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Research on the Synergic Influences of Digital Capabilities and Technological Capabilities on Digital Innovation

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Abstract: Digital innovation is the key for enterprises to obtain core competitiveness in today's increasingly fierce market environment. Based on a sample of high-tech manufacturing companies listed in the Shanghai and Shenzhen A-shares from 2011 to 2020, this paper empirically tests the impact mechanism of the synergic influence of digital capabilities and technological capabilities of enterprises on digital innovation by using static panel regression, dynamic panel regression, and the moderation of social capital on their relationship. The results show that the synergic influence of digital capability and technology absorptive capability has a positive correlation with enterprise digital innovation. The synergy of digital capabilities and technological innovation capabilities has a positive correlation with enterprise digital innovation. Social capital plays a positive moderating role in the impact of the two synergic influences on digital innovation. The results imply that strengthening the coordinated development of digital capabilities and technological capabilities is essential for enterprises to carry out digital innovation, which is of great significance for the high-quality development of the manufacturing industry.

Keywords: digital capability; digital innovation; technical capability; social capital; high-tech manufacturing companies

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1. Introduction

Since entering the 21st century, modern society has entered the era of digital economy. The deep integration of new generation information technology such as big data, cloud computing, artificial intelligence and industrial economy has accelerated the digitalization of the industrial economy. Digital economy leads the way in future business trends and has become the development trend of emerging economic society. Major countries in the world encourage enterprises to carry out digital innovation and regard it as the main driving force for enterprise development. Digital innovation has become a compulsory course for enterprise survival and sustainable development, so it has become the consensus of all industries to develop digital innovation [1,2].

Digital innovation is of great significance to the survival and development of contemporary enterprises. It is not only an important source of success for Google, Alibaba, and other internet companies, but it is also an inevitable way for many traditional enterprises to achieve digital transformation. Digital innovations take place not only in innovations themselves, but they are also a result of the broader, socio-technical transformations of markets and industries [3]. Rapid technological advances and the globalization of services have put pressure on companies [4]. High-tech enterprises are not only a stabilizer of macroeconomic growth, but they are also the main force that can ensure employment and promote entrepreneurship. High-tech enterprises play a vital role in promoting both regional innovation capability and the quality of economic development [5]. Digital innovation will help manufacturing enterprises establish core competitiveness. There have been many studies on how digital development enables enterprise innovation [6,7].

The use of digital technology is the principal way for enterprises to obtain, use and manage data, which can effectively reduce the operating costs of enterprises and improve their production efficiency, and digital capabilities based on digital technology change the value creation logic of traditional enterprise capabilities [8]. Digital technology is the core resource of enterprises in the era of a digital economy, the role of digital technology is rapidly shifting from a driver of modest efficiency to a driver of fundamental innovation and disruption [9]. In view of the continuing widespread prevalence of coronavirus since 2019, whose potential transmission can be minimized through social restrictions, more and more difficulties with traditional transactions or interactions have emerged and they have become unpopular. Therefore, various manufacturing enterprises around the world are more committed to accelerating the development of digital technology [2]. In addition to recognizing the importance of digital technology, enterprises also need to have other capabilities to manage and make the best use of digital technology in the innovation process because enterprises need to accelerate the innovation process by integrating various capabilities and mobilizing human resources to exploit technological advantages and rationally make use of resources [10]. Enterprise technology capability is an important way for enterprises to obtain a long-term competitive advantage and is the basis for maintaining and expanding competitive advantage [11]. The social capital accumulated by enterprises can provide internal and external scarce resources for enterprises in the process of technological innovation and can also provide powerful conditions for enterprises to carry out digital innovation.

From the above literature analysis, it can be seen that enterprises' digital capabilities are the main source of their competitive advantages in the digital era. Although many studies support the relationship between technological capability and innovation based on resource capability theory and dynamic capability theory, there are few empirical studies supporting the impact of digital capabilities on digital innovation in previous studies. Further research on the collaborative development of enterprises' digital capabilities and technological capabilities can better realize the commercialization of enterprises' core technologies. On this basis, this paper analyzes the impact mechanism of the synergic influence of digital capabilities and technological capabilities of enterprises on their digital innovation and the moderation of social capital on their relationship with the hope to provide a practical reference for China's corporate digital innovation at this stage.

