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Does the Digital Transformation of Manufacturing Improve Technological Innovation Capabilities of Enterprises—Empirical Evidence from China

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Abstract: This study uses fixed effect model, instrumental variable method, propensity score matching double difference method, threshold regression and quantile regression model to empirically test the effect of digital transformation on technological innovation in manufacturing industry. The study found that: (1) Digital transformation can improve technological innovation. (2) The mediating study found that digital transformation can improve technological innovation by supressing cost stickiness. (3) The heterogeneity study found that the technological innovation improming effect of digital transformation is greater in enterprises with larger scale, technology intensive, lower asset intensity and strong innovation. According to the research conclusions, enterprises should actively carry out digital transformation to improve technological innovation, get rid of the extensive development model and achieve sustainable growth. The data mainly come from China's A-share listed manufacturing enterprises, which limits the generalizability of the research conclusions. We will further study unlisted enterprises to analyze whether there is heterogeneity.

Keywords: digital transformation; technological innovation; cost stickiness; green productivity

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1. Introduction

"New quality productivity" is a new concept proposed by Chinese scholars in recent years to meet the challenges of modern economic development. This concept combines scientific and technological productivity, green productivity and digital productivity. Scientific and technological productivity emphasizes the direct contribution of advanced technology to productivity improvement[36]. Green productivity focuses on sustainable resource utilization, circular economy model, energy efficiency and emission reduction, placing technology at the forefront of ecological responsibility[6,7,19]. Digital productivity emphasizes the transformative potential of technologies such as big data, cloud computing and artificial intelligence in reshaping corporate operations and promoting data-driven management strategies[25].

China's manufacturing industry is a typical example of the challenges faced by new quality productivity[26]. In the past, reliance on the extensive growth model led to excessive resource consumption, inefficiency and environmental degradation[20–23]. In addition, China's manufacturing industry has weak independent innovation and R&D capabilities, most industries are at the middle and low end of the global value chain, and have a high dependence on imports of key technologies and high-end components[4,5]. Therefore, China's manufacturing industry urgently needs to achieve transformation and upgrading from low-end to high-end through technological innovation[1,3],. At the same time, with the increasing advancement of cutting-edge digital technologies such as big data, cloud computing, and artificial intelligence, digital transformation is expected to become a new "engine" for technological innovation in China's manufacturing industry[2,8,9].

Regarding the connotation of digital transformation, there is currently no consensus in the academic community. Chanias et al. (2019) and Legner et al. (2017) believe that enterprises can be

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considered to be digital transforming if they choose to achieve transformation and upgrading through information technology. Fitzgerald et al. (2018) interpret digital transformation as the use of digital technologies (such as social media, embedded devices, etc.) to carry out major business transformation. Liu et al. (2021) define the essence of the digital transformation process from the perspective of management as enterprises widely apply digital technologies to multiple links related to enterprise growth, such as enterprise production and manufacturing, technology replacement, operation management, and marketing. This paper believes that digital transformation means that enterprises use digital technologies such as big data, cloud computing, and artificial intelligence to comprehensively innovate business models, operation processes, products and services to improve efficiency, and create new value. In the manufacturing environment, this is specifically reflected in production automation, intelligence, digital management of the supply chain, and personalized customer service.

This paper further studies the mediating mechanism effect of cost stickiness. Cost stickiness refers to the phenomenon that when the income of an enterprise decreases, the decrease in cost is less than the increase in cost when the income increases (Anderson et al., 2003). Banker et al. (2011) pointed out that adjustment costs, managers' optimistic expectations and opportunistic motivations are the most fundamental reasons for cost stickiness. With the advancement of digital transformation, the business processes of enterprises are becoming more transparent (Qi, 2020). Digital transformation improves the flexibility of enterprises to adjust costs when output changes, that is, it reduces cost stickiness, thereby increasing corporate profits and enabling enterprises to invest more funds in technological innovation activities.

With the rapid development of social economy and the continuous advancement of science and technology, the connotation of the manufacturing industry innovation concept is also constantly evolving and deepening[35]. American economist Joseph Schumpeter(1911) proposed the concept of "innovation" in the early 20th century, laying the foundation for the development of the manufacturing industry innovation concept. He is considered a pioneer of modern innovation theory. In his 1911 book "Theory of Economic Development", he proposed that innovation is the core driving force of economic development. He defined five types of innovation: new products, new methods, new markets, new sources of raw materials, and new organizational forms (such as new business practices). Since then, many scholars have conducted in-depth research on the concept of manufacturing innovation, such as Clayton Christensen and Michael Porter. This paper focuses on technological innovation, which is the ability of enterprises to continuously launch new and valuable results in product development, processes, services, etc. Digital transformation provides powerful data analysis and processing capabilities, which can help enterprises accelerate technological innovation.

This paper proposes three main research questions.First, What is the effect of digital transformation on technological innovation in China's manufacturing industry.Secondly,What is the mediation of accounting cost stickiness between the effect of digital transformation on technological innovation investment in China's manufacturing industry.Finally, What is the moderation between the effect of digital transformation on technological innovation output in China's manufacturing industry.

The academic contribution of this paper is that it enriches the theoretical framework of the manufacturing technology innovation driving system, incorporates digital factors into it, and provides new perspectives and ideas for related research. At the same time, novel methods such as text mining technology are used to evaluate the degree of digital transformation, which improves the accuracy and objectivity of measurement. At the same time, this paper also broadens the research field of digital transformation from a micro level, filling the research gap in this field at the micro level.

This paper deeply explores the effect of digital transformation on technological innovation in China's manufacturing industry, reveals the role of digital transformation as a new engine of

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technological innovation, and provides an important reference for manufacturing enterprises to improve their technological innovation and achieve sustainable development.

