A Study on the Mechanism of Digital Transformation and Corporate Innovation——Taking a Listed Manufacturing Company as an Example

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Abstract: With innovation driving the high-quality development of the manufacturing industry and digitalization empowering the manufacturing industry being an important issue in China's economic development pattern, the research on the relationship between digital transformation and innovation in the manufacturing industry has become more and more critical. In view of this, this paper empirically examines the relationship between the two and analyzes its mechanism of action by selecting A-share listed manufacturing companies in Shanghai and Shenzhen from 2016 to 2020 as research samples. The study finds that digital transformation can promote corporate innovation and absorptive capacity; absorptive capacity plays a part in mediating the relationship between digital transformation and corporate innovation. Further, by considering two influencing factors, namely whether the overseas branch is located in a Belt and Road country and the level of digital development in the region, it was found that manufacturing companies with overseas branches in a Belt and Road country can significantly increase Digital transformation has a significantly higher impact on innovation and absorptive capacity, while the former has a weaker mediating effect than the latter; manufacturing companies in the first tier of regional digital development have a significantly weaker impact on innovation and absorptive capacity than those in the second tier, while those in the third tier have no significant impact on innovation and an impact on absorptive capacity. . The role of absorptive capacity in mediating digital transformation and corporate innovation gradually increases from the first to the third echelon. This paper expects that the research findings obtained can be of some reference value for China's manufacturing enterprises in terms of enterprise innovation and knowledge absorption decisions under the wave of digital economy, so as to change the unfavourable situation of manufacturing enterprises being large but not strong, and transform from a "large manufacturing country" to a "strong manufacturing country". This will change the unfavourable situation of manufacturing enterprises which are big but not strong, and transform from "big manufacturing country" to "strong manufacturing country".

Key words: digital transformation; enterprise innovation; absorptive capacity; "One Belt, One Road"; regional digital development level.

1. Introduction

Artificial intelligence, blockchain, cloud computing, big data and other products of the new round of information technology revolution and development have propelled the world into the era of digital economy. The Central Committee of the Party attaches full importance to the development of the digital economy and has clearly proposed in the report of the 19th National Congress that "we should promote the deep integration of the Internet, big data, artificial intelligence and the real economy". At present, China's digital economy is gaining momentum, with the size of China's digital economy reaching RMB 39.2 trillion in 2020, accounting for 38.6% of GDP. The digital economy has broken the boundary nature of market players and changed the ecological environment in which enterprises previously lived, with the trend of interpenetration and mutual influence among enterprises gradually increasing, and a wider range of access to and absorption of external information (Xiao Xu et al., 2019), and a more flexible way of resource deployment and allocation. For this reason, more and more countries are focusing their digital transformation on manufacturing, such as the United States, which is revitalizing advanced manufacturing, Germany, which is actively implementing Industry 4.0, and Japan, which is building a smart society with technological innovation and "connected industry" as the key. As the world's largest developing country, China's manufacturing industry has been expanding since the reform and opening up, and has become a veritable factory of the world. However, for a long time, the development of the manufacturing industry has been in the unfavourable situation of being large but not strong, comprehensive but not excellent, and weak in science and innovation. Under this historical condition, by opening the road of digital transformation, digital transformation is taken as the strategic core of enterprises, and the combination of digital technology and physical manufacturing is used to promote the innovative development of enterprises. Therefore, whether manufacturing enterprises can adequately seize the opportunity in the digital wave and give full play to the empowering effect of digital transformation in innovation is an important direction for current theoretical research and practical exploration.

In recent years, many researchers at home and abroad have conducted research on the relationship between digital transformation and enterprise innovation. Abouzeedan et al (2013) point out that when companies introduce Internet-based management into their management paradigm, they can flexibly respond to the unique challenges posed by innovation, and can also be able to develop their own innovation strategies. Nwankp et al (2017) verified the positive relationship through a questionnaire survey. Xiao Renqiao et al (2021) found an inverted U-shaped relationship between the level of digitalisation and product innovation development based on the dual innovation theory. An Tongliang et al. (2022) used A-share listed companies as a sample and found that digital transformation positively promoted innovation behaviour, while the positive effect of digital transformation on innovation was significantly higher than the application of digital technology alone. Using a questionnaire survey method, Yu Wei et al. (2022) found that digital transformation plays a mediating role in entrepreneurial capabilities and innovation performance, and that entrepreneurs should increase their digital development efforts to enhance corporate innovation capabilities. Based on rooting theory, Liu Qilei et al. (2022) studied two enterprises, Xuzhou Engineering Group and Shaanxi Automobile Group, and elucidated the mechanism of digitalisation's role in empowering enterprise innovation from different strategic levels and different paths such as supply and demand sides. All in all, previous scholars have laid a deep foundation for the relationship between digital transformation and enterprise innovation behaviour, which facilitates further research by future generations, but there are also some shortcomings. Firstly, when it comes to the relationship between digital transformation and corporate innovation, existing scholars have not yet studied the influencing mechanisms in depth, resulting in an incomplete construction of this theoretical model. Secondly, most scholars use questionnaires to quantify the degree of digital transformation, which is affected by the uneven distribution of respondents and subjective factors, leading to some limitations in the measured results to a certain extent. In view of this, this paper further refines the findings in this area by taking a sample of manufacturing companies on the main board listed on the Shanghai and Shenzhen A-shares from 2016-2020, combining the data presented in the Guotaian (CSMAR) database using textual analysis to measure digitalisation, and using the indicator of absorptive capacity to identify intermediate mechanisms.

