Digitalization and Management Innovation II
R.J. Dwyer (Ed.)
© 2023 The Authors.
This article is published online with Open Access by IOS Press and distributed under the terms of the Creative Commons Attribution Non-Commercial License 4.0 (CC BY-NC 4.0).
doi:10.3233/FAIA230739

Digital Transformation, Dynamic Capabilities and Enterprise Innovation Performance Based on Dynamic Capability Theory and Upper Echelon Theory

Yuan Jin, Hong Xu[1] and Xujuan Su
[a] *School of Economics and Management, Shanghai Maritime University, China*

Abstract. In the era of digital economy, digital transformation has become a hot issue for both academia and industry, especially for those manufacturing enterprises that are not "naturally digital", it is important to use digitalization to reconstruct their capabilities and drive their innovation development. This study aims to analyse the impact of digital transformation on enterprise innovation performance, using data of Chinese manufacturing listed enterprises from 2008 to 2020. The results show that digital transformation can significantly improve enterprise innovation performance. Based on dynamic capability theory and upper echelon theory, we also empirically test the mediating role of dynamic capability and the moderating role of top management's technical background and social capital. The results show that digital transformation can reconstruct the dynamic capability, which in turn affects their innovation performance. And top management's technical background can strengthen the positive relationship between digital transformation and dynamic capability, while their social capital weakens the positive relationship between digital transformation and dynamic capability.

Keywords. digital transformation, dynamic capabilities, top management's technical background, top management's social capital, enterprise innovation performance

1. Introduction

With the deepening development of the digital economy, digital transformation has become an important source of competitive advantage for enterprises. According to the China Digital Economy Development Report (2022), Chinese digital economy made a new breakthrough in 2021, and the digital economy has reached 45.5 trillion yuan, accounting for 39.8% of GDP. Enterprises are the cells of the macroeconomics and determine the vitality of macro digital economy development, digital transformation is gradually mapped in the specific production behavior changes of enterprises [1]. Digital technology can facilitate the exchange of knowledge both internally and externally, alleviate the resource constraints, thereby promote enterprises to get innovation breakthrough. Chinese manufacturing industry has been at the low end of the value chain for a long time, due to a lack of innovation. However, compared with Internet-based

[1] Corresponding Author, Hong Xu, School of Economics and Management, Shanghai Maritime University, China; Phone: 19821735615; Email: 202130710231@stu.shmtu.edu.cn.

companies, manufacturing enterprises are not “natural digital” [2]. In order to realize industry upgrading, how Chinese manufacturing enterprises should seize the opportunities of the digital era to promote innovation has become a hot issue for both academia and industry.

The topic of "digital transformation and innovation performance" has been actively explored by scholars. In terms of the methodology of the study, there are two main types: One is case studies, which is the main form of early research. Vial [2] and Li [3] theoretically analyzed the impact of digital transformation on the phenomenon of enterprise innovation. Liu et al. [4] explored the process of digitally empowered enterprise innovation through a case study analysis of two smart manufacturing companies, Xuzhou Construction Machinery Group and Shaanxi Automobile Group. The second is to conduct quantitative research, where relevant studies have found that digital transformation can improve the information management of Chinese companies [5], reduce the costs of various aspects of daily activities of companies ([6], [7], [8]), and have a catalytic effect on technological innovation of companies [9]. Singh et al. [10] conducted a questionnaire study of 124 manufacturing firms in India and proved that organizational culture, competitive pressures, and awareness readiness all can affect the digital transformation. Although research on digital transformation and innovation performance has enriched existing theories and provided theoretical guidance for management practice, there are still many areas that need to be explored in depth. For example, the quantitative research on digital transformation is yet to be enriched and improved, the measurement of digital transformation is still unable to accurately reflect the digital development of enterprises and the mechanism between digital transformation and innovation performance is still ambiguous. Based on this, this paper selects a sample of manufacturing companies listed in Shanghai and Shenzhen A-shares in order to figure out the impact of digital transformation on innovation performance, and on this basis further considers the mediating role of dynamic capabilities and the moderating role of executive team characteristics.

This paper may make contributions in three areas: First, based on the digital economy, we have provided theoretical guidance on digital transformation for manufacturing enterprises that do not have "naturally digital" characteristics. Second, we have crawled the keywords of digital transformation in the annual reports of listed manufacturing companies based on Python. And this can provide a new and precise method to measure enterprise digitalization. Finally, combining dynamic capability theory and upper echelon theory, we have explored whether digital transformation can reconstruct the dynamic capability of enterprises and thus affect innovation performance. This will enrich the existing theoretical research on digital transformation.