2. Literature Review and Research Hypothesis

2.1. Digital Capabilities, Technical Capabilities and Digital Innovation

The concept of digital innovation was formally proposed by Yoo et al. [1]. That is, to produce novel products through new combinations of digital and physical components to distinguish them from traditional IT-innovation-led process creation. This concept has been continuously enriched, focusing on three aspects: digital technology, innovation process and innovation results. Based on the research results of existing scholars, digital innovation can be seen as both the innovation of digital technology itself and innovation and activities in the context of digital technology. Digital innovation includes both the innovation process and innovation results. This paper refers to the definition of digital innovation by Liu et al. That is, digital innovation refers to the combination of information, computing, communication, and connection technologies used in the innovation process, which brings new products, improves production processes, changes organizational models, provides innovation, and brings about changes in the business model [12]. Scholars generally believe that digital capabilities are transformed from dynamic capabilities, and dynamic capabilities theory is developed from resource-based theory and enterprise capabilities theory, which is used to explain how enterprises maintain a sustainable competitive advantage in a turbulent external environment [13,14]. David et al. proposed that digital capabilities can be regarded as dynamic capabilities. According to the theory of dynamic capabilities, digital capabilities can be described as the ability of an organization to create new products and processes and to respond to changing market environments [15]. Faraj et al. believe that the use of big data, artificial intelligence, and other digital technologies to obtain user information and needs can help enterprises better absorb external knowledge, allow customers to participate in innovation, and adjust original products and develop new products in a timely manner according to changes in needs to reduce the risk of enterprise digital innovation [16,17]. Digital capability is an important requirement for realizing digital innovation because the success of digital product development largely depends on how enterprises manage digital technology [10].

Teece pointed out that technological innovation is often an important driving force for business model innovation [18]. Guo et al. pointed out that generative capability can be a path toward continual innovation. Firms can ultimately build their own core com- petencies and gain sustained competitiveness through the development of generative capabilities [19]. Svahn et al. pointed out that enterprises' equipment embedded digital capabilities and the promotion of its technology will allow enterprises to carry out digital innovation [6]. Urbanati et al. pointed out that digital technology plays an important role in information integration, product development, improving operation efficiency, accelerating process innovation, etc., and is an important factor in promoting enterprise digital innovation [20]. Erevelles et al. argue that through the rational use of big data, enterprises can better predict consumer demand and integrate resources, thereby optimizing product prices and improving user satisfaction, which, to a certain extent, has driven business model innovation and thus realized digital innovation [21]. Zhou argued that companies with digital capabilities need to accept new technologies to bring new products with competitive advantages. Therefore, digital capabilities and digital orientation complement each other in realizing product innovation because innovation is proved to be triggered by technology orientation and realized by technology capabilities [22]. Khin et al. believe that a successful digital transformation requires an organization to develop multiple capabilities in many different fields, which the specific needs of specific industries and organizations may determine. Enterprises with digital capabilities also need technical capabilities to develop and innovate new products to gain a competitive advantage [10].

Throughout the existing research results, the positive impact of technological capabilities on innovation has been widely supported. Jansen et al. believe that a strong technology absorption capacity could help enterprises to cross organizational and technological boundaries, improve the breadth and depth of organizational research, and conduct exploration and development innovation through knowledge restructuring. On the contrary, enterprises with a weak absorptive capacity generally have difficulty entering new technological fields, can only maintain their existing market share as followers, and cannot break through the constraints of the mature technology development track [23]. Debra believes that the technological innovation capability of enterprises could encourage organizations to create new ideas and ultimately transform these innovative ideas into market-oriented products or services, thus bringing excess profits to enterprises [24]. Barton argues that the core of an enterprise's technological innovation capability is the people who master professional knowledge and help to form an organizational culture that includes innovative values. Good technological innovation capability is conducive to the coordination of internal codes of conduct and processes, as well as the clarification of innovative strategic intentions and the promotion of new product development [25]. Naqshbandi and Jasimuddin suggested that organizations with a good internal knowledge foundation may have a sophisticated level of absorptive capacity for the better exploitation of external information and ideas [26].

Digital capability is an important requirement for realizing digital innovation in the digital environment because the success of digital product development depends largely on how enterprises manage digital technology [10]. Yu explained the importance of digital capabilities to enterprises from the perspective of resource allocation [27]. From the perspective of information processing, Chu believed that information technology (IT) could help enterprises quickly obtain relevant information and provide an information basis for enterprise innovation. In addition, IT can effectively manage innovation processes. In the increasingly competitive market environment, manufacturing enterprises need to use emerging digital technologies (such as the Internet of Things and cloud computing technology) to achieve public welfare innovation and product innovation, so as to obtain a sustainable competitive advantage. IT capabilities can help enterprises integrate internal and external resources, provide a resource base for commonwealth innovation and product innovation, and effectively manage and coordinate specific innovation processes to ensure innovation activities among enterprises [28,29]. Heredia et al. believe that digital capabilities positively influence firm performance only through technological capabilities [30].

Based on this, this paper proposes the following research assumptions:

H1: *The synergy of enterprise digital capabilities and technology absorption capabilities has a significant positive impact on enterprise digital innovation.*

H2: *The synergy of enterprise digital capabilities and technological innovation capabilities has a significant positive impact on enterprise digital innovation.*

2.2. The Moderating Role of Social Capital

According to social capital theory, against a background of institutional complexity, the survival of enterprises is initially constrained by the internal members of the organization and their own capabilities, but it is also affected by the social network of senior executives [31]. Johnson and King argued that corporate social networks could help enterprises obtain market conditions and capital operation information in a timely and comprehensive manner, thereby helping to improve enterprise economic performance and stimulate innovative behavior [32,33]. Nambisan believes that digital technology has not only given enterprises new development momentum but has also changed the organizational innovation model and industrial innovation pattern in the industrial economy era [34]. The introduction of new technology and the organizational strategic change it causes must be supported by certain resources and capabilities. Enterprise resource base and enterprise core competence are important guarantees for strategic transformation [35,36]. Hallam argues that corporate social capital is a collection of social network relationships [37]. Mesquita and Lazzarini found through empirical research that market social capital is more likely to become a key cooperative resource for enterprises because enterprises in the same industry face similar market opportunities, have the same or similar activities, and are more likely to form a consistent strategic direction [38]. Using social capital, enterprises can identify and obtain more market opportunities, more reliable information, and more favorable resources. High-tech manufacturing companies need to fully exploit their social capital to obtain sufficient market information because of fast product renewal. The higher the social capital, the more they can promote their digital and technological capabilities, thus promoting digital innovation.

