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RESEARCH ARTICLE

How Digital Innovation in Manufacturing Enterprises Promotes Performance*

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Abstract

To explore the process mechanism of digital innovation in manufacturing enterprises to promote enterprise performance and to reveal its synergistic, diffusion, and value-added effects, as well as the contextual effects of continuous digital investment, this study categorizes digital innovation into three types: efficiency-based, novelty-driven, and convergence-oriented. Furthermore, digital capability is classified into three dimensions: digital collaboration capability, digital innovation diffusion capability, and digital value-added capability. An empirical study is conducted based on a sample of 251 Chinese manufacturing enterprises. The following conclusions are drawn. (1) Digital innovation can significantly improve enterprise performance. (2) Digital innovation can promote enterprise performance by promoting the reconfiguration of digital capabilities. (3) Different types of key digital capabilities play a mediating role between digital innovation and enterprise performance. Specifically, digital innovation diffusion capability plays a mediating role between novelty-driven digital innovation and enterprise performance, while digital value-added capability plays an intermediary role between convergence-oriented digital innovation and enterprise performance. (4) The continuity of digital investment plays an important role in the digital innovation process of enterprises, which can positively moderate the relationship between digital innovation and enterprise performance, as well as the relationship between digital innovation and digital capabilities. In addition, it also positively moderates the relationship between efficiency-based digital innovation and digital collaboration capability. In summary, this study provides theoretical guidance and practical inspiration for manufacturing enterprises to successfully carry out digital innovation.

Keywords digital innovation; digital capability; digital investment; enterprise performance; dynamic capabilities theory

1 Introduction

In the new era, promoting the high-quality development of manufacturing enterprises and facilitating China's transformation from a manufacturer of quantity to one of quality has become an important topic for both academia and industry. Innovation serves as the primary driving force for development and is the key source of competitive advantage for manufacturing enterprises. With the rapid advancement of emerging digital technologies such as cloud computing, the Internet of Things (IoT), big data, and artificial intelligence (AI), a new paradigm of innovation, i.e., digital innovation, has emerged in the manufacturing sector

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(Fichman et al., 2014). Digital innovation refers to the extensive application of emerging digital technologies, data elements, and their integration in the innovation process and outcomes. This includes digital innovation behaviors about improving business processes, developing new forms of smart products, providing novel digital services, and transforming business models (Liu et al., 2020).

Unlike traditional innovation, digital innovation is characterized by the deep integration and application of digital technologies and data elements (Hund et al., 2021). For instance, Midea Group has incorporated IoT technology with physical home appliances to develop smart home ecosystems, while Tesla has embraced the concept of "software-defined vehicles (SDV)" to create intelligent connected cars. Increasingly, global manufacturing enterprises are actively implementing digital innovation, leveraging emerging digital technologies in process, product, and service innovation. However, few studies have explored how digital innovation contributes to enterprise performance improvement. Therefore, it is necessary to uncover the "black box" of the impact of digital innovation on enterprise performance.

Digital innovation, as an emerging research field, has attracted widespread attention (Bogers et al., 2022; Wang & Li, 2022). Existing research has primarily focused on the conceptualization of digital innovation and its antecedents (Wang et al., 2022), as well as its impact on enterprise performance (Scott et al., 2017), innovation performance, and environmental performance (Wang & Teng, 2022). While there is a consensus in academia that digital innovation positively influences enterprise development, the question remains: How exactly does digital innovation promote enterprise performance? The existing literature has yet to unveil the underlying process mechanisms with the following key limitations. First, the concept of digital innovation remains relatively broad. Only a few scholars, based on literature reviews, have classified digital innovation into process innovation, product innovation, and business model innovation (Fichman et al., 2014; Wiesböck & Hess, 2020). However, research that dissects the specific dimensions of digital innovation within manufacturing enterprises remains scarce. Second, prior studies have not thoroughly examined the process mechanism through which digital innovation improves enterprise performance. The impact pathways of different dimensions of digital innovation on performance may vary. Essentially, digital innovation is a process of digital empowerment, yet existing literature lacks a discussion on the specific types of empowerment that digital innovation provides to enterprises. Third, existing research primarily focuses on the absolute level of digital investment in the digital innovation process while neglecting the impact of its variation over time. In other words, ensuring the continuity and stability of digital investment is critical. Therefore, exploring the contextual effect of the persistence of digital investment in the process of digital innovation facilitating enterprise performance improvement has both theoretical significance and practical value.

This study constructs a conceptual model that links digital innovation, digital capability, persistence of digital investment, and enterprise performance. Using Chinese manufacturing enterprises as the research sample, a questionnaire survey method is employed for theoretical analysis and empirical validation. The objective is to reveal the underlying mechanisms through which digital innovation influences enterprise performance, uncover the "black

box" of this relationship, and examine the mediating role of digital capabilities as well as the moderating effect of persistence of digital investment.

2 Theoretical Foundation and Research Hypotheses

2.1 Digital Innovation

The concept of digital innovation is first introduced by Yoo et al. (2010) and Lee and Berente (2012), defining it as the process of combining digital and physical components to create new products. Building on this foundation, this study draws upon the research findings of Yu et al. (2017), Bharadwaj et al. (2013), Vial (2019), and Liu et al. (2020) to define digital innovation in manufacturing enterprises as the extensive application of emerging digital technologies and data elements in the innovation process and outcomes. This includes improving business processes, developing new forms of smart products, providing novel digital services, and transforming business models through digital innovation activities. Fichman et al. (2014) are among the earliest scholars to categorize digital innovation into process innovation, product innovation, and business model innovation. Wiesböck and Hess (2020) follow this classification, further dividing digital innovation into digital product & service innovation, digital process innovation, and digital business model innovation.

Existing research on digital innovation has predominantly focused on internet-based software companies such as Google and Alibaba, with limited attention to manufacturing enterprises. In contrast, the concept of digital innovation remains broad, and prior research has rarely provided a systematic classification of its dimensions. Most of the proposed classifications are based on literature review-driven modular approaches rather than empirical studies that take into account the specific characteristics and strategic orientation of manufacturing enterprises. Therefore, a context-specific classification of digital innovation in manufacturing enterprises is a critical theoretical foundation for unveiling the mechanism through which digital innovation drives enterprise performance improvement.

