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Research on the Impact Mechanism of Digital Capability on Enterprise Innovation Performance

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Keywords: Digital capability; Dual capability; Enterprise innovation performance; Environmental uncertainty

Abstract: In the digital age, the variability, uncertainty, complexity and fuzziness of the business environment are particularly prominent, and the innovation performance of enterprises is facing great challenges. In this paper, the theory of digital capability reveals the impact path of digital capability on innovation performance from the perspective of dual capability. Based on the empirical data of Chinese enterprises, the results show that: Digital capability helps to promote the innovation performance of enterprises; Digital capability can promote innovation performance by improving dual capability (exploration capability and utilization capability); when the degree of environmental uncertainty is low, the utilization ability has a strong positive effect on the improvement of innovation performance. However, with the improvement of environmental uncertainty, the advantage of Exploration capacity is gradually highlighted. This study takes dual capabilities as the key path to reveal the mechanism of digital capabilities on innovation performance improvement. The research results help to open the black box of the mechanism of digital capabilities on innovation performance improvement, and provide important practical guidance for promoting the development of Chinese enterprises.

1. Introduction

The digitalization of cross industry enterprises through new digital technologies, such as the Internet of things, big data analysis, artificial intelligence and cloud computing, is an emerging field phenomenon. These companies must successfully transform technologies that support major business improvements through digital technologies, such as enhancing customer experience and participation, streamlining operations and creating new business models, otherwise, they will gradually lose their competitiveness in the process of competitors' competition[1]. For manufacturing enterprises to digitize their products, services or business functions, they need to integrate new digital solutions, such as market intelligence software using artificial intelligence (AI) technology, to determine the trends of target customers, so as to help organizations customize their products accordingly. Given the benefits of digitalization, innovative digital solutions are seen as a key driver of cross industry enterprise digitalization, involving multiple functions such as marketing, customer service, human resource management, logistics and production. Therefore, if we do not accept the innovative digital solutions, systems and support provided by manufacturing enterprises that play an important role in the digital ecosystem, manufacturing enterprises are far from ready for digital transformation. In this sense, digital capabilities can be conceptualized as innovative IT solutions, integrating emerging digital technologies to support the digitalization of non-technical businesses such as banking, healthcare, manufacturing, retail, etc. With the increasing importance of digitalization and the increasing demand for new digital solutions, digitalization capability has become an important research agenda. Despite the growing interest in digital capabilities,

The literature on digital capabilities is still in its infancy. Most studies on digital capabilities look at innovation from the perspective of technology, architecture or information systems[2,3], rather than from the perspective of management. In addition, the background of these studies is not manufacturing enterprises. Therefore, this study uses digital capabilities to select how dual capabilities (exploration capabilities and utilization capabilities) can promote innovation performance for enterprises, so as to transform other traditional businesses, products and services, and even create new businesses. In addition, there is no research that can explain how manufacturing enterprises use digital technology to create innovative digital products and services. Although many studies have studied the innovation contribution factors of various industries, there is a lack of literature on the driving factors of manufacturing enterprise digital capability to enterprise innovation.

2. Model Construction and Research Assumptions

2.1. Model Construction

The digital capabilities of manufacturing enterprises in the new era, such as the ability to master and utilize digital technologies such as cloud computing, big data and the Internet of things, can effectively simplify the existing business processes of manufacturing enterprises and make them more automated and intelligent. A large number of relevant studies have proved that there is a positive correlation between digital capability and enterprise technological innovation. Chen et al [4] found through research that information capability is the most basic element of technological innovation capability, and information capability needs to act on other elements to have an impact on technological innovation capability. Higher information capability can ensure the effective development of information activities, enable enterprises to timely and effectively obtain market information and technical information, and realize information exchange and sharing, thus generating organizational knowledge. The technological innovation information accumulated by enterprises can be continuously materialized into technological innovation products to promote the improvement of technological innovation ability. Peng et al, 2020pointed out that in the process of product development, effective management of the knowledge and skills of unique employees can ensure that the information system will not be easily copied by competitors[5]. As the unique information knowledge and skills of enterprises are evolved from enterprise practices, under this exponential and turbulent digital revolution, the exploration and utilization ability to reflect the organizational duality is very important for enterprise innovation performance[6]. Therefore, this study believes that in the increasingly complex digital environment, it is not enough for enterprises to only have the Exploration capacity or utilization ability, but they need to have these two abilities at the same time[7]. These two abilities are complementary and indispensable. Compared with the dual capabilities of enterprises under the traditional scenario, the dual capabilities of enterprises under the digital scenario show obvious new characteristics.