The main research contents of this paper are: first, to analyze whether digital transformation can improve technological innovation in the manufacturing industry; second, to analyze whether digital transformation can improve technological innovation by suppressing cost stickiness; finally, to conduct heterogeneity analysis from the perspectives of enterprise scale and technology intensity. This paper enriches the research on innovation systems by introducing digital factors, uses text mining technology to measure the degree of digital transformation, and provides empirical support from the micro level.

2. Theoretical Framework and Research Hypotheses

Relevant scholars have studied the effect of the digital transformation on technological innovation from different angles. The effect of digital transformation on enterprise technological innovation is reflected in quantity and quality, and quantity and quality may be heterogeneous [Liu et al., 2021]. The digital transformation has a dual role in improving technological innovation. In terms of improving technological innovation in manufacturing enterprises, infrastructure, digital industrialization, industrial digitalization and digital governance play a dual positive role [Wang & Wei, 2023]. Digital transformation has a significant positive effect on the enterprise value of manufacturing industry. Digital transformation can improve the enterprise value through technological innovation, business model innovation and their combination [Ma et al., 2022]. The synergy between digital transformation capabilities and technological innovation capabilities is positively related to corporate digital innovation. Social capital plays a positive moderating role in the effect of two collaborative factors on digital innovation [Wang et al.,2023]. Digital inclusive finance can effectively alleviate the financing constraints of small and medium-sized enterprises, thereby improving the technological innovation of small and medium-sized enterprises. Reasonable financial supervision and adaptive government subsidies have a positive regulatory effect on the innovation incentive effect of digital inclusive finance [Zhang et al.,2023]. Enterprise digital transformation has greatly improved the quantity and quality of green technological innovation. Driven by the intermediary function of optimizing resource allocation, this technological transformation improves green technological innovation by improving human capital composition, reducing information asymmetry and improving technological innovation investment [Liu et al.,2024]. Digital transformation will improve green technological innovation cooperation. Green technological innovation cooperation is an intermediary factor between digital transformation and green technological innovation. External environmental orientation regulates the relationship between digital transformation and green technological innovation cooperation [Li & Wang,2022]. Digital transformation can improve the technological innovation performance of enterprises. Digital transformation can improve the synergy between demand-side policies and supply-side policies, and improve the positive effect of demand-side policies on technological innovation performance, but reduces the incentive effect of supply-side policies [Chen et al.,2023] Digital finance has spatial spillover effects that improve technological innovation [Yang et al.,2023].

The above-mentioned relevant studies show that the digital transformation has shown positive effects in multiple dimensions such as improving human capital efficiency, easing financing constraints, reducing information asymmetry, and optimizing resource allocation, thereby improving technological innovation.Therefore, digital transformation can improve technological innovation, get rid of the extensive development model, thereby improving resource efficiency and reducing environmental impact, and achieving sustainable growth.Based on the above theoretical derivation and the measurement of the two dimensions of technological innovation output, and technological innovation input, this section proposes the following overall and specific hypotheses:

H1. *Digital transformation has a significant positive effect on technological innovation in China's manufacturing industry.*

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H1.1. *Digital transformation has a significant positive effect on technological innovation output in China's manufacturing industry.*

H1.2. *Digital transformation has a significant positive effect on technological innovation investment in China's manufacturing industry.*

Suppressing cost stickiness is crucial for cost - reduction, profit - improvement, and financing digital transformation in manufacturing. But can digital transformation actually suppress cost stickiness? In practice, when management anticipates a temporary business volume decline, they may retain unused production capacity instead of cutting it immediately. This causes an asymmetry between production costs and business volume, resulting in cost stickiness. Although this retained capacity can help seize market share when the market recovers, removing certain capacities is difficult due to factors like disposal costs for machinery and pressure/costs associated with employee layoffs [28]. Digital transformation impacts enterprises directly and indirectly. Directly, it optimizes information handling via an integrated digital platform, enabling real - time resource - usage tracking for better resource allocation and system optimization, thus reducing costs and enhancing efficiency. Indirectly, it bolsters internal control, governance, and information transparency, reducing agency problems and curbing managers' self - interested behavior. As a result, cost stickiness is suppressed, profits rise, and more funds are available for innovation. Scholarly research offers insights. Digital transformation suppresses cost stickiness by reducing adjustment costs and easing financing constraints, though management myopia can counteract this (Li et al., 2024) [10]. It also significantly curbs cost stickiness through lowering adjustment costs and managers' optimism, with a sustainable effect (Chen et al., 2023) [11]. Intelligent manufacturing helps via resource and information - processing efficiency (Shahzad et al., 2024) [12]. Customers' digital transformation can spill over to suppress suppliers' cost stickiness (Li et al., 2024) [13]. Additionally, digital transformation affects cost stickiness through internal control, resource adjustment, and manager optimism (Du et al., 2024) [14]. Data assets enhance flexibility (Ma et al., 2024) [15], and the Cybersecurity Law has a similar effect (Wang et al., 2024) [16]. Digital transformation also suppresses tax stickiness through tax avoidance (Zhou et al., 2022) [17], and investment efficiency and cost stickiness moderate its impact on risk - taking levels (Luo et al., 2024) [18].