This study focuses on manufacturing enterprises and categorizes digital innovation into three types based on two dimensions: innovation process (process digitalization) and innovation outcomes (product digitalization). These three types are efficiency-based digital innovation, novelty-driven digital innovation, and convergence-oriented digital innovation (Shen et al., 2022). As illustrated in Figure 1, each type of digital innovation has distinct characteristics. Efficiency-based digital innovation refers to a strategic approach that leverages digital technologies to optimize innovation processes and improve efficiency. It primarily aims to enhance the digitalization of enterprise processes, with its main manifestation being process innovation. Novelty-driven digital innovation focuses on empowering product creativity, design, and innovation output through digital technologies. It emphasizes the integration of digital technologies with products, aiming to enhance the intelligence of enterprise products. This type is primarily reflected in product innovation. Convergence-oriented digital innovation represents a comprehensive and deep integration of digital technologies across all innovation activities within an enterprise. It combines characteristics of both efficiency-based and novelty-driven digital innovation, aiming to enhance the digital service capabilities of enterprises.

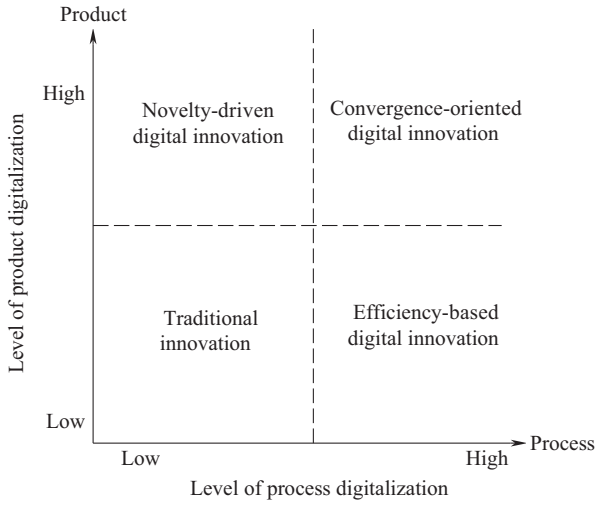

Figure 1 Classification of Enterprise Digital Innovation

2.2 Digital Capability

The digital capability of manufacturing enterprises refers to their ability to leverage digital technologies, data resources, and other key production factors in the digital economy era to transform innovation paradigms, gain competitive advantages, and achieve digital innovation (Hou & Liu, 2022). Currently, research on digital capability in manufacturing enterprises is still in its early stages, and there is no unified definition of its scope. Most studies explain the formation of digital capability from the perspective of dynamic capabilities theory. According to the hierarchical view of capability, digital capability represents a higher-order dynamic capability. Capability reconfiguration refers to the process by which enterprises reorganize and upgrade their existing capabilities in response to a volatile external environment, thereby forming new dynamic capabilities (Pavlou & El Sawy, 2010). It is a crucial mechanism for enterprises to build competitive advantages (Chen & Qiu, 2022). For traditional manufacturing enterprises to successfully implement digital innovation, they must develop new capabilities—specifically, digital capabilities.

Scholars have contextualized the concept of digital capability. Yet, research has not fully explored its dimensions and functional mechanisms in the digital innovation process of manufacturing enterprises. The formation and development of digital capabilities exhibit significant differences between internet companies and traditional manufacturing enterprises. For example, Yi et al. (2022) propose that the digital capabilities of internet firms comprise digital sensing capability, digital operation capability, and digital resource coordination capability. In contrast, manufacturing enterprises prioritize digital innovation diffusion capability, which emphasizes the deep integration of digital technologies with product innovation processes. Hou and Liu (2022) further refine this perspective by identifying digital collaboration and digital diffusion as the core dimensions of digital capabilities in manufacturing enterprises.

Moreover, existing research has largely overlooked the inclusion of digital value-added capability within the digital capability framework of manufacturing enterprises. As these enterprises increasingly embrace servitization and platform-based transformations, factors such as data, users, and platforms have become critical drivers of success. The ability to derive value directly from data has gained significant importance (Zhang et al., 2022). Digital value-added capability not only represents a higher-order dynamic capability but also serves as a pivotal enabler of service innovation in manufacturing enterprises.

Thus, in the digital innovation process, manufacturing enterprises can enhance their performance by developing digital capabilities, with different types of digital innovation influencing digital capability development in distinct ways. Within the digital innovation context, key digital capabilities can be summarized as digital collaboration capability, digital innovation diffusion capability, and digital value-added capability. These capabilities contribute to enterprise performance improvement through synergistic effects, diffusion effects, and value-added effects, respectively (Zhang et al., 2022).

2.3 Digital Innovation and Enterprise Performance

In the digital economy era, digital innovation in manufacturing enterprises primarily influences enterprise performance through digital process innovation, digital product innovation, and digital service innovation (Liu et al., 2020). First, digital process innovation leverages digital technologies to optimize research and development (R&D) and production processes, thereby reducing costs and increasing efficiency. Second, digital product innovation enhances the competitiveness and appeal of smart products, leading to increased sales and improved customer satisfaction. Finally, digital service innovation facilitates the transformation of manufacturing enterprises toward servitization. In addition to providing physical smart products and equipment, enterprises offer digital value-added services. For instance, users can subscribe to digital services provided by intelligent and connected vehicle (ICV) companies such as NIO and Tesla. Hanelt et al. (2021) conduct empirical research using a longitudinal dataset of 30 global automobile manufacturers and find that digital innovation has a positive impact on enterprise performance. Therefore, this study proposes the following hypothesis.

H1: Digital innovation significantly enhances enterprise performance.