First, from the perspective of the main body of dual capabilities, due to the boundlessness, openness, strong interaction and other characteristics of the digital scene, enterprises are more likely to interact with multi-party main bodies and give full play to dual capabilities in the value network to obtain knowledge and resources[8]. Second, from the perspective of technical means to give play to dual capabilities, enterprises mainly use digital technologies such as online Internet to explore and utilize knowledge and resources; Third, from the perspective of the elements of exploration and utilization of dual capabilities, enterprises mainly explore and utilize digital elements, such as digital resources and digital capabilities[9]; Fourth, from the perspective of the effect of dual capabilities, most enterprises provide digital products and services.

To sum up, based on the digital capability theory and dual capability theory, this paper believes that digital capability is conducive to enterprises to acquire knowledge and resources between networks, promote knowledge creation within enterprises, form exploration capability and utilization capability to cope with complex environment, so as to improve enterprise innovation performance. In the turbulent environment of rapid technological development, environmental uncertainty, as an important external environmental factor, will affect the effect of digital capability on innovation performance. Therefore, the theoretical research model constructed in this paper is shown in Figure 1.

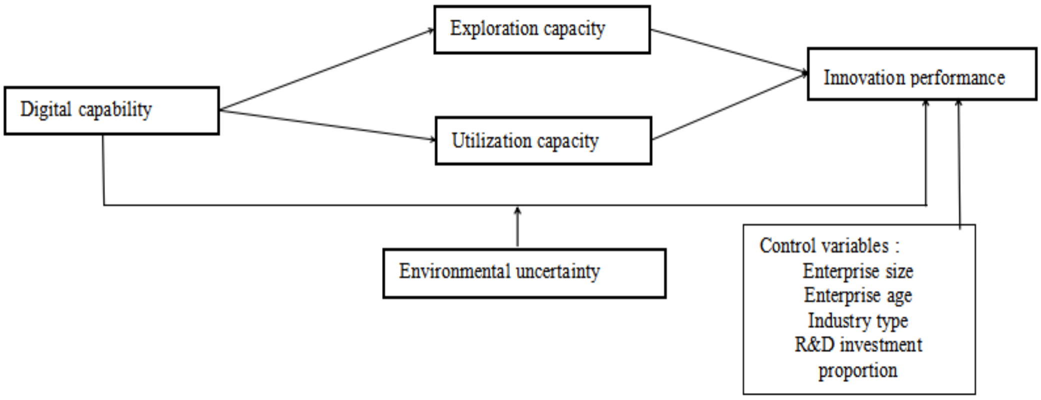

Figure 1: Theoretical research model

2.2. Research Assumptions

2.2.1. Digital capability and dual capability

Digital capability strategy helps enterprises form dual capabilities, which can guide the specific operation of the organization and form organizational practices. Relevant literature also found that the duality of decision-making and leadership can promote the duality of enterprise organization[10]. Kristal et al [11]verified the positive direct relationship between the dual strategy of supply chain and the combined competitiveness of manufacturing enterprises. In enterprise practice, the management of the core enterprise pays attention to exploring new business opportunities and innovation points by using digital technology, which will help to promote adaptability and integration in daily business processes and business activities, such as establishing a new cooperative business process with partners, or providing online query of transaction information and status. Based on the above point of view, this paper will put forward the following assumptions:

Hypothesis H1a: digital ability has a positive impact on Exploration capacity.

Hypothesis H1b: digital capability has a positive impact on utilization capability.

2.2.2. Dual capability and enterprise innovation performance

At present, there is no consensus in the literature on the impact of dual capabilities on corporate performance. In theory, for the development innovation and exploratory innovation, the dual capability has a balancing effect, which can positively promote the improvement of enterprise innovation performance. Some scholars believe that dual capabilities have a positive impact on the sales growth rate of enterprises. Xiao & Zhu made an empirical analysis on the relationship between the interaction and balance of dual capabilities and innovation performance, and concluded that both have a significant positive effect on innovation performance[12]; Enterprises can achieve duality and promote innovation performance through externally oriented exploration modes (such as mergers and acquisitions or alliances) or through development activities of internal organizations[13]. Based on the above point of view, this paper will put forward the following assumptions:

Hypothesis H2a: exploration capability has a positive impact on enterprise innovation performance.

Hypothesis H2b: utilization capacity has a positive impact on innovation performance.