The possible research contributions of this paper are: firstly, further refinement and expansion of the research subject, which is limited to manufacturing enterprises, filling the research gap that most studies in this field in the literature have not distinguished between different types of enterprises. Secondly, based on the verification of the role of digital transformation in promoting innovation behaviour, this paper explores the role of absorptive capacity in mediating digital transformation and innovation behaviour, opening up the "black box" of the relationship between cause and effect. Thirdly, considering that the enterprise is an open system, this paper provides some insights into the influence of the degree of internationalisation of the enterprise and the level of digital development of the city in which the enterprise is located on the digital transformation and the enterprise in the heterogeneity analysis, so as to provide some insights into the external environment of the enterprise when formulating digital transformation strategies and innovation strategies.

2. Formulation of the hypothesis

2.1 Digital transformation and enterprise innovation

Digital transformation is usually reflected in the use of digital technology in various functional modules of the company and the embedding of digital devices into the business processes of the company, which counts as an organisational change for manufacturing companies. As mentioned by Vial (2019), the digital transformation process is a shift in the way value is created, further improving the efficiency of production operations and ultimately the competitive position of the company. Innovation, on the other hand, is precisely the transformation of a company's existing resource portfolio at a certain level of management, through the creation of new things as a way to gain certain economic benefits and further gain a real competitive advantage under the competitive market. Studies have shown that digital transformation has a positive effect on innovation in three ways: firstly, it reduces the risk of innovation, and the investment in digital technologies (e.g. MES and ERP software) enables companies to achieve fine-grained management and improve their control of their own innovation activities. Good management of innovation activities through organisational planning, division of labour, authorisation and approval, and independent responsibility systems can effectively avoid the possibility of risk-taking by managers at all levels (Rui Lun, 2016), reduce over-exploitation, and enable innovation investments to be rewarded accordingly. Secondly, digital transformation drives the efficiency of enterprise innovation. With cloud computing, computer software and big data analysis, enterprises are better able to use the past as a reference to predict the future and gather multiple players to collaborate on innovation, enabling them to effectively assess market opportunities and threats, make optimal decisions, and precisely create new high value-added products with better market fit and wider market coverage (Yin Qun et al. 2021), for example, Haier Group, by creating a human-unit integration and taking advantage of the convenience brought by the IoT, has been able to remove the traditional appliance label and use more perfect products and scenarios to create a high quality of life for its users. Finally, digital transformation saves companies the cost of innovation. Through the use of digital devices, all kinds of cost information in innovation can be quickly transmitted to other departments, and through the analysis of data, scientific and reasonable financial budgets can be formulated. In addition, it allows financial personnel to fully understand the actual production and operation of manufacturing enterprises big data analysis activities to ensure the successful completion of cost refinement management objectives, reduce cost expenditure and increase competitive advantage. Based on the above analysis, this paper puts forward the following hypotheses.

H1: Digital transformation and enterprise innovation are positively correlated

2.2 Digital transformation and absorptive capacity

According to Cohen and Levinthal, absorptive capacity is the ability of a firm to identify new knowledge in a particular field that has potential for use and to evaluate and digest that new knowledge so that it can be commercially applied. The first step is to identify a piece of knowledge and select the potentially valuable knowledge that fits its development plan and its conditions. The final step is to apply the knowledge, which by now has the characteristics of an enterprise and can be flexibly used by the enterprise to create new market value and commercialise it.

At this stage, "digitalisation" will be used throughout the entire process of applying absorptive capacity, and companies that undergo digital transformation will have a good impact on their absorptive capacity. In the identification stage, digital transformation can significantly improve the ability of enterprises to identify and acquire knowledge, and enterprises undergoing digital transformation increasingly show an open organisation without boundaries across time and space, and the acquisition of knowledge does not only occur in the workplace (Swap. et al, 2001). that enterprises have more diversified access to knowledge, the structure of knowledge is more complete, and enterprises choose knowledge to provide room for more flexible solutions for subsequent application to different scenarios. The investment in digital technology brings more heterogeneous knowledge to enterprises, and Jiang Lixin et al. (2022) point out that the existence of heterogeneous knowledge drives the integration of knowledge in enterprises. In the integration stage, digital technology inputs are carried out to enable integrated learning through the updating of knowledge inventories and the filling of technological discontinuities, so that the newly drawn knowledge of the enterprise collides and merges with the existing knowledge (Jiang, Lixin et al., 2022). The last stage is the application stage, where for enterprises, greatly satisfying customer needs and enhancing customer experience is the focus of commercialisation. Driven by big data, the chances of successful commercialisation processing are also greater and the efficiency of application is significantly improved by accurately identifying target user information through website visitor capture and mobile application user acquisition, analysing user preferences and deriving a user market that matches the enterprise. Based on the above analysis, this paper proposes the following hypothesis.

H2: Digital transformation is positively correlated with absorptive capacity

2.3 The mediating role of absorptive capacity

Digital transformation facilitates the ability of companies to absorb knowledge to further drive innovation. Through digital transformation, companies can access not only customer needs but also information about competitors, upstream suppliers and downstream distributors. In addition, in today's information explosion, companies undergoing digital transformation have more diverse access to information, reducing the dependence on time and space for information acquisition. When information converges in an enterprise, its innovative value can only be exploited if it is fully utilised. The stronger the absorption capacity of different functional departments, the stronger their ability to control the information they come into contact with, and the greater the possibility of stripping out useful knowledge from the information. The direction of product, process and service innovation of the enterprise that is applicable to the current business environment is found, and innovation is promoted (Xie Hongming et al., 2007). Based on the above analysis, this paper proposes the following hypothesis.

H3: Absorptive capacity plays a mediating role between digital transformation and corporate innovation.

