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

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Abstract: At present, China's manufacturing industry is urgently in need of a transition, as well as an upgrade from low- to high-end production. Concurrently, as digital technology continues to advance, the enterprise-level digital transformation is anticipated to emerge as a new "engine" driving technological innovation. This study is centered on China's A-share listed manufacturing enterprises, as we aim to explore the impact of digital transformation on technological innovation. Employing a fixed-effect model, the instrumental variable method, and propensity score matching, combined with a difference-in-differences approach, threshold regression, and a quantile regression model, we empirically examine the influence of digital transformation on technological innovation within the manufacturing sector. Our findings reveal the following: (1) Digital transformation enhances technological innovation. (2) Mediation analysis indicates that digital transformation boosts technological innovation by mitigating cost stickiness. (3) The heterogeneity analysis shows that the effect of digital transformation on technological innovation is more pronounced in larger enterprises, particularly those with lower technological intensity, lower asset intensity, and stronger innovation capabilities. The outcome of this study provides a decision-making reference for governments and enterprises, whereby the government can formulate industrial and fiscal policies, as well as helping enterprises to carry out digital transformation through policy guidance and support. Enterprises can formulate differentiated transformation strategies based on their own characteristics, optimize their cost structure through digital transformation, release resources for technological innovation, and improve their own technological innovation capabilities.

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

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1. Introduction

"New quality productivity" is a novel concept, proposed by Chinese scholars in recent years, for addressing the challenges posed by modern economic development; this concept integrates the scientific and technological, green, and digital areas of productivity. Scientific and technological productivity underscores the direct contribution of cutting-edge technology to productivity enhancement [1]. Green productivity is centered on sustainable resource utilization, circular economy models, energy efficiency, and emission reduction, positioning technology at the forefront of ecological responsibility [2–4]; meanwhile, digital productivity highlights the transformative potential of technologies such as big data, cloud computing, and artificial intelligence in reshaping corporate operations and fostering data-driven management strategies [5].

Among these, scientific and technological innovation serves as a pivotal factor in driving productivity growth, enhancing production efficiency and product quality through the introduction of new technologies, methodologies, and concepts, thereby fueling economic growth and social progress. Green productivity constitutes the core component of new quality productivity and is the linchpin supporting green development, emphasizing the pursuit of economic benefits while giving due consideration to resource efficiency and environmental friendliness. Through scientific and technological innovation, model innovation, institutional innovation, and other avenues, green productivity facilitates the green and low-carbon transformation and upgrading of industries, ultimately achieving comprehensive, coordinated, and sustainable development of the economy and society. Digital productivity is another key aspect of new quality productivity. In recent years, numerous Chinese manufacturing enterprises have extensively adopted digital technologies such as cloud computing, big data, the mobile Internet, and smart hardware. The application of these technologies is continually propelling the manufacturing industry toward networking, intelligence, and digitalization. The utilization of such digital technologies not only aids in cost reduction, efficiency improvement, innovation promotion, and management optimization in the short-term, but also fosters the stable growth of corporate operating performance in the long run.

Amidst the global tide of digitalization, seizing digital opportunities is vital for enhancing China's core economic competitiveness. The rapid advancement of digitalization has spurred enterprises to embrace emerging digital technologies in order to facilitate digital transformation and bolster their digital capabilities [6]. To this end, the Chinese government has rolled out a series of policies, including the "Special Action Plan for Digital Empowerment of Small and Medium-sized Enterprises" and the "Notice on Accelerating the Digital Transformation of State-owned Enterprises", to support the digital transformation of enterprises.

At present, there is no consensus within the academic community regarding the definition of digital transformation. Chanias et al. (2019) have argued that, if an enterprise opts to achieve transformation and upgrading through information technology, it can be deemed that the enterprise is undergoing digital transformation [7]. Fitzgerald et al. (2018) interpreted digital transformation as the leveraging of digital technologies (such as social media, embedded devices, etc.) to effect significant business transformation [8]. Liu et al. (2021) [1] defined the essence of the digital transformation process from a management standpoint; namely, enterprises undergoing digital transformation broadly apply digital technologies to various aspects related to enterprise growth, including production and manufacturing, technology updates, operations management, marketing, and so on. In their study, they posited that digital transformation refers to enterprises that utilize digital technologies such as big data, cloud computing, and artificial intelligence to comprehensively innovate business models, operational processes, products, and services; enhance efficiency; and create new value. In the manufacturing context, this transformation is specifically manifested in production automation, artificial intelligence, digital supply chain management, and personalized customer service.