2. Theoretical Framework

2.1. Digital Transformation and Enterprise Innovation Performance

In this study, we define the digital technology as Artificial Intelligence, Blockchain, Cloud Computing and Big Data (ABCD technology). And digital transformation is thereby defined as the application of those ABCD digital technology, in order to enhance the digitalization of the existing technology systems in the enterprises. The essence of digital transformation is an innovation activity, and digital transformation drives innovation performance in three main ways [11]: First, the popularity and application of digital technology has led to fundamental changes in the way firms interact with consumers [12], which facilitates access to user needs. Second, digital transformation brings an increase in the efficiency of enterprise innovation. The application of digital technology provides faster and easier ways to exchange knowledge and information internally and externally. Third, digital transformation can ease the pressure on enterprises' resources and reduce the cost of innovation. Problems such as resource barriers, resource constraints are also alleviated by the embedding of digital technologies [13].

H1: Digital transformation positively affects enterprise innovation performance.

2.2. The mediating role of dynamic capabilities

The innovation performance brought by digital transformation cannot be supported without resources and capabilities, dynamic capabilities play an important role in the innovation process. In this paper, based on the division of dynamic capability dimensions by scholars and considering the needs of enterprises for digital transformation, the multidimensional construct of dynamic capability is divided into externally oriented opportunity perception capability, environmental adaptation capability and internally oriented coordination and integration capability and learning and absorption capability.

First, opportunity perception capability: firms with abundant digital resources are better able to identify risks and rewards, broaden information and opportunity search channels, identify new technological opportunities and adjust their innovation strategies in a timely manner [14], thus enhancing innovation performance. Second, environmental adaptation capability: adaptability is the ability of a firm to quickly use its existing resources to respond to dynamic changes. The application of digital technology can completely disrupt the development model and business processes on which enterprises depend, enhance the ability of enterprises to adapt to the environment, then optimize the product technology innovation of enterprises and the whole value chain, then win valuable competitive time for enterprises to introduce new products. Again, coordination and integration capabilities: dynamic capabilities with integration functions are nested in organizational practices [15], and effective integration of resources can enhance the success rate of new product development. Keller [16] pointed out in an empirical study, that cross-department collaborative innovation must rely on a firm's ability to integrate resources or knowledge. The stronger coordination and integration capability mean that firms can quickly allocate or reconfigure their internal and external resource, and can adjust their organizational structure more flexibly when facing opportunities, thus enhancing their innovation capability. Finally, learning and absorbing ability: digital technology can break the barrier between enterprises, accelerate the integration of enterprises ecological environment, truly realize the interactive learning of internal resources and external environment, internalize and absorb knowledge to bring technology and product innovation, and incubate more new technologies and new products.

H2: Dynamic capabilities and its four sub-dimensions play a mediating role between digital transformation and enterprise innovation performance.

2.3. Moderating role of top management's technical background

The top management's technical background moderates the effect of digital transformation on dynamic capabilities in two main ways. On the one hand, psychological research shows that individual characteristics are shaped by features of the environment [17]. Top management who have been working in R&D for a long time will be more inclined to digital technologies and their long-term background in R&D gives them more product knowledge and expertise to give more guidance in the process of technology development implementation. On the other hand, in those listed companies with a high number of technical executives, the common technical background makes the decision-making more power and it is easier to solve problems in a group when facing technical problems [18]. Moreover, top management with technical backgrounds have a rich network of technical resources, and this network will help them learn more quickly about innovation information from external units [19], all of which help firms capture the dynamics of technology and market opportunities, promote collaborative innovation among network relationship members, and spread R&D risks, which in turn enhance firms' learning to integrate information and adapt to environmental changes.

H3: The top management's technical background positively moderates the positive relationship between digital transformation and dynamic capabilities.

Combining H2 and H3, we propose the following hypothesis:

H4: The top management's technical background positively moderates the mediating effect of dynamic capabilities between digital transformation and firm innovation performance.