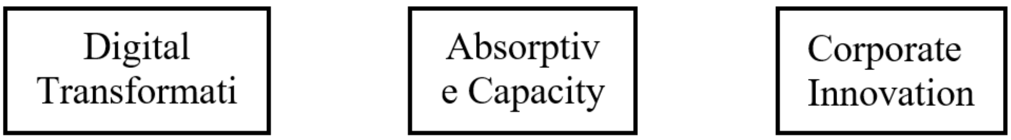

Fig. 1 Schematic diagram of the research model

3. Research design

3.1 Sample selection and sources

The reason for taking 2016 as the starting year of the study is that in May 2015, the State Council issued the strategy document "Made in China 2025", which is the action plan to promote the strategy of manufacturing power in China. According to the "PEST" analysis method, changes in the policy environment will, to a certain extent, cause certain fluctuations in the statistics of the adjacent two years, and therefore need to be avoided.

With reference to the experience of other scholars and in line with this paper's research ideas, the data were processed as follows: (1) ensure that the duration of the company covers five years from 2016 to 2020; (2) exclude companies in the financial sector; (3) exclude ST and *ST companies; (4) exclude companies with serious data deficiencies. The data of listed companies were obtained from the Guotaian (CSMAR) database and supplemented by the Wind database, resulting in 5,520 observations for manufacturing companies. The data processing software used in this paper is Stata 17.0.

3.2 Definition of variables

3.2.1 Explanatory variable: innovation investment (R&D)

Referring to the study by Yang Yaping et al. (2021), given the availability of data for listed companies, this paper chooses the ratio of R&D investment to operating revenue to measure corporate innovation investment.

3.2.2 Explanatory variable: digital transformation (DT)

Referring to the study of domestic scholars (Lou Ruping, 2022), the ratio of software investment to total assets in digital investment is used to measure, with software investment coming from accounting accounts where software or information system investment is digital technology-related in the intangible assets of the enterprise's annual report.

3.2.3 Mediating variable: absorptive capacity (AC)

Absorptive capacity is the key ability of enterprises to digest and effectively use knowledge, which is subject to individual cognitive ability and built on top of individual cognitive level, so the quality of enterprise employees enterprise's absorptive capacity has an important role. In this paper, based on studies such as Luo Min et al. (2009), Liu Yaolong (2017) and Zhang Nana (2019), the proportion of employees with a bachelor's degree or above to the total number of employees is selected for measurement.

3.2.4 Control variables.

Combining the studies of different scholars such as Liu Yaolong (2017) as well as Wang Molin et al. (2021), the following indicators that would have an impact on firms' innovation behaviour were selected and introduced as control variables: firm size (Size), gearing (Lev), nature of ownership (Soe), firm value (TobinQ), years of listing (ListAge), years of firm establishment (FirmAge), shareholding ratio of top shareholder (Top1), shareholding ratio of institutional investors (INST), shareholding ratio of management (Mshare), management expense ratio (Mfee), and capital employed by major shareholders (Occupy). The year (Year), industry (Ind) and province (Province) are also controlled for.

The specific variables above are detailed in Table 1.

Table 1. Variable names, symbols and descriptions

Varible	Symbol	Illustrate
Independable Varible	$R\&D$	The ratio of R&D to operating revenue
Dependable Varible	DT	The ratio of software investment to total assets
Mediating Variable	AC	The ratio of employees with bachelor degree or above to total employees
	$Lnsize$	Natural logarithm of total business assets
	Lev	The ratio of year-end total liabilities to year-end total assets
	Soe	The value of state-owned holding company is 1, the other is 0.
	$TobinQ$	The ratio of sum of market value of tradable shares and product of number of non-tradable shares and net assets per share and book value of liabilities to total assets
	$Listage$	Natural logarithm of the current year minus the year of establishment plus 1
	$FirmAge$	Natural logarithm of the current year minus listing year plus 1
Controls Variables	$Top1$	The ratio of the number of shares held by the largest shareholder to the total number of shares
	$INST$	The ratio of the number of shares held by institutional investors to the total number of shares
	$Mshare$	The ratio of the number of shares held by management's shareholding the total number of shares
	$Mfee$	The ratio of management costs to operating revenue
	$Occupy$	The ratio of other receivables to total assets
	$Year$	Year dummy variable
	Ind	Industry dummy variable
	$Province$	Province dummy variable

3.3 Model

$$R\&D_{i,t,j} = \alpha_0 + \alpha_1 DT_{i,t,j} + \sum\alpha_k Control_{i,t,j} + \sum Year + \sum Ind + \sum Province + \varepsilon_{i,t,j} \quad (1)$$

$$AC_{i,t,j} = \beta_0 + \beta_1 DT_{i,t,j} + +\sum\beta_k Control_{i,t,j} + \sum Year + \sum Ind + \sum Province + \delta_{i,t,j} \quad (2)$$

$$R\&D_{i,t,j} = \gamma_0 + \gamma_1 DT_{i,t,j} + \gamma_2 AC_{i,t,j} + \sum\gamma_k Control_{i,t,j} + \sum Year + \sum Ind + \sum Province + \tau_{i,t,j} \quad (3)$$

In above models, i represents the enterprise, t represents the time, and j represents the province, α_0, β_0 and γ_0 represent the intercept terms of their respective models, $\alpha_1 \sim \alpha_k$, $\beta_1 \sim \beta_k$ and $\gamma_1 \sim \gamma_k$ isthe regression coefficient of the corresponding variable, Contral is the controls variables , Year is the year dummy variable, Ind is the industry dummy variable, Province is the province dummy variable, $\varepsilon_{i,t,j}$, $\gamma_{i,t,j}$ and $\tau_{i,t,j}$ are the random disturbance terms of their respective models.

