A study on Innovation Quality in the Digital Transformation process

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Abstract. In the context of global competition and rapid technological iteration, enhancing innovation quality has become a pressing issue for China's manufacturing industry. Digital transformation, driven by emerging technologies, provides new opportunities for improving firms' innovation capabilities. This study empirically investigates the relationship between digital transformation and innovation quality using panel data of Chinese A-share listed manufacturing enterprises from 2009 to 2024. The findings confirm that digital transformation significantly promotes innovation quality, with stronger effects in high-tech firms and enterprises located in eastern and central regions. The innovation of this paper lies in shifting the focus from innovation quantity to innovation quality, and in analyzing manufacturing enterprises as a unique sector with distinct innovation paths. This research not only enriches the theoretical understanding of digital transformation and innovation quality, but also provides practical implications for policymakers and enterprises seeking to leverage digitalization for sustainable industrial upgrading.

Keywords: Innovation Quality, Digital Transformation, Manufacturing Enterprises.

1. Introduction

Innovation quality, as a core evaluation indicator distinct from mere innovation quantity, measures the comprehensive level of innovation activities and their outcomes across dimensions such as technical content, originality, practical value, economic and social benefits, and sustainability[1]. There remains significant room for improvement in China's innovation quality. China has faced repeated technological bottlenecks in core technologies such as lithography machines and chips. Against this backdrop, the Chinese government has put forward new requirements for enterprise innovation: strengthening enterprises' dominant role in innovation, advancing original and leading scientific and technological research, improving the market-oriented mechanism for technological innovation, and enhancing innovation quality. The 2023 Government Work Report also includes important directives such as promoting collaborative research on key core technologies and strengthening research on disruptive and cutting-edge technologies.

Being a profound transformation driven by new-generation information and communication technologies, digital transformation has turned the digital economy into a new engine that fuels China's economic growth[2]. The 2023-2024 Annual Report on Research into Digital Transformation of China's Manufacturing Industry indicates that the market size of digital transformation in China's manufacturing industry reached 462.3 billion yuan in 2023, accounting for 9.7% of the global market, with a year-on-year growth rate of 8.8%. As microeconomic entities and main forces of innovation, enterprises have seen digital transformation play a crucial role in enhancing enterprise value, improving innovation performance, and driving productivity growth[3].

For the manufacturing industry, digital transformation leverages technologies like the industrial internet and artificial intelligence to enable intelligent production processes, collaborative supply chains, and data-driven decision-making. These improvements, in turn, significantly boost production efficiency, product quality, and market response speed—thereby strengthening enterprises' core competitiveness[4]. It is reasonable to anticipate that, under the context of digital transformation, China's manufacturing industry is likely to achieve greater development.

This paper mainly addresses the following two research questions: (1) Does digital transformation help enhance the innovation quality of manufacturing enterprises? (2) Does heterogeneity exist in the impact of digital transformation on these firms' innovation quality? To explore these research questions, this paper conducts an empirical analysis using data from A-share listed manufacturing companies spanning 2009 to 2024. The study's key findings are as follows: digital transformation significantly boosts the innovation quality of manufacturing enterprises, and this impact exhibits distinct heterogeneous characteristics.

One marginal contribution of this paper is its focused examination of the link between digital transformation and manufacturing firms' innovation quality. Existing literature has explored the influence of digital transformation on enterprise innovation behavior. However, most studies are confined to digital transformation's impact on innovation quantity or performance[5-6], overlooking innovation quality—a core dimension determining firms' competitive edge[7]. Another marginal contribution lies in its focus on manufacturing enterprises. Most existing studies focus on all A-share listed enterprises when analyzing the impact of digital transformation on innovation quality[8]. However, manufacturing, as the pillar of the national economy, has innovation paths, resource input modes, and achievement conversion logic that differ from other industries[9]. Focusing on manufacturing data rather than whole-industry data may not only capture the unique characteristics or operating rules of the manufacturing industry but also help maintain the practical guiding value of the research findings.