Based on this, this paper proposes the following research assumptions:

H3: *Corporate social capital plays a positive moderating role in the synergetic impact of corporate digital capabilities and technology absorption capabilities on corporate digital innovation.*

H4: *Corporate social capital plays a positive moderating role in the synergetic impact of corporate digital capabilities and technological innovation capabilities on corporate digital innovation.*

Based on the above four assumptions, the conceptual model shown in Figure 1 was constructed.

The empirical test in this paper is mainly divided into two parts: the main effect test and the moderating effect test. The main effect test was used to test research hypotheses H1 and H2 regarding the impact of the synergy of digital capabilities and technical capabilities on digital innovation. The moderating effect test was used for H3 and H4, that is, to examine the moderating role of social capital in the synergic impact of digital capabilities and technological capabilities on digital innovation.

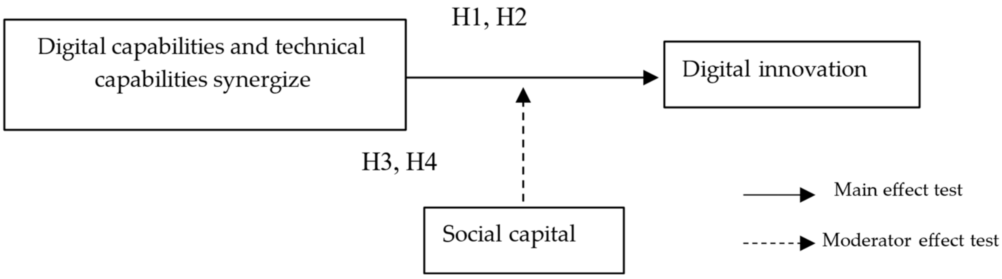

Figure 1. Conceptual model.

3. Research Design

3.1. Sample Selection and Data Source

As the sample for this paper, high-tech companies listed in the Shanghai and Shenzhen stock exchanges recognized by the high-tech certification authority (the high-tech enterprise certification management website) and according to the national economic industry classification GB/T4754-2017 were selected. The high-tech manufacturing enterprises in Shanghai and Shenzhen A-shares from 2011 to 2020 were selected as the research sample, excluding ST, *ST and enterprises with incomplete data, and finally 198 sample enterprises were selected. According to the Statistical Classification Catalog of High-tech Industries issued by the National Bureau of Statistics in 2017, six high-tech industries were selected, namely, pharmaceutical manufacturing; manufacturing of aviation, spacecraft, and equipment; manufacturing of electronic and communication equipment; computer and office equipment manufacturing; manufacturing of medical instruments and equipment and manufacturing of information chemicals. Table 1 lists the distribution of the six high-tech industries. The relevant data for the research design are from the 2011–2020 annual reports of the listed manufacturing enterprises, WIND database, CSMAR database and patent information network, and all continuous variables are winsorized by 1%.

Table 1. Sample distribution.

Industry Name	Number of Companies	Proportion%
Electronics and communication equipment manufacturing	104	52.52%
Computer and office equipment manufacturing	71	35.86%
Aerospace, spacecraft, and equipment manufacturing	7	3.53%
Pharmaceutical manufacturing	6	3.03%
Medical equipment and instrument manufacturing	5	2.53%
Information chemicals manufacturing industry	5	2.53%
Total	198	100%

3.2. Variable Selection and Measurement

Explained variable: Digital innovation (DI). Patent is an important indicator to measure innovation output. This paper used the number of digital innovation patents applied by enterprises in a certain year to measure their digital innovation level [39,40]. Referring to the five dimensions listed by Wu et al., with "intelligence, blockchain, big data, machine learning, cloud computing, cloud, Internet, Internet of Things, informatization, digitalization, remote, robot, face recognition, virtual" as the keywords, samples of digital technology innovation patents included in the citation information [41,42] were extracted, and the data source used was the Enterprise Know Patent Information Network.

Explanatory variable: (1) Digital ability (DA). From the perspective of digital capabilities, digital capabilities are defined as basic skills in using digital technologies and tools to create new products, improve production processes, optimize service processes, etc. [10,43]. Digital capability refers to the ability of enterprises to understand, apply and utilize digital technology (a new generation of information technology represented by artificial intelligence, cloud computing, big data, etc.). This paper used the number of digital related words in the 2011–2020 annual reports of the listed companies to measure digital capability [44,45]. (2) Technical capability: technical capability includes technology absorption capability (TAC) and technology innovation capability (TIC). This paper used the proportion of R&D funds within the operating income to measure technological absorption capability (TAC) [24,46] and the proportion of R&D personnel to measure technological innovation capability (TIC) [47]. The data are from the CSMAR database and WIND database, and some missing data are filled by linear interpolation.