China's manufacturing industry exemplifies the challenges confronted by new quality productivity [9]. Historically, reliance on an extensive growth model led to excessive resource consumption, inefficiency, and environmental degradation [10–13]. The development of the quality level and core competitiveness in China's manufacturing industry has lagged behind its scale expansion, and the present challenges facing this industry primarily include weak independent innovation and R&D capabilities, the majority of industries occupying the middle and low ends of the global value chain, high dependence on imports of key technologies and high-end components [14,15], and overall low product quality. Consequently, China's manufacturing industry urgently needs to transition from low- to high-end through technological innovation [16,17]. Meanwhile, with the progressive advancement of cutting-edge digital technologies such as big data, cloud computing, and artificial intelligence, digital transformation is poised to become a new "engine" for technological innovation in China's manufacturing industry [18–21].

Therefore, examining the impact of digital transformation on technological innovation in China's manufacturing industry holds immense value. Some scholars have already begun exploring the relationship between digital transformation and technological innovation; for instance, Wei et al.(2021) Big data can enhance enterprises' competitive advantages [22,23]. Xu et al. (2022) found, through industry-level empirical analysis, that the level of digitalization positively influences both exploratory innovation and developmental innovation, with a stronger impact on the latter over the former [24]. Chen et al. (2024) constructed an analytical framework from the perspective of factor flow and discovered that digitalization significantly positively impacts the efficiency of innovation factor allocation, particularly by promoting the efficiency of innovation capital allocation [25]. The flow of innovation factors serves as a crucial transmission through which mechanism for digitalization can enhance the efficiency of innovation factor allocation. Lin et al. (2024) found the following: (1) industrial digitalization exerts a significant positive influence on China's regional innovation efficiency; and (2) industrial digitalization improves regional innovation efficiency by optimizing industrial structure effects and human capital effects [26]. Guo et al. (2023) conducted an empirical test using a provincial digital information database spanning from 2012 to 2018, and found that green digitalization markedly promotes environmental innovation, and that this effect can be realized by increasing R&D investment [27]. These studies contribute theoretically and practically to promoting digital transformation and enhancing innovation.

However, existing studies have predominantly analyzed the impact of digital transformation on technological innovation from a macro perspective, lacking micro-level evidence. In this study, we open up a novel research perspective, specifically by delving into the impact of digital transformation on technological innovation in China's manufacturing industry using enterprise micro-level data, thereby shrinking the research scope to that of a micro perspective. Secondly, to obtain enterprise microdata, we employ text mining technology and other methods to develop a comprehensive set of enterprise digital transformation indicators, providing a more precise measurement framework for related research. Thirdly, we integrate digital transformation elements into the technology innovation driving system, thereby enriching innovation-driven theory.

The aim of this study is to empirically test the effect of enterprise digital transformation on technological innovation, as well as to deeply explore the relationship between enterprise digital transformation and technological innovation at the micro-level. We further analyze whether digital transformation can increase investment in technological innovation through suppressing cost stickiness; explore the heterogeneity of digital transformation among different enterprise sizes, as well as among those that are technology-intensive, asset-intensive, and have different levels of technological innovation; and provide valuable policy recommendations for enterprises with different characteristics and decision makers.

This study is of great significance as it shows how to use digital technology to support technological innovation and strengthen core technological breakthroughs, thereby scrapping the coarse development model, improving resource efficiency, reducing environmental impact, and achieving sustainable development.

2. Literature Review

2.1. Theoretical Analysis

Innovation Ecosystem Theory: Digital transformation fosters a more open and collaborative innovation ecosystem, within which enterprises, research institutions, suppliers, customers, and other stakeholders are tightly interconnected through digital platforms, facilitating the sharing of resources, knowledge, and information; this highly collaborative innovation model accelerates the research, development, and application of new technologies, thereby enhancing the efficiency and quality of technological innovation.