Based on the above theoretical deduction,Cost stickiness has a mediation between the effect of digital transformation on technological innovation investment in China's manufacturing industry.The following two hypotheses are needed to test the mediating effect of cost stickiness:

H2. *Digital transformation has a significant negative effect on cost stickiness in China's manufacturing industry..*

H3. *Cost stickiness has a significant negative effect on technological innovation investment in China's manufacturing industry.*

3. Research Design

3.1. Sample Selection and Data Source

The data are obtained from the annual reports of China's A-share listed manufacturing companies. The sample period is the annual data from 2010 to 2022, with a total of 19,047 sample points. There are 13,376 companies in eastern China, 2,509 in central China, and 3,222 in western China, covering manufacturing companies in all regions of the country. In addition, from the perspective of industry distribution, this sample covers all specific manufacturing industries, including electrical machinery and equipment, textile industry, non-metallic mineral products industry, waste resource comprehensive utilization industry, ferrous metal smelting and rolling processing industry, and chemical fiber manufacturing industry， and so on.Therefore, this sample can represent the whole.When cleaning the sample data, first, the ST samples during the sample

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period, the samples whose IPO time is in the sample period, the samples whose delisting time is in the sample period, and the samples with missing key variables are eliminated. Secondly, the adjacent values are filled for some missing values, and the continuous variables are double-sided shrinking at the 1% and 99% levels to alleviate the impact of extreme outliers on the empirical results. The data comes from the China Securities Market and Accounting Research Database (CSMAR), a precise research database focusing on China's financial and economic fields, and the China Research Data Service (CNRDS), a high-quality, open, platform-based comprehensive data platform for China's economic, financial and business research.

3.2. Variable Definition

①Dependent variable: Technological innovation (Innov). Includes technological innovation output (Innov_out) and technological innovation input (Innov_inv). Among them, technological innovation output (Innov_out) is measured by taking the natural logarithm of the number of invention patent authorizations plus 1 [30–32]. Technological innovation input (Innov_inv) is measured by taking the enterprise's annual R&D expenditure as a percentage of total revenue

②Independent variable: Digital transformation (Dig). Drawing on the theoretical framework of digital transformation by Qi et al. (2020), a digital transformation degree evaluation index system was constructed. The index system consists of five digital core modules: digital technology (logarithmization of artificial intelligence, logarithmization of big data, logarithmization of cloud computing, and logarithmization of blockchain) and digital technology application (business model). Based on the index system, a text vocabulary of keywords related to digital transformation was constructed. Annual reports of A-share listed manufacturing enterprises in China from 2010 to 2022 were collected. Keywords related to digital transformation were extracted from the annual reports using Python crawler function. Then, the frequency of digital keywords was counted to characterize the degree of digital transformation. The higher the frequency, the higher the degree of digital transformation (Yuan et al., 2021) [33,34].

③Mediator variable: Cost stickiness(CS). The Weiss model is used to measure cost stickiness. This model quantifies cost stickiness. The specific calculation method is as follows:

$$CostStickiness = Ln(\Delta \cos t/\Delta sale)_{up} - Ln(\Delta \cos t/\Delta sale)_{down} \quad (1)$$

where sale is the total business revenue of the enterprise, up indicates the latest quarter in which the business revenue of the enterprise increased in four consecutive quarters of the year, and down indicates the latest quarter in which the business revenue of the enterprise decreased in four consecutive quarters of the year. Δcost=Δcost i,t - Δcost i,t-1, Δsale=Δsale i,t -Δsale i,t-1 ,t denotes quarter. When the value of cost stickiness is positive, it indicates the existence of cost stickiness in the enterprise, and the larger its value is, the higher the level of cost stickiness is. If the value of cost stickiness is negative, it indicates the existence of cost anti-stickiness[27,29].

④Moderator Variables: Enterprise size(Size),which is measured by total enterprise assets. Technology-intensive(TI),Technology-intensive is 1, otherwise 0[24]. Asset-intensive(AI), Asset-intensive is 1, otherwise 0[24]. Technological innovation output(Innov_out),which is measured by natural logarithm of the number of patents granted plus one.

⑤Control variables(CVs): Enterprise size(Size), Number of employees(Employee), Gearing ratio (Lev), Two jobs in one(Dual), Average age of management(TMTAge), Combination of production and financing(FinInst), Management Expense Ratio (Mfee), Capital accumulation ratio(RCA), Financial leverage(FL), Equity concentration(Top5), Total asset turnover ratio(ATO).

In order to minimize the endogeneity problem when studying the effect of digital transformation on technological innovation, this paper adds the above control variables when conducting regression analysis.

Enterprise size (Size) and number of employees (Employee): These variables are closely related to the enterprise's technological innovation capabilities and resource input. Controlling these

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variables can eliminate the effect of differences in enterprise size and number of employees on technological innovation and more accurately evaluate the role of digital transformation.

Gearing ratio(Lev): It reflects the financial leverage level and debt repayment ability of the enterprise. Controlling it helps to eliminate the potential impact of financial status on technological innovation input and output.

Other control variables: such as Two jobs in one (Dual), Average age of management (TMTAge),Combination of production and financing (FinInst), management expense ratio (Mfee), capital accumulation rate (RCA), Financial leverage (FL), Equity concentration (Top5), Total asset turnover ratio (ATO), etc., respectively control from the aspects of enterprise governance structure, management characteristics, financial strategy, and operational efficiency, which helps to fully strip away the endogenous effect of these factors on technological innovation, thereby more accurately revealing the effect of digital transformation on technological innovation.

Table 1. Variable Name Specifications, Definitions, and Related Descriptions.