4. Analysis of the empirical results

4.1 Descriptive statistical analysis

Table 2 presents the descriptive statistical characteristics of all variables. Accordingly, it can be seen that the innovation behaviour (R&D) of listed manufacturing enterprises in China varies very significantly. According to the previous calculation method, the mean value of the average R&D expenditure of the sample observation enterprises is 0.05 and the standard deviation is 0.050, while the difference between the maximum value and the minimum value is about 76.3%, which is a significant difference, indicating that the innovation level of manufacturing enterprises in China varies. This is basically consistent with the results of existing studies. Secondly, there is also a significant difference in the status of digital transformation (DT) among enterprises in China, with a standard deviation of 1.11. The difference in the stage and degree of digital transformation among different enterprises is continuously expanding, but overall, the digital transformation of enterprises is showing a rapid development trend. Again, the mean value of learning absorption capacity (AC) is 23.012, indicating that the percentage of employees with a bachelor's degree or above in the sample companies is about 23%, and the average education level of employees is low. From an economic logic analysis, the differential development of the digital transformation of enterprises and the lack of high-end talents are possible reasons for the differences in innovation behaviour of enterprises. Finally, the statistical characteristics of other control variables also deserve our attention: from the firm-level data, the mean value of management shareholding ratio (Mshare) is at 14.4%, with a standard deviation of 0.208, indicating that the sample firms generally attach importance to executive shareholding incentives, and the proportion of executive shareholding is relatively stable; in addition, the differences between firms in terms of firm size (Size) and profitability (TobinQ) are In addition, there are large differences between companies in terms of company size and profitability.

Table 2. Descriptive Statistics for Primary Variables

Variable	size	Mean	SD	Max	Min
R&D	5520	0.05	0.050	0.763	0
DT	5522	0.105	0.165	0.999	0
AC	5520	23.012	17.583	91.44	0.007
Size	5520	22.42	1.213	27.547	17.954
Lev	5520	0.412	0.182	1.748	0.008
Soe	5520	0.28	0.449	1	0
TobinQ	5520	1.983	1.718	58.592	0
ListAge	5520	2.201	0.838	3.434	0
FirmAge	5520	2.959	0.292	3.989	1.792
Top1	5520	0.333	0.146	0.891	0.029
INST	5520	0.39	0.241	3.267	0
Mshare	5520	0.144	0.208	3.198	0
Mfee	5520	0.082	0.119	7.284	0.002
Occupy	5520	0.013	0.024	0.447	0

4.2 Correlation analysis

The results of the correlation analysis and discussion of the main variables in this paper are shown in Table 3 below. from the correlation coefficient matrix, it can be seen that: firstly, the digital transformation and innovation behaviour of enterprises are significantly positive at the 1% significance level, which means that the digital transformation construction of enterprises can further enhance their R&D investment intensity and strengthen their innovation capability. Secondly, the correlation coefficient between digital transformation and absorptive capacity is 0.302, which passes the 1% significance level test. There is a positive correlation between digital transformation and absorptive capacity, which indicates that the higher the degree of digital transformation of an enterprise, the stronger its ability to learn and absorb new knowledge from the outside world. Thirdly, there is also a significant positive relationship between absorptive capacity and innovation behaviour. This initially supports the research hypothesis of this paper. In addition, the relationship between the control variables, the explanatory variables and the explained variables is consistent with what was expected during the design of the aforementioned variables.

Further, the correlation coefficient between the variables was less than 0.7, indicating a low correlation between the variables. Meanwhile, this paper conducted variance inflation factor tests on all explanatory variables, and the results showed that the average VIF of all explanatory variables was 1.46, which was much smaller than the threshold value of 10, ruling out the possibility of serious multicollinearity among the explanatory variables. Overall, the relationships of the variables selected in this paper are all in line with expectations, and linear regression of the above variables is appropriate, and the influential relationships between the variables can be further confirmed through the following empirical process.

Table 3. Spearman's correlation coefficient between the variables

	R&D	DT	AC	Size	Lev	Soe	TobinQ
R&D	1.000						
DT	0.218***	1.000					
AC	0.489***	0.302***	1.000				
Size	-0.105***	-0.058***	0.060***	1.000			
Lev	-0.156***	-0.034**	-0.048***	0.441***	1.000		
Soe	-0.072***	0.027**	0.116***	0.317***	0.204***	1.000	
Tobinq	0.187***	0.055***	0.115***	-0.254***	-0.142***	-0.037***	1.000
ListAge	-0.053***	-0.054***	0.099***	0.457***	0.275***	0.406***	0.012
FirmAge	-0.082***	-0.035***	0.007	0.161***	0.115***	0.241***	0.010
Top1	-0.144***	-0.035***	-0.109***	0.079***	-0.030**	0.177***	-0.008
INST	-0.127***	-0.048***	0.005	0.450***	0.160***	0.367***	0.065***
Mshare	0.094***	0.042***	-0.015	-0.331***	-0.217***	-0.389***	-0.011
Mfee	0.442***	0.064***	0.184***	-0.150***	-0.053***	-0.031**	0.146***
Occupy	-0.003	0.040***	0.079***	-0.014	0.138***	-0.026*	0.102***
	ListAge	**FirmAge**	**Top1**	**INST**	**Mshare**	**Mfee**	**Occupy**
ListAge	1.000						
FirmAge	0.473***	1.000					
Top1	-0.156***	-0.048***	1.000				
INST	0.402***	0.197***	0.352***	1.000			
Mshare	-0.544***	-0.258***	-0.031**	-0.533***	1.000		
Mfee	-0.020	-0.059***	-0.068***	-0.096***	0.000	1.000	
Occupy	0.095***	0.024*	-0.110***	-0.034**	-0.050***	0.049***	1.000

Note: ***, ** and * indicate significant at the 1%, 5% and 10% levels respectively.