2.4. Moderating role of top management's social capital

Social capital is an important form of informal social institution [20]. Social capital refers to the connections between individuals or groups, which are the resources brought to people by their position in the social structure. These resources can alleviate the information asymmetry of various parties and thus reduce transaction costs, but top management rely too much on the social capital may stick to the rules, thus hindering the development of the company. Especially for the manufacturing industry, the core is innovation, and maintaining social capital may be a burden for manufacturing companies. This negative effect is mainly manifested in the following three aspects. First, the high social capital of the top management may form a path dependence in the process of enterprise development, and this path dependence may make the enterprise develop organizational inertia, lack initiative and creativity. From the perspective of firm growth, social capital is a hindrance for an organization with higher capacity and better governance mechanisms [21]. Second, it may be costly for firms to use social capital to obtain resources from outside. While the political capital of enterprises plays the role of "helping hand", it may also play the role of "predatory hand" to obtain political support from enterprises for some political purposes [22]. Xiao and Wang [23] argue that the rent-seeking behavior behind government subsidies leads to the phenomenon of "emphasizing relationships over innovation", and that the benefits brought by social relationships are more rapid, which leads to a lack of incentive for enterprises to innovate. Finally, social capital, as a huge network of top management, requires a lot of resources to maintain, and the resources needed for digital transformation and the cost of maintaining social capital are likely to be in conflict, and this conflict also becomes a reason to hinder the digital transformation of enterprises.

H5: Top management's social capital negatively moderates the positive relationship between digital transformation and dynamic capabilities.

Combining H2 and H5, we propose the following hypothesis:

H6: Top management's social capital negatively moderates the mediating effect of dynamic capabilities between digital transformation and firm innovation performance.

3. Method

3.1. Sample

The research sample of this paper includes the listed manufacturing enterprises in Shanghai and Shenzhen A-shares in China from 2008 to 2020. In this paper, the following treatments are made to the data: (1) exclude the companies that are ST and *ST in the sample; (2) remove the companies with serious omissions in the key data; (3) to avoid the influence of errors due to outliers, a 1% tailing adjustment is made to each continuous variable in this paper. After the above processing of the values, a total of 14785 observations for 2234 manufacturing companies were obtained. The information of enterprise annual reports required for the construction of digital transformation keyword frequencies was obtained from Juchao Information Website; the marketization level data were obtained from the Report on China's Marketization Index by Provinces (2018) compiled by Wang et al. [24], and for years with missing data, the average growth of the marketization index in previous years was used for prediction by referring to Ma et al. [25]; The opportunity perception capability was calculated by using python to crawl the first three digits of the enterprise patent classification number and calculate the number of large groups; the data of dynamic capability was calculated by using the entropy value method with reference to Li et al. [14]; the rest of the data were obtained from CSMAR database (China Stock Market Accounting Research) and CNRDS database (Chinese Research Data Services). The data processing software is Stata17.

3.2. Variables

Dependent variable: enterprise innovation performance (EIP). In existing literature, there are two main ways to measure innovation performance, namely patents and sales of new products. However, since China does not require enterprises to disclose sales of new products in annual reports, obtaining sales of new products poses certain difficulties. So this paper uses the natural logarithm of the total number of patent applications add 1 to measure EIP then delaying innovation performance by one year.

Independent variable: digital transformation (DT). In this paper, we use Python to crawl the annual reports of manufacturing listed enterprises by using the keywords on ABCD technology and digital technology applications. Then we construct the digital transformation as the natural logarithm of the keyword frequency plus 1 [1].

Mediating variable: dynamic capability(DC). In this paper, dynamic capability is divided into four sub-dimensions, and dynamic capability is calculated after assigning different weights to the four sub-dimensions using the entropy value method [14].

- Opportunity perception capability (DC_Op): the breadth of knowledge base is measured by the number of technical fields involved in the invention patents. In the article, the five-year window period of the number of large groups in the International Technical Classification (IPC) of patents represents the strength of opportunity perception ability [26].

- Environmental adaptability (DC_Ad): the coefficient of variation of three key expenditures, R&D, capital, and advertising, reflects the flexibility of a firm to allocate resources in a dynamic environment [27]. The coefficient is calculated as follows: DC_Ad = - σ / m(%), where m and σ denote the mean and standard deviation of the intensity of the three expenditures of advertising, R&D, and capital, respectively.

- Coordination and integration capability (DC_Co): In this paper, we choose the asset turnover ratio to measure the coordination and integration capability of enterprises. The coordination and integration capability of dynamic capability can be measured by the net asset turnover ratio, which is calculated as follows. DC_Co = Operating income / [(Total net assets at the beginning of the period + Total net assets at the end of the period) / 2].

- Learning Absorption Capacity (DC_Ab): This paper draws on the study of Wu et al. [28] to measure the learning absorption capacity of firms in terms of R&D investment intensity (R&D investment / operating revenue).