Variable Nature	Variable Name	Abbr. of Variable Name	Variable number	Variable Definition
Dependent Variable	Technological innovation output	Innov_out	Y1	Natural logarithm using the number of patents granted for inventions plus 1[30–32]
Dependent Variable	Technological innovation investment	Innov_inv	Y2	Enterprise's annual R&D expenditure as a percentage of total revenue[30–32]
Independent Variable	Digital transformation	Dig	X1	Logarithmization of the total digitized index, obtained by text mining methods. [33,34].
Mediator Variable	Cost stickiness	CS	M	Weiss micro-measurement model[27,29]
Moderator Variable	Enterprise size	Size	X2	Total Enterprise Assets
Moderator Variable	Technology-intensive	TI	X3	Technology-intensive is 1, otherwise 0.[24]
Moderator Variable	Asset-intensive	AI	X4	Asset-intensive is 1, otherwise 0.[24]
Moderator Variable	Level of technological innovation	LTI	X5	Natural logarithm of the number of patents granted plus one.
Control Variable	Enterprise size	Size	X6	Natural logarithm of annual total assets
Control Variable	Number of employees	Employee	X7	Number of employees taken as natural logarithm
Control Variable	Gearing ratio	Lev	X8	Total liabilities at the end of the year / Total assets at the end of the year

Control Variable	Two jobs in one	Dual	X9	1 if the chairman and general manager are the same person, 0 otherwise.
Control Variable	Average age of management	TMTAge	X10	Average age of directors and supervisors
Control Variable	Combination of production and financing	FinInst	X11	Whether holding shares of other financial institutions
Control Variable	Management expense ratio	Mfee	X12	Administrative Expenses / Operating Income
Control Variable	Capital accumulation ratio	RCA	X13	Current year's equity / Previous year's equity - 1
Control Variable	Financial leverage	FL	X14	(Net profit + Income tax expense + Financial expense) / (Net profit + Income tax expense)
Control Variable	Equity concentration	Top5	X15	Number of shares held by top five shareholders / Total number of shares
Control Variable	Total asset turnover ratio	ATO	X16	Operating Income / Average Total Assets

3.3. Research Model Construction

In order to test Hypothesis 1(H1.1,H1.2), Hypothesis 2 (H2) ,and Hypothesis 3(H3), this paper constructs the following three fixed effects regression models.①According to model (2),Regress digital transformation and enterprise technological innovation. If the coefficient is positive and significant, it means that digital transformation can improve technological innovation, and hypothesis 1 (H1.1,H1.2) passes the test.②According to model (3),Regress digital transformation and cost stickiness. If the coefficient is negative and significant, it means that digital transformation can suppress cost stickiness, and hypothesis 2(H2) passes the test. ③According to model (3),Regress digital transformation, cost stickiness, and technological innovation. If the coefficient of cost stickiness is negative and significant, it indicates that cost stickiness has an negative effect on Technological innovation, hypothesis 3(H3) passed the test. In addition, if the coefficient of digital transformation is insignificant or significant but the absolute value of the coefficient is reduced, based on the three-step theory of mediating effect testing, it is proved that enterprise digital transformation can improve technological innovation by suppressing cost stickiness, that is, cost stickiness has a mediating effect.

$$Innov_{i,t} = a_0 + a_1 Dig_{i,t} + a_j CVs_{i,t} + \sum a_k Year + \sum a_l Firm + \varepsilon_{i,t} \quad (2)$$

$$Mediator_{i,t} = b_0 + b_1 Dig_{i,t} + b_j CVs_{i,t} + \sum b_k Year + \sum b_l Firm + \varepsilon_{i,t} \quad (3)$$

$$Innov_{i,t} = c_0 + c_1 Dig_{i,t} + c_2 Mediator_{i,t} + c_j CVs_{i,t} + \sum c_k Year + \sum c_l Firm + \varepsilon_{i,t} \quad (4)$$

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Among them, the dependent variable is the technological innovation (Innov), which is measured from two dimensions: technological innovation output（Innov_out）, and technological innovation investment(Innov_inv).the independent variable is digital transformation(Dig).The mediating variable(Mediator) is cost stickiness.CVs represent control variables, which can better control endogeneity and thus more accurately reveal the effect of digital transformation on technological innovation.Furthermore, in order to weaken endogenous disturbances, the three models also introduces dummy variables of time (Year) and individual (Firm) to absorb the effect of unobservable factors at the time and individual level as much as possible. i represents the unique identification id of a specific listed enterprise, that is, the stock code, t represents the year of data statistics, and ε is the random error term of the model.

4. Results and Discussions

4.1. Analysis of Fixed Effect Regression Results.

Columns (1) and (3) in Table 2 are the regression results based on Model 2.The regression coefficients are 0.078 and 0.002 respectively, and are significant at the 1% statistical level. Columns (2) and (4) in Table 2 are the regression results after the square of digital transformation(Dig) is introduced in Model 2.Column (2) of Table 2 shows the regression results of technological innovation output after adding the square of the independent variable digital transformation to the model. The coefficient of digital transformation is -0.006, but it is not significant. The square term coefficient of digital transformation is 0.018 and is significant at the 1% statistical level. Column (4) of Table 2 shows the regression results of technological innovation input after adding the square of the independent variable digital transformation to the model. The coefficient of digital transformation is -0.002 and is significant. The square term coefficient of digital transformation is 0.001 and is significant at the 1% statistical level. The regression results show that digital transformation has a U-shaped effect on enterprise technological innovation. That is, as the degree of digital transformation changes from low to high, the technological innovation performance of enterprises shows a nonlinear evolution trend of first decreasing and then increasing. Specifically, in the early stages of digital transformation, enterprises may need to invest a lot of resources (including funds, technology and human resources) to establish digital infrastructure and processes, which may have a certain hindering effect on the innovation ability of enterprises. However, as digital transformation deepens, enterprises gradually adapt to new operating models and organizational structures, internal frictions and conflicts are effectively resolved, and a large amount of digital experience and data are accumulated. These factors enable enterprises to better utilize these resources and capabilities to improve technological innovation, thereby significantly improving innovation capabilities. Therefore, from an overall perspective, digital transformation can improve the technological innovation of enterprises.The regression results of columns (1) and (2) test H1. 1,and the regression results of columns (3) and (4) test H1. 2.