4.3 Analysis of regression results

Table 4 presents the results of the regression analysis, with all regressions controlling for year, industry and province fixed effects in order to prevent omission of time-, industry- and province-level characteristic variables. Column (1) is the baseline model and includes all control variables. Column (2) introduces explanatory variables to explore the role of digital transformation (DT) of enterprises on innovation behaviour (R&D), and finds that the regression coefficient of DT is significantly positive at the 1% significance level, indicating that digital transformation can significantly promote enterprises' innovation behaviour and increase R&D investment, supporting hypothesis H1.

This paper refers to the recursive equation of Wen Zhonglin et al. for further testing of mediating effects. Column (3) tests the effect of the explanatory variable (DT) on the mediating variable (AC) and finds that DT is significantly positively correlated with AC, indicating that digital transformation also has a significant facilitating effect on firms' learning absorption capacity, proving hypothesis H2. The coefficients of AC and DT in the regression results of column (4) are still significantly positive, but the coefficient value and significance of DT are significantly lower compared with column (2), which implies The existence of a partially mediated transmission effect, i.e. that digital transformation can facilitate firms' innovative behaviour by promoting learning absorptive capacity, is verified by hypothesis H3.

To ensure the robustness of the intermediate mechanism, this paper uses the Sobel test to test the above intermediate path: firstly, three significance tests are provided during the Sgmediation command test, namely the Sobel, Goodman1 and Goodman2 tests, all of which are significant; secondly, in terms of effect size, the coefficient of the intermediate effect of firm absorptive capacity is 0.03342645 (p=0.000), further validating the existence of the mediating effect.

The above empirical results further confirm the mechanism of the effect of digital transformation on enterprises' innovation behaviour, i.e. "digital transformation-learning absorptive capacity-innovation behaviour". 2016-2020 Chinese manufacturing enterprises There are two paths for digital transformation and upgrading to influence the innovation behaviour of enterprises: one is the direct promotion effect, and the other is the indirect promotion effect mediated by absorptive capacity, in which the indirect promotion effect mediated by absorptive capacity accounts for 61.91% of the total effect.

Table 4. Results of regression analysis

Variable	Explanatory variables			
	(1)	(2)	(3)	(4)
	R&D	R&D	AC	R&D
DT		0.0176***	10.52***	0.00993*
		(3.94)	(6.45)	(2.33)
AC				0.000730***
				(15.46)
Controls	Control	Control	Control	Control
Year	Control	Control	Control	Control
Province	Control	Control	Control	Control
Industry	Control	Control	Control	Control
_cons	-0.0629***	-0.0654**	-50.89***	-0.0283
	(-2.707)	(-2.84)	(-9.42)	(-1.22)
N	5520	5520	5520	5520
R-squared	0.4875	0.4988	0.4748	0.5332
Sobel Testing	0.03342645（z=18.99）			
Goodman Testing1	0.03342645（z=18.99）			
Goodman Testing2	0.03342645（z=19）			
Intermediation effect factor	0.03342645（z=18.992）			
Intermediary effect ratio	0.61911536			

Note: ***, ** and * represent significant at the 1%, 5% and 10% levels respectively; t-statistic in brackets; cons are intercept variables.

4.4 Robustness test

Considering that bias in the selection of samples and estimation methods may lead to biased estimation results, this paper tests the robustness of the mediated effects model results.

4.4.1 Bootstrap Self-sampling

In this paper, Bootstrap self-service sampling was used to randomly repeat sampling of the existing sample, set to draw 5000 times, with the same sample size as the original sample size each time, and the confidence interval was set to 95% to further test the robustness of the baseline model regression results, which are shown in Table 5. Table 5 shows that the mediating effect of digital transformation affecting firms' innovation behaviour through absorptive capacity is 0.0334265 and the direct effect is 0.0205642, both significant at the 1% significance level, and the CI of the confidence interval corresponding to both the direct and indirect effects does not contain 0. This indicates that the direct facilitation effect of digital transformation on digital transformation and the mediating effect through absorptive capacity are both significantly present, and the robustness of the regression results of the benchmark model is verified.

Table 5. Results of the Bootstrap intermediate effects test

Effect	Learning absorption capacity			
	Estimated values	z	P>|z|	95% Confidence interval
Ind－Eff	0.0334265	9.32	0.000	[0.026396—0.00404569]
Dir－Eff	0.0205642	4.36	0.000	[0.0113218—0.0298067]
Tot－Eff	0.0539907	8.50	0.000	[0.0415298—0.0664415]

Note: The significance of the Bootstrap study method focuses on the confidence intervals, which are significant if they do not contain 0 and insignificant if they do.

4.4.2 Substitution of core explanatory variables

Referring to Wu Fei et al.'s (2021) research idea of using the frequency of key words related to digital transformation in enterprises' annual reports as digital transformation indicators, the data of the four related subdivision indicators of artificial intelligence technology, blockchain technology, cloud computing technology and big data technology in the "digital economy" series of the Cathay Capital (CSMAR) database were summed up and added up to the natural logarithm. The data were summed up and the natural logarithm was taken by adding 1. In order to test the reliability of the results, the explanatory variables were replaced with the main test for robustness. The results of the regression analysis in Table 6 show that the coefficient of the frequency of words related to digital transformation is significantly positive at the 1% level of significance, indicating that the percentage of digital transformation still has a significant positive effect on the innovation behaviour of enterprises, and the hypothesis H1 of this paper still holds. In addition, the sign and significance of the estimated coefficients of the core explanatory variables and mediating variables are consistent with the baseline regression model in Table 4, H2 and H3, and the relationship between the total effect, direct effect and mediating effect is also consistent with the baseline regression model, indicating that the estimated results of this paper's model are somewhat robust.