Moderator variable: social capital. Referring to Hu's research, this paper divides social capital into three categories: political capital, commercial capital and academic capital; the measurement value of social capital was obtained by adding the scores after measuring using the positioning method. The data are from the CSMAR database [48].

Control variables: after referring to relevant studies in several articles, enterprise asset level (TA), fixed asset ratio (FAR): (net fixed assets/total assets) ∗ 100, current ratio (CR): current assets/current liabilities, and equity concentration ratio (OC): the sum of the shareholding ratios of the top five major shareholders of the company were selected as the control variables for this paper [49–51]. The data are from the CSMAR database. The definition of each control variable is shown in Table 2. A descriptive statistical analysis of variables is shown in Table 3.

Table 2. Variable definition.

Variable Name	Variable Symbol	Variable Definition
Enterprise scale	TA	Natural logarithm of total assets at the end of the year
Fixed assets ratio	FAR	(Net fixed assets/total assets) ∗ 100
Current ratio	CR	Current assets/current liabilities
Equity concentration ratio	OC	The sum of shareholding ratio of the top five major shareholders of the company

Table 3. Descriptive statistics.

Variable	Observations	Mean Value	Standard Deviation	Maximum	Minimum
DI	198	9.931	52.750	1009	0
DA	198	17.304	32.427	290	0
TAC	198	6.750	5.153	47.48	0.35
TIC	198	20.673	12.273	66.77	0.395
CSC	198	4.362	2.117	12	0
TA	198	140.879	270.540	1928	7.358
FAR	198	16.628	10.305	58.616	0.298
CR	198	2.690	2.924	34.495	0.524
OC	198	36.766	18.296	88.513	0.715

3.3. Model Design

The panel data model was selected for this paper and was analyzed using the mixed regression (OLS), fixed effect model (FE) and random effect model (RE), respectively. The panel data model set in this paper is as follows:

$$DI_{it} = c_1 + \beta_{11}DA_{it}TAC_{it} + \beta_{12}TA_{it} + \beta_{13}FAR_{it} + \beta_{14}CR_{it} + \beta_{15}OC_{it} + \varepsilon_{it} \tag{1}$$

$$DI_{it} = c_2 + \beta_{21}DA_{it}TIC_{it} + \beta_{22}TA_{it} + \beta_{23}FAR_{it} + \beta_{24}CR_{it} + \beta_{25}OC_{it} + \varepsilon_{it} \tag{2}$$

$$DI_{it} = c_3 + \beta_{31}DA_{it}TAC_{it} + \beta_{32}CSC_{it} + \beta_{33}DA_{it}TAC_{it}CSC_{it} + \beta_{34}FAR_{it} + \beta_{35}CR_{it} + \beta_{36}OC_{it} + \varepsilon_{it} \tag{3}$$

$$DI_{it} = c_4 + \beta_{41}DA_{it}TIC_{it} + \beta_{42}CSC_{it} + \beta_{43}DA_{it}TIC_{it}CSC_{it} + \beta_{44}FAR_{it} + \beta_{45}CR_{it} + \beta_{46}OC_{it} + \varepsilon_{it} \tag{4}$$

DI is the explained variable, which means digital innovation; DA stands for digital capability; TAC stands for technology absorption capacity; TIC stands for technological innovation capability; TA stands for enterprise asset level; FAR stands for fixed asset ratio; CR stands for current ratio; OC refers to equity concentration. i represents the ith enterprise, and t represents the year. $DATAC$ represents the degree of synergy between digital capabilities and technology absorption capabilities, and $DATIC$ represents the degree of synergy between digital capabilities and technology innovation capabilities; CSC is corporate social capital, β_{11}–β_{46} is the coefficient of each variable; ε is random error; c is a constant term.

4. Metrological Analysis and Discussion

4.1. Main Effect Test

Based on the above econometric model design, we used stata15.0 statistical analysis software to conduct empirical research and tests. In this paper, we selected the panel data of A-share listed companies from 2011 to 2020, and used mixed regression (OLS), a fixed effect model (FE), and a random effect model (RE) for analysis. We judged whether to use a fixed effect model or a random effect model according to the *p*-value of the Hausman test. The regression results are shown in Table 4.

Table 4. Main effect test.