Table 2. Fixed effect regression results_the effect of digital transformation on technological innovation output(Innov_out) and technological innovation investment(Innov_inv).

	(1)	(2)	(3)	(4)
Variables	Innov_out	Innov_out	Innov_inv	Innov_inv
Dig	0.078***	-0.006	0.002***	-0.002**
	(0.017)	(0.033)	(0.001)	(0.001)
Dig*Dig		0.018***		0.001***
		(0.006)		(0.000)
CVs	controlled	controlled	controlled	controlled
Year	controlled	controlled	controlled	controlled

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Firm	controlled	controlled	controlled	controlled
N	19047	19047	19047	19047
R2	0.222	0.223	0.176	0.179

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Note: To save space, the coefficients of control variables and constant terms are not reported, and the following tables are the same.

4.2. Robustness Analysis

The digital transformation of the manufacturing industry will affect enterprise technological innovation, and conversely, enterprise technological innovation may also affect digital transformation. Therefore, there may be a two-way causal relationship, leading to endogeneity. Therefore, the instrumental variables method and the propensity score matching- difference in differences method (PSM-DID) are further used to overcome endogeneity:

4.2.1. Instrumental Variable Method

To investigate the effect of digital transformation on technological innovation, the study employs a two-stage least squares (2SLS) regression with robust standard errors. The instrumental variable used is the mean quantitative digital writing indicator of enterprises in the same industry (excluding the target firm) within the same fiscal year, denoted as IV_mean_Ind.Based on the definition and conditions of instrumental variables. The instrumental variable must be highly correlated with the endogenous explanatory variable, uncorrelated with the error term, and be an exogenous variable. Since the market environment and technological trends faced by enterprises in the same industry are similar, the level of digitalization is also similar. Therefore, the mean of enterprises in the same industry is highly correlated with the company's digitalization level, meeting the first condition. At the same time, the digitalization process of other companies in the same industry is unrelated to the company, and there is no two-way causal relationship. The mean indicator does not contain the company's specific error term information, so it meets the conditions of exogeneity and irrelevance to the error term. In summary, it is reasonable to select the mean of companies in the same industry as an instrumental variable.

Table 3 shows the regression results of Model 2 using the instrumental variable method, analyzing the effect of digital transformation on technological innovation across two dimensions: technological innovation output(Innov_out), and technological innovation investment(Innov_inv). The respective coefficients are **0.595**, and **0.023**, all statistically significant at the 1% level. The robustness of findings for Hypothesis 1 is confirmed

Table 3. Instrumental variable method regression results.

Variables	(1) Innov_out	(2) Innov_inv
Dig	0.595***	0.023***
	(0.018)	(0.001)
CVs	controlled	controlled
Year	controlled	controlled
Firm	controlled	controlled
N	19043	19043
R2	0.304	0.283

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2. Propensity Score Matching-Difference in Differences（PSM-DID）

To ensure the robustness of the findings, this study applies the propensity score matching-difference in difference (PSM-DID) method, addressing the potential issue of enterprises superficially reporting digital transformation without actual implementation.

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Experimental and Control Groups: Enterprises are classified into an experimental group (treat = 1) and a control group (treat = 2). If the frequency of digital transformation-related words in an enterprise's annual reports is consistently low across all years, it is deemed as not having undergone actual digital transformation and is placed in the control group. Conversely, enterprises with high digital transformation word frequency in at least one year are categorized in the experimental group.In the propensity score matching stage, we selected multiple covariates to construct the propensity score model, including the company's initial innovation level and other covariates in Table 1. Through propensity score matching, we attempt to balance the experimental and control groups in all observable characteristics except the treatment variable, thereby controlling for potential baseline differences.

Pre- and Post-Experiment Periods: For the experimental group, the year in which the digital transformation index first exceeds the threshold marks the start of digital transformation (post-experiment, period = 1), while prior years are considered pre-experiment (period = 0). This design accommodates varying initiation years of digital transformation among enterprises.

Table 4 reports the regression results based on Model 2 using the PSM-DID method. Columns (1) and (2) show the effect of digital transformation on technological innovation output(Innov_out) and technological innovation input(Innov_inv), with coefficients of 0.282 and 0.011 respectively. The robustness of findings for Hypothesis 1 is further confirmed

Table 4. PSM-DID regression results.

Variables	(1) Innov_out	(2) Innov_inv
Period	-0.032	-0.005***
	(0.037)	(0.001)
Treat	0.211***	0.004***
	(0.028)	(0.001)
_diff	0.282***	0.011***
	(0.043)	(0.001)
N	13831	13829
R2	0.030	0.029

Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

4.3. Empirical Analysis of the Mediating Effect of Cost Stickiness

4.3.1. Analysis of the Empirical Results of Digital Transformation on Cost stickiness

Table 5 (1) shows the regression results of digital transformation (Dig) on cost stickiness(CS) based on Model 3. the coefficient is -0.032, which is significant at the 10% level. This result suggests that digital transformation can suppress cost stickiness. However, in the early stages of digital transformation, due to factors such as initial investment, trial and error adjustments, and employee training, cost stickiness may not be immediately suppressed and may even improve. Over time, digital transformation can significantly suppress cost stickiness as it brings process optimization, data-driven decision making, and economies of scale.

To further investigate these dynamics, the moderating effect of time was analyzed by introducing the time variable as a moderator. Column (2) of Table 5 is the regression result after introducing the interaction term between digital transformation and time based on Model 3. The coefficient of digital transformation (Dig) is 0.066, which is significant at the 10% level, while the coefficient of the interaction term (Dig*Year) is -0.009, which is highly significant at the 1% level. This suggests that time has a significant moderating effect. Specifically, digital transformation improves

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cost stickiness initially and suppresses cost stickiness over time. These results test hypothesis 2 (H2) that digital transformation suppresses cost stickiness in the long run.