2.2.3. Digital capability and enterprise innovation performance

As for the relationship between digital capability and enterprise innovation performance, most scholars believe that information technology can improve enterprise innovation performance. Aca et al studied the involvement of small and medium-sized enterprises (SMEs) in recycling plastic waste to produce innovative products[14]. These SMEs have adopted digital technologies such as 3D printing and block chain to gain competitive advantage from the business model based on circular economy. Its research results show that small and medium-sized enterprises focusing on the circular economy initiative show the ability to develop and adapt in the use of their circular economy resources, followed by the ability to explore and adapt in the implementation of digital technology. Its research extends the resource-based perspective and combines it with dual dexterity to explain the role of specific circular and digital resources and capabilities that SMEs need to provide value to customers. The improvement of digital capability can promote the cost reduction and profit margin increase of enterprises, Zhou, 2012; Zhu believes that digital capability refers to an enterprise's ability to improve R&D capability, reduce R&D costs, and achieve higher product flexibility and innovation[15,16]. Manufacturing enterprises adjust their service innovation strategies and business strategies according to the coordinated development goals. This task requires enterprises to continuously enhance their digital capabilities, so as to realize the interaction between enterprises and customers, and promote service innovation on the basis of technological innovation. Digital capability can help enterprises establish a development model of enterprise interaction, increase the efficiency of service delivery, and improve the competitiveness of enterprise services. As a strategic resource, service can promote the efficiency of enterprise sharing resources and capabilities, and promote the development and innovation performance of enterprise products and services. The interactive digitalization capability builds a new service development model for enterprises, thus promoting the improvement of collaboration benefits between enterprises and customers, and helping to realize interactive innovation. Based on the above point of view, this paper will put forward the following assumptions:

Hypothesis H3: digital capability has a positive impact on enterprise innovation performance.

2.2.4. Intermediary role of dual ability

Under digital empowerment, the dual ability to flexibly adjust production strategies according to customer needs. According to the dual capability theory, in order to achieve growth, enterprises not only need to optimize existing organizational capabilities to improve efficiency, but also may need to disrupt existing processes and structures to find new opportunities. Dual capabilities play a key role in this process [7, 9]. Exploration capability refers to an enterprise's ability to find new opportunities in search, discovery, experiment and innovation, while utilization capability refers to an enterprise's ability to reduce costs and increase efficiency through repeated refining, selection, refinement, implementation and strengthening activities [5]. According to the theory of digitalization capability, the digitalization capability of enterprises provides the basis for the transmission and sharing of resources and knowledge. Relying on the development of diversified digital technologies, enterprises are in a more open environment. They can not only create knowledge, develop new technologies and products, and improve the innovation performance of enterprises, but also fully search and acquire resources and knowledge from various parties, so as to promote the generation of new ideas and new integration methods, Realize the complementarity of multi-party resources and capabilities, and improve the dual capabilities of organizations[17]. In the digital age, the external environment of organizations shows higher uncertainty. Enterprises should not only consider short-term financial performance, but also meet the needs of long-term development. The role of dual capabilities is particularly important. Therefore, this paper argues that dual capabilities have a mediating effect in the relationship between digital capabilities and innovation performance.

First, with the help of digital technology, enterprises with strong digital capabilities share information and resources with network members, promote knowledge acquisition and creation of enterprises, realize the improvement of Exploration capacity, and then master more new knowledge and resources through continuous search, discovery, experiment and innovation, create new technologies, new products, explore new markets, seek new market opportunities, and realize the improvement of innovation performance[16]. Specifically, the Exploration capacity helps enterprises search and collect new external knowledge and resources, especially data resources, by using digital technology, and mine the potential value of the digital resources obtained through data analysis. Big data predicts the future market trend and customer needs, helps enterprises find new opportunities, and maintains a new development state in the unpredictable digital market environment, So as to improve innovation performance[16]. Enterprises give full play to their Exploration capacity, try to sublimate new value from existing knowledge and resources, improve the depth and breadth of existing knowledge, especially use advanced digital technology to deeply mine the business value behind existing data, create new digital products and services, meet new market demands, improve the market position of enterprises, and help to improve innovation performance [7].

Second, in the digital context, enterprises also need to improve their utilization capacity to expand existing knowledge, technologies and paradigms through repeated refinement, selection, refinement and implementation to achieve growth [18]. Specifically, with the help of digital technology, enterprises with strong digital capabilities share information and resources with network members to break the barriers between the original organizations, promote the flow of resources between organizations without boundaries, help enterprises obtain reliable, specific and effective mature knowledge from digital capabilities, internalize with their own capabilities, and constantly improve existing products and services to create value, To improve the utilization capacity of enterprises [19]. The enterprise gives full play to its ability to continuously refine, copy, select, refine and use the existing knowledge to strengthen the skills, processes and structures that are the same as the original development track of the enterprise, and broaden the existing resources and capabilities of the organization [20].

