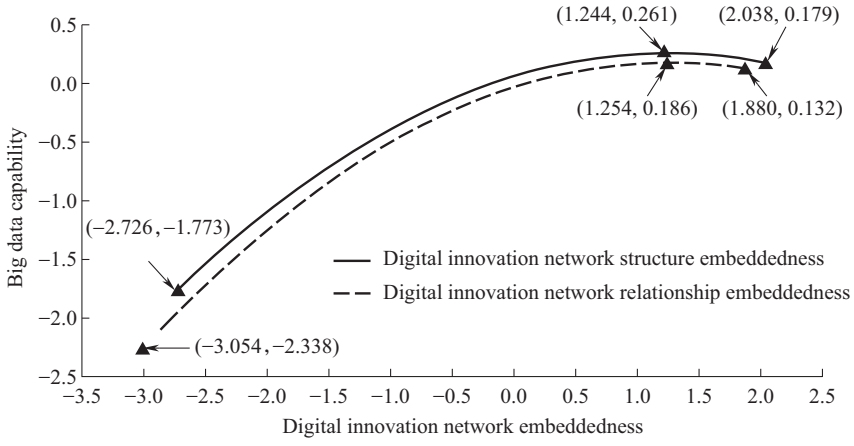

Figure A1 Inverted U-shaped Relationship Function between Digital Innovation Network Structure Embeddedness, Relationship Embeddedness, and Big Data Capability

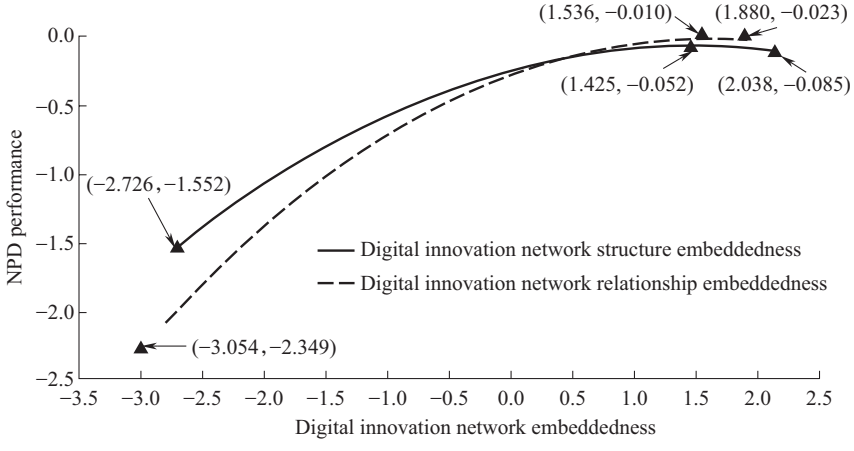

Figure A2 U-shaped Relationship Function between Digital Innovation Network Structure Embeddedness, Relationship Embeddedness, and NPD Performance

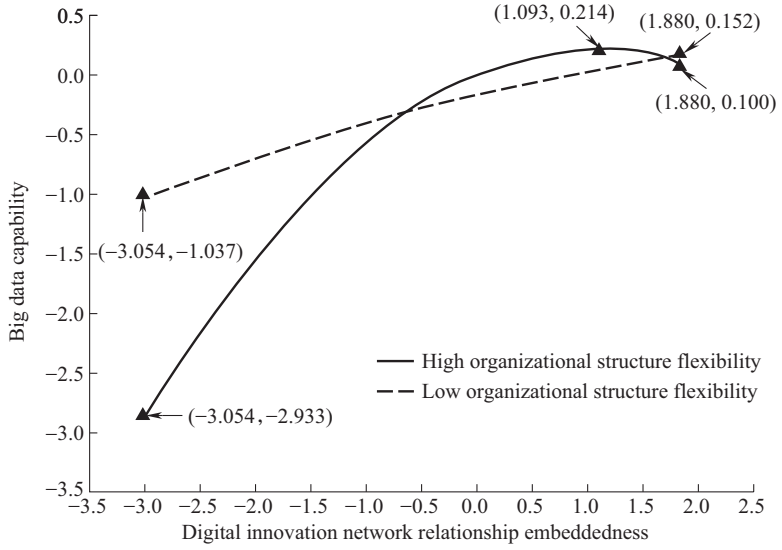

Figure A3 The Moderating Effect of Organizational Structure Flexibility on the Relationship between Digital Innovation Network Relationship Embeddedness and Big Data Capability

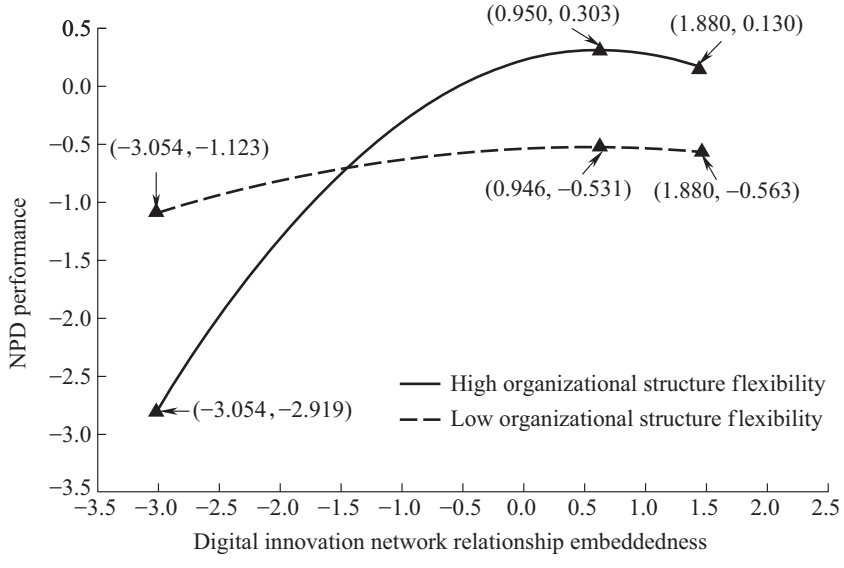

Figure A4 The Moderating Effect of Organizational Structure Flexibility on the Relationship between Digital Innovation Network Relationship Embeddedness and Big Data Capability