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Digital Innovation, Dynamic Capabilities and Enterprise Innovation Performance

—Empirical Analysis from China's A-Share Listed Companies from 2010-2021

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Abstract

Using data from Chinese A-share listed companies from 2010-2021, this paper empirically analyzes how digital innovation affects enterprise innovation performance the role of dynamic capabilities in it, and analyzes the impact of institutional environment and enterprise size heterogeneity. The study shows that: digital innovation has a significant promoting effect on enterprise innovation performance, and the three sub-dimensions of dynamic capabilities, absorptive capability, innovative capability and adaptive capability, all play a mediating role in this relationship. Compared with regions with better institutional environments, digital innovation in poorer institutional environments is more likely to promote enterprise innovation performance; compared with small and medium-sized firms, digital innovation has a more obvious promoting effect on the innovation performance of large-scale enterprises. This study contributes to the body of knowledge regarding the connection between digital innovation and enterprise innovation performance, and can provide useful reference for the formulation of digital innovation policy and enterprise innovation performance management in China.

Keywords

Digital Innovation, Enterprise Innovation Performance, Dynamic Capabilities

1. Introduction

With the deep integration of digital technology represented by big data, the Internet of Things (IoT), cloud computing and artificial intelligence with economic development, the digital economy has developed rapidly. The size of China's digital economy in 2022 was 50.2 trillion yuan, and its share of the country's GDP was 41.5%. As more businesses start to rely on digital technology for digital innovation, the digital economy has emerged as a new engine to promote continuous economic growth (Huang & Wang, 2022; Yan, Ji, & Xiong, 2021) and high-quality development (Zhang & Tong, 2023). Digital innovation is the use of digital technology in the innovation process, in which the structure and nature of products and services have been changed (Nambisan et al., 2017), and the traditional enterprise value creation process, value delivery channels (Vial, 2021) and even the entire business model have been reshaped (Warner & Wäger, 2019). Under the influence of digital innovation, traditional innovation theories are severely challenged and have an important impact on enterprises innovation performance (Hinings et al., 2018; Yu & Wang, 2022). Research on the connection between enterprise innovation performance and digital innovation has significant theoretical significance and practical benefit in this setting.

Research has been done on how digital innovation affects enterprise innovation performance, according to the available literature. Some scholars have explored the relationship between them, but their views are not consistent. According to some academics, digital innovation promotes enterprise innovation performance by driving product digitisation, process digitisation, and business model reshaping and innovation (Benitez et al., 2022; Lv et al., 2022). Some scholars believe that digital innovation has no significant impact on innovation performance, and the application of digital technology may bring certain risks to enterprises (Usai et al., 2021; Tamvada et al., 2022). It should be pointed out that dynamic capabilities play an important role in digital innovation and enterprise innovation performance, but existing research has paid little attention to it. Dynamic capabilities are the ability of organisations to integrate and reconstruct corporate resources in the rapidly changing external environment. On the one hand, by using digital technology and digital devices, enterprises can more easily collect a wide range of information and resources, from which they can analyse and evaluate market trends, and improve their opportunity perception and learning ability (Vial, 2021); on the other hand, digital innovation can make use of an organisation's learning and absorptive capability to absorb and transform internal and external resources, create more digital opportunities, and transform digital opportunities into innovation performance (Warner & Wäger, 2019). Based on this, this paper incorporates dynamic capabilities into the research framework of the relationship between digital innovation and enterprise innovation performance, takes China's A-share listed companies from 2010 to 2021 as the research samples to empirically test the impact of digital innovation on enterprise innovation performance, explore the role of dynamic capabilities, and analyze the impact of institutional environment and enterprise size heterogeneity on the above relationship, with the aim of providing theoretical guidance and practical evidence for enterprises to use digital innovation to improve innovation performance.

The research structure of this paper is as follows. In the second part, the relevant literature on digital innovation and dynamic capabilities is reviewed and research hypotheses are formulated. In the third part, the selection of research samples, the measurement of variables, and the construction of the research model are presented. In the fourth part, the empirical analyses and the robustness tests are conducted. In the fifth part, the conclusions of the study and the research revelations are drawn based on the results of the empirical analyses.