Variable	Model 1 (OLS)	Model 1 (FE)	Model 1 (RE)	Model 2 (OLS)	Model 2 (FE)	Model 2 (RE)
DATAC	0.0094 **	0.0058 ***	0.0062 ***			
	(0.0043)	(0.0018)	(0.0017)			
DATIC				0.0046 **	0.0028 ***	0.0030 ***
				(0.0018)	(0.0006)	(0.0006)
TA	0.0714 ***	0.0593 ***	0.0634 ***	0.0705 ***	0.0566 ***	0.0616 ***
	(0.0161)	(0.0042)	(0.0034)	(0.0160)	(0.0042)	(0.0034)
FAR	−0.3211 **	−0.1902 **	−0.2227 ***	−0.2596 **	−0.1706 **	−0.1971 ***
	(0.1313)	(0.0785)	(0.0707)	(0.1292)	(0.0785)	(0.0708)
CR	0.1303	0.4276 *	0.4059 *	0.2014	0.5227 **	0.4911 **
	(0.2548)	(0.2541)	(0.2406)	(0.2529)	(0.2527)	(0.2395)
OC	−0.0052	0.0897 ***	0.0760 **	0.0038	0.0862 **	0.0738 **
	(0.0531)	(0.0335)	(0.0317)	(0.0527)	(0.0334)	(0.0316)
_cons	2.0856	−1.9910	−1.5492	−0.0507	−2.5321	−2.3555
	(3.5361)	(2.0774)	(2.3781)	(3.6514)	(2.0724)	(2.3650)
hausman		Prob>chi2 = 0.1785			Prob>chi2 = 0.1993	
R^2	0.3555	0.1239	0.1237	0.3671	0.1292	0.1290

Note: ***, ** and * indicate that the parameter estimation is significant at the levels of 0.01, 0.05 and 0.1, respectively.

For fixed effects, the F statistic is used to test whether all individual effects are significant overall. The probability of the F statistic is 0.0000. The test results show that the fixed effect model is due to the mixed OLS model. For the random effect, the value of p obtained by LM test was 0.0000, indicating that the random effect is very significant. The random effect model is also better than the mixed OLS model. According to the results of the Hausman test, the p values of model (1) and model (2) are both greater than 0.05, so the random effect (RE) model is better than the fixed effect (FE) model.

According to the estimation results of the random effect RE of model (1), the synergy of digital capability and technology absorptive capability had a significant positive impact on digital innovation, with an effect coefficient of 0.0062 (0.0017) and passed the 1% test. It shows that with the improvement of the collaborative level of enterprises' digital capabilities and technology absorption capabilities, enterprises have been better able to carry out digital innovation. Therefore, Hypothesis 1 is proved.

For the RE estimation results of model (2) random effects, the synergy of digital capabilities and technological innovation capabilities had a significant positive impact on digital innovation, with an effect coefficient of 0.0030 (0.0006) and passed the 1% test. This shows that with the improvement of the synergy level of enterprises' digital capabilities and technological innovation capabilities, enterprises have been promoted to carry out digital innovation. It shows that the synergy between enterprises' capabilities and digital capabilities is very important for digital innovation, whether based on the absorption and transformation of new technologies or the input of technicians. Therefore, Hypothesis 2 is proved.

In the estimation results of model (1) and model (2), each control variable has a significant impact on digital innovation, among which TA, CR and OC had a significant positive impact on enterprise digital innovation (passing the tests of 1%, 10% and 5% respectively). This shows that large-scale enterprises are more capable of carrying out innovative activities; the higher the liquidity ratio is, the stronger the enterprise's liquidity is, and the stronger the short-term solvency is, the more conducive the enterprise is to innovation; enterprises with concentrated equity are more conducive to digital innovation. FAR has a significant negative impact on enterprise digital innovation and passed the 1% test. Enterprises with a low fixed asset ratio can flow faster. From the perspective of capital operation capability, the lower the fixed asset ratio, the stronger the enterprise's operation capability and the more conducive it is to digital innovation activities.

4.2. Moderating Effect Test

Models 3 and 4 were used to test the moderating effect of social capital. According to the results of the Hausman test, the p values of model (3) and model (4) were both greater than 0.05, so the random effect (RE) model is better than the fixed effect model (FE). After adding social capital into model (3) and model (4), the regression results show that social capital has no significant impact on digital innovation ($\beta_{32} = 0.0078$, $p > 0.05$; $\beta_{42} = -0.1587$, $p > 0.05$). To reduce the impact of possible multicollinearity on the regression results, the variables DATAC, DATIC and CSC were centralized and multiplied, respectively. After multiplication, two interaction items were generated, namely, DA $*$TAC $*$ CSC and DA $*$ TIC $*$ CSC, and the interaction items were put into the model for the moderating effect test. The regression results are shown in Table 5.

Table 5. Moderator effect test.