2.4 Digital Innovation and Digital Capability

Digital innovation in manufacturing enterprises is a dynamic and continuous process that incorporates cloud computing, IoT, big data, AI, and other emerging digital technologies into key areas of process innovation, product innovation, and service innovation. This process integrates, reorganizes, and updates existing routines, knowledge, experience, and resources, sometimes even disrupting established practices. By deconstructing existing capabilities and developing new and higher-order dynamic capabilities, enterprises achieve digital capability reconfiguration through digital innovation, also known as the digital empowerment process (Zhang et al., 2022). Digital innovation facilitates the development of digital capability

through an ambidextrous innovation mechanism (Chi et al., 2022). From one perspective, it strengthens digital capabilities through an incremental innovation mechanism, which focuses on optimizing and refining existing processes and products using digital technologies. For example, the adoption of 5G and IoT technologies can upgrade and enhance present equipment and production lines, enabling intelligent sensing and seamless connectivity across information systems. For another perspective, digital innovation reshapes digital capabilities through a breakthrough innovation mechanism, which involves leveraging digital technologies to develop intelligent products and expand digital services. For instance, home appliance manufacturers are utilizing AI algorithms to produce adaptive and self-regulating smart air conditioners. Therefore, this study proposes the following hypothesis.

H2: Digital innovation drives the development of digital capability in enterprises.

2.5 Digital Capability and Enterprise Performance

From the perspective of dynamic capabilities theory, enterprises can possess the ability to perceive opportunities, seize opportunities, and integrate/reconfigure resources. In the digital economy era, digital capability is considered a higher-order dynamic capability (Annarelli et al., 2021) and a key source of sustained competitive advantage (Zomer et al., 2020). Traditional manufacturing enterprises should adopt, absorb, and integrate emerging digital technologies to develop their digital capabilities. Digital capability influences enterprise performance through two key aspects: efficiency and effectiveness. From an efficiency perspective, stronger digital capability leads to significant improvements in R&D, production, supply chain management, logistics, and services, ultimately enhancing enterprise performance. From an effectiveness perspective, high-level digital capability enables enterprises to disrupt existing product structures and functions, creating high-value smart products and digital services, which gain more profits. Zomer et al. (2020) find that digital transformation capability significantly enhances enterprise performance. Therefore, this study proposes the following hypothesis.

H3: Digital capability has a significant positive impact on enterprise performance.

2.6 The Mediating Role of Digital Capability

The impact of digital innovation on enterprise performance in manufacturing enterprises is mediated through the reconfiguration of digital capabilities. As discussed above, digital innovation enhances enterprise performance and drives the development of digital capability. From this perspective, capability evolution is a result of enterprise innovation and transformation and often serves as an intermediary mechanism between innovation and performance. For manufacturing enterprises, digital innovation influences enterprise performance through three key dimensions: process, product, and service innovation. Specifically, different strategic orientations lead to variations in digital capabilities, with these three core digital capabilities playing collaboration, diffusion, and value-added effects (Li et al., 2022).

First, in the digital process innovation stage, manufacturing enterprises typically adopt

efficiency-based digital innovation, which is fundamentally production-driven. This type of innovation primarily focuses on cost, efficiency, and system optimization, aligning closely with digital collaboration capability. Digital collaboration capability enables enterprises to integrate data, connect systems, and achieve full-scale digital and networked coordination across vertical decision-making processes, horizontal business processes, and end-to-end supply chain processes. This integration helps reduce costs, improve efficiency, and enhance interconnectivity, ultimately boosting enterprise performance. This reflects the collaboration effect of digital innovation (Hou & Liu, 2022).

Second, in the digital product innovation stage, manufacturing enterprises implement novelty-driven digital innovation, which is fundamentally product-driven. Novelty-driven digital innovation focuses on R&D, knowledge management, and application scenarios. By deeply integrating digital technology into the innovation process, enterprises accelerate innovation diffusion, overcoming geographical and temporal limitations. Over time, they develop digital innovation diffusion capability, which aligns with product innovation and contributes to enhanced enterprise performance. This reflects the diffusion effect of digital innovation (Hou & Liu, 2022).

Third, in the digital service innovation stage, enterprises engage in convergence-oriented digital innovation, which is fundamentally service-driven. This type of innovation emphasizes data, users, and platforms and fosters collaborative value creation with stakeholders such as users, suppliers, and partners through the development of industrial internet platforms, e-commerce platforms, and other digital ecosystems. This results in the formation of digital value-added capability, which aligns with service innovation. By offering digital services and comprehensive system solutions, enterprises gain value-added capabilities, ultimately enhancing enterprise performance. This reflects the value-added effect of digital innovation (Zhang et al., 2022).

Based on the above analysis, this study proposes the following hypotheses.

H4: Digital capability mediates the relationship between digital innovation and enterprise performance.

H5: Digital collaboration capability mediates the relationship between efficiency-based digital innovation and enterprise performance.

H6: Digital innovation diffusion capability mediates the relationship between novelty-driven digital innovation and enterprise performance.

H7: Digital value-added capability mediates the relationship between convergence-oriented digital innovation and enterprise performance.

2.7 The Moderating Role of Persistence of Digital Investment

Persistence of digital investment refers to the consistent and sustained allocation of resources by manufacturing enterprises over a period of time to intelligent equipment, digital technologies, digital platforms, and digital infrastructure. In the digital era, digital innovation is a long-term and continuous process. If digital investment ceases or lacks continuity, enterprises will struggle to maintain the competitive advantages of digital innovation. Therefore, persistence of digital investment is a critical factor influencing enterprise

performance.

Persistence of high digital investment enhances the economic benefits of digital innovation. Maintaining consistent digital investment enables enterprises to expand the depth and scope of digital process innovation, digital product innovation, and digital service innovation. This sustained investment fosters an in-depth integration of digital technologies into the innovation process and outcomes, ultimately enhancing enterprise performance.