Third, in the face of changes and market competition in the digital age, enterprises need to have unique competitiveness. Digital capabilities can promote the improvement of their internal innovation performance, accelerate the updating of their internal products, knowledge and technology, and improve their utilization capacity [19]. The utilization ability helps the enterprise to select and refine the internal existing knowledge and resources, improve the organization's development and utilization of existing resources, especially repeatedly refine and mine the value of data resources, improve the data application ability, apply the data to customer relationship management, form linkage with customers, and update and iterate the digital products and services according to the needs of existing customers, Effectively create growth opportunities for enterprises [7].To sum up, this paper believes that dual capability is the key path of the relationship between digital capability and innovation performance improvement. Therefore, this study proposes the following assumptions:

H4a: Digital capability promotes innovation performance by improving exploration capability.

H4b: Digital capability promotes innovation performance by improving utilization capability.

2.2.5. Regulation of environmental uncertainty

External environmental pressure will not only affect the allocation of enterprise capability resources, but also affect the acquisition of external resources. The most influential factor among the external environmental factors is the uncertainty of the environment, which is also a significant feature of the external environment. Digital ability will change due to internal factors, such as organizational culture, senior leaders' decision-making, etc; it will also indirectly affect the level of enterprise performance due to changes in the external environment. Environmental uncertainty refers to the instability or change of the environment caused by changes in customer preferences, new product development, new technologies and market competition. Environmental uncertainty is mainly manifested in two aspects: first, the market demand, customer preference and competitor's strategy are difficult to predict due to market dynamics; Second, technological dynamism represents the uncertainty brought about by the breakthrough of information technology and its impact on the existing digital capabilities of enterprises, which will affect the relationship between digital capabilities and enterprise performance[16]. Du et al, found through research that the dynamic change and competitiveness of the environment will change the process in which enterprise digital capabilities affect performance[21]. Therefore, if the enterprise is facing a complex and changeable external environment, the impact of digital capability on enterprise performance is more significant. Stoel & Muhanna, believe that the complexity, variability and diversity of the environment will affect the interaction between digital capability and performance[22]. Under the environmental background of different characteristics, the process of enterprise digital capability affecting enterprise performance will also have corresponding differences. Based on the above discussion, this study proposes the following assumptions:

H5: environmental uncertainty weakens the effect of digital capability on enterprise innovation performance.

3. Research Design

3.1. Study Samples and Data Collection

This paper uses interview and questionnaire survey methods to collect data, mainly for middle and senior managers who have worked in the enterprise for more than three years. Firstly, this paper designs a questionnaire according to the existing maturity scale and the characteristics of enterprises; Then, choose 76 business owners as a small sample to test, analyze the reliability and validity of the questionnaire, and modify the questionnaire in combination with the interview; Finally, a simple random sampling method was used to select 400 business owners for a questionnaire survey, and the survey objects were entrepreneurs. The questionnaire survey time is from February 2022 to June 2022. A total of 300 questionnaires were distributed in this survey, 238 were recovered, and 27 samples with incomplete and missing options were excluded, of which 211 were valid. The effective rate reached 70.03%. It can be seen from the description of enterprise scale that 125 enterprises with less than 100 employees (59.24%), 46 enterprises with 100-500 employees (21.80%), 13 enterprises with 500-1000 employees (6.16%), 7 enterprises with 1000-2000 employees (3.32%), and 20 enterprises with more than 2000 employees (9.48%). As shown in Table 1:

Table 1: Characteristics of valid samples (N=211)

Characteristics	Category	Number of enterprises	Percentage (%)
Enterprise size	1-100 persons	125	59.24%
	100-500persons	46	21.80%
	500-1000persons	13	6.16%
	1000-2000persons	7	3.32%
	Above 2000persons	20	9.48%
Enterprise age	Within 3 years	50	23.70%
	4-6 years	46	21.80%
	7-10 years	34	16.11%
	10-20 years	55	26.07%
	More than 20 years	26	12.32%
Industry type	State owned enterprises	41	19.43%
	Collective enterprises	5	2.37%
	Private enterprises	96	45.50%
	Foreign invested enterprises	5	2.37%
	Joint stock enterprise	26	12.32%
	cooperative enterprise	10	4.74%
	other	28	13.27%
Principal business	Clothing, textile	25	11.85%
	Metals	9	4.27%
	Medicine	11	5.21%
	Material Science	6	2.84%
	Furniture	10	4.74%
	Architecture	11	5.21%
	Mould	3	1.42%
	Leather products	1	0.47%
	Automobile	3	1.42%
	Mechanics	12	5.69%
	Electronics	6	2.84%
	other	114	54.03%
R&D investment proportion	Less than 1%	61	28.91%
	1%-3%	51	24.17%
	3%-5%	39	18.48%
	5%-8%	29	13.74%
	More than 8%	31	14.69%
Asset size	Within 3 million	63	29.86%
	300-500 million	20	9.48%
	500-1000 million	29	13.74%
	1000-3000 million	30	14.22%
	Above 3000 million	69	32.7%

3.2. Variable Measurement

In order to ensure the reliability and validity of the measurement results, this study uses the measurement research variables of the maturity scale at home and abroad for reference, and uses the two-way translation method to translate and proofread the existing maturity scale repeatedly until the Chinese and English versions show few substantive differences. Before the formal survey, 76 digital enterprises were presurveyed, and the questionnaire was revised according to the feedback of the survey results to form the final questionnaire and measurement items.