Possible reasons why digital transformation can suppress cost stickiness: First, digital transformation improves the cost allocation structure. By introducing advanced cost management systems and data analysis tools, digital transformation can track and allocate costs more accurately. This helps companies identify and eliminate unnecessary parts of costs, thereby reducing cost stickiness. For example, through digital means, companies can monitor resource consumption in the production process in real time, adjust production plans in a timely manner, and avoid overproduction or waste of resources. Second, digital transformation optimizes labor management. Digital transformation also promotes the optimization of labor management, such as reducing the fluctuation of labor costs through intelligent scheduling systems, remote work technologies, and automated processes. These technologies enable companies to adjust labor allocation more flexibly to cope with changes in market demand, thereby reducing cost stickiness.

Table 5. Fixed effects regression results of the impact of digital transformation on cost stickiness.

	(1)	(2)
Variables	CS	CS
Dig	-0.032*	0.066*
	(0.017)	(0.037)
Year		0.001
		(0.005)
Dig*Year		-0.009***
		(0.003)
CVs	controlled	controlled
Year	controlled	controlled
Firm	controlled	controlled
N	19047	19047
R2	0.013	0.006

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3.2. Empirical Results of Cost Stickiness Mediation Effect

This paper uses a three-step regression method to analyze the mediating role of cost stickiness.

Column (1) of Table 6 is the regression result based on Model 2, that is, there is no cost stickiness in the model, and the coefficient of digital transformation on technological innovation (Innov_inv) is 0.00193.

Column (2) of Table 6 shows the regression results based on Model 3. The regression coefficient of digital transformation on cost stickiness is -0.032, which is significant at the 10% level, indicating that digital transformation significantly suppresses cost stickiness.Furthermore, column (3) of Table 6 shows the regression results based on Model 4. The regression coefficient of cost stickiness is -0.001, which is significant at the 1% level, indicating that cost stickiness has a negative effect on technological innovation(Innov_inv). This means that cost stickiness plays a mediating role in the relationship between digital transformation and technological innovation(Innov_inv). The magnitude of the mediating effect can be measured by the product of the regression coefficient of digital transformation on cost stickiness and the coefficient of cost stickiness on technological innovation.

In column (1), the coefficient of digital transformation on technological innovation (Innov_inv) is 0.00193. In column (3), when cost stickiness is introduced into the model, the coefficient decreases to 0.00191. This comparison suggests that cost stickiness plays a partial mediating role.

Thus, it is confirmed that digital transformation improves technological innovation (Innov_inv) by suppressing cost stickiness, and cost stickiness plays a partial mediating role in this relationship.We also note that after the introduction of the mediating variable, the regression coefficient of digital transformation drops slightly from 0.00193 to 0.00191. The possible reason is that cost stickiness is only one of many mediating variables.

Table 6. Empirical results of the mediating effect of accounting cost stickiness.

	(1)	(2)	(3)
Variables	Innov_inv	CS	Innov_inv
Dig	0.00193***	-0.032*	0.00191***
	(0.001)	(0.017)	(0.001)
CS			-0.001***
			(0.000189)
CVs	controlled	controlled	controlled
Year	controlled	controlled	controlled
Firm	controlled	controlled	controlled
N	19047	19047	19047
R2	0.176	0.013	0.177

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Heterogeneity Analysis of the Impact of Digital Transformation on Technological Innovation in Manufacturing

The improvement of the technological innovation level in manufacturing enterprises is often closely related to both external conditions and internal capabilities. Under heterogeneous conditions—such as those involving manufacturing enterprises of different sizes, varying levels of innovation maturity, technology-intensive versus non-technology-intensive enterprises, and asset-intensive versus non-asset-intensive enterprises—the effect of digital transformation on technological innovation may vary. For instance, due to significant differences in the scale of manufacturing enterprises, a nonlinear relationship could potentially exist. In light of these variations, this paper conducts a heterogeneity analysis to better capture these diverse influences."

These changes clarify the idea of heterogeneity analysis while maintaining the focus on how digital transformation's impact on innovation might differ depending on various factors.

4.4.1. Heterogeneity Analysis of Manufacturing Enterprise Size

Enterprises of different sizes differ in resources, organizational structure, market positioning, etc. Large enterprises usually have more resources and stronger affordability, and can invest more funds in technological innovation and talent introduction. Small and medium-sized enterprises, on the other hand, face problems such as limited resources and tight funds. Therefore, the effect of digital transformation on technological innovation may be different, and there may be a threshold effect of enterprise size.Threshold effect regression model is an econometric analysis method used to capture and explain the nonlinear relationship between economic variables. The core idea is that when one variable (called the threshold variable) reaches a certain value (called the threshold value), the relationship between the independent variable and the dependent variable changes significantly. This change is usually manifested as a sudden change in the slope of the linear relationship, that is, the relationship between the two variables presents different linear patterns within different threshold value intervals. The threshold effect regression model is based on the structural mutation theory. It divides the sample data into different intervals by setting threshold variables and threshold

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values, and estimates the relationship between the dependent variable and the independent variable in different intervals. The threshold effect regression model can identify the mutation point of the relationship between variables, that is, the threshold value, so that the model can explain more complex economic phenomena and improve the explanatory power of the model. In order to test the existence of this threshold effect, a threshold effect regression model based on enterprise scale is established as follows:

$$Innov_{i,t} = d_0 + d_1 Dig_{i,t}(size < Y_1) + d_2 Dig_{i,t}(Y_1 \le size < Y_2) + \ldots$$
$$+ d_n Dig_{i,t}(size < Y_n) + \sum d_m CVs_{i,t} + \sum Year + \sum Firm + \varepsilon_{i,t} \quad (5)$$

In the model, the threshold variable is Enterprise Size,which is measured by the total assets.Yn is the threshold value to be estimated. The necessary condition for using the panel threshold effect regression model is to pass the threshold effect test, and use the Bootstrap self-sampling method to find the critical value when testing the threshold effect, and obtain the threshold value Yn . when the threshold variable is less than the threshold value Y_1, the relationship between digital transformation and technological innovation is determined by d_1.When the threshold variable is greater than or equal to the threshold value Y_1 and less than Y_2, the relationship between digital transformation and technological innovation is determined by d_2, and so on.