Persistence of digital investment accelerates the development of key digital capabilities in the digital innovation process. From the perspective of dynamic capabilities theory, regular and sustained digital investment strengthens an enterprise's absorptive capacity, facilitating the accumulation of digital innovation knowledge. This process optimizes existing routines and gradually develops new digital capabilities. Conversely, a lack of persistence of digital investment restricts the adoption, absorption, diffusion, and convergence of digital technologies such as big data, IoT, and AI across different stages of digital innovation—including processes, products, and services. As a result, enterprises may struggle to develop the critical digital capabilities needed to support their digital innovation efforts.

Based on the above analysis, this study proposes the following hypotheses.

H8: Persistence of digital investment positively moderates the relationship between digital innovation and enterprise performance.

H9: Persistence of digital investment positively moderates the relationship between digital innovation and digital capability.

H10: Persistence of digital investment positively moderates the relationship between efficiency-based digital innovation and digital collaboration capability.

H11: Persistence of digital investment positively moderates the relationship between novelty-driven digital innovation and digital innovation diffusion capability.

H12: Persistence of digital investment positively moderates the relationship between convergence-oriented digital innovation and digital value-added capability.

In summary, this study follows the logical framework of "innovation behavior–capability evolution–performance outcomes," exploring the relationships between digital innovation, digital capability, and enterprise performance, as well as the moderating role of persistence of digital investment in the digital innovation process. By doing so, this study aims to uncover the underlying mechanisms of digital innovation's impact on enterprise performance, effectively uncovering the "black box" of this relationship. The theoretical framework is illustrated in Figure 2.

3 Research Design

3.1 Variable Measurement

The questionnaire items in this study are primarily adapted from established scales, modified to fit the specific context. A 7-point Likert scale is used for measurement, ranging from 1 ("strongly disagree") to 7 ("strongly agree"). To ensure the quality of the measurement scale, a translation-back translation process is conducted for English scales, followed by interviews with senior executives to refine the questionnaire. Specifically, drawing on the research findings of Shen et al. (2022) and Wei et al. (2021), digital innovation is categorized into efficiency-based,

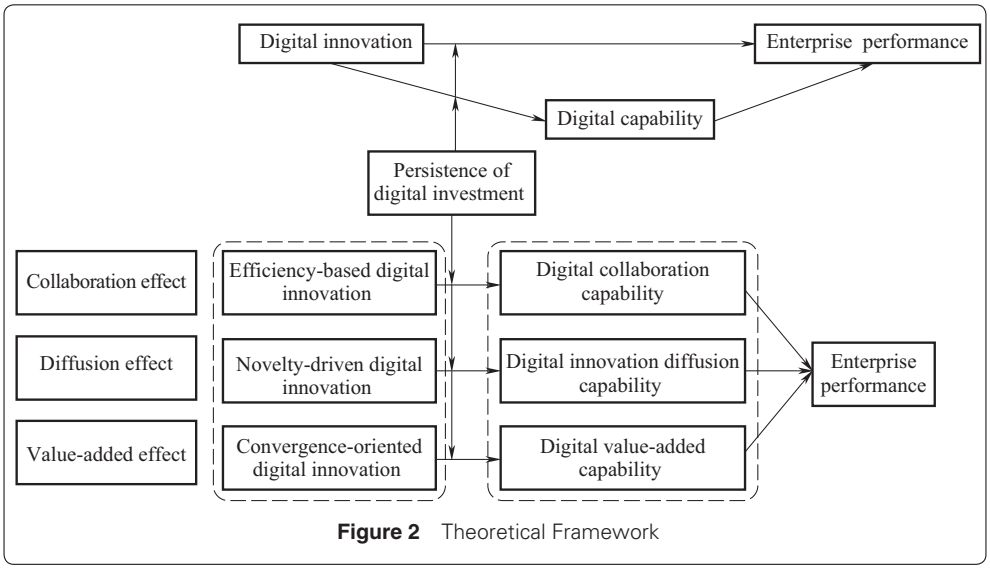

Figure 2 Theoretical Framework

novelty-driven, and convergence-oriented innovation, and measured using a total of nine items. Referring to the studies by Hou and Liu (2022) and Nasiri et al. (2020), digital capability is further divided into digital collaboration capability, digital innovation diffusion capability, and digital value-added capability, and assessed through nine items. Building on the research of Yu and Fan (2021) and Bajpai et al. (2022), persistence of digital investment is measured using annual budget allocation, investment amount, and the number of digital projects. Finally, based on the measurement scales from Yu et al. (2020) and Yu et al. (2022), enterprise performance is evaluated in terms of financial performance and innovation performance, with a total of nine measurement items.

3.2 Data Collection

This study employs a questionnaire survey to collect primary data for empirical analysis. The survey targets manufacturing enterprises that have adopted digital technologies and engaged in digital innovation. The respondents are middle-level managers and senior-level executives within these enterprises. The questionnaires are distributed through the following channels. First, by leveraging participation in national and provincial-level vertical research projects, as well as horizontal enterprise collaboration projects, surveys were distributed to senior executives during entrepreneurial roundtable meetings organized by government departments and industry associations. Second, surveys were distributed to senior executives participating in specialized training programs, such as the Smart Manufacturing Development Seminar and the Advanced Equipment Industry Technology and Management Seminar, hosted by the Department of Industry and Information Technology of Guangdong Province. Finally, surveys were also distributed through the alumni network of South China University of Technology, targeting executives within their respective enterprises. After collection, responses that were unmatched, inconsistent in reverse and positive coding items, or otherwise invalid were excluded. A total of 251 valid

questionnaires are retained for analysis. Overall, the sampled enterprises represent a diverse range of firm sizes, ages, industry characteristics, industry attributes, and positions within the industrial value chain, ensuring strong representativeness. The basic characteristics of the valid sample are summarized in Table 1.