2. Theoretical Analysis and Research Hypothesis

2.1. Digital Innovation and Enterprises Innovation Performance

Enterprise innovation performance is a comprehensive reflection of enterprise innovation behaviour and innovation results. Enterprise innovation performance is influenced by a variety of factors. The features of the senior management team and the degree of R & D spending are examples of internal factors that have an impact on innovation success. External determinants include the national fiscal policy and the level of industry competitiveness. In the age of the digital economy, digital innovation has emerged as a fresh trend in business innovation, and the use of digital technology has sparked a complete overhaul of enterprises' business models, organization structures, and methods of production. However, whether digital innovation will promote the improvement of innovation performance is still controversial in the academic community. Hanelt et al. (Hanelt et al., 2021) investigated the impact of digital mergers and acquisitions on digital innovation and verified the positive impact of digital innovation on enterprise performance. Taking 32 listed enterprises as samples, Zhang & Yang (Zhang & Yang, 2021) concluded that the digital technology capabilities of enterprises can promote business model innovation and performance improvement. Usai et al. (Usai et al., 2021) discovered, however, that enterprise R & D spending is the primary element determining the improvement of innovation performance, with little effect from the deployment of digital technology. Tamvada et al.'s (Tamvada et al., 2022) study also showed that the application of Industry 4.0-related technologies brings risks to SMEs in the areas of finance, operation, technology, and network security. Therefore, an additional study of the connection between digital innovation and enterprise innovation performance is warranted.

From the perspective of information access, digital innovation can expand information access channels and optimize resource allocation by building digital platforms. Using digital technology to build a digital platform, the participating enterprises of the digital platform can achieve technology standardisation and share infrastructure, reduce the cost of enterprise information exchange and communication, and reduce the degree of information asymmetry, so as to improve the efficiency of resource allocation, screen the knowledge resources required by the enterprise, and then classify, transform and integrate these resources to promote the integration and transformation of the resources, prepare for the ensuing technological innovation (Benitez et al., 2022). Big data and the

IoT are used to acquire customer consumption habits, transform enterprise innovation from experience-driven to data-driven, and make enterprises more agile, able to quickly respond to market changes and take corresponding actions to develop new products and services, thus improving the innovation performance of enterprises (Ge et al., 2023). From the perspective of R & D costs, digital innovation can help companies reduce R & D investment costs and increase the success rate of innovation. Digital twin technology supported by digital technologies can simulate physical objects and their environments, and the virtual objects created by digital twins accompany the physical objects throughout their life cycle (VanDerHorn & Mahadevan, 2021). Through digital twin technology, companies can track and simulate changes in products, represent and estimate past, present and future states to improve product development and manufacturing, reduce product development costs and risks, and increase the success rate of innovation activities (Parmar et al., 2020).

Based on the above analyses, the hypothese is formulated:

H1: Digital innovation positively affects enterprise innovation performance.

2.2. The Mediating Role of Dynamic Capabilities

Dynamic capability means that an enterprise integrates and reconstructs its internal and external resources to cope with the rapidly changing external environment, and builds unique and difficult-to-replicate capabilities to establish and maintain sustainable competitive advantages (Teece, 2007). In the era of the digital economy, the application of digital technology promotes enterprise integration and reconstruction of internal and external resources, structures and processes, and drives the generation and evolution of dynamic capabilities (Warner, & Wäger, 2019). Digital innovation itself implies uncertainty, dynamic capabilities can help firms adjust their existing innovation strategies and innovation behaviours in a timely manner to match their resource endowments and market demands, thereby improving innovation performance. Drawing on Wang & Ahmed's (Wang & Ahmed, 2007) study, this paper further categorises dynamic capabilities into three dimensions: absorptive capability, innovative capability and adaptive capability. Absorptive capability refers to the ability of enterprises to identify, digest and absorb internal and external knowledge and information; innovative capability refers to the ability of enterprises to develop and use new products and services, explore new markets, and carry out independent innovation activities; adaptive capability emphasises the ability to adjust internal and external resources in order to adapt to changes in the external environment.