Moderating variables: in this paper, the top management is defined as the president, CEO, general manager, vice president, chief financial officer, and other executive members disclosed in the annual report [14]. Top management's technical background (TMTB) is set as a dummy variable, and the variable top management's technology background takes the value of 1 if there are top management who have worked in R&D, otherwise it takes 0 [29]. Top management's social capital specifically refers to the capital closely related to politics, which is measured by the ratio of the number of top managers who has ever been employed by the governments (TMSC) to the total number ([30], [31]).

Control variables: Based on relevant studies, double dual positions (Dual), proportion of independent directors (Ind ratio), firm size (Size), age of listing (List age), ownership (SOE), equity concentration (Top1), gearing ratio (Ge ratio), firm cash flow (Cash), growth (Grow), firm performance (Roa), marketability index (Market index), organizational redundancy (Redundancy), year dummy variables (Y) and industry dummy variables (Ind) were selected as control variables for the study. The relevant measurement methods are kept for reference.

3.3. Model Setting and Empirical Strategy

Equations (1) and (2) are set up to test the mediating role of dynamic capabilities and the moderating role of top management's background. Other similar variables in the model are replaced in the corresponding positions.

$$EIP_{i,t+1} = \alpha_1+\alpha_2 DT_{i,t}+\alpha_3 DC_{i,t}+\Sigma\,\alpha CVs+\Sigma\,\alpha Y+\Sigma\,\alpha Ind+\varepsilon \tag{1}$$

$$DC_{i,t} = \alpha_1+\alpha_2 DT_{i,t}+\alpha_3 TMTB_{i,t}+\alpha_4 (DT*TMTB)_{i,t}+\Sigma\,\alpha CVs+\Sigma\,\alpha Y+\Sigma\,\alpha Ind+\varepsilon \tag{2}$$

In order to enhance the reliability of the regression results, the following treatments are made in this paper: First, considering that there is a certain time lag from the enterprise R&D patent to the patent application, this paper treats the innovation performance with a one-year delay. Second, this paper adopts the clustering robust standard error Cluster-adjusted t-statistic. Third, in order to control as many fixed effects as possible, the above regression equation controls the dummy variables of Year and Industry.

4. Results

4.1. Main and Mediating Effects

Drawing on the method of Wen and Ye [32], the results of the main effect and dynamic capability mediating effect test are shown in Table 1, M1 is a model with only control variables, M2 shows that the regression coefficient of innovation performance and digital transformation passes the significance test at 1% level, and H1 was tested. M3 analyzes the relationship between digital transformation and dynamic capabilities, and the regression coefficients also passes the significance test at the 1% level. The coefficient of digital transformation and dynamic capability in M4 is significant, and the coefficient of digital transformation decreases compared to M2, so the partial mediating role of dynamic capability is tested.

Table 1. Test for Main Effects and Mediating Effects

Variables	M1	M2	M3	M4
	F.EIP	F.EIP	DC	F.EIP
DT		0.145***	0.012***	0.088***
		(8.29)	(8.53)	(5.45)
DC				5.010***
				(22.16)
Cs/Y/Ind	YES	YES	YES	YES
Cons	-13.852***	-13.319***	-0.182***	-12.404***
	(-25.97)	(-25.15)	(-4.50)	(-26.68)
N	12444	12444	14785	12444
Adj.R^2	0.470	0.479	0.355	0.550

The results of the mediation test of dynamic capability sub-dimensions are shown in Table 2. In M1-M4, the regression coefficients of opportunity perception capability, environmental adaptation capability, coordination and integration capability, and learning and absorption capability on digital transformation all pass the significance test at the 1% level. Compared with the coefficients of M2 in Table 1, the coefficients of innovation performance and digital transformation are reduced after adding the mediating variables, and all of them pass the significance test at the 1% level, indicating that all four sub-dimensions of dynamic capabilities pass the test of partial mediation.

Table 2. Test for Mediating Effects on the Sub-dimension of Dynamic Capabilities

Variables	M1	M2	M3	M4	M5	M6	M7	M8
	DC_Op	DC_Ad	DC_Ci	DC_Ab	F.EIP	F.EIP	F.EIP	F.EIP
DT	0.071***	0.015***	0.031***	0.389***	0.104***	0.137***	0.143***	0.119***
	(5.18)	(3.83)	(2.76)	(6.45)	(7.25)	(7.89)	(8.20)	(6.76)
DC_Op					0.587***			
					(28.67)			
DC_Ad						0.592***		
						(9.01)		
DC_Ci							0.053*	
							(1.73)	
DC_Ab								0.068***
								(10.55)
Cs/Y/Ind	YES	YES	YES	YES	YES	YES	YES	YES