Table 1 Basic Characteristics of Valid Sample Enterprises ($N = 251$)

Characteristic	Description	*n*	Proportion (%)	Characteristic	Description	*n*	Proportion (%)
Ownership type	State-owned enterprise (SOE)	59	23.5	Industry type	Strategic emerging industry	133	53
	Private enterprise	188	74.9		Traditional industry	118	47
	Other	4	1.6	Industry chain position	Upstream/ midstream	203	80.9
Firm size	⩽ 300 employees	78	31.1		Downstream	48	19.1
	301–1000 employees	119	47.4	Firm age	3–6 Years	13	5.2
	> 1000 employees	54	21.5		6–10 Years	72	28.7
—	—	—	—		>10 Years	166	66.1

4 Empirical Test Results and Analysis

4.1 Reliability and Validity Tests

(1) The factor loadings of the measurement items are assessed first. As shown in Table 2, the factor loadings for efficiency-based digital innovation (0.732–0.805), novelty-driven digital innovation (0.772–0.826), convergence-oriented digital innovation (0.774–0.809), digital collaboration capability (0.650–0.808), digital innovation diffusion capability (0.757–0.841), digital value-added capability (0.722–0.820), persistence of digital investment (0.779–0.857), and enterprise performance (0.728–0.825) are all above 0.6, indicating that the factor loadings meet the required standards.

(2) To evaluate reliability, Cronbach's α coefficient and Composite Reliability (CR) are used, while Average Variance Extracted (AVE) is applied to measure convergent validity. The results show that Cronbach's α coefficients for digital innovation (0.873), digital capability (0.866), and enterprise performance (0.903) all exceed 0.8, while Cronbach's α for all variables is above 0.6, demonstrating high internal consistency. Except for digital collaboration capability, which has a CR value of 0.799, all other variables have CR values exceeding 0.8, further confirming strong internal reliability. Additionally, the AVE values for all variables surpass the acceptable threshold of 0.5, indicating high convergent validity.

Table 2 Questionnaire Measurement Items and Reliability / Validity Analysis Results (N = 251)

Variable & measurement item	Factor loading
Efficiency-based digital innovation (Cronbach's α = 0.644, CR = 0.810, AVE = 0.587)	
We introduce digital technologies to improve efficiency, including production, R&D, and communication efficiency.	0.805
We introduce digital technologies to reduce costs across R&D, production, and sales.	0.732
We introduce digital technologies to reduce information asymmetry by establishing digital platforms for system connectivity and data sharing.	0.759
Novelty-driven digital innovation (Cronbach's α = 0.721, CR = 0.843, AVE = 0.642)	
We introduce digital technologies for novel design and knowledge creation.	0.805
We introduce digital technologies to develop intelligent new products and services.	0.772
We introduce digital technologies to expand new application scenarios for smart products.	0.826
Convergence-oriented digital innovation (Cronbach's α = 0.700, CR = 0.834, AVE = 0.626)	
We introduce digital technologies to achieve data-driven enterprise development.	0.809
We introduce digital technologies to develop more competitive digital business models.	0.790
We introduce digital technologies to co-create value with users, suppliers, and other stakeholders.	0.774
Digital collaboration capability (Cronbach's α = 0.620, CR = 0.799, AVE = 0.572)	
We have the capability to achieve vertical decision-making collaboration across senior, middle, and junior levels, as well as with equipment.	0.800
We have the capability to achieve horizontal business collaboration across R&D, production quality control, and marketing services.	0.650
We have the capability to achieve end-to-end supply chain collaboration with upstream suppliers and downstream customers.	0.808
Digital innovation diffusion capability (Cronbach's α = 0.726, CR = 0.846, AVE = 0.648)	
We have the capability for digital R&D, online design, and agile development.	0.841
We have the capability to efficiently absorb and apply digital technologies and integrate them deeply with product innovation.	0.757
We have the capability to continuously iterate product innovation.	0.814
Digital value-added capability (Cronbach's α = 0.687, CR = 0.827, AVE = 0.614)	
We have the capability to convert data assets into value-added business opportunities.	0.722
We have the capability to enhance profitability by providing digital services to users.	0.806
We have the capability to enhance profitability by offering digital solutions to partners.	0.820
Persistence of digital investment (Cronbach's α = 0.749, CR = 0.856, AVE = 0.666)	
We plan digital investments annually and include them in the corporate budget.	0.810
Our actual digital investment amount remains stable or shows steady growth each year.	0.779
The number of digital projects we implement annually remains stable or continues to grow.	0.857

(*To be continued*)

(*Continued*)

Variable & measurement item	Factor loading
Enterprise performance (Cronbach's α = 0.903, CR = 0.885, AVE = 0.632)	
Compared to industry peers, our main business revenue growth in the past year has been better.	0.825
Compared to industry peers, our cash flow growth in the past year has been better.	0.771
Compared to industry peers, our profit growth in the past year has been better.	0.789
Compared to industry peers, our market share growth in the past year has been better.	0.801
Compared to industry peers, our customer satisfaction growth in the past year has been better.	0.728
Compared to industry peers, our patent number growth in the past year has been better.	0.823
Compared to industry peers, our new product development project growth in the past year has been better.	0.819
Compared to industry peers, our improvement in new product development projects in the past year has been better.	0.760
Compared to industry peers, our proportion of new product sales in the past year has been better.	0.821

4.2 Common Method Bias Analysis

This study employs both procedural design and post-hoc statistical tests to control and identify common method bias (Podsakoff et al., 2003). First, to minimize social desirability bias, the research purpose and variable definitions are concealed from respondents. Second, measurement items are randomly assigned within the questionnaire, and reverse coding items are included to check for respondent attentiveness. Additionally, respondents are assured of confidentiality to alleviate privacy concerns. Finally, Harman's single-factor test is conducted. The results indicate that the first factor accounts for 15.299% of the variance, which is below the 40% threshold, with a total explained variance of 68.420%. These findings suggest that common method bias is not a significant concern. Table 3 presents the descriptive statistics and correlation analysis results for all variables.