Table 6. Results of regression analysis with replacement of core explanatory variables

Variables	Explanatory variables		
	(1)	(2)	(3)
	R&D	AC	R&D
DT	0.00348***	3.133***	0.00120**
	(5.96)	(14.73)	(2.08)
AC			0.000726***
			(15.05)
Controls	Control	Control	Control
Year	Control	Control	Control
Province	Control	Control	Control
Industry	Control	Control	Control
_cons	-0.0549*	-42.13***	-0.0243
	(-2.34)	(-7.70)	(-1.05)
N	5520	5520	5520
R-squared	0.4999	0.4922	0.5328
Sobel Testing		0.00666429（z=22.81）	
Goodman Testing1		0.00666429（z=22.81）	
Goodman Testing2		0.00666429（z=22.81）	
Intermediation effect factor		0.006664（z=22.814）	
Intermediary effect ratio		0.57939223	

Note: ***, ** and * represent significant at the 1%, 5% and 10% levels respectively; t-statistic in parentheses; cons are intercept variables.

4.4.3 Excluding unusual years

In order to make the sample random, the sample during the New Coronary Pneumonia outbreak (2020) was excluded from this paper for robustness testing, and the results of the regression analysis are shown in Table 7. The results show that the magnitude and direction of the coefficients and the significance level of each variable remain basically the same as the previous baseline regression after excluding the samples of the outlier years, which proves that the findings of the study are robust.

Table 7. Results of the regression analysis excluding abnormal years

Variables	Explanatory variables		
	(1)	(2)	(3)
	R&D	AC	R&D
DT	0.00306***	3.203***	0.000857*
	(4.66)	(13.18)	(1.79)
AC			0.000718***
			(13.09)
Controls	Control	Control	Control
Year	Control	Control	Control
Province	Control	Control	Control
Industry	Control	Control	Control
_cons	-0.0737**	-44.41***	-0.0249
	(-2.65)	(-7.12)	(-0.96)
N	4255	4255	4255
R-squared	0.4923	0.5374	0.5451
Sobel Testing		0.00657659（z=19.84）	
Goodman Testing1		0.00657659（z=19.83）	
Goodman Testing2		0.00657659（z=19.85）	
Intermediation effect factor		0.011058（z=18.9334）	
Intermediary effect ratio		0.59475355	

Note: ***, ** and * represent significant at the 1%, 5% and 10% levels respectively; t-statistic in parentheses; cons are intercept variables.

4.5 Endogenous processing

4.5.1 Instrumental variables approach

Drawing on the idea of Zhang Dong et al. in selecting instrumental variables, this paper uses the lagged period of digital transformation (L.DT) as an instrumental variable and uses IV-2SLS estimation methods for endogeneity testing. The logic of setting the instrumental variables in this way is that the relevance and exogeneity requirements of the instrumental variables are satisfied as the level of digital transformation in the lagged period is directly related to the importance that firms place on their own digital transformation, but does not directly affect their innovation behaviour.

Table 8 presents the results of the two-stage estimation regression. Column (1) shows the results of the first stage estimation, where the L.DT coefficient is significantly positive at the 1% statistical level, while the F-value of the first stage is much larger than the weak instrumental variable identification of 9.08 given by Stock et al. indicating that the instrument facilitates ah that validity and there is no weak instrumental variable problem. Column (2) shows the results of the second stage estimation, showing that the coefficient of the digital transformation regression is significantly positive at the 1% statistical level, indicating that the significance of digital transformation on firms' innovative behaviour remains largely consistent with the previous benchmark regression after controlling for endogeneity issues, and therefore the study's findings are robust.

4.5.2 Heckman two-stage method

The descriptive statistical analysis shows that not all companies in the sample have undergone digital transformation and some have not, leading to a possible sample selectivity bias in the sample. In view of this, this paper draws on the treatment of other scholars and conducts a Heckman two-stage method to re-run the regression analysis. The two-stage approach is mainly reflected in the following: in the first stage, the probability of digital transformation is obtained using a Probit model with control variables such as year, industry and province, based on the introduction of a dummy variable of whether the firm underwent digital transformation (Dum_DT), with a value of 1 for firms that underwent digital transformation and 0 for those that did not. The inverse Mills ratio (IMR) is obtained by calculating the fitted probability density function and the cumulative distribution function. In the second stage, the IMR was re-run by introducing it into the model and the regression results are shown in column (4). The results are generally consistent with the previous section and therefore the conclusion that the H1 hypothesis holds in this paper is robust.