Digital innovation can improve enterprise innovation performance by absorbing and transforming heterogeneous information through absorptive capability. On the one hand, digital innovation has a direct impact on absorptive capability. The expansion of the Internet, the development of e-commerce, and the use of emerging technologies such as the IoT, artificial intelligence and blockchain have increased the opportunities for enterprises to enter the global market and contact more partners and customers. Through the interconnection with other partners and competitors, enterprises can access more diversified technical knowledge and information (Kastelli et al., 2022). At the same time, through the use of big data, IoT and other technologies, enterprises can obtain huge amounts of data from interaction with external organisations, from which they can discover key information and resources such as the actual needs of consumers and market trends, absorb and transform them into capabilities of the enterprise itself. On the other hand, absorptive capability directly affects the innovation performance of enterprises. Firstly, enterprises with strong absorptive capability are more likely to identify which knowledge and technologies are key to the future development of the enterprise and can bring more value to the enterprise, so as to optimise the investment of innovation resources. Secondly, the acquisition of heterogeneous knowledge from internal and external sources cannot directly improve the performance and capability of enterprises, but more importantly, it is to digest and absorb it into the enterprise's own capability. If the enterprise does not have a strong absorptive capability, it will not be able to effectively integrate internal and external knowledge and resources, and it will not be able to improve the innovation performance of the enterprise.

The following hypothesis is proposed based on the analysis presented above:

H2: Absorptive capability mediates the relationship between digital innovation and innovation performance.

Digital innovation improves enterprise innovation performance through innovative capabilities. Firstly, digital innovation can improve the innovation efficiency of enterprises. On the one hand, the wide application of digital technology helps enterprises break through their own resource constraints through cross-border search, tap external innovation elements, and develop new resources and capabilities, so as to overcome the bottleneck of innovation (Lyu et al., 2022). With the support of digital technology, cross-border search can also help employees get rid of their existing experience, learn differentiated knowledge and skills, stimulate innovative thinking, and strengthen their innovative capability. On the other hand, digital technology breaks down the information barriers that exist among enterprises, promotes joint R & D activities, and strengthens the flow of knowledge and information (Lyu & Li, 2021). Secondly, digital innovation enhances the ability to identify innovation opportunities. When big data technology is embedded in the business management process and product production and sales of enterprises, based on the analysis of user data, it is easier for enterprises to find the differences between the actual demands of users and the products and services provided by enterprises, and to fully explore the opportunities hidden under the actual demands of users, thus enhancing the marginal output of data elements (Shi & Sun, 2022). The stronger the innovative capability of an enterprise is, the more it can help it utilize digital technology to improve innovation efficiency and identify potential innovation opportunities, thereby driving the improvement of innovation performance.

The following hypothesis is proposed based on the analysis presented above:

H3: Innovative capability mediates the relationship between digital innovation and innovation performance.

Digital innovation improves enterprise innovation performance through adaptive capability. Adaptive capability is the dynamic ability of an enterprise to reconfigure internal and external resources in a timely and effective manner in response to changes in the external environment. It is further divided into market adaptive ability, technology adaptive ability and management system adaptive ability (Keskin et al., 2022). Among them, market adaptive ability refers to the enterprise's response to market demand and opportunities, the investigation and evaluation of the market operating environment, and the timely adjustment of the enterprise's investment in strategic resources. The use of digital technology enhances an organization's ability to scan its external environment and quickly make strategic modifications, which helps the organization become more market-adaptive. Technology adaptive ability refers to the ability of enterprises to keep an eye on the latest external technological changes, introduce and learn relevant technologies and knowledge in a timely manner, and achieve technological complementarity, thus improving innovation efficiency and performance. For example, during the epidemic period, Ding Talk, Tencent Meeting and other applications have become important tools for many enterprises to conduct telecommuting and online teaching. The management system's adaptive ability refers to the application of digital technology to promote transformation in the management mode of enterprises, breaking the original organisational inertia and path dependence (Zhang & Long, 2022). Enterprises with higher adaptive capability are more capable of feeling the changes in the market environment, grasping the key technological needs, and adjusting the organisational structure and management system to respond to external environment changes with the aid of digital technology, ultimately improving the innovation performance of enterprises.

The following hypothesis is proposed based on the analysis presented above:

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

3. Research Design

3.1. Sample Selection and Data Sources

In this paper, China's A-share listed companies from 2010 to 2021 are selected as the initial research sample. The main reason for taking 2010 as the starting point of the sample study is to avoid the influence of the 2008 financial crisis and its aftermath on the study's conclusions, and the choice of 2021 as the termination year of the study lies in the fact that the most recent and complete data available during the data collection phase of this paper is in the year of 2021, and taking into consideration of the timeliness and availability of the data, this paper chooses the time interval of 2010-2021. The data are processed according to the following criteria: 1) eliminating enterprises treated by ST and *ST during the sample period; 2) eliminating samples with missing data; and 3) eliminating enterprises in the financial industry. The Winsorize method is used to reduce all continuous variables by 1%, preventing the effects of outliers on the outcomes of the model estimate, and a total of 16,921 observations are obtained after processing. The sample data were obtained from CSMAR database, CNRDS database and WIND database.