1) Digital capability. In terms of digital capability, this study adopts the method of Khin & Ho[23]. Five of them are the capabilities of digital cameras, which are measured by Richter's 7-point scale, ranging from 1= "strongly disagree" to 7= "strongly agree", to self-evaluate the capabilities and technologies of the surveyed companies related to the application of digital technologies.

2) Dual capability. The dual capability of digital enterprises reflects the underlying logic of simultaneous exploration and utilization in digital capability activities[24]. Therefore, this paper uses the research of Li et al and Guo et al for reference to measure the dual capability from the two aspects of exploration capability and utilization capability, including 5 items respectively[7, 8]. Measure with seven-point Likert-like scale, ranging from 1= "strongly disagree" to 7= "strongly agree".

3) Improve the innovation performance of enterprises. Innovation performance is mainly based on the research of Peng et al [5]. It is obtained by using 5 items and measured by seven-point Likert-like scale, ranging from 1= "strongly disagree" to 7= "strongly agree".

4) Environmental uncertainty. Zhu, and Peng, used 4 items of the level 7 scale to measure the change characteristics of environmental turbulence[16, 25]. For the external environment analyzed in this paper, four items are used to measure environmental uncertainty by referring to the items of the above scale, Measure with seven-point Likert-like scale, ranging from 1= "strongly disagree" to 7= "strongly agree".

5) Control variables. Previous studies have shown that the scale, establishment years, nature and R&D investment of enterprises may affect the innovation performance of enterprises. In this paper, the enterprise scale, establishment years, Industry type and R&D investment are included in the model as control variables.

4. Empirical Analysis and Results

4.1. Reliability Analysis

Cronbach's α Coefficient tests the reliability of the scale. The test results are shown in Table 2. Cronbach's of each variable α The coefficients are greater than 0.7, which meets the standard requirements of reliability test, indicating that all variables show good internal consistency, and the stability of the scale is good.

4.2. Exploratory Factor Analysis

In this paper, SPSS is used to conduct exploratory factor analysis on the questionnaire data. Five factors are extracted through principal component analysis to explain 89.478% of the total variation, which are digital ability, Exploration capacity, utilization ability, environmental uncertainty and enterprise innovation performance improvement. The KMO value of the questionnaire is 0.916, and Bartlett's spherical test (χ^2=7888.547; Df= 276, $p<0.01$) showed that the data were suitable for factor analysis.

Table 2: Test results of scale items, variable reliability and validity

Variable name	Questionnaire items	Factor Loading	AVE	CR
Digital capability	The enterprise has a high level of capability in acquiring important digital technologies	0.820	0.687	0.917
	The enterprise has a strong ability to identify new digital opportunities	0.840		
	The enterprise can well cope with digital transformation	0.841		
	The enterprise has mastered the most advanced digital chnology	0.824		
	The enterprise can make good use of digital technology to develop innovative products / services / processes	0.820		
Exploration capacity	The enterprise has acquired new technologies and skills	0.846	0.714	0.926
	The enterprise has learned new product R&D skills and processes in the industry	0.848		
	The company has acquired new management and organizational skills	0.850		
	For the first time, the company has learned new skills in areas such as investment in new technologies, R&D and training	0.847		
	The company enhances innovation skills in areas without prior experience	0.834		
Utilization capacity	The company has updated its existing knowledge and skills related to products and technologies	0.847	0.724	0.929
	The company invests in enhanced skills to leverage proven technologies to improve the productivity of current innovative operations	0.862		
	The enterprise has improved its ability to find solutions imilar to existing solutions rather than new customer solutions	0.833		
	The enterprise has upgraded the skills of product utilization process with rich experience	0.864		
	The enterprise has enhanced the knowledge and skills that can improve the efficiency of existing innovation activities	0.848		
Innovation performance	Compared with peers, the company often takes the lead in launching new products / services in the industry	0.847	0.723	0.929
	Compared with peers, the company often takes the lead in applying new technologies in the industry	0.862		
	Compared with peers, the company has a very good market response to product improvement and innovation	0.833		
	Compared with peers, our products contain first-class advanced technologies and processes	0.864		
	Compared with peers, the success rate of new product development of our company is strongly agree	0.846		
Market uncertainty	The products (or services) in this industry are updated quickly	0.802	0.619	0.866
	The technology in this industry has made rapid progress	0.797		
	The industry is increasingly competitive in product quality and innovation	0.820		
	The demand of customers in this industry is getting higher and higher	0.724		