Table 8. Treatment of endogenous problems

Note: ***, ** and * represent significant at the 1%, 5% and 10% levels respectively; t-statistic in parentheses; cons are intercept variables.

variables	Instrumental variables approach		Heckman two-stage method	
	(1)	(2)	(3)	(4)
	DT	R&D	Dum_DT	R&D
DT		0.1563712***		0.0193098***
		(4.28)		（4.14）
L.DT	0.0219383***			
	(7.37)			
IMR				-0.5838193***
				（-5.49）
Controls	Control	Control	Control	Control
Year	Control	Control	Control	Control
Industry	Control	Control	Control	Control
Provin	Control	Control	Control	Control
_cons	-0.1669934*	-0.07923***	2.654985**	0.0485431
	(1.65)	(-2.90)	（2.31）	（1.41）
N	4651	4651	5369	5369
R-squared	0.2318	0.3518		0.5098

5. Heterogeneity analysis

5.1 Establishment of overseas branches in countries along the "Belt and Road"

The implementation of the digital transformation of enterprises is inextricably linked to the internationalisation of enterprises. Existing scholars believe that the "One Belt, One Road" policy, which China has been vigorously advocating, has established a multilateral trade environment for China and other countries and promoted the flow of factors of production in the international community, which to a certain extent has an impact on the digital transformation and innovation of enterprises. This has an impact on the digital transformation and innovation of enterprises. In order to analyse the heterogeneous effect of digital transformation on the innovation behaviour of enterprises in more depth, this paper refers to the research methods of other scholars and classifies the sample of manufacturing enterprises with overseas branches into those participating in the Belt and Road and those not participating in the Belt and Road, according to the classification criteria of whether the overseas branches of enterprises are located in Belt and Road countries. The sample of manufacturing enterprises with overseas branches was grouped into two categories: those participating in "One Belt, One Road" and those not participating in "One Road".

The hypotheses for H1 and H2 correspond to columns (1)(3) and (2)(4) in Table 9, and the test for mediating effects is the Sobel test. The regression results in Table 9 show that digital transformation can significantly contribute to the innovation behaviour and absorptive capacity of enterprises, regardless of the presence or absence of overseas branches in countries along the "Belt and Road", while the mediating effect is significant; however, in the "Belt and Road" countries "This may be due to the fact that in today's globalised economy and globalised technology, when an enterprise can invest and set up factories in a host country, it can enjoy more policy support and This may be due to the fact that in today's globalised economy and globalised technology, when a company can invest in a host country, it can enjoy more policy support and access to knowledge in the host country. At the same time, the mediating role of absorptive capacity is higher for firms that do not invest in overseas branches in countries along the Belt and Road than for the other group, and this paper argues that firms that do not invest in factories in countries along the Belt and Road need to assimilate knowledge due to the lack of technological exchange and policy support. In this paper, it is suggested that enterprises that do not invest in factories in countries along the Belt and Road will need to absorb the knowledge before they can use it properly.

Table 9. Heterogeneity analysis results based on the differences in the establishment of overseas subsidiaries in countries along the Belt and Road

Variables	Established overseas branches in countries along the "Belt and Road" route		No overseas branches in countries along the "Belt and Road" route	
	(1)	(2)	(3)	(4)
	R&D	AC	R&D	AC
DT	0.0358**	10.56***	0.0200***	9.628***
	(2.36)	(2.58)	(3.55)	(4.27)
Controls	Control	Control	Control	Control
Year	Control	Control	Control	Control
Province	Control	Control	Control	Control
Industry	Control	Control	Control	Control
_cons	-0.123**	-32.05**	-0.115***	-70.01***
	(-2.44)	(-2.16)	(-4.50)	(-9.92)
N	624	624	3018	3018
R-squared	0.6688	0.5748	0.5581	0.5173
Sobel Testing	0.03381303（z=5.352）***		0.2813807（z=13.28）***	
Intermediary effect ratio	0.42151317		0.487724	

Note: ***, ** and * represent significant at the 1%, 5% and 10% levels respectively; t-statistic in parentheses; cons are intercept variables.

5.2 Grading of regional digital development levels

The China Regional Digital Development Index Report (2020) constructs an index system for China's regional digital development by evaluating the digital innovation factor investment, digital infrastructure construction, digital economy development, digital society and digital government construction of 31 provinces, municipalities directly under the Central Government and autonomous regions in China in a comprehensive manner. From the measurement results and ranking, China's regional digital development level shows obvious ladder-like characteristics, and each province and municipality is classified in a hierarchical assignment system. The first tier includes Guangdong, Zhejiang, Beijing, Jiangsu and Shanghai; the second tier includes thirteen provinces and cities in Shandong, Sichuan, Fujian, Chongqing, Shaanxi, Hubei, Anhui, Liaoning, Tianjin, Henan, Hunan, Jiangxi and Hebei, with high potential for subsequent growth; the third tier includes Hainan, Yunnan, Guizhou, Ningxia, Guangxi, Qinghai, Inner Mongolia, Tibet, Shanxi, Gansu, Xinjiang, Jilin and Heilongjiang thirteen provinces and regions, the digital development index score is low and present in the sub-indicators, the future digital level needs to be improved.

The hypotheses for H1 and H2 correspond to columns (1) (3) (5) and (2) (4) (6) in Table 10, and the test for mediating effects is the Sobel test. Table 10 reports the regression results for the sub-sample. Compared to the first and second echelons, the third echelon region has a higher share of mediating effects for firms' learning absorptive capacity at 77.59%. This may be due to the significant knowledge shortage constraint of firms in the region, resulting in the inability of firms to directly influence innovation behaviour through digital transformation, and the need to internalise advanced knowledge such as development experience from other regions before they can further increase R&D investment through decision-making. Companies in the first and second tier regions, where economic and financial development is faster, can directly influence innovation behaviour through digital transformation, and can also promote their R&D investment by facilitating learning and absorption capabilities. However, it is worth noting that the promotion effect of digital transformation on innovation and on absorptive capacity is smaller in the first tier than in the second tier. This may be due to the fact that the cities in the first tier are mostly eastern cities with more prominent market risks, more pronounced competition and more complex knowledge, which to a certain extent weakens the positive effect of digital transformation on enterprise innovation.