2. Theoretical analysis and research hypotheses

In recent years, digital transformation has become a critical path for manufacturing enterprises to enhance their competitiveness and achieve high-quality innovation. To explore the impact of digital transformation on the innovation quality of manufacturing enterprises, this study conducts theoretical analysis using three theories: Dynamic Capabilities Theory, Information Communication Theory, and the Resource-Based View.

2.1. Dynamic Capabilities Theory

The Dynamic Capabilities Theory argues that in rapidly changing and uncertain environments, firms must continuously build and renew their capabilities in three interrelated processes—sensing opportunities and threats, seizing opportunities through resource allocation, and reconfiguring organizational assets—to sustain competitive advantage[5]. This theory has been widely applied in innovation research to explain how firms adapt their resource base and processes to enhance innovation performance and quality[6].

In the context of digital transformation, manufacturing enterprises might significantly strengthen all three dimensions of dynamic capabilities. First, digital technologies such as big data analytics, AI, and the industrial internet greatly enhance firms' sensing ability by enabling real-time monitoring of market shifts, technological frontiers, and customer preferences[7-8]. This helps enterprises identify emerging innovation opportunities and potential risks earlier than competitors. Second, digital platforms and cloud-based collaboration tools improve seizing ability, as they facilitate cross-departmental integration, accelerate decision-making, and optimize the allocation of financial, human, and knowledge resources toward promising innovation projects[9]. Finally, digital transformation drives organizational reconfiguring by enabling flexible production systems, digital twins, and process automation, which allow firms to continuously adapt business models and production structures in line with technological changes[10-11]. By reinforcing sensing, seizing, and reconfiguring, digital transformation ensures that innovation processes are not only more efficient but also more original and market-oriented, ultimately improving the overall quality of innovation outcomes in manufacturing enterprises.

2.2. Information Communication Theory

Information Communication Theory holds that information transmission involves links such as information source, encoding, channel, decoding, and receiver, and the effective transmission of information is affected by factors such as channel noise, encoding distortion, and delay[12]. In an organizational context, this theory emphasizes that the accuracy, timeliness, and comprehensibility of information are crucial for decision-making and innovation[13]. In research on enterprise innovation, Information Communication Theory is often used to explain how information flow affects R&D efficiency and the quality of outcomes: smooth information flow reduces redundant work, shortens R&D cycles, and improves the market fit of outcomes; in contrast, information distortion or delay may lead to resource waste, incorrect technical paths, or products that fail to meet market demands[14].

Digital transformation optimizes the information transmission mechanisms of manufacturing enterprises. First, digital systems such as IoT (Internet of Things), ERP (Enterprise Resource Planning), and MES (Manufacturing Execution System) enable real-time data collection and sharing in production, supply chain, and market feedback processes, significantly reducing information delay and inconsistency[15]. Second, big data analytics and artificial intelligence technologies can quickly process and screen massive amounts of information, reducing noise interference and making it easier for innovation teams to grasp key trends and potential opportunities[16]. The acceleration and precise transmission of information flow enable enterprises to iterate more rapidly in product R&D and process innovation and more accurately match market demands, thereby improving the technical content and market competitiveness of innovation outcomes[17]. Therefore, from the perspective of Information Communication Theory, digital transformation provides important support for improving the innovation quality of manufacturing enterprises by enhancing the efficiency and quality of information transmission.

2.3. Resource-Based View

The Resource-Based View (RBV) argues that an enterprise's competitive advantage stems from its scarce resources and capabilities that are difficult for competitors to obtain or imitate[18]. Barney proposed the well-known VRIN framework (Valuable, Rare, Inimitable, Non-substitutable) to judge whether resources can bring sustainable competitive advantages. These resources can be tangible (e.g., machinery and equipment, funds), intangible (e.g., brands, patents, data assets), or organizational capabilities (e.g., R&D capabilities, management processes, and corporate culture)[19].