Cons	-11.297***	-0.353***	1.846***	5.750***	-6.617***	-13.132***	-13.413***	-13.723***
	(-25.77)	(-2.98)	(4.31)	(4.48)	(-13.74)	(-25.15)	(-25.11)	(-26.68)
N	14785	14785	14785	14785	12444	12444	12444	12444
Adj.R^2	0.500	0.144	0.519	0.323	0.589	0.490	0.480	0.497

4.2. Test for Moderating Effects

The results of testing the moderating effect of top management's characteristics are shown in Table 3. M1 tests the moderating effect of top management's technical background, and the interaction term between top management's technical background and digital transformation passes the significance test at the 5% level, indicating that top management's technical background positively moderates the relationship between digital transformation and dynamic capability. When it comes to M2, the interaction term of social capital and digital transformation passes the significance test at the 10% level. H3 and H5 are tested. M3 added top management's technology background and social capital to the regression, and the conclusion still holds.

Table 3. Test for Moderating Effects

Variables	**M1**	**M2**	**M3**
	DC	**DC**	**DC**
DT	0.008***	0.011***	0.007***
	(3.58)	(8.45)	(3.45)
TMTB	0.021***		0.021***
	(6.89)		(6.89)
DT*TMTB	0.005**		0.005**
	(2.20)		(2.24)
TMSC		0.006	0.004
		(0.75)	(0.53)
DT*TMSC		-0.012*	-0.012*
		(-1.81)	(-1.87)
Cs/Y/Ind	YES	YES	YES
Cons	-0.188***	-0.182***	-0.188***
	(-4.67)	(-4.50)	(-4.67)
N	14785	14785	14785
adj.R^2	0.363	0.355	0.363

4.3. Test for the Moderated Mediation

In this paper, referring to Wen and Ye [33], the moderated mediation is tested using sequential analysis, and the test results are shown in Table 4. M1 indicates that there is no moderating effect of top management's technical background on digital transformation and innovation performance, there is no direct effect of moderation, M2 indicates that there is a moderating effect of top management's technical background on digital transformation and dynamic capability, M3 shows that the regression between dynamic capability and innovation performance passes the significance test at 1% level, and the moderating effect of top management's technical background is effective through the intermediary path, and H4 is tested. The interaction term between top management's social capital and digital transformation in M4 is not significant, indicating that there is no moderating effect of social capital on the direct path, M5 shows that there is a moderating effect of top management's social capital on digital transformation and dynamic capability, and M6 shows that there is a moderating effect of top management's social capital on digital transformation and innovation performance. The regression coefficient of innovation performance on dynamic capability in M6 is significant, indicating that top management's social capital is regulating the relationship between digital transformation and innovation performance through the mediating path, and H6 is tested.

Table 4. Test for the Moderated Mediation

Variables	M1	M2	M3	M4	M5	M6
	F.EIP	DC	F.EIP	F.EIP	DC	F.EIP
DT	0.179***	0.008***	0.140***	0.144***	0.011***	0.088***
	(5.36)	(3.58)	(4.78)	(8.15)	(8.36)	(5.42)
DC			5.033***			5.005***
			(22.20)			(22.13)
TMTB	0.084*	0.021***	-0.028			
	(1.87)	(6.89)	(-0.71)			
DT*TMTB	-0.0430	0.005**	-0.067**			
	(-1.28)	(2.20)	(-2.25)			
TMSC				0.252**	0.00600	0.237**
				(2.37)	(0.69)	(2.57)
DT*TMSC				-0.075	-0.012*	-0.005
				(-0.94)	(-1.81)	(-0.07)
Cs/Y/Ind	YES	YES	YES	YES	YES	YES
Cons	-13.389***	-0.188***	-12.431***	-13.243***	-0.182***	-12.326***
	(-25.31)	(-4.67)	(-26.77)	(-25.01)	(-4.50)	(-26.55)
N	12444	14785	12444	12444	14785	12444
adj.R^2	0.480	0.363	0.551	0.480	0.355	0.551

4.4. Robustness Tests

Endogeneity test: Instrumental variables approach. Given the problem of possible reverse causality between digital transformation and innovation performance, this paper refers to the ideas of Zhao et al. [34] and Zhang et al. [35], uses the mean of other firms in the same industry (Other_DT), lag-1 (L.DT) and lag-2 (L.2DT) digital transformation over the same period of time as instrumental variables. Table 5 presents the regression results of the instrumental variables at two stages, M1 shows that the regression coefficient between the mean level of digital transformation of enterprises in the same industry and the level of digital transformation with one and two lags is significant, which is consistent with the instrumental variable correlation and also passes the weak instrumental variable test (F=4743.23), over-identification test (p=0.7039) and endogeneity test (p=0.0012), M2 shows that the regression coefficient of innovation performance on digital transformation passes the significance test at the 1% level after controlling for the endogeneity issue, and the positive relationship between the two still holds.