4.3. Confirmatory Factor Analysis

First, Amos is used to test the discriminant validity between variables. As shown in Table 3, among all the combined models established, the five factor model has the best fitting validity

(χ^2/df=2.515<3, IFI =0.913 >0.9, TLI=0.909>0.9, CFI=0.903>0.9, RMSEA=0.071<0.08, SRMR=0.070 <0.08), and all indicators reached acceptable levels. Secondly, the aggregate validity was tested by calculating the mean variance extraction value (AVE) and the combined reliability (CR). As shown in Table 2, the factor load of each measurement item was greater than 0.6, and the ave and Cr values of all variables were greater than the critical values of 0.5 and 0.7, indicating that the aggregate validity among variables was good. In addition, as shown in Table 3, the value of ave square root of all variables (BOLD numbers on the diagonal of the table) is greater than the correlation coefficient of the row or column in which they are located, which further indicates that the discrimination validity between variables is good.

Table 3: Confirmatory factor analysis results

Model	χ2(df)	χ2/df	IFI	TLI	CFI	RMSEA	SRMR
5factor	357.178(142)	2.515	0.913	0.909	0.903	0.071	0.070
4factor	536.630(146)	3.675	0.886	0.846	0.845	0.091	0.079
3factor	789.476(149)	5.298	0.887	0.837	0.767	0.107	0.089
2factor	998.128(151)	6.610	0.771	0.636	0.708	0.123	0.103
1factor	1392.518(152)	9.161	0.639	0.531	0.612	0.151	0.113

4.4. Common Method Deviation Inspection

In this study, measures are taken to reduce the common method deviation in both procedural control and statistical control. In terms of procedure control, the questionnaire data are only used for academic research, and the anonymity of respondents is protected. All proper terms are explained. In terms of statistical control, this paper first uses Harman's single factor test method to conduct non rotating principal component analysis on all items. The results show that the variance of the first principal component interpretation extracted by factor analysis is 40% lower than the critical point, indicating that there is no serious common method deviation in this study.

4.5. Descriptive Statistical Analysis and Correlation Test

Table 4: Correlation analysis results of sample data

	1	2	3	4	5	6	7	8	9
Enterprise size	1								
Established age	0.485**	1							
Industry type	-0.168*	-0.004	1						
R&D investment	0.282**	.174*	-0.086	1					
Digital capability	0.192**	0.110	-0.043	0.318**	0.828				
Exploration capacity	0.083	-0.002	-0.038	0.306**	0.633**	0.844			
Utilization capacity	0.112	0.03	-0.058	0.286**	0.625**	0.738**	0.851		
Innovation performance	0.089	0.01	-0.056	0.335**	0.596**	0.734**	0.737**	0.850	
Market uncertainty	0.028	0.072	-0.018	0.272**	0.496**	0.554**	0.593**	0.588**	0.787
mean	1.830	2.830	3.510	2.620	4.672	4.775	4.879	4.837	5.210
S.D.	1.276	1.375	1.873	1.406	1.598	1.512	1.484	1.534	1.390

Note: * * at Significant correlation at level 01 (bilateral) * significant correlation at level 0.05 (bilateral).

The descriptive statistical analysis and correlation coefficient test of main variables are shown in Table 4: the mean value of each variable is between 1.830-5.210, and the standard deviation is between 1.276 -1.873. The correlation coefficient is between 0.496-0.738 (p<0.01). The pairwise correlation coefficient between variables shows that digital capacity, exploration capacity, utilization capacity, environmental uncertainty and the improvement of enterprise innovation performance are significantly correlated. These results are basically consistent with the assumption direction of this study, providing a preliminary basis for hypothesis testing.

4.6. Hypothesis Test

Based on Baron & Kenny, Wen et al, Lin & Yu, and Liu et al on the intermediary role test steps, the interaction mechanism between binary ability and innovation performance is tested, as shown in Table 5[25-28]. This paper first tests the variance expansibility factors of model1-model4 variables in Table5. Through the test, it is found that the range of variance expansibility factors of model1-model4 variables is between (0, 5). Therefore, it can be considered that there is no serious problem of multiple collinearity between model1-model4 variables.