Variable	Model 3 (OLS)	Model 3 (FE)	Model 3 (RE)	Model 4 (OLS)	Model 4 (FE)	Model 4 (RE)
DATAC	0.0088 **	0.0040 **	0.0046 ***			
	(0.0044)	(0.0019)	(0.0018)			
DATIC				0.0041 **	0.0021 ***	0.0023 ***
				(0.0018)	(0.0006)	(0.0006)
CSC	0.1363	−0.0643	0.0078	0.0432	−0.2552	−0.1587
	(0.6820)	(0.2974)	(0.2809)	(0.6519)	(0.2952)	(0.2787)
DATACCSC	0.0012	0.0030 ***	0.0028 ***			
	(0.0019)	(0.0008)	(0.0007)			
DATICCSC				0.0008	0.0014 ***	0.0014 ***
				(0.0005)	(0.0002)	(0.0002)
TA	0.0714 ***	0.0597 ***	0.0638 ***	0.0711 ***	0.0585 ***	0.0630 ***
	(0.0161)	(0.0041)	(0.0034)	(0.0161)	(0.0042)	(0.0034)
FAR	−0.3234 **	−0.1757 **	−0.2131 ***	−0.2647 **	−0.1558 **	−0.1869 ***
	(0.1340)	(0.0783)	(0.0707)	(0.1326)	(0.0773)	(0.0700)
CR	0.1494	0.4298 *	0.4166 *	0.2371	0.5690 **	0.5420 **
	(0.2530)	(0.2537)	(0.2404)	(0.2519)	(0.2494)	(0.2369)
OC	−0.0041	0.0890 ***	0.0758 **	0.0059	0.0842 **	0.0730 **
	(0.0538)	(0.3334)	(0.0317)	(0.0537)	(0.0329)	(0.0312)
_cons	2.0706	−2.1591	−1.6771	−0.1400	−2.9854	−2.7235
	(3.5684)	(2.0704)	(2.3786)	(3.6892)	(2.0419)	(2.3499)
hausman		Prob>chi2 = 0.1901			Prob>chi2 = 0.2857	
R^2	0.3561	0.1313	0.1310	0.3709	0.1565	0.1560

Note: ***, ** and * indicate that the parameter estimation is significant at the levels of 0.01, 0.05 and 0.1, respectively.

According to the random effect estimation results of model 3 and model 4, the two interaction terms DATAC $*$ CSC and DATIC $*$ CSC had significant positive effects on digital innovation. Meanwhile, R^2 of model (3) rose from 0.1237 in model 1 to 0.1310, and R^2 of model (4) rose from 0.1290 in model (2) to 0.1560 of model (4). This shows that the moderating effect of social capital is established. That is, the stronger the corporate social capital is, the stronger the positive impact of the synergy of digital capabilities and technological capabilities on corporate digital innovation will be. Therefore, Hypothesis 3 and Hypothesis 4 are proved.

To better demonstrate the moderating effect of social capital on digital capability and technological capability synergy on digital innovation, a schematic diagram of its moderating effect was drawn and is shown in Figures 2 and 3.

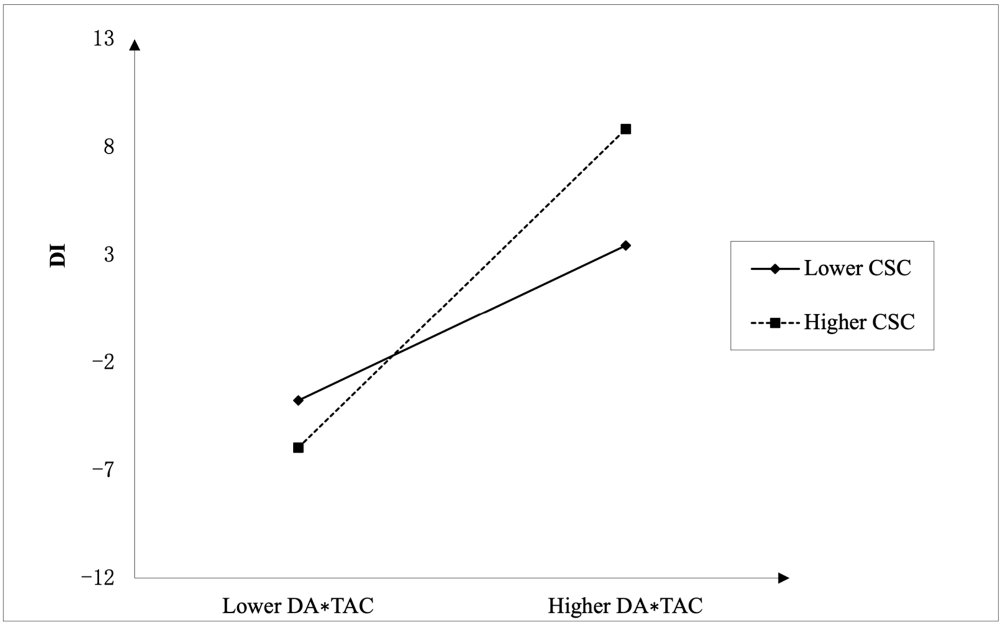

Figure 2. The moderating effect of social capital on DA ∗ TAC.