Table 10. Results of the heterogeneity analysis based on the regional digital development level classification

Variables	First tier		Second tier		Third tier	
	(1)	(2)	(3)	(4)	(5)	(6)
	R&D	AC	R&D	AC	R&D	AC
DT	0.0152***	7.538***	0.0189***	14.36***	0.0144	19.18***
	(2.66)	(3.53)	(2.74)	(5.42)	(0.94)	(3.29)
Controls	Control	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control	Control
Province	Control	Control	Control	Control	Control	Control
Industry	Control	Control	Control	Control	Control	Control
_cons	-0.0882**	-60.62***	-0.0627*	-47.01***	-0.0967*	-29.39
	(-3.01)	(-8.44)	(-2.42)	(-4.76)	(-2.19)	(-1.70)
N	3199	3199	1797	1797	524	524
R-squared	0.4490	0.4875	0.5895	0.5075	0.5500	0.4724
Sobel Testing	0.03115887（z=13.7）***		0.03164384（z=11.06）***		0.03975726（z=6.41）***	
Intermediary effect ratio	0.59637396		0.60887881		0.77595992	

6. Conclusion and discussion

6.1 Conclusions of the study

In recent years, the digital transformation of enterprises has gradually become a development trend, and more and more enterprises are stepping into the ranks of digital transformation as a means to empower innovation. This paper empirically examines the relationship between the two and analyses the mechanism of their role by selecting the main board manufacturing companies listed on A-shares in Shanghai and Shenzhen from 2016 to 2020 as a research sample, and draws the following conclusions.

First, digital transformation can promote corporate innovation as well as absorptive capacity; absorptive capacity plays a partially mediating role between digital transformation and corporate innovation. The article uses panel data to overcome the errors caused by the use of questionnaires, and the conclusions are still valid after robustness tests and endogeneity treatments, to a certain degree of scientific validity. Furthermore, digital transformation is not something that can be done behind closed doors. When companies set up branches abroad, especially in countries along the "Belt and Road", the digital transformation has a stronger impact on innovation and absorption capacity. Finally, manufacturing enterprises in the first echelon of regional digital development have a significantly weaker impact on innovation and absorptive capacity than those in the second echelon, while digital transformation in the third echelon has no significant impact on innovation and an impact on absorptive capacity. The role of absorptive capacity in mediating digital transformation and corporate innovation gradually increases from the first to the third echelon. Therefore, when choosing a location, it is important to look at the external environment and not just the opportunities it presents, but also the "rapids" behind it.

6.2 Policy Suggestions

This paper combines the findings of the study from the following, and makes the following policy recommendations.

First, manufacturing enterprises need to recognize the real purpose of digital transformation. Digital transformation is not a "cosmetic project" for any enterprise, and it is not a transformation to catch up with the trend, but a key factor for enterprises to get a place and seek sustainable development in the context of digital economy. This is why it is so important to understand the purpose. In view of this, all levels of the company need to actively guide the digital transformation, fully empower employees, change the perceptions and attitudes of members of the company and motivate them to participate in it.

Secondly, as the epidemic becomes more normalised, the risk of uncertainty increases and companies may face shutdowns at any time, so manufacturing companies need to think far ahead, combine their strategies and core strengths, plan their digital transformation programmes rhythmically and regularly, and thus promote innovation. The lack of prior planning and sound analysis did not have a significant impact on improving the situation. However, there were also many companies that used their accumulated prior reserves to accelerate their digital transformation, using tools such as big data platforms and artificial intelligence to pinpoint the right decisions, increase their willingness and intensity to innovate, identify business opportunities to turn around their plight and achieve growth in the face of adversity.

Third, the absorptive capacity of enterprises is a key bridge to digital transformation to promote innovation, and the absorptive capacity of enterprises can be reflected from the quality of employees, so enterprises should pay full attention to the role of human resources. When recruiting, on the one hand, employees' understanding of digital technology and innovative thinking should be examined, while attention should be paid to the pre-socialisation of employees, analysing the behavioural characteristics of candidates and judging whether their values are in line with the culture of digital transformation carried out by enterprises, to ensure that new employees are quickly integrated in the specific corporate context of digital transformation.

Fourthly, there is a synergy between the government's improved infrastructure development and the manufacturing industry's rational choice of location. The manufacturing industry usually considers the resource endowment of the location when choosing a site, so that the higher the level of regional digital development is, the region often has more unique advantages, the stronger the positive effect of digital transformation on enterprise innovation, but the higher the level of regional digital development is usually the first-tier major cities in China, with fierce competition and obvious competition for talent. Therefore, the manufacturing industry cannot take the higher level of the region as an external guarantee for its own development, thus abandoning the less developed areas where competition is slightly weaker, but this requires the government to create a digital platform, so that resources can be integrated, from the point to the line and then to the surface to help the digital transformation of enterprises.

6.3 Research gaps and prospects

This paper still has shortcomings in the following areas and needs to be further improved in future research. Firstly, the perspective of the core variables needs to be further supplemented. Future research could look at the number of patents and inventions in terms of innovation output, the number of R&D personnel invested in terms of human capital invested in innovation behaviour, and the innovation approach of breakthrough innovation or incremental innovation. Second, the mechanism of the role of digital transformation and firm innovation needs to be further deepened. However, the choice of mediating variables is not limited to this, and future research needs to open up this black box of effects from other perspectives. Finally, the selection of the sample needs further refinement. Unlike the sample selection of previous scholars, this paper argues for this relationship from the perspective of the manufacturing industry, but other types of enterprises, such as tourism and polluting enterprises, may lead to different conclusions in this study, and further refinement is needed in the future.

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