In Table 5, in model1, the regression analysis is conducted with enterprise size, Established age, Industry type, R&D investment as self variables and exploration capacity as dependent variables. On the basis of model1, the regression analysis of model2 with enterprise size, Established age, Industry type, R&D investment and digital capacity as self variables and exploration capacity as dependent variables shows that the results of model2 show that digital capacity has a positive impact on exploration capacity , indicating the scope and depth of digital capacity improving exploration capacity(β=0.785,$p<0.001$),; In Model3, the regression analysis was conducted with enterprise size, Established age, Industry type, R&D investment as self variables and utilization capacity as dependent variables. On the basis of Model3, the regression analysis of model4 with enterprise size, Established age, Industry type, R&D investment and digital capacity as self variables and utilization capacity as dependent variables shows that the results of model4 show that digital capacity has a positive impact on utilization capacity(β=0.764,$p<0.001$) , indicating that digital capacity improves utilization capacity, and verifies the hypothesis that H1a and H1b are supported.

Table 5: Regression analysis results of digital capability on binary capability

Variable	Exploration capacity		Utilization capacity	
	Model1	Model2	Model3	Model4
Constant	4.068*** (11.683)	1.283*** (5.346)	4.198*** (12.200)	1.486*** (6.084)
Enterprise size	0.034** (0.357)	-0.071 (-1.321)	0.058 (0.628)	-0.044 (-0.796)
Established age	-0.077 (-0.070)	-0.084+ (-1.758)	-0.046 (-0.550)	-0.053 (-1.094)
Industry type	-0.006 (-0.104)	0.005 (-0.172)	-0.021 (-0.383)	-0.020 (-0.644)
R&D investment	0.333 (4.446)	0.077+ (1.742)		0.044+ (0.332)
Digital capability		0.785*** (20.586)		0.764*** (19.706)
R^2	0.098	0.709	0.085	0.687***
$\triangle R^2$		0.611		0.602
F	5.484***	98.282***	4.734**	88.681***

Note: 1) *** Indicates $p<0.001$, * * indicates $p<0.01$, * indicates $p<0.05$, + indicates $p<0.1$ two tailed test; 2) the values in brackets are t values; 3. the regression coefficients in the Table are all non standardized regression coefficients

As shown in table 6. In the first step, the variance expansibility factors of model5-model 11 variables in table 6 are tested. Through the test, it is found that the range of variance expansibility factors of model5-model11 variables is between (0, 5). Therefore, it can be considered that there is no serious multicollinearity problem between model 5-model 11 variables.

Table 6: Impact of digital level on enterprise innovation performance and regression results of adjustment effect

Variable	Model5	Model6	Model7	Model8	Model9	Model10	Model11
Constant	4.074*** (11.653)	1.425*** (5.365)	0.287+ (1.686)	0.097 (0.586)	0.048 (0.321)	0.271 (1.041)	0.952 (1.668)
Enterprise size	0.021 (0.225)	-0.078 (-1.315)	-0.015 (-0.425)	-0.039 (-1.155)	-0.025 (-0.804)	0.006 (0.115)	0.003 (0.052)
Established age	-0.064 (-0.760)	-0.072 (-1.351)	-0.003 (-0.096)	-0.024 (-0.788)	-0.006 (-0.233)	-0.100 (-2.241)	-0.094 (-2.082)
Industry type	-0.020 (-0.364)	-0.020 (-0.572)	-0.016 (-0.724)	-0.001 (-0.075)	-0.006 (-0.357)	-0.017 (-0.583)	-0.021 (-0.716)
R&D investment	0.369*** (4.904)	0.126* (2.555)	0.057+ (1.918)	0.086** (3.069)	0.067* (2.598)	0.084* (2.004)	0.087 (2.071)
Digital capability		0.747*** (17.699)	0.051 (1.137)	0.063 (1.537)		0.450*** (9.219)	0.274* (1.960)
Exploration capacity			0.887*** (19.002)		0.433*** (6.774)		
Utilization capacity				0.894*** (20.464)	0.540*** (8.354)		
Market uncertainty						0.492*** (8.823)	0.363*** (3.273)
Digital capability× Market uncertainty							-0.098*** (-8.231)
R2	0.116	0.653	0.876	0.888	0.907	0.752	0.861
△R2		0.537	0.223	0.235	0.791	0.122	0.109
F	6.637***	76.127***	236.75***	264.324***	328.204***	101.413***	205.649***

Note: 1) *** Indicates p<0.001, * * indicates p<0.01, * indicates p<0.05, + indicates p<0.1 two tailed test; 2) the values in brackets are t values; 3. the regression coefficients in the table are all non standardized regression coefficients