Endogeneity test: Heckman. In the sample of this study, sample bias may exit because of the inconsistency of companies undergoing digital transformation. To correct for possible sample selection bias, this paper uses the Heckman two-stage method to conduct the test. First, Dum_DT was assigned a value of 1 for firms that underwent digital transformation and a value of 0 for firms that did not. In M3, Dum_DT was regressed on control variables by using Dum_DT as the explained variable. Next, the probit model is applied to calculate the inverse mills ratio (imr). Finally, in M4, the inverse mills ratio (imr) is substituted into the equation for regression. M4 shows that the Imr coefficient is not significant and the sample is not severely biased.

Endogenous test: Propensity score matching method (PSM). In this paper, the propensity score matching method is used to eliminate the interference of non-treatment factors. First, the grouping is based on whether or not the company has undergone digital transformation, with Dum_DT assigned as 1 for the experimental group if the company has undergone digital transformation and 0 for the control group if the company has not undergone digital transformation. Second, the propensity scores were calculated using logit models based on the grouping variable Dum_DT, and finally, one-to-one nearest neighbor matching, radius matching, and kernel matching were performed based on the calculated weights. M5, M6, and M7 indicate that the regression coefficients of innovation performance on digital transformation passes the significance test at the 1% level for all three matching results.

Table 5. Endogeneity test results

Variables	Instrumental Variables		Heckman		PSM		
	M1	M2	M3	M4	M5	M6	M7
	DT	F.EIP	Dum_DT	F.EIP	One-to-One	Radius	kernel
DT		0.170***		0.128***	0.172***	0.144***	0.144***
		(11.68)		(5.49)	(8.80)	(8.24)	(8.24)
Other_DT	-0.092**						
	(-1.99)						
L.DT	0.693***						
	(53.15)						
L2.DT	0.154***						
	(11.49)						
Imr				0.121			
				(0.46)			
Cs/Y/Ind	YES	YES	YES	YES	YES	YES	YES
Cons	-0.635***	-12.585***	-5.902***	-13.333***	-13.393***	-14.403***	-13.430***
	(-3.09)	(-38.16)	(-10.81)	(-11.06)	(-19.89)	(-24.75)	(-24.75)
N	8300	8300	14784	7145	4973	12338	12338
Adj.R^2	0.741	0.485		0.475	0.434	0.472	0.472

Other robustness tests: The following robustness tests are conducted in this paper, and the specific results are kept for reference due to the limitation of space: (1) Sample strengthening test for digital transformation. In order to reduce the episodic nature of digital transformation, this paper increases the identification constraints of digitally transformed firms and selects those firms that have both utilized the underlying technology and conducted digital technology applications for analysis. (2) Change the core independent variables. Based on the indicators of the five dimensions of enterprise digital transformation, the entropy value method is further used to calculate the enterprise digital transformation index [36]. (3) Bootstrap test, which tests mediating effects, moderating effects, and moderated mediating effects on a sample of 5000 samples. (4) Sub-sample testing. Considering that enterprises with different ownership nature, different life cycles, and different geographical locations have large differences in various aspects of the enterprises, this paper divides the sample into sub-samples according to ownership, life cycles and geographical locations.

5. Discussion

5.1. Conclusions

This paper empirically tests the influence mechanism between digital transformation, dynamic capability and innovation performance, and investigate the variability of this mechanism under different top management's characteristics. The conclusions are as follows. First, digital transformation significantly affects innovation performance. Second, digital transformation affects innovation performance by influencing dynamic capabilities, including opportunity perception, environmental adaptation, coordination and integration, and learning and absorption. Finally, the more the top management has technical backgrounds, the more digital transformation can significantly contribute to enterprise innovation performance through enhancing dynamic capabilities. However, top management's social capital negatively moderates the relationship between digital transformation and dynamic capabilities.

5.2. Management Implications

Chinese manufacturing industry often encounters bottlenecks in industry upgrade. With digital era coming, digital transformation can be a sharp weapon for the manufacturing industry to get breakthrough by improving the enterprises' dynamic capabilities, which can integrate enterprise resources, improve the efficiency of resource utilization, and then promote the innovation of enterprises. As an important process capability of enterprises, dynamic capabilities are limited by the inertia of the organization. Enterprises need to actively explore new models, resolutely overcome old-fashionedism, and vigorously advocate the corporate culture of innovation for development. The dynamic capability should be evolved and then become an important support to serve the innovation of enterprises.