In innovation research, RBV emphasizes that innovation outcomes depend on enterprises' reserves of internal unique resources and capabilities, and the ability to acquire, integrate, and update these resources directly affects the quality and sustainability of innovation[20].

Digital transformation is a process of reconstructing enterprises' resource structures and capability systems. On one hand, digital technologies enable enterprises to integrate scattered data, knowledge, and experience, forming valuable and scarce digital resources (e.g., industrial big data, algorithmic models, and digital twin systems)[21]. On the other hand, digital transformation enhances enterprises' dynamic capabilities—i.e., the ability to sense market changes, rapidly reorganize resources, and implement innovations[22]. These newly formed, hard-to-imitate resources and capabilities provide unique and sustainable support for innovation activities, ensuring high-quality performance of innovation outcomes in both technical and market terms[23]. Therefore, from the perspective of the Resource-Based View, digital transformation might significantly strengthen enterprises' core competitive resources and capabilities, thereby improving the innovation quality of manufacturing enterprises. Based on the preceding discussion, this study proposes:

H1: Digital transformation can enhance the innovation quality of manufacturing enterprises.

3. Research design

3.1. Sample and data

This study selects Chinese A-share manufacturing listed companies from 2009 to 2024 as the research sample, with the following screening criteria applied: ① excluding companies with special treatment (ST), special treatment with delisting risk (*ST), or particular transfer (PT) status in the current year; ② excluding delisted companies; ③ excluding companies listed in the current year; ④ excluding samples with missing values in the variables involved in the regression. All continuous variables in this paper are subjected to 1% two-tailed winsorization. Financial data of listed companies are obtained from the CSMAR database, and announcement data of listed companies are sourced from CNINFO. The empirical sample consists of 18,016 observations, data from 1,126 firms over 16 years.

3.2. Variable selection

3.2.1 Dependent variables

The dependent variable in this research is innovation quality (*INQU*), measured by the count of non-self citations of patents. The expected benefits of patent technology in the process of commercialization, industrialization, and marketization are key factors in evaluating its market value. An increase in the number of non-self citations of a patent often indicates enhanced market recognition of the patent, along with increased expected benefits from its commercialization, which objectively reflects the quality of the patent [24].

3.2.2 Independent variable

The independent variable in this study is digital transformation (*DIG*). Drawing on the research [25], this study uses Python technology to extract terms related to digital transformation from the text of the Management Discussion and Analysis (MD&A) section, count the frequency of these digital transformation-related terms, and divide this frequency by the total length of the MD&A text to obtain the digital attention index. The MD&A section in corporate annual reports reflects managers' strategic directions and development philosophies. By analyzing this section, we get relatively accurate trends regarding the digital transformation of enterprises.

3.2.3 Control variables

The control variables are mainly as follows:① Firm leverage (*Lev*), measured as the ratio of total liabilities to total assets; ② Firm age (*Age*), obtained by subtracting the year of establishment of the firm from the observation year in the panel data;③ Return on assets (*Roa*), calculated as the ratio of the firm's net profit in the current year to total assets; ④ Cash flow (*Cashflow*), measured as the ratio of net cash flow from operating activities to total assets; ⑤ Tobin's Q (*Tobinq*), calculated as the ratio of the market value of the firm to the replacement cost of its assets;⑥ Liquidity (*Liquid*), measured as the ratio of current assets to current liabilities. Variable definitions are presented in Table.1

Table.1. Variable definition

Variable Type	Abbreviation	Definition
Dependent variable	*INQU*	The count of non-self citations of patents.
Independent variable	*DIG*	*DIG* = (DT_Freq)/(MD&A_Len), where DT_Freq is the frequency of digital transformation-related terms in MD&A, and MD&A_Len is the total length of the MD&A text.
Control variable	*Lev*	The ratio of total liabilities to total assets.
	Age	Years from the firm's establishment year to the observation year in the panel data.
	Roa	The ratio of the firm's net profit in the current year to total assets.
	Cashflow	The ratio of net cash flow from operating activities to total assets.
	Tobinq	The ratio of the market value of the firm to the replacement cost of its assets.
	Liquid	The ratio of current assets to current liabilities.