When Bootstrap sampling is performed 300 times, the threshold effect test results are as follows. In Table 7(1), only the single threshold model has a P value of 0.000, indicating that there is a single threshold, and there is no double threshold effect or triple threshold effect. Table 7(2) shows that the threshold value is 24.0024. Therefore, the single threshold model is selected to estimate the coefficient value in the regression. Further, through the threshold effect regression, the coefficient change of the effect of digital transformation on technological innovation before and after the threshold value is tested. The size threshold effect regression results are shown in Table 7(3). In the model, when the enterprise size is less than the threshold value of 24.0024, the coefficient is 0.0937 and the t value is 3.43, indicating that the digital transformation of manufacturing enterprises with less size has a less effect on technological innovation. However, when the enterprise size is greater than the threshold value of 24.0024, the coefficient is 0.425 and the t value is 5.88, indicating that the digital transformation of manufacturing enterprises with greater size has a greater effect on technological innovation. This shows that: first, regardless of the size of manufacturing enterprises, digital transformation can always improve technological innovation; second, the greater the size of manufacturing enterprises, the greater the technological innovation effect. In general, there is a threshold effect in the effect of digital transformation on technological innovation in the manufacturing industry, which is a sudden change in the size of the positive force rather than a sudden change in the positive and negative direction of the force.

Table 7(1). Regression results of the scale threshold effect test.

Threshold effect test (bootstrap = 300):							
Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	2987.3021	0.5921	33.69	0.000	11.963	13.545	17.442
Double	2981.9224	0.5911	9.10	0.157	10.309	12.558	16.412
Triple	2976.4458	0.5900	9.28	0.577	18.801	23.512	32.527

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Table 7(2). Regression results of scale threshold effect test.

Threshold estimator (level = 95):			
model	Threshold	Lower	Upper
Th-1	24.0024	23.9068	24.0496

Table 7(3). Regression results of scale threshold effect test.

Robust _cat#c.Dig	Coefficient	std. err.	t	P>|t|	[95% conf. interval]	
0	.0938492	.0273868	3.43	0.001	.0400933	.1476051
1	.4235536	.0735485	5.76	0.000	.2791898	.5679173

4.4.2. Analysis of Technology-Intensive Heterogeneity

There are obvious differences between technology-intensive manufacturing and other manufacturing industries in terms of technology content, labor productivity, resource consumption, proportion of scientific and technological personnel, complexity of product technical performance, reflection of the national scientific and technological development level, economic benefits, social benefits, etc. Therefore, The technological innovation effects of digital transformation may vary. In order to test the existence of this heterogeneity, fixed effect tests were conducted on technology-intensive manufacturing and other manufacturing industries based on Model 2. Table 8 reports the regression results. The coefficient of technology-intensive manufacturing is 0.074, with a statistical significance level of 1%. The coefficient of other manufacturing industries is 0.046, which is not significant.The digital transformation of technology-intensive enterprises has a more significant effect on technological innovation, thanks to their rich technical resources, high-quality talent pool and open innovation environment, which jointly promote the deep integration of digitalization and innovation.

Table 8. Regression results of technology-intensive manufacturing and non-technology-intensive manufacturing.

	(1)	(2)
Variables	TI	TI_no
Dig	0.074***	0.046
	(0.020)	(0.029)
CVs	controlled	controlled
Year	controlled	controlled
Firm	controlled	controlled
N	11198	7849
R2	0.249	0.174

Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

4.4.3. Analysis of Asset-Intensive Heterogeneity

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There are obvious differences between asset-intensive(AI) manufacturing enterprises and non-asset-intensive(AI_no) manufacturing enterprises in terms of asset investment, capital intensity, supply chain characteristics, operational complexity, technological innovation challenges, risks and benefits. Therefore, the effect of digital transformation on technological innovation is may be different. In order to test the existence of this heterogeneity, fixed effect tests were conducted on asset-intensive manufacturing enterprises and non-asset-intensive manufacturing enterprises based on Model 2. Table 9 reports the regression results, with the coefficient for asset-intensive manufacturing being 0.072, which is not statistically significant, and the coefficient for non-asset-intensive manufacturing firms being 0.084, which is statistically significant at the 1% level.

Table 9. Regression results of asset-intensive manufacturing and non-asset-intensive manufacturing.