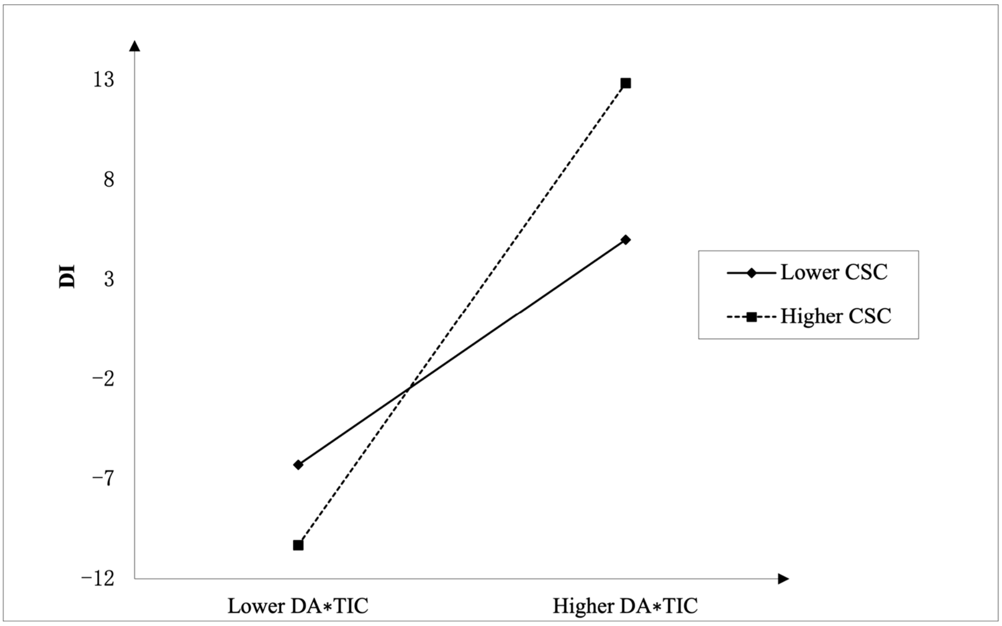

Figure 3. The moderating effect of social capital on DA ∗ TIC.

Social capital plays a positive role in moderating the synergy between digital capacity and technology absorption capacity. The stronger the corporate social capital is, the stronger the positive impact of digital capability and technology absorption capability on digital innovation is.

Social capital plays a positive role in moderating the synergy between digital capabilities and technological innovation capabilities. The stronger the corporate social capital, the stronger the positive impact of digital capabilities and technological innovation capabilities on digital innovation.

5. Robust Test

The robust test method can help researchers to investigate whether the main estimators are robust when the model is set with reasonable changes. At present, there is no uniform standard for robust tests. Considering that enterprise digital innovation may have a long-term impact, to verify the stability of the research results, this paper used the system generalized moment estimation (SYS-GMM) for robust testing. To overcome the influence of autocorrelation of DI caused by its lag of one period, in this paper, the lag of one period DI_1 of the explained variable was added to the regression Equations (1)–(4) and dynamic panel regression was conducted. In general, the generalized moment estimation (SYS-GMM) of the system can better control the endogenous [52,53] than the differential generalized moment estimator (DIF-GMM). Based on this, the dynamic regression equation was established as follows, and the test results are shown in Table 6.

$$DI_{it} = c + \beta_{51} DI\_1_{it} + \beta_{52} DA_{it} TAC_{it} + \beta_{53} TA_{it} + \beta_{54} FAR_{it} + \beta_{55} CR_{it} + \beta_{56} OC_{it} + \varepsilon_{it} \quad (5)$$

$$DI_{it} = c + \beta_{61} DI\_1_{it} + \beta_{62} DA_{it} TIC_{it} + \beta_{63} TA_{it} + \beta_{64} FAR_{it} + \beta_{65} CR_{it} + \beta_{66} OC_{it} + \varepsilon_{it} \quad (6)$$

$$DI_{it} = c + \beta_{71} DI\_1_{it} + \beta_{72} DA_{it} TAC_{it} + \beta_{73} CSC_{it} + \beta_{74} DA_{it} TAC_{it} CSC_{it} + \beta_{75} FAR_{it} + \beta_{76} CR_{it} + \beta_{77} OC_{it} + \varepsilon_{it} \quad (7)$$

$$DI_{it} = c + \beta_{81} DI\_1_{it} + \beta_{82} DA_{it} TIC_{it} + \beta_{83} CSC_{it} + \beta_{84} DA_{it} TIC_{it} CSC_{it} + \beta_{85} FAR_{it} + \beta_{86} CR_{it} + \beta_{87} OC_{it} + \varepsilon_{it} \quad (8)$$

Table 6. Robust test.

Variable	Model 5	Model 6	Model 7	Model 8
DI_1	0.8050 ***	0.8130 ***	0.6583 ***	0.6663 ***
	(0.0213)	(0.0215)	(0.0482)	(0.0410)
DATAC	0.0028 ***		0.0020 *	
	(0.0011)		(0.0011)	
DATIC		0.0016 ***		0.0015 ***
		(0.0003)		(0.0003)
CSC			−0.2581	−0.5798 **
			(0.2074)	(0.2271)
DATACCSC			0.0020 ***	
			(0.0007)	
DATICCSC				0.0009 ***
				(0.0002)
TA	0.0151 ***	0.01514 ***	0.0105 *	0.0138 **
	(0.0018)	(0.0019)	(0.0063)	(0.0059)
FAR	−0.0973 ***	−0.020 *	−0.1290 ***	−0.0192
	(0.0359)	(0.0386)	(0.0352)	(0.0360)
CR	0.1487	1.1339 **	0.0503	1.5140 ***
	(0.4201)	(0.4588)	(0.3929)	0.4305
OC	0.2080 ***	0.3345 ***	0.0158	0.1586 ***
	(0.0665)	(0.0649)	(0.0546)	(0.0544)
_cons	−6.4346 **	−15.0976 ***	3.0251	−8.5736 ***
	(3.2666)	(3.3880)	(3.1036)	(3.1830)
AR (2)	0.565	0.552	0.190	0.104

Note: ***, ** and * indicate that the parameter estimation is significant at the levels of 0.01, 0.05 and 0.1, respectively.