Table 3 Descriptive Statistics and Correlation Coefficient Matrix

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Enterprise performance	5.477	0.880	1							
2. Efficiency-based digital innovation	5.766	0.849	0.361**	1						
3. Novelty-driven digital innovation	5.640	0.957	0.508**	0.386**	1					

(*To be continued*)

(*Continued*)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
4. Convergence-oriented digital innovation	5.717	0.902	0.410**	0.538**	0.447**	1				
5. Digital collaboration capability	5.680	0.780	0.510**	0.439**	0.502**	0.494**	1			
6. Digital innovation diffusion capability	5.517	0.938	0.569**	0.348**	0.522**	0.412**	0.483**	1		
7. Digital value-added capability	5.582	0.855	0.598**	0.414**	0.509**	0.480**	0.551**	0.542**	1	
8. Persistence of digital investment	5.633	0.890	0.517**	0.450**	0.444**	0.461**	0.519**	0.544**	0.521**	1

Note. ** $p < 0.01$.

4.3 Hypothesis Test

This study employs hierarchical regression analysis to test the hypotheses, with regression results presented in Tables 4–6. Additionally, variance inflation factors (VIFs) are used to test for multicollinearity. The results show that all VIF values are below 2.0, indicating that multicollinearity is not a concern in the regression model.

Table 4 Regression Results on the Relationship between Digital Innovation, Digital Capability, and Enterprise Performance

Variable	Enterprise performance model (1)	Digital capability model (2)	Enterprise performance model (3)
Digital innovation	0.539*** (9.372)	0.690*** (17.803)	–0.085 (–1.221)
Digital capability			0.904*** (11.927)
Ownership type	–0.161 (–1.619)	–0.060 (–0.895)	–0.107 (–1.349)
Firm age	–0.087 (–1.055)	–0.024 (–0.426)	–0.065 (–1.001)
Industry sector	–0.016 (–1.206)	–0.003 (–0.343)	–0.013 (–1.254)
Firm size	–0.004 (–0.053)	0.095* (2.087)	–0.090 (–1.651)
Industry type	–0.209* (–2.000)	–0.054 (–0.767)	–0.160 (–1.926)

(*To be continued*)

(*Continued*)

Variable	Enterprise performance model (1)	Digital capability model (2)	Enterprise performance model (3)
Industry chain position	–0.047 (–0.415)	–0.060 (–0.790)	0.008 (0.084)
Firm type	–0.277*** (–2.637)	–0.154* (–2.178)	–0.137 (–1.633)
Constant	3.786*** (7.853)	2.043*** (6.287)	1.940*** (4.693)
Sample size	251	251	251
R^2	0.423	0.653	0.637
Adjusted R^2	0.404	0.641	0.624
F-value	22.221***	56.835***	47.085***

Note. *** $p < 0.001$ and * $p < 0.05$. Values in parentheses represent *t*-values.

Table 5 Regression Results on the Relationship between Digital Innovation Dimensions, Digital Capability Dimensions, and Enterprise Performance

Variable	Enterprise performance model (4)	Digital collaboration capability model (5)	Digital innovation diffusion capability model (6)	Digital value-added capability model (7)	Enterprise performance model (8)
Efficiency-based digital innovation	–0.042 (–0.490)	0.482*** (9.620)			–0.077 (–1.105)
Novelty-driven digital innovation	0.294*** (4.500)		0.617*** (13.213)		0.012 (0.205)
Convergence-oriented digital innovation	0.270*** (3.162)			0.595*** (13.266)	–0.015 (–0.208)
Digital collaboration capability					0.218*** (3.333)
Digital innovation diffusion capability					0.336*** (5.289)
Digital value-added capability					0.326*** (4.654)
Ownership type	–0.166 (–1.688)	–0.081 (–0.872)	–0.032 (–0.337)	–0.064 (–0.714)	–0.112 (–1.406)
Firm age	–0.072 (–0.886)	0.073 (0.957)	–0.057 (–0.739)	0.003 (0.037)	–0.053 (–0.801)
Industry sector	–0.014 (–1.070)	–0.002 (–0.130)	0.010 (0.820)	–0.014 (–1.161)	–0.013 (–1.163)
Firm size	–0.001 (–0.019)	–0.005 (–0.080)	0.148* (2.305)	0.138* (2.277)	–0.098 (–1.784)
Industry type	–0.210* (–2.026)	–0.013 (–0.132)	–0.177 (–1.782)	–0.064 (–0.682)	–0.151 (–1.789)

(*To be continued*)

(*Continued*)

Variable	Enterprise performance model (4)	Digital collaboration capability model (5)	Digital innovation diffusion capability model (6)	Digital value-added capability model (7)	Enterprise performance model (8)
Industry chain position	–0.080 (–0.717)	0.002 (0.017)	–0.108 (–1.017)	–0.154 (–1.525)	0.002 (0.018)
Firm type	–0.241* (–2.315)	–0.260** (–2.695)	–0.172 (–1.713)	–0.160 (–1.714)	–0.131 (–1.539)
Constant	3.844*** (8.024)	3.278*** (7.643)	2.555*** (5.947)	2.616*** (6.547)	2.039*** (4.835)
Sample size	251	251	251	251	251
R^2	0.443	0.364	0.542	0.509	0.642
Adjusted R^2	0.420	0.343	0.527	0.492	0.622
F-value	19.088***	17.306***	35.859***	31.301***	32.687***

Note. *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. Values in parentheses represent *t*-values.

Table 6 Bootstrap Mediation Effect Analysis Results

Effect	Effect size	*SE*	Bootstrapping bias-corrected 95% CI		Result
			Lower limit	Upper limit	
Digital innovation → digital capability → enterprise performance	0.623	0.066	0.449	0.709	*H4* supported
Efficiency-based digital innovation → digital collaboration capability → enterprise performance	0.028	0.023	–0.008	0.080	*H5* not supported
Novelty-driented digital innovation → digital innovation diffusion capability → enterprise performance	0.139	0.042	0.075	0.238	*H6* supported
Convergence-oriented digital innovation → digital value-added capability → enterprise performance	0.122	0.043	0.050	0.219	*H7* supported

The results of the regression analysis examining the relationship between digital innovation, digital capability, and enterprise performance are shown in Table 4. After controlling for relevant variables, Model (1) indicates that digital innovation has a significant positive effect on enterprise performance ($\beta = 0.539$, $t = 9.372$, $p < 0.001$). Thus, *H1* is supported by empirical data. Model (2) shows that digital innovation has a significant positive effect on digital capability ($\beta = 0.690$, $t = 17.803$, $p < 0.001$), providing empirical support for *H2*. Model (3) reveals that digital capability has a significant positive effect on enterprise performance ($\beta = 0.904$, $t = 11.927$, $p < 0.001$), supporting *H3*. Based on Baron and Kenny's (1986) mediation effect testing method, the results confirm that digital capability mediates the relationship between digital innovation and enterprise performance, thereby supporting *H4*.