3.2. Definition of Variables

Digital innovation. Current academic research on digital innovation focuses mostly on theoretical construction, and no consensus has been reached on its measurement. Some scholars use a scale to measure digital innovation (Wei et al., 2022). The research of Wu et al. (Wu et al., 2021) and Lu & Dong (Lu & Dong, 2020), which measures the degree of digital innovation scenario construction over a predetermined amount of time, is referenced in this paper in light of the accessibility of data. By using the Python text analysis method and combined with the annual reports of A-share listed companies, the characteristic words reflecting the digital scenarios of enterprises, including artificial intelligence technology, cloud computing technology, big data technology, blockchain technology, and digital technology application, are collated, their frequency of occurrence is counted and summed up, and finally, the total frequency is added by 1 for logarithmic processing to form the digital innovation measurement index.

Innovation performance. The number of patent applications, the number of patents granted, the sales of new products, the number of R & D employees, and the amount of R & D investment are a few of the ways that innovation performance is currently measured in academia. Since sales data for new products are difficult to obtain, the number of patents is currently a more popular indicator for gauging an organization's performance in terms of innovation, as it directly and impartially reflects the organization's capacity for technological advancement. Meanwhile, considering that the number of patents granted has a certain lag in time, and the number of patents granted is highly correlated with the number of patent applications, this paper measures the innovation performance with the number of invention patent applications of enterprises, adding 1 to the number of invention patent applications that have been obtained, and then taking the natural logarithm to calculate.

Dynamic capability. Referring to the research method of Zhao et al. (Zhao et al., 2016), dynamic capability is divided into three dimensions: absorptive capability, innovative capability and adaptive capability. Absorptive capability is measured by the intensity of R & D expenditure, that is, the proportion of R & D expenditure to operating income, the larger the value, the stronger the absorptive capacity, denoted as RD. Innovative capability is evaluated by a combination of two indicators, namely the intensity of R & D expenditure and the proportion of technicians, which are standardised and summed up to form a measure of innovative capability, denoted as IA. Adaptive capability is measured by the negative value of the coefficient of variation of R & D expenditure, capital expenditure and advertising expenditure, and the larger the adjusted coefficient of variation, the stronger the adaptive capability of the enterprise, denoted as ACV.

Control variables. This paper chooses the following variables—enterprise size (Size), return on total assets (ROA), asset-liability ratio (Lev), cash flow (Cashflaw), growth of the enterprise (Growth), ownership concentration (Top1), enterprise nature (SOE), and number of years listed (Listage)—as control variables in accordance with the theories of previous studies. Table 1 provides a description of the variable definitions and measurements.

3.3. Model Design

The following empirical model is created in this research based on the theoretical analysis mentioned above:

$$\ln \text{apply}_{i,t} = \alpha + \beta \text{DI}_{i,t} + \phi \text{Control}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{1}$$

where ln apply represents enterprise innovation performance, DI represents digital innovation, Control represents control variables, i represents enterprise, t represents the year, μ_{it} is year-fixed effects, η_{it} is industry fixed effects, and ε_{it} is a random perturbation term.

In order to further verify the mediating role of dynamic capabilities between digital innovation and innovation performance, this paper draws on Wen & Ye's (Wen & Ye, 2014) testing method for the mediating effect model, constructs the following model with hierarchical regression method:

$$\text{RD}_{i,t} = \alpha + \beta \text{DI}_{i,t} + \phi \text{Control}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$\ln \text{apply}_{i,t} = \alpha + \beta \text{DI}_{i,t} + \gamma \text{RD}_{i,t} + \phi \text{Control}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$\text{IA}_{i,t} = \alpha + \beta \text{DI}_{i,t} + \phi \text{Control}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{4}$$

$$\ln \text{apply}_{i,t} = \alpha + \beta \text{DI}_{i,t} + \gamma \text{IA}_{i,t} + \phi \text{Control}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{5}$$

$$\text{ACV}_{i,t} = \alpha + \beta \text{DI}_{i,t} + \phi \text{Control}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{6}$$

$$\ln \text{apply}_{i,t} = \alpha + \beta \text{DI}_{i,t} + \gamma \text{ACV}_{i,t} + \phi \text{Control}_{i,t} + \mu_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \tag{7}$$