	(1)	(2)
Variables	AI	AI_no
Dig	0.072	0.084***
	(0.052)	(0.018)
CVs	controlled	controlled
Year	controlled	controlled
Firm	controlled	controlled
N	3667	15380
R2	0.224	0.222

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.4. Heterogeneity Analysis at Different Technological Innovation Levels

Enterprises with high technological innovation levels usually have stronger technology absorption and innovation capabilities and can more effectively use digital technologies to improve technological innovation. However, Enterprises with low technological innovation levels may be limited in resources, technology and talent, and digital transformation may be difficult. The effect on technological innovation may be relatively weak. Therefore, in order to test the existence of this heterogeneity, based on Model 2, quantile regression is used to test the effect of digital transformation on technological innovation at different technological innovation levels (10%, 25%, 50%, 75% and 90%). Table 10 reports the quantile regression results based on different levels of technological innovation. For the group with the lowest level of technological innovation (q0.1), the coefficient is -0.000271, and the effect of digital transformation on technological innovation is negative, but the effect is not significant; for the group with low level of technological innovation (q0.25 q0.5) , with coefficients of 0.157 and 0.181 respectively. The technological innovation effect of digital transformation has turned into a positive influence, but the effect is not significant. In the group with higher technological innovation level and the highest group (q0.75 q0.9), the coefficients are 0.176 and 0.177, respectively, with statistical significance levels of 10% and 1%, respectively. Digital transformation has a strong positive effect on technological innovation. It can be found that the higher the level of technological innovation of an enterprise, the stronger the effect of digital transformation on technological innovation.The digital transformation effect has no significant impact on the technological innovation of low-level innovative enterprises, and the possible factors are the lack of technology or human resources， and digital transformation has a significant impact on the technological innovation of high-level innovative enterprises, mainly because these enterprises usually have strong technological accumulation and innovation resources. They can quickly absorb and apply new technologies, optimize R&D processes through digital means, improve innovation efficiency, and thus promote breakthroughs in technological innovation.

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Table 10. Quantile regression results.

	(1)	(2)	(3)	(4)	(5)
Variables	0.1	0.25	0.5	0.75	0.9
Dig	-0.000271	0.157	0.181	0.176*	0.177***
	(0.043)	(1.200)	(0.214)	(0.096)	(0.046)
N	19047	19047	19047	19047	19047
R2					

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions

The research purpose of this paper is to analyze the effect of digital transformation on technological innovation in China's manufacturing industry. The empirical test confirms that digital transformation can improve technological innovation in manufacturing enterprises,hypothesis 1 (H1) is tested. The study further found that cost stickiness plays a mediating role in the relationship between digital transformation and technological innovation, that is, digital transformation suppresses cost stickiness, allowing enterprises to invest more resources in technological innovation activities, thereby improving the technological innovation of enterprises, hypothesis 2 (H2) and hypothesis 3 (H3) is tested. In addition, the study also found that the effect of digital transformation on technological innovation varies depending on the characteristics of the enterprise. Greater-size enterprises, technology-intensive, non-asset-intensive enterprises, and enterprises with greater technological innovation capabilities can better improve their technological innovation in digital transformation.

6. Implications of the Findings for both Theory and Practice

6.1. Implications of the Findings for Theory

Future research should focus on expansion and incorporate new elements of digital transformation into the theoretical framework of the technological innovation driving system to more fully understand its role as a new engine of technological innovation. At the same time, we should explore the use of novel methods such as text mining technology to evaluate the degree of digital transformation and improve the accuracy and objectivity of measurement. In addition, the study of digital transformation can start from the micro level and deeply explore its impact on specific levels such as enterprises and industries, which will help to form a more comprehensive and systematic theoretical system.

6.2. Implications of the Findings for Practice

6.2.1. Implications at the Level of Enterprises

To formulate a differentiated digital transformation strategy, the scale of the enterprise needs to be considered. Large enterprises should rely on their financial and technological advantages, integrate resources through mergers and acquisitions, strengthen internal management, and lead the transformation; small and medium-sized enterprises should strengthen digital transformation training programs and cooperate with large enterprises to learn. Technology-intensive manufacturing industries should increase R&D investment, maintain technological leadership, optimize R&D processes, and explore new business models such as platformization and service-oriented. Asset-intensive manufacturing industries should use big data, the Internet of Things, etc. to optimize supply chain management and achieve transparency and efficiency.

6.2.1. Implications at the Level of Government

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The government should actively promote the digital transformation of the manufacturing industry. The primary task is to strengthen policy support, improve the policy system, clarify the transformation goals and paths, encourage enterprise transformation through fiscal subsidies, tax incentives and other measures, and establish digital transformation standards and evaluation systems. At the same time, establish a demonstration project library, focus on supporting representative projects, lead the overall transformation of the industry, and strengthen cross-regional and cross-industry policy coordination. Secondly, it is necessary to improve infrastructure, especially increase investment in underdeveloped areas, promote the construction of new facilities, improve service efficiency, and strengthen the network security system. In addition, it is necessary to strengthen public services, establish a digital transformation platform, provide one-stop services, protect intellectual property rights, and promote data openness and sharing. Finally, promote the close integration of industry, academia, research and application, encourage cooperative innovation, support industrial alliances, build an innovation ecosystem, and help start-ups and small and medium-sized enterprises develop.

7. Potential limitations and Future Research Directions

7.1. Technological Innovation Indicators

This paper analyzes the role of digital transformation in improving invention patents. This perspective is undoubtedly profound and representative, but it also inevitably exposes the limitations of the research. There are obvious differences in the nature of innovation among invention patents, utility patents and design patents. Invention patents emphasize originality, utility patents focus on technical improvements, and design patents focus on aesthetic value. Therefore, digital transformation may have different effects on improving these three types of patents. Future research should broaden the horizons and deeply analyze the differentiated impact of digital transformation on different types of patent innovation.

7.2. Data Source

The data source of this article has limitations, mainly relying on the A-share data of listed companies in China's manufacturing industry. Although listed companies are representative, they may not fully reflect the actual situation of the entire manufacturing industry. Non-listed companies play an important role in the manufacturing industry, but they are often overlooked due to the difficulty in obtaining data. Future research needs to broaden the data source and strengthen the research on non-listed companies in order to have a more comprehensive and in-depth understanding of the impact of digital transformation.

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