In Model 5, the regression analysis is carried out with enterprise size, Established age, Industry type and R&D investment as self variables and enterprise innovation performance as dependent variables. On the basis of Model5, the regression analysis of Model6 with enterprise size, Established age, Industry type, R&D investment and digital capability as self variables and enterprise innovation performance as dependent variables shows that the results of Model6 show that digital capability has a positive impact on enterprise innovation performance (β=0.747,p<0.001), indicating that digital capability improves enterprise innovation performance, and the hypothesis H3 is verified.. On the basis of Model6, the regression analysis of Model7 with enterprise size, Established age, Industry type, R&D investment, digital capacity and exploration capacity as self variables and enterprise innovation performance as dependent variables shows that the statistical significance of the impact of model7digital capacity on innovation performance is weakened, and the non standardized regression coefficient is no longer statistically significant from β=0.747(p<0.01)to β=0.747(p>0.1), Based on the research results of Baron & Kenny [25]and Wen et al [26], it is shown that exploration capacity plays a partial intermediary role between digital capacity and innovation performance, and the hypothesis H4a is verified. Model8 adds exploration capacity to Model6. The regression results show that the impact of exploration capacity on innovation performance is statistically significant β=0.445(p<0.001). The statistical significance of the impact of digital capacity on innovation performance is weakened, and the non-standard regression coefficient is no longer statistically significant from β=0.747(p<0.01) to β=0.063(p>0.1). Based on the research results of Baron & Kenny [25]and Wen et al, [26], it shows that utilization capacity plays a partial intermediary role between digital capacity and innovation performance, which verifies the hypothesis H4a. Model9 adds exploration capacity and utilization capacity to Model6. The regression results show that exploration capacit β=0.433(p<0.001) and utilization capacity β=0.445(p<0.001) have statistically significant effects on innovation performance. The hypothesis H2a、H2b are verified.

Model10 adds market uncertainty on the basis of Model6. The regression results show that market uncertainty β=0.492(p<0.001) has a statistically significant impact on innovation performance. Model11 adds the interaction items of digital capability and market uncertainty to model10. The regression results show that the interaction items β=-0.098(p<0.001) have a statistically significant impact on innovation performance. It shows that environmental uncertainty weakens the effect of digital capability on enterprise innovation performance, and verifies the hypothesis H5.

Based on the research results of MacKinnon et al, [29], using the process developed by preacher & Hayes, [30], bootstrap method is used to test the robustness of mediation. Bootstrap method is a non parametric estimation method, which does not rigidly require that the sampling samples must obey the normal distribution. Different from the test methods based on the assumption of normal distribution (such as multiple regression analysis), bootstrap estimates the confidence interval of mediation through repeated sampling. When the confidence interval does not include 0, it is considered that the mediation is significant. At present, many scholars recommend this method Yang et al., [18], and the test results are shown in Table 7.

Table 7: BOOTSTRAP mediation test

Mediation influence path	Point estimation	SE(boot)	95%CI	
			lower	upper
Digital capability-Exploration capacity-Innovation performance	0.706	0.052	0.609	0.811
Digital capability-Utilization capacity-Innovation performance	0.696	0.059	0.585	0.819

Based on 211 enterprise samples collected through formal investigation, this paper tests the intermediary role of binary capabilities between digital capability and innovation performance through 5000 resampling runs of SPSS plug-in process. Under the 95% confidence interval, the intermediary role of binary capabilities can be considered statistically significant if 0 is not included in the confidence interval of binary capabilities. It can be seen from Table 7 that the test of exploration capacity on the intermediary effect between digital capacity and innovation performance shows that 0 is not included in the confidence interval (LLCI=0.609,ULCI=0.811), so the intermediary effect is statistically significant. The test of the intermediary effect of exploration capacity between digital capacity and innovation performance shows that 0 is not included in the confidence interval (LLCI=0.585,ULCI=0.819),therefore, the mediating effect is statistically significant.

5. Conclusion

In the wave of digitalization, new generation information technologies such as big data, cloud computing and artificial intelligence have improved the digitalization level of enterprises. The improvement of enterprise innovation performance is an important driving force for China's digital economic growth, and enterprise strategy is the guiding direction for the future survival and development of enterprises. In order to deeply explain the relationship between digital capability and enterprise innovation performance improvement, this paper reveals the mechanism and boundary conditions based on digital capability theory and dual capability theory. Specifically, this study finds that: (1) digital capability has a positive direct impact on the improvement of enterprise innovation performance. (2) Digital capacity promotes the improvement of enterprise innovation performance by improving dual capabilities, namely exploration capacity and utilization capacity. (3) Environmental uncertainty strengthens the positive effect of exploration capacity on the growth of digital start-ups.

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