3.3. Empirical model

This paper employs a panel regression model to estimate the impact of digital transformation of manufacturing enterprises on their innovation quality.

$$INQU_{it}=\alpha+\beta \cdot DIG_{it}+\boldsymbol{\gamma} \cdot \boldsymbol{X_{it}}+\mu_i+\lambda_t+\varepsilon_{it} \tag{1}$$

where $INQU_{it}$ denotes the innovation quality of firm i in year t; DIG_{it} represents the digital transformation level of firm i in year t; $\boldsymbol{X_{it}}$ is the set of control variables; μ_i and λ_t denote firm and year fixed effects, respectively; ε_{it} is the random error term; α is the constant term; β and $\boldsymbol{\gamma}$ are the coefficients to be estimated.

Table.2. Descriptive statistics

VARIABLES	N	Mean	SD	Min	Max
DIG	18,016	4.477	1.394	0.000	7.562
INQU	18,016	0.599	0.142	0.000	0.688
Lev	18,016	0.391	0.190	0.052	0.907
Roa	18,016	0.045	0.065	-0.235	0.214
Cashflow	18,016	0.050	0.066	-0.176	0.247
Age	18,016	2.893	0.347	1.386	3.611
Tobinq	18,016	2.149	1.271	0.849	7.885
Liquid	18,016	2.720	2.610	0.307	16.980

The descriptive statistics of the variables used in the benchmark regression of this section are presented in Table.2. There are a total of 18,016 firm-year observations of listed manufacturing companies. For the dependent variable, innovation quality (*INQU*), the mean value is 0.599, the standard deviation is 0.142, and the maximum value is 0.688, indicating significant differences in innovation outcomes among enterprises. For the key explanatory variable, digital transformation (*DIG*), the mean value is 4.477, the standard deviation is 1.394, and the maximum value is 7.562, highlighting the asymmetric distribution of digital resource endowment among enterprises and the imbalance in the digitalization process across different enterprises.

4. Empirical results

4.1. Baseline regression

This study explores the impact of digital transformation on innovation quality (*INQU*) among Chinese A-share manufacturing listed companies from 2009 to 2024. The regression results are presented in Table.3. Column (1) presents the regression result of digital transformation on innovation quality without control variables, while columns (2) through (7) present the regression results with gradually added control variables. Across all columns, the coefficient of the digital attention index (*DIG*) is significantly positive at the 1% level, indicating that corporate digital transformation consistently enhances innovation quality, thereby supporting *H1*. Digital transformation often possesses transformative potential, leveraging emerging technologies and digital strategies to reshape traditional management models and reconfigure conventional innovation patterns within firms.

Table.3. Benchmark results

	INQU (1)	*INQU* (2)	*INQU* (3)	*INQU* (4)	*INQU* (5)	*INQU* (6)	*INQU* (7)
DIG	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lev		0.026**	0.038***	0.038***	0.031**	0.029**	0.017
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
Roa			0.077***	0.077***	0.084***	0.084***	0.084***
			(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
Cashflow				-0.004	-0.008	-0.001	-0.001
				(0.019)	(0.019)	(0.019)	(0.019)
Age					0.058***	0.061***	0.059***
					(0.012)	(0.012)	(0.012)
Tobinq						-0.003**	-0.003**
						(0.001)	(0.001)
Liquid							-0.001*
							(0.001)
Cons	0.215***	0.209***	0.200***	0.201***	0.109***	0.111***	0.123***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.029)	(0.029)	(0.029)
ID FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18016	18016	18016	18016	18016	18016	18016
adj.R^2	0.346	0.346	0.346	0.347	0.347	0.348	0.348

Note: This table explores digital transformation's impact on innovation quality among 2009–2024 Chinese A-share manufacturing firms. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are standard errors.