4. Empirical Analysis

4.1. Descriptive Statistics and Correlation Analysis

The descriptive data are shown in Table 2. The enterprise innovation performance (lnapply) ranges from 0 to 4.344 in Table 2, which shows that there are significant variances in innovation performance between the sample enterprises. Digital innovation (DI) ranges from 0 to 5.081, with the standard deviation of 1.419 and the mean value that is higher than the median. This data shows that some sample enterprises have achieved a higher level of DI while also showing that there is a significant variation in DI between sample enterprises. The mean value of innovative capability (IA) is −0.017 and the mean value of adaptive capability (AVC) is −0.836, both of which are negative, indicating that the average

Table 1. Definitions of the variables.

Variable type	Variable name		Variable symbol	Variable Definition
Explanatory variable	Digital innovation		DI	The natural logarithm is taken after adding 1 to the word frequency of the digitized situational characteristic words in the annual report
Explained variable	Innovation performance		lnapply	Number of patent applications for inventions plus 1 in natural logarithms
Mediating Variables	Dynamic capability	Absorptive capability	RD	R & D expenditure/operating income
		Innovative capability	IA	Intensity of R & D expenditure and proportion of technicians are standardised and summed separately
		Adaptive capability	ACV	ACV = −∂/mean, with ∂ being the standard deviation of the intensity of R & D expenditures, the intensity of capital expenditures, and the intensity of advertising expenditures, and mean being the average of all three
Control variable	Enterprise size		Size	Natural logarithm of total assets
	Asset-liability ratio		Lev	Total liabilities/total assets
	Return on total assets		ROA	Net profit/total assets
	Cash flow		Cashflow	Net cash flows from operating activities/total assets
	Enterprise growth		Growth	Growth rate of operating income
	Ownership concentration		Top1	Shareholding ratio of the largest shareholder
	Enterprise nature		SOE	Dummy variables, 1 for state-owned enterprises and 0 for private enterprises
	Number of years listed		Listage	Natural logarithm of the number of years listed

Source: Author.

Table 2. Descriptive statistics of variables.

Variable	N	Mean	p50	SD	Min	Max
lnapply	16,921	0.584	0	1.002	0	4.344
DI	16,921	1.536	1.386	1.419	0	5.081

Continued

RD	16,921	0.051	0.0380	0.0500	0	0.291
IA	16,921	−0.017	−0.407	1.176	−1.412	3.980
ACV	16,921	−0.836	−0.805	0.263	−1.390	−0.183
Size	16,921	22.04	21.86	1.172	20.00	25.64
Lev	16,921	0.383	0.367	0.194	0.0500	0.859
ROA	16,921	0.049	0.047	0.066	−0.230	0.228
Cashflow	16,921	0.049	0.048	0.065	−0.132	0.238
Growth	16,921	0.177	0.123	0.351	−0.470	2.055
Top1	16,921	0.332	0.311	0.141	0.087	0.703
SOE	16,921	0.260	0	0.439	0	1
ListAge	16,921	1.900	2.079	0.946	0	3.332

Source: Author.

level of adaptive capability and innovative capability of the sample enterprises is weak.

Table 3 displays the correlation analysis' findings. Table 3 shows that the Pearson correlation coefficient of digital innovation with innovation performance is 0.1 and the Spearman correlation coefficient is 0.09, both of which pass the 10% significance level test, indicating that there is a positive correlation between innovation performance and digital innovation. The Pearson correlation coefficients between digital innovation and absorptive capability, innovative capability, and adaptive capability are 0.29, 0.4, and 0.1, respectively, while the Spearman correlation coefficients are 0.21, 0.27, and 0.12, respectively. These values all pass the 10% significance level test, indicating a positive correlation between digital innovation and absorptive capability, innovative capability, and adaptive capability. The Pearson correlation coefficients of absorptive capability, innovative capability, and adaptive capability with innovation performance are 0.06, 0.1, and 0.03, respectively, while the Spearman correlation coefficients are 0.09, 0.11, and 0.03, respectively, and all pass the 10% significance level test, indicating that there is a positive correlation between absorptive capability, innovative capability, and adaptive capability with innovation performance, which initially supports the hypothesis of this paper.