Chinese manufacturing enterprises should also build a reasonable top management team, in order to make full use of their talents and social capital. On the one hand, the enterprises could be better to employ top managers with technical background. These managers understand the importance of technology for enterprise development, and the scientific principle of technological innovation. Therefore, they have more willingness to promote the application of digital technology, and then improve the dynamic capabilities of the enterprises. On the other hand, the enterprises should not courage their top managers to enhance their social capital. Because top managers with high social capital will invest more energy in the establishment of social networks, other than the digital transformation.

5.3. Limitations and Future Directions

There are still some limitations in this study. Firstly, the research object of this study is manufacturing enterprises, whether the conclusions can be generalized to other industries has to be further verified. Secondly, dynamic capability has been divided into four dimensions from both external and internal orientation in this study. However, there still exists other decomposition dimensions of dynamic capabilities. So a different delineation of dynamic capabilities may possibly provide a new perspective for subsequent studies. Finally, based on dynamic capability theory and upper echelon theory, this study has only explored the mediating role of dynamic capability and the moderating role of the top management's features. Other mediating effects and moderating effects can be explored in the future researches.

References

[1] Wu Fei, Hu Huizhi, Lin Huiyan, Ren Xiaoyi. Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity [J]. Management World, 2021 ,37(07): 130-144.
[2] Vial, G. Understanding Digital Transformation: A Review and A Research Agenda [J]. The Journal of Strategic Information Systems, 2019, 28(2): 118-144.
[3] Li, F. The Digital Transformation of Business Models in the Creative Industries: A Holistic Framework and Emerging Trends [J]. Technovation, 2020, 92-93: 102012.
[4] Liu Qilei, Zhang Yuan, Lei Yuyan, Chen Guanju. Research on Process, Logic and Implementation Mechanism of Digital Enabling Enterprise Innovation [J]. Studies in Science of Science, 2022, 40(01): 150-159.
[5] Shen Guobing, Yuan Zhengyu. The Effect of Enterprise Internetization on the Innovation and Export of Chinese Enterprises [J]. Economic Research Journal, 2020, 55(1): 33-48.
[6] Qi Huaijin, Cao Xiuqin, Liu Yanxia. The Influence of Digital Economy on Corporate Governance: Analyzed from Information Asymmetry and Irrational Behavior Perspective [J]. Reform, 2020, (04): 50-64.
[7] Zhao Chenyu, Wang Wenchun, Li Xuesong. How Does Digital Transformation Affect the Total Factor Productivity of Enterprises? [J]. Finance and Trade Economics, 2021, 42(7): 114-129.
[8] Zhang Yongkun, Li Xiaobo, Xing Mingqiang. Enterprise Digital Transformation and Audit Pricing [J]. Audit Research, 2021, (3): 62-71.
[9] Manesh, M. F., M. M. Pellegrini, and G. Marzi, et al. Knowledge Management in the Fourth Industrial Revolution: Mapping the Literature and Scoping Future Avenues [J]. Transactions on Engineering Management, 2021, 68(1): 289-300.
[10] Singh, S., M. Sharma, and S. Dhir. Modeling The Effects of Digital Transformation in Indian Manufacturing Industry [J]. Technology in Society, 2021, 67: 101763.
[11] Zhang Jichang, Long Jing. Digital Transformation, Dynamic Capability, and Enterprise Innovation Performance: Empirical Evidence from High-Tech Listed Companies [J]. Economy and Management, 2022, 36(03): 74-83.
[12] Matarazzo, M., L. Penco, and G. Profumo, et al. Digital Transformation and Customer Value Creation in Made in Italy SMEs: A Dynamic Capabilities Perspective [J]. Journal of Business Research, 2021, 123: 642-656.
[13] Jafari Sadeghi, V., and P. P. Biancone. How Micro, Small and Medium-sized Enterprises Are Driven Outward The Superior International Trade Performance? A Multidimensional Study on Italian Food Sector [J]. Research in International Business and Finance, 2018, 45: 597-606.
[14] Li Mei, Zhu Yun, Zhao Qiao, Sun Siwan. R&D Internationalization, Dynamic Capability and Innovation Performance [J]. China Soft Science, 2022, (06): 169-180.
[15] Wang, C. L., and P. K. Ahmed. Dynamic Capabilities: A Review and Research Agenda [J]. International Journal of Management Reviews, 2007, 9(1): 31-51.
[16] Keller, R. T. Predictors of The Performance of Project Groups in R&D Organizations [J]. The Academy of Management Journal, 1986, 29(4): 715-726.
[17] Brousseau, K. R., and J. B. Prince. Job-person Dynamics: An Extension of Longitudinal Research [J]. Journal of Applied Psychology, 1981, 66(1): 59-62.
[18] Guo Lixin. Technical Executives, R&D Investment and Company Performance—From the Perspective of Dynamic Endogenous [J]. Journal of Technology Economics and Management, 2019, (04): 55-60.
[19] Faleye, O., T. Kovacs, and A.Venkateswaran. Do Better-Connected CEOs Innovate More? [J]. Journal of Financial And Quantitative Analysis, 2014, 49(5-6): 1201-1225.
[20] You Jiaxing, Zou Yufei. Social Capital, Diversification Strategy and Firm Performance: Based on the Perspective of the Entrepreneur's Embedded Network [J]. Nankai Business Review, 2014, 17(05): 91-101.
[21] Qin Shuangquan, Xin Minglei, Xiong Chaohui. Empirical Analysis on Relationship between Ability of TMT and Enterpise Performance: Considering Regulatory Effect of CEO'Guanxi [J]. Techno-economic, 2014, 33(06): 117-123.
[22] Li Jing, He Xiaogang. Entrepreneurial Teams' Financial Capital and Firm Innovative Performance [J]. Scientific Management Research, 2014, 34(1): 201-207.
[23] Xiao Xingzhi, Wang Yinpan. Government Subsidies and Enterprise Decision of Social Capital Investment-Evidence from Strategic Emerging Industries [J]. China Industrial Economics, 2014, (09): 148-160.
[24] Wang Xiaolu, Fan Gang, Hu Lipeng. China Marketability Index Report by Province (2018) [M]. Social Science Literature Press, 2019.