4.2. Robustness tests

4.2.1 Replacing the independent variable

Considering that the quality of innovation depends not only on the market value of patents but also on the complexity and breadth of knowledge covered by patents [26], this paper uses the knowledge breadth method to measure innovation quality, so as to test the robustness of the benchmark regression conclusions. This paper obtains the IPC classification numbers of invention patents and utility model patents from the State Intellectual Property Office to evaluate the technical complexity of patents.

According to Table.4, the regression results show the promoting effect of digital transformation on innovation quality still exists after replacing the measurement method of innovation quality.

Table.4. Robustness tests-Replacing the Independent Variable

Variables	*INQU*
	(1)
DIG'	0.103***
	(0.008)
Lev	0.761***
	(0.067)
Roa	-1.232***
	(0.123)
Cashflow	0.266*
	(0.109)
Age	1.227***
	(0.087)
Tobinq	0.045***
	(0.006)
Liquid	-0.038***
	(0.004)
Cons	-3.898***
	(0.299)
ID FE	Yes
Year FE	Yes
N	18016
adj.R^2	0.815

Note: This table shows digital transformation's promotion of innovation quality persists when digital transformation is measured by breadth method. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are standard errors.

4.2.2 Instrumental variable

To address the endogeneity problem, this section adopts an instrumental variable approach. Drawing on existing methodological practices[27], this paper uses the average digital transformation level of other firms in the same industry as the instrumental variable.

In the empirical analysis, the two-stage least squares (2SLS) method is employed to estimate the two measures of digital transformation. The regression results in Columns (1) and (3) of Table.5 show that, in the test of digital transformation, the coefficients of the instrumental variables in the first-stage regression are all statistically significant at the 1% level. The results in Columns (2) and (4) of Table.5 indicate that the regression coefficients of enterprise digital transformation in the second stage are all statistically significant and positive at the 1% level, with F-statistics all greater than 10, suggesting no issue of weak instrumental variables. This demonstrates that the instrumental variables selected in this paper have good explanatory power, and the results of the benchmark regression are robust

Table.5. Robustness tests-Instrumental variable Test

Variables	*DIG* (1)	*INQU* (2)	*DIG* (3)	*INQU* (4)
IV	1.005***		1.435***	
	(0.022)		(0.040)	
DIG		0.0262***		1.417***
		(0.003)		(0.102)
Lev	0.0166	0.0659***	0.195*	0.196
	(0.059)	(0.008)	(0.097)	(0.210)
Roa	0.364***	0.224***	0.526**	-0.238
	(0.110)	(0.020)	(0.176)	(0.300)
Cashflow	-0.0977	0.0234	-0.693***	-0.364
	(0.094)	(0.018)	(0.155)	(0.239)
Age	0.557***	0.00397	0.084	-0.805**
	(0.038)	(0.003)	(0.074)	(0.272)
Tobinq	-0.022***	-0.011***	0.0791***	0.113***
	(0.005)	(0.001)	(0.008)	(0.015)
Liquid	-0.015***	-0.004***	-0.0235***	-0.00604
	(0.003)	(0.001)	(0.006)	(0.011)
Cons	1.641***	0.454***	0.334	-1.729***
	(0.089)	(0.017)	(0.179)	(0.402)
ID FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	18016	18016	18016	18016
adj.R^2	0.353		0.185	

Note: This table shows first-stage instrumental variable coefficients and second-stage digital transformation coefficients are 1% significant, confirming valid instruments and robust benchmark results when using the average digital transformation level as instrumental variable. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are standard errors.

4.3. Heterogeneity analysis

4.3.1 The heterogeneity of technological level

Drawing on the method for defining high-tech corporations, this paper divides the sample into two subsamples: high-tech corporations and non-high-tech corporations [28]. Table.6 reports industry technological heterogeneity results: Column (1) for non-high-tech, Column (2) for high-tech subsamples. Digital transformation coefficients are insignificant in non-high-tech but significantly positive at the 1% level in high-tech, indicating it boosts innovation quality there—likely as high-tech industries, with technology intensity and digital dependence, have better-aligned organizational structures to leverage digital transformation for information/knowledge utilization.