Data Intelligence Theory: Digital transformation empowers enterprises to collect, process, and analyze vast amounts of data, gaining insights into market trends, user needs, and technological advancements. Based on the intelligent analysis of these data, enterprises can more precisely identify innovation directions and optimize product design and service processes. Furthermore, data intelligence supports innovative applications, such as predictive maintenance and intelligent scheduling, further boosting production efficiency and product quality.

Dynamic Capability Theory: Digital transformation necessitates that enterprises possess the ability to swiftly adapt to market changes and technological developments. Dynamic capability theory emphasizes that enterprises should have the capacity to integrate and reconfigure internal and external resources, as well as to promptly respond to environmental shifts. Through digital transformation, enterprises can more flexibly adjust their organizational structures, optimize business processes, and enhance the agility and flexibility of their technological innovation efforts.

2.2. Existing Research

2.2.1. Technological Innovation Effect from Digital Transformation

Scholars have examined the impact of digital transformation on technological innovation from various perspectives. The effect of digital transformation on enterprise technological innovation is manifested in both quantity and quality, with potential heterogeneity in these aspects [1]. Digital transformation can enhance an enterprise's value through improving technological innovation, fostering business model innovation, and integrating the two. Digital inclusive finance effectively alleviates financing constraints for small- and medium-sized enterprises, thereby enhancing their technological innovation capabilities. Enterprise digital transformation promotes green technological innovation through improving the composition of human capital, reducing information asymmetry, and increasing investments in technological innovation [15]. Digital transformation can also boost green technological innovation by strengthening cooperation in this field [28]. Digital finance exhibits a spatial spillover effect in improving technological innovation [20]. Li et al. (2022) empirically analyzed the impact of digital transformation on enterprise innovation by constructing three dimensions of digital transformation (digital investment, digital technology, and business model transformation), finding that digital transformation significantly promotes technological innovation activities within enterprises [28]. Tu et al. (2023) utilized machine learning technology to empirically analyze the impact of digital transformation on corporate mergers and acquisitions, revealing that digital transformation can improve merger and acquisition performance, indirectly supporting the role of digital transformation in promoting technological innovation [29]. Chen et al. (2023) explored the relationship between digital transformation and innovation, finding that digital transformation has a promoting effect on corporate innovation, with knowledge flow, technical personnel, R&D investment, and innovation awareness serving as important mediating paths [30]. Gaglio C. et al. (2022) discovered that selected digital communication technologies (including the use of social media and business mobile phones for internet browsing) have positive impacts on innovation [31]. Shao et al. (2024) found that the presence of foreign executives in senior management teams promotes enterprise innovation performance by facilitating digital transformation, while financing constraints play a moderating role [32].

Based on the aforementioned theoretical derivation, the following hypotheses are proposed:

H1. *Digital transformation has the potential to significantly enhance the technological innovation capabilities of Chinese manufacturing enterprises.*

H1a. *Digital transformation is likely to substantially boost the technological innovation output of Chinese manufacturing enterprises.*

H1b. *Digital transformation may lead to a significant increase in technological innovation investments by Chinese manufacturing enterprises.*

2.2.2. The Mediating Role of Cost Stickiness in the Process of Digital Transformation Affecting Technological Innovation

In this study, we further examine the mediating mechanism of cost stickiness in the relationship between digital transformation and technological innovation. Cost stickiness pertains to the phenomenon whereby a decrease in a company's revenue results in a smaller reduction in costs compared to the increase in costs when revenue rises. Adjustment costs, managers' optimistic expectations, and opportunistic motivations constitute the primary underlying causes of cost stickiness. In practical terms, factors such as exorbitant machine disposal costs and significant pressure to lay off employees impede the elimination of production capacity. When business volume declines, management may opt to retain unused production capacity, instead of immediately reducing it, due to various reasons. This decision gives rise to an asymmetry between costs and business volume, whereby costs fail to adjust proportionately with changes in business volume, thus manifesting as cost stickiness (i.e., the rate of cost reduction lags behind the rate of business volume reduction) [33].