[25] Ma Lianfu, Wang Lili, Zhang Qi. The optimal choice of mixed ownership system: the logic of the market [J]. China Industrial Economics, 2015, 33(7): 5-20.
[26] Cai Hong, Liu Yan, Xiang Xiyao. The Influence of Knowledge Base on Technology Collaboration: A test in Chinese Electrical & Electrical Industry [J]. Journal of Management, 2013, 10(6): 875-881.
[27] Zhao Feng, Wang Tienan, Wang Yu. External Technology Acquisition in Open Innovation and Product Diversification: The Moderating Effect of Dynamic Capabilities [J]. Business Review, 2016, 28(6): 76-85.
[28] Wu, J., C. Wang, and J. Hong, et al. Internationalization And Innovation Performance of Emerging Market Enterprises: The Role of Host-country Institutional Development [J]. Journal Of World Business, 2016, 51(2): 251-263.
[29] Hao Panpan, Zhang Xindong, He Yanan. Research on the Influence of CEO's R&D Experience on R&D Activities of Enterprises [J]. Soft Science, 2019, 33(8): 7-13.
[30] Du Xingqiang, Zeng Quan, Du Yinjie. Do Political Ties Have a "Crowding Out" Effect on R&D Investments by Chinese Listed Companies? [J]. Investment Research, 2012, 31(05): 98-113.
[31] Sheng Yuhua, Zhu Sailin. Study on the Influence of Independent Directors on Corporate Strategic Change-Based on the Perspective of Human Capital and Social Capital [J]. Soft Science, 2021, 35(02): 60-66.
[32] Wen Zhonglin, Ye Baojuan. Analyses of Mediating Effects: The Development of Methods and Models [J]. Advances in Psychological Science, 2014, 22(05): 731-745.
[33] Wen Zhonglin, Ye Baojuan. Different Methods for Testing Moderated Mediation Models: Competitors or Backups?[J]. Psychology Journal, 2014, 46(05): 714-726.
[34] Zhao Le, Wang Kun, Ren Hongda. CFO Executive Ranking and Corporate Investment Efficiency [J]. China Accounting Review, 2020, 18(3); 407-436.
[35] Zhang Dong, Hu Wenlong, Mao Xinshu. Power of R&D Background Executives and Corporate Innovation [J]. China Industrial Economics, 2021, (4): 156-174.
[36] Guo Feng, Yang Shangguang, Chai Zeyang. Does Digital Transformation of Enterprises Improve the Quantity and Quality of Green Technology Innovation? Text Analysis Based on Annual Reports of Chinese Listed Companies [J]. Southern Economy, 2023, 401(02): 146-162.