Next, the sub-dimensions of digital innovation (efficiency-based, novelty-driven, and convergence-oriented digital innovation) and digital capability (digital collaboration capability, digital innovation diffusion capability, and digital value-added capability) are included in the regression model. The results, shown in Table 5, are as follows: Model (4) shows that novelty-driven digital innovation ($\beta = 0.294$, $p < 0.001$) and convergence-oriented digital innovation ($\beta = 0.270$, $p < 0.001$) are positively correlated with enterprise performance. However, efficiency-based digital innovation does not show a significant positive correlation with enterprise performance. Model (5) indicates that efficiency-based digital innovation is positively correlated with digital collaboration capability ($\beta = 0.482$, $p < 0.001$). Model (6) reveals that novelty-driven digital innovation is positively correlated with digital innovation diffusion capability ($\beta = 0.617$, $p < 0.001$). Model (7) shows that convergence-oriented digital innovation is positively correlated with digital value-added capability ($\beta = 0.595$, $p < 0.001$). Model (8) indicates that digital collaboration capability ($\beta = 0.218$, $p < 0.001$), digital innovation diffusion capability ($\beta = 0.336$, $p < 0.001$), and digital value-added capability ($\beta = 0.326$, $p < 0.001$) are all positively correlated with enterprise performance. Based on Baron and Kenny's (1986) mediation model, the results suggest that *H5* is not supported, while *H6* and *H7* are supported by empirical evidence. These findings demonstrate that novelty-driven digital innovation enhances enterprise performance through digital innovation diffusion capability, while convergence-oriented digital innovation improves enterprise performance through digital value-added capability.

To further examine the mediating effects of digital capability, digital collaboration capability, digital innovation diffusion capability, and digital value-added capability, this study adopts the Bootstrap method, following the approach of Preacher and Hayes (2008). The mediation effect test is conducted with 5,000 bootstrap samples and a bias-corrected 95% confidence interval (CI). The results are presented in Table 6. As shown in Table 6, the mediating effect of digital innovation on enterprise performance is significant (effect size = 0.623, *SE* = 0.066), and the 95% CI [0.449, 0.709] does not contain zero, further supporting *H4*. The mediating effect of novelty-driven digital innovation on enterprise performance is significant (effect size = 0.139, *SE* = 0.042), with a 95% CI [0.075, 0.238] that does not contain zero, providing additional support for *H6*. The mediating effect of convergence-oriented digital innovation on enterprise performance is significant (effect size = 0.122, *SE* = 0.043), and the 95% CI [0.050, 0.219] does not contain zero, further validating *H7*. However, it is important to note that the mediating effect of efficiency-based digital innovation on enterprise performance is not significant. The 95% CI [−0.008, 0.080] includes zero, indicating that *H5* is not supported by the mediation effect test.

The results of the moderating effect test on persistence of digital investment are presented in Table 7. Before conducting the regression analysis, all interaction terms were standardized. Model (10) shows that the interaction between persistence of digital investment and digital innovation is positively correlated with enterprise performance ($\beta = 0.100$, $p < 0.01$), supporting *H8*. Model (11) indicates that the interaction between persistence of digital investment and digital innovation is positively correlated with digital capability ($\beta = 0.067$, $p < 0.01$), supporting *H9*. Model (12) demonstrates that the interaction between persistence of

digital investment and efficiency-based digital innovation is positively correlated with digital collaboration capability ($\beta = 0.075$, $p < 0.01$), supporting *H10*. Model (13) shows that the interaction between persistence of digital investment and novelty-driven digital innovation is not significantly correlated with digital innovation diffusion capability, meaning *H11* is not supported. Model (14) reveals that the interaction between persistence of digital investment and convergence-oriented digital innovation is not significantly correlated with digital value-added capability, meaning *H12* is not supported. These findings suggest that persistence of digital investment facilitates digital innovation in reconstructing digital capabilities, ultimately enhancing enterprise performance. Specifically, for efficiency-based digital innovation, persistence of digital investment strengthens its relationship with digital collaboration capability. However, for novelty-driven and convergence-oriented digital innovation, the positive moderating effect of persistence of digital investment is not significant.

Table 7 Regression Results of the Moderation Effect of Persistence of Digital Investment

Variable	Enterprise performance model (9)	Enterprise performance model (10)	Digital capability model (11)	Digital collaboration capability model (12)	Digital innovation diffusion capability model (13)	Digital value-added capability model (14)
Digital innovation × Persistence of digital investment		0.100** (3.253)	0.067** (3.272)			
Efficiency-based digital innovation × Persistence of digital investment				0.075** (2.825)		
Novelty-driven digital innovation × Persistence of digital investment					–0.029 (–1.163)	
Convergence-oriented digital innovation × Persistence of digital investment						0.038 (1.484)
Persistence of digital investment	0.267*** (3.852)	0.288*** (4.214)	0.232*** (5.127)	0.365*** (6.419)	0.337*** (5.702)	0.237*** (4.167)
Digital innovation	0.318*** (3.980)	0.480*** (5.170)	0.617*** (10.012)			
Efficiency-based digital innovation				0.347*** (5.001)		
Novelty-driven digital innovation					0.373*** (6.350)	

(*To be continued*)

(*Continued*)