4.2. Benchmark Regression Results

Regression analysis is performed in accordance with the model created above to examine how digital innovation affects enterprise innovation performance. The regression findings are displayed in Table 4. The coefficient of digital innovation, which is 0.073 and is significant at the 1% level according to the regression results in column (1) of the table, indicates that digital innovation can significantly promote the improvement of enterprise innovation performance, supporting the study's hypothesis H1.

Table 3. Correlation analysis result.

Variable	lnapply	DI	RD	IA	ACV
lnapply	1	0.09*	0.09*	0.11*	0.03*
DI	0.10*	1	0.21*	0.27*	0.12*
RD	0.06*	0.29*	1	0.67*	0.21*
IA	0.10*	0.40*	0.69*	1	0.07*
ACV	0.03*	0.10*	0.14*	0.04*	1

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Author.

Table 4. Benchmark regression result.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnapply	RD	IA	ACV	lnapply	lnapply	lnapply
DI	0.073***	0.006***	0.184***	0.023***	0.057***	0.047***	0.069***
	(0.006)	(0.000)	(0.007)	(0.002)	(0.006)	(0.006)	(0.006)
RD					2.783***		
					(0.183)		
IA						0.142***	
						(0.008)	
ACV							0.155***
							(0.027)
cons	−7.583***	0.096***	0.782***	−0.614***	−7.850***	−7.694***	−7.488***
	(0.197)	(0.008)	(0.168)	(0.048)	(0.197)	(0.195)	(0.197)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16921	16921	16921	16921	16921	16921	16921
r2	0.215	0.318	0.412	0.121	0.229	0.232	0.217
r2_a	0.214	0.316	0.410	0.119	0.227	0.230	0.215

Note: Standard errors in parentheses, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ (same below) Source: Author.

The coefficients of digital innovation are 0.006, 0.184, and 0.023, respectively, and are all positive at the 1% level, according to the regression results in columns (2), (3), and (4) in **Table 4**. This suggests that digital innovation positively affects the innovation performance of enterprises. The three variables of dynamic capabilities (absorptive capability, innovative capability, and adaptive capability) are added to the model (1) in order to investigate if the mediating effect of dynamic capabilities exists in this study. Model (5) presents the regression results after adding absorptive capability, in which the regression coefficient of digital innovation is 0.057 and the regression coefficient of absorptive capability is 2.783, both of them are significantly positive at 1% level. In contrast to the regression results of model (1), in model (5) after adding absorptive capability, although the regression coefficient value of digital innovation decreases, it passes the test of the significance level of 1%, which indicates that the mediating effect of absorptive capability exists, and the hypothesis H2 can be verified. Model (6) presents the regression results after adding innovative capability, in which the regression coefficient of digital innovation is 0.047 and the regression coefficient of innovative capability is 0.142, and both of them are significantly positive at 1% level. Compared with the regression results of model (1), the value of regression coefficient of digital innovation decreases in model (6) after adding innovative capability, but it still passes the test of significance level of 1%, which indicates that there is a mediating effect of innovative capability, and the hypothesis H3 is verified. Model (7) presents the regression results after adding adaptive capability, in which the regression coefficient of digital innovation is 0.069 and the regression coefficient of adaptive capability is 0.155, and both of them are significantly positive at 1% level. The value of the regression coefficient of digital innovation in model (7) after adding adaptive capability decreases in comparison to the regression results of model (1), but passes the test of significance level of 1%, indicating that the mediating effect of adaptive capability exists and the hypothesis H4 is confirmed.

4.3. Endogeneity Test

Since there may be a causal relationship between digital innovation and innovation performance, that is, while digital innovation promotes the development of enterprise innovation performance, the improvement of enterprise innovation performance may also promote the improvement of their digital innovation level, in order to alleviate the impact of endogeneity problem, this paper adopts the method of instrumental variable to solve this problem. For the two-stage least squares estimation, the digital innovation with a one-period lag is used as an instrumental variable, in accordance with Yu's (Yu, 2023) research. **Table 5** shows the regression results. Results of the first stage of regression are displayed in the first column. The regression coefficient of the instrumental variable L.DI is 0.855 and is significantly positive at the 1% level, which accords with the correlation of instrumental variables. The second column displays the results of the second-stage regression; the coefficient for digital innovation is 0.094, and it is significantly positive at the 1% level, suggesting that even after the endogeneity issue has been taken into account, digital innovation still positively affects enterprise innovation performance. The results presented above are therefore accurate.