In the empirical results of SYS-GMM model reported in Table 6, AR (2) is greater than 0.1. The direction of action of the main explanatory variables is consistent with the original research, and the significance has passed the t-test. The coefficient of variables has only a small difference, indicating that the research conclusions in this paper are relatively stable, the empirical conclusions are more reliable, and further verify the previous assumptions.

6. Conclusions and Implications

Combined with dynamic capability theory, this paper is based on a sample of high-tech manufacturing companies listed in the Shanghai and Shenzhen A-shares from 2011 to 2020. This paper empirically tests the impact mechanism of the synergic influence of digital capabilities and technological capabilities of enterprises on digital innovation by using static panel regression, dynamic panel regression, and the moderation of social capital on their relationship.

The synergy between digital capabilities and technological capabilities is positively correlated with digital innovation. This shows that the synergy of digital capabilities and technological capabilities can effectively promote digital innovation, which indicates that enterprises should recognize the importance and development of the synergy of digital capabilities and technological capabilities. In the era of the digital economy, improving technological innovation capability is an inevitable requirement for China's high quality economic and social development. Enterprises with high R&D investment can further explore their valuable core technologies. For example, Huawei continues to increase its R&D investment in basic fields and pays attention to training R&D talents. Huawei's R&D investment has increased yearly, and the proportion of R&D personnel has remained stable at 50%. The second concern is technology absorption capacity. Enterprises should pay attention to the digestion, absorption and investment of imported technology. Enterprises should constantly learn and absorb external technologies for use by enterprises, transform external technologies into their core competitiveness, and create better conditions for new products to adapt to the market, thus promoting digital innovation.

Enterprise digital capabilities can help enterprises create new products and obtain more resources at speed and a lower cost. The application of digital technology helps enterprises to expand their research and development system and using digital technology to obtain favorable information creates conditions for enterprises to produce products and provide services. For example, Huawei takes full advantage of its connection capabilities, computing, cloud, and other digital technologies to provide products and a product portfolio. Therefore, enterprises should pay close attention to the development of digital technology, promote the synergy of digital and technological capabilities of enterprises, and help enterprises improve innovation efficiency and promote digital innovation. It is necessary for China's high-tech enterprises to fully exploit their technological innovation capacity and technological absorption capacity. It is necessary to promptly find advanced technologies suitable for introducing and absorbing enterprises, and constantly improve enterprises' absorption and digestion capacity for new technologies. Making full use of digital technology can help enterprises acquire new technologies more quickly to bring competitive advantages to enterprises. At the same time, enterprises should increase their R&D investment and train R&D talents to better develop their technological capabilities.

Social capital plays a positive moderating role in the impact of the two synergic influences on digital innovation. This shows that when enterprises fully use the synergistic effect of digital capabilities and technological capabilities, the higher social capital they have and the better they will promote digital innovation. Enterprises need to take full advantage of the positive role of social capital. The production and value creation of enterprises depend on the existence of social networks. Social capital can supplement and adjust the market's resource allocation, thus alleviating the problem of insufficient R&D investment of enterprises. Enterprises should pay attention to the accumulation and maintenance of social capital, pay attention to its role in digital innovation activities, and create favorable conditions for enterprises to obtain more effective external information.

This paper has empirically tested the impact mechanism of the synergic influence of digital capabilities and technological capabilities of enterprises on digital innovation by using static panel regression, dynamic panel regression, and the moderation of social capital on their relationship. The research conclusion has strong stability, but the research also has certain limitations. First, the data selected in this article have limitations. In this research sample, the electronics and communication equipment manufacturing industry accounts for a large proportion of the sample, and the sample distribution of each industry is uneven. Due to the different levels of digital innovation development and digital transformation consciousness of each industry in China, the environment of enterprises is also very different, which will have a certain impact on the conclusions of this research. Therefore, more industries can be included in future research to conduct a more comprehensive study. Second, the selection of control variables has limitations. In this paper, enterprise asset level, fixed asset ratio, current ratio, and equity concentration ratio were selected as control variables. Due to the difference in the economic level of the city where the enterprise is located, the competition intensity of each industry and other factors, the digital innovation level of the enterprise will be affected to a certain extent, which will have a certain impact on the research results. In future research, more control variables can be included in the research to improve the reliability of hypothesis testing. Third, this paper only considers the impact of enterprise technology factors on digital innovation. Enterprise organizational factors such as organizational strategy, and environmental factors such as policy support can be included in further research.

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