4.3.2 The heterogeneity of geographical location

Using the National Bureau of Statistics' regional divisions, the sample is split into eastern, central, and western subsamples based on listed manufacturing firms' registered locations. Table.6 presents regional heterogeneity results, with column 3 for eastern regions, column 4 for central regions, and column 5 for western regions. Results show the digital transformation coefficient (*DIG*) is 1% significantly positive in the east region, indicating a strong promotion of innovation quality. In the central region, the coefficient is 5% significantly positive with a slightly weaker effect. In the west region, the coefficient is also 5% significantly positive but smaller in magnitude than that in the east region.

These findings reflect that digital transformation benefits innovation quality across all regions, with the strongest effect in the east—likely due to its developed digital infrastructure, high human capital, and strong integration of digital technologies into production.

Table.6. Heterogeneity Analysis

Variables	Technological Heterogeneity		Geographical Heterogeneity		
	Non-High-Tech	High-Tech	East	Central	West
	INQU	*INQU*	*INQU*	*INQU*	*INQU*
	(1)	(2)	(3)	(4)	(5)
DIG	0.001	0.008***	0.007***	0.011**	0.009*
	(0.009)	(0.001)	(0.002)	(0.004)	(0.005)
Lev	0.030	0.012	0.028*	-0.057	-0.057
	(0.073)	(0.011)	(0.013)	(0.030)	(0.039)
Roa	0.192	0.101***	0.110***	0.063	0.152*
	(0.133)	(0.021)	(0.023)	(0.057)	(0.073)
Cashflow	-0.009	-0.009	-0.028	0.017	0.066
	(0.117)	(0.018)	(0.021)	(0.047)	(0.065)
Age	-0.028	0.033*	0.014	0.068	0.026
	(0.138)	(0.015)	(0.017)	(0.038)	(0.057)
Tobinq	0.002	-0.005***	-0.004**	-0.005	-0.002
	(0.005)	(0.001)	(0.001)	(0.003)	(0.003)
Liquid	0.001	0.001	0.001	-0.001	-0.002
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)
Cons	0.591	0.472***	0.519***	0.387***	0.489**
	(0.420)	(0.043)	(0.049)	(0.112)	(0.169)
ID FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	1328	16688	13024	3136	1856
adj.R^2	0.347	0.310	0.308	0.314	0.362

Note: This table shows digital transformation has no significant effect on innovation quality in non-high-tech enterprises but significantly boosts it at the 1% level in high-tech ones. Regionally, it strongly promotes innovation quality at the 1% level in eastern China, with a slightly weaker 5% significant effect in central China and a smaller-magnitude 5% significant effect in western China. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. The values in parentheses are standard errors.

5. Conclusions and Policy Recommendations

The overall analysis demonstrates that digital transformation plays a crucial role in enhancing the innovation quality of China's manufacturing enterprises. Empirical evidence shows its significant positive impact, with stronger effects observed in high-tech firms and enterprises located in the eastern and central regions. These findings suggest that digital transformation not only reshapes traditional innovation patterns but also provides a feasible path for improving competitiveness in the manufacturing sector. Looking forward, the integration of digital transformation with green transition, cross-regional collaboration, and intelligent upgrading will further strengthen the sustainability of innovation quality. Future research may explore the long-term dynamic effects of digitalization, as well as the interaction between digital policies, resource allocation, and innovation ecosystems.

Based on the above conclusions, this paper puts forward the following policy recommendations: Promote manufacturing digital transformation, especially in high-tech enterprises, to boost innovation quality and realize the synergy between digitalization and green transition. Implement differentiated regional strategies: Eastern regions consolidate advantages to deepen cutting-edge digital R&D; central regions accelerate infrastructure and resource introduction; western regions prioritize capabilities and technology transfer via pilots/cooperation. Establish a national digital innovation platform for manufacturing to enable data sharing and cross-regional collaboration, forming transformation synergy.

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