Not all businesses will implement digital innovation because of a number of influences. To address the issue of sample self-selection, this paper employs the PSM approach for testing and draws on the research of Zhang, Li, & Xing (Zhang et al., 2021) and Li, Liu, & Shao (Li et al., 2021). Specifically, DI_dum is side-coded, if the

Table 5. The endogenous test with one period lag.

Variable	(1)	(2)
	first stage	second stage
	DI	lnapply
L.DI	0.855***	
	(0.005)	
DI		0.094***
		(0.008)
Constant	−0.131	−7.961***
	(0.145)	(0.202)
Observations	13,495	13,495
R-squared	0.789	0.215

Source: Author.

enterprise has carried out digital innovation, DI_dum is coded as 1, otherwise, it is coded as 0. In addition, board size (Board), enterprise size (Size), proportion of independent directors (Indep), ownership concentration (Top1), number of years listed (ListAge), and enterprise nature (SOE) are selected as the covariates, and the corresponding control group was found for the treatment group based on the principle of 1:1 nearest neighbor matching. After matching, Table 6 displays the regression results, and the regression coefficient for digital innovation is 0.073, significant at the 1% level, demonstrating that the research findings are still robust even when the sample self-selection bias is taken into account.

4.4. Robustness Test

This research uses the method of replacing the explained variable to carry out the robustness test in order to confirm the robustness of the findings mentioned above. This paper incorporates utility model and design patent applications into the measurement criteria, weights invention patents, utility model patents, and design patents in accordance with the ratios of 0.5, 0.3, and 0.2, adds 1 to the total number of applications, and calculates the natural logarithm, denoted as lnapply2, in order to measure innovation performance more thoroughly. Table 7 displays the results of the regression. The table shows that the regression results with the explained variable replaced agree with the benchmark regression findings, demonstrating once more the validity of the conclusions made therein.

4.5. Heterogeneity Test

Heterogeneity analysis based on institutional environment. Digital innovation is characterised by high returns and high risks, successful innovation activities can bring enterprises excessive profits, while enterprises will face higher costs if

Table 6. Benchmark regression results after PSM matching.

Variable	lnapply
DI	0.073***
	(0.008)
cons	−6.813***
	(0.240)
Control	Yes
industry	Yes
year	Yes
N	7624
r2	0.192
r2_a	0.189

Source: Author.

Table 7. Robustness test results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnapply2	RD	IA	ACV	lnapply2	lnapply2	lnapply2
DI	0.070***	0.006***	0.184***	0.023***	0.057***	0.046***	0.066***
	(0.006)	(0.000)	(0.007)	(0.002)	(0.006)	(0.006)	(0.006)
RD					2.353***		
					(0.164)		
IA						0.128***	
						(0.008)	
ACV							0.179***
							(0.025)
_cons	−7.389***	0.096***	0.782***	−0.614***	−7.615***	−7.489***	−7.279***
	(0.198)	(0.008)	(0.168)	(0.048)	(0.198)	(0.197)	(0.197)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16921	16921	16921	16921	16921	16921	16921
r2	0.226	0.318	0.412	0.121	0.237	0.241	0.228
r2_a	0.225	0.316	0.410	0.119	0.235	0.239	0.227

Source: Author.

innovation activities fail. A good institutional environment means a perfect intellectual property protection system and credit system, which can provide protection for enterprises' innovation activities (Wu & Tang, 2016). Due to the influence of natural geography, open policy and other factors, the institutional environment in different regions of China is quite different, so this paper will examine how digital innovation affects enterprise innovation performance in various institutional environments.

The market index data of each province from 2010-2019 are obtained from the China market index database, the market index of 2020 and 2021 is calculated by referring to the approach of Yang, Zhang, & Wu (Yang et al., 2014). Based on this, an institutional environment dummy variable is constructed. If the market index of the region where the sample enterprises are located in the current year is higher than or equal to the median of the entire country, it indicates that the institutional environment of the region is better and takes the value of 1, otherwise, it is 0. The regression coefficients for digital innovation are all positive and significant at the 1% level, as can be seen from columns (1) and (2) in **Table 8**, which is consistent with the findings of the benchmark regression. However, the regression coefficient of digital innovation in the region with better institutional environment is 0.067, which is lower than the regression coefficient of digital innovation in the region with poorer institutional environment, which is 0.092. This finding suggests that the impact of digital innovation on the performance of enterprises innovations is more significant in the region with poorer institutional environment.