Variable	Enterprise performance model (9)	Enterprise performance model (10)	Digital capability model (11)	Digital collaboration capability model (12)	Digital innovation diffusion capability model (13)	Digital value-added capability model (14)
Convergence-oriented digital innovation						0.504*** (7.615)
Ownership type	–0.177 (–1.832)	–0.137 (–1.430)	–0.046 (–0.730)	–0.077 (–0.888)	–0.074 (–0.843)	–0.057 (–0.651)
Firm age	–0.066 (–0.824)	–0.076 (–0.972)	–0.014 (–0.260)	0.091 (1.284)	–0.050 (–0.696)	0.007 (0.097)
Industry sector	–0.017 (–1.313)	–0.016 (–1.259)	–0.003 (–0.377)	–0.001 (–0.065)	0.005 (0.436)	–0.014 (–1.210)
Firm size	–0.037 (–0.563)	–0.034 (–0.524)	0.070 (1.611)	–0.042 (–0.716)	0.113 (1.888)	0.107 (1.799)
Industry type	–0.175 (–1.715)	–0.183 (–1.822)	–0.031 (–0.468)	0.035 (0.393)	–0.125 (–1.346)	–0.024 (–0.267)
Industry chain position	0.000 (0.001)	0.008 (0.077)	–0.016 (–0.225)	0.049 (0.506)	–0.017 (–0.171)	–0.100 (–1.016)
Firm type	–0.199 (–1.910)	–0.167 (–1.628)	–0.069 (–1.014)	–0.101 (–1.097)	–0.076 (–0.805)	–0.068 (–0.731)
Constant	6.682*** (20.998)	6.520*** (20.627)	5.724*** (27.281)	5.662*** (19.918)	5.874*** (20.131)	5.771*** (20.088)
Sample size	251	251	251	251	251	251
R^2	0.457	0.480	0.696	0.462	0.611	0.543
Adjusted R^2	0.437	0.458	0.683	0.440	0.595	0.524
F-value	22.529	22.141	54.926	20.631	37.735	28.505

Note. *** $p < 0.001$ and ** $p < 0.01$. Values in parentheses represent *t*-values.

5 Conclusions and Discussions

5.1 Conclusions

To explore the mechanism by which digital innovation enhances enterprise performance and to uncover the "black box" of their relationship, this study constructs a basic framework of "innovation behavior–capability evolution–performance outcomes." Using empirical data from 251 Chinese manufacturing enterprises, theoretical analysis and empirical tests lead to the following conclusions:

(1) Digital innovation significantly enhances enterprise performance. This finding aligns with Hanelt et al. (2021) and contributes to the empirical evidence on Chinese manufacturing enterprises.

(2) Digital innovation improves enterprise performance by fostering digital capability. This conclusion is consistent with Annarelli et al. (2021) and Chi et al. (2022). Additionally, this study introduces the perspective that digital capability is a higher-order dynamic capability

within the hierarchical view of capabilities.

(3) Different types of key digital capabilities mediate the relationship between digital innovation and enterprise performance. Specifically, digital innovation diffusion capability mediates the relationship between novelty-driven digital innovation and enterprise performance. Digital value-added capability mediates the relationship between convergence-oriented digital innovation and enterprise performance. These findings extend the research of Hou and Liu (2022) and Yi et al. (2022), constructing a theoretical model of digital innovation's impact on enterprise performance.

(4) Persistence of digital investment plays a moderating role in the digital innovation process. It positively moderates the relationship between digital innovation and enterprise performance, as well as the relationship between digital innovation and digital capability. Additionally, persistence of digital investment strengthens the link between efficiency-based digital innovation and digital collaboration capability. This highlights the critical role of persistence of digital investment as a key contextual factor for the success of digital innovation in manufacturing enterprises.

5.2 Theoretical Contributions

(1) Unlike previous studies that define digital innovation from a single-dimensional perspective (Hanelt et al., 2021), this study categorizes digital innovation into efficiency-based, novelty-driven, and convergence-oriented digital innovations. This classification provides important theoretical insights into the distinct digital innovation behaviors of manufacturing enterprises. By improving the research of Li et al. (2023), Shen et al. (2022), and Liu et al. (2020), this study enriches the conceptual framework of digital innovation in manufacturing enterprises.

(2) While prior studies have primarily focused on the antecedents of digital innovation (Wang & Li, 2022; Wang et al., 2022), they often overlook its impact on enterprise performance (Pavlou & El Sawy, 2010). This study addresses this gap by revealing the mechanism through which digital innovation enhances enterprise performance, thereby uncovering the "black box" of their relationship. Building on the findings of Zhang et al. (2022), Li et al. (2022), Hou and Liu (2022), Hanelt et al. (2021), and Scott et al. (2017), this study identifies digital capability as a key mediating factor. Furthermore, by linking different types of digital innovation behaviors to specific digital capabilities, this study advances the theoretical understanding of digital innovation.

(3) By incorporating the persistence of digital investment as a contextual variable, this study makes up the gap in existing research and further highlights the long-term effects of digital innovation in manufacturing enterprises (Scott et al., 2017). This contribution extends the theoretical boundaries of digital innovation study.

5.3 Policy Recommendations

(1) Manufacturing enterprises should prioritize the development of digital capabilities. In the digital economy era, achieving competitive advantage requires manufacturing enterprises

to undergo organizational transformation, break away from existing routines, and build new digital capabilities. By leveraging collaboration, diffusion, and value-added efforts, enterprises can realize economic benefits.

(2) Manufacturing enterprises should ensure persistence of digital investment to achieve the expected outcomes of digital innovation. Digital innovation requires substantial financial and resource investments and cannot be approached inconsistently. Enterprises must not only maintain investment intensity but also ensure long-term continuity to sustain innovation success.

5.4 Limitations and Prospects

This study has certain limitations. The sample size constraints and the reliance on cross-sectional data may affect the generalizability of the findings. Future research could explore multi-source data approaches, including financial data, textual data, and patent data, to measure digital innovation investments and outcomes, thereby enriching empirical research. Additionally, future studies could investigate the contextual effects of digital capability in the digital innovation process, particularly examining whether the initial state of digital capability influences the relationship between digital innovation and enterprise performance.

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