Table 8. Heterogeneity regression result.

Variable	Better institutional environment	Poorer institutional environment	Large-scale enterprises	Small and medium-sized enterprises
	(1)	(2)	(3)	(4)
	lnapply	lnapply	lnapply	lnapply
DI	0.067***	0.092***	0.125***	0.035***
	(0.006)	(0.020)	(0.011)	(0.006)
_cons	−7.931***	−4.823***	−10.841***	−3.962***
	(0.211)	(0.491)	(0.382)	(0.307)
Controls	Yes	Yes	Yes	Yes
industry	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
N	14898	1985	8322	8568
r2	0.230	0.165	0.211	0.049
r2_a	0.228	0.151	0.207	0.045

Source: Author.

Heterogeneity analysis based on enterprise size. Compared with small and medium-sized enterprises, large-scale enterprises tend to have more innovation resources and innovation opportunities to support their digital innovation activities. In order to verify whether digital innovation of enterprises of different sizes will have different impacts on their innovation performance, this paper uses the total assets of enterprises to represent the enterprise size, and defines enterprises with total assets higher than and equal to the median as large-scale enterprises, while those with total assets lower than the median as small and medium-sized enterprises. Table 8 displays the test results. The regression results of digital innovation can be seen in columns (3) (4) of Table 8 are all positive and significant at the 1% level. However, in large-scale enterprises, the coefficient of digital innovation is 0.125, which is higher than that of 0.035 in small and medium-sized enterprises, indicating that in large-scale enterprises, digital innovation has a more significant promoting effect on enterprise innovation performance. The fact that large-scale enterprises have a more elite talent pool and substantial financial backing may be the cause, allowing them to produce more innovative digital outcomes.

5. Research Findings and Policy Implications

This paper empirically analyses the relationship between digital innovation, dynamic capabilities and enterprise innovation performance using data from China's A-share listed firms from 2010-2021, and explores the effects of institutional environment and firm size heterogeneity. The research conclusions and policy implications are as follows:

Digital innovation has a significant contribution to enterprise innovation performance. The advancement of enterprise innovation performance and high-quality development is greatly aided by digital innovation. For enterprises, it is necessary to follow the trend of digital development, give full play to the technological advantages of informationisation and digitalisation, and incorporate digital innovation into their future development strategy. The government, it must actively support enterprises in implementing digital technology innovation, introduce relevant incentive policies, create a solid and efficient policy support system, fully realize the potential of digital innovation, and encourage its use and growth.

In the relationship between digital innovation and enterprise innovation performance, the three dynamic capabilities—absorptive capability, innovative capability, and adaptive capability—all have a mediating influence. Therefore, for enterprises, they should pay attention to the enhancement of dynamic capabilities including absorptive capability, innovative capability and adaptive capability, flexibly utilise their own resources and capabilities, timely insight into market changes, seek market opportunities, and find their own digital innovation development strategies and business models to improve their innovation performance. For the government, the relevant departments can encourage enterprises to set up industry association platforms to strengthen exchanges, learning and cooperation among different enterprises, as well as between enterprises and universities and research institutes, so as to promote the flow of heterogeneous knowledge among different organisations; the government also needs to strengthen the construction of digital infrastructure to facilitate interconnection among enterprises, and to reduce the costs of their innovation activities.

In comparison to regions with better institutional environments, digital innovation in regions with poorer institutional environments is more likely to promote enterprise innovation performance. In comparison to small and medium-sized enterprises, digital innovation has a greater impact on promoting the innovation performance of large-scale enterprises. Therefore, for enterprises, managers of large-scale enterprises should be aware of their own resource endowment advantages, strengthen the investment of resources needed for digital innovation according to their own situation, and make good use of the resources and support policies provided by the government; enterprises in regions with poorer institutional environments should strengthen the scanning and monitoring of external environments to avoid the operating risks caused by imperfect policies and systems. The government, on the one hand, should improve the relevant laws and regulations and intellectual property protection system, build a good credit system, create a fair and just market competition environment, provide protection for enterprises engaging in digital innovation activities, lessen the risk enterprises face when engaging in these activities, and boost business motivation and confidence. On the other hand, the government can introduce relevant policies to support the digital technology investment and digital innovation activities of small and medium-sized enterprises through differentiated means, including tilting the financial subsidy policy, and the cultivation and recruitment of digital talents.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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