Several scholars have investigated the cost-suppressing effects of digital transformation. For instance, digital transformation optimizes information processing through an integrated digital platform and enables resource usage tracking, facilitating better resource allocation and system optimization, thereby mitigating cost stickiness [34]. Additionally, digital transformation can curb cost stickiness by enhancing corporate information transparency and alleviating agency problems [35,36], as well as through lowering adjustment costs and easing financing constraints [37]. Furthermore, digital transformation adjusts managers' optimism, thereby suppressing cost stickiness. Smart manufacturing enhances resource and information processing efficiency [38], strengthening internal control and optimizing resource adjustment, which further diminishes cost stickiness [39]. Moreover, digital transformation adjusts tax planning that suppresses tax stickiness [40]. As digital transformation progresses, enterprise business processes become increasingly transparent. Through incorporating advanced cost management systems and data analysis tools, digital transformation enables more precise cost tracking and allocation, which aid companies in identifying and eliminating unnecessary cost components, thus reducing cost stickiness [41]. It also facilitates more flexible labor allocation to accommodate fluctuations in business volume, thereby mitigating cost stickiness [42]. Consequently, digital transformation enhances enterprises' flexibility in adjusting costs in response to changes in business volume (i.e., it reduces cost stickiness), thereby boosting corporate profits and enabling companies to allocate more funds to technological innovation activities.

Based on the aforementioned theoretical framework, cost stickiness serves as a mediator of the impact of China's manufacturing digital transformation on technological innovation investment. To validate the mediating effect of cost stickiness, the following two specific hypotheses are proposed:

H2. *Digital transformation can markedly reduce cost stickiness in China's manufacturing industry.*

H3. *Reducing cost stickiness can significantly enhance the technological innovation investment in China's manufacturing industry.*

3. Research Design

3.1. Sample Selection and Data Source

The data originated from the annual reports of Chinese A-share listed manufacturing companies. The sample encompasses annual data spanning from 2010 to 2022, totaling 19,047 sample points from 13,376 companies in Eastern China, 2509 in Central China, and 3222 in Western China, thus covering manufacturing companies across all regions of the country. Furthermore, in terms of industry distribution, this sample encompasses all specific manufacturing industries, such as electrical machinery and equipment, textiles, non-metallic mineral products, comprehensive utilization of waste resources, ferrous metal smelting and rolling processing, and chemical fiber manufacturing, among others; consequently, this sample is representative of the whole.

During the data cleaning process, we first eliminated ST samples, samples with IPO dates, and samples with delisting dates within the sample period, as well as samples with missing key variables. Secondly, we imputed missing values using adjacent values and performed two-sided winsorization on continuous variables at the 1% and 99% levels to mitigate the impacts of extreme outliers on the empirical results. The data were sourced from the China Securities Market and Accounting Research Database (CSMAR) and the China Research Data Service (CNRDS).

3.2. Variable Definition

Dependent Variable: technological innovation (Innov), which comprises technological innovation output (Innov_out) and technological innovation investment (Innov_inv). Specifically, technological innovation output (Innov_out) is measured with the natural logarithm of the number of invention patent authorizations plus 1 [43–45]. Technological innovation investment (Innov_inv) is calculated as the proportion of the enterprise's annual R&D expenditure to total revenue.

Independent Variable: digital transformation (Dig). we constructed a digital transformation degree evaluation index system, consisting of the following core digital modules: digital technologies (logarithmization of artificial intelligence, big data, cloud computing, and blockchain) and digital technology application (business model). Based on the index system, we developed a text vocabulary of digital transformation-related keywords. Annual reports of Chinese A-share listed manufacturing companies from 2010 to 2022 were collected, and keywords related to digital transformation were extracted using a Python 3.10 crawler function. The frequency of each keyword was then counted to characterize the degree of digital transformation, where a higher frequency indicates a higher degree of digital transformation [46–48].

Intermediary Variable: cost stickiness (CS). The Weiss model was employed to measure and quantify cost stickiness; its specific calculation method is as follows:

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

where 'sale' represents the total business revenue of the enterprise, 'up' denotes the latest quarter within a series of four consecutive quarters in a year during which the business revenue increased, and 'down' indicates the latest quarter within the same four-quarter period during which the business revenue decreased; $\Delta cost = \Delta cost_{i,t} - \Delta cost_{i,t-1}$, $\Delta sale = \Delta sale_{i,t} - \Delta sale_{i,t-1}$; and t denotes quarter. A positive value for cost stickiness signifies the presence of cost stickiness in the enterprise, with a larger value indicating a higher level of cost stickiness. Conversely, a negative value for cost stickiness suggests the existence of cost anti-stickiness [27,29].

Moderating variables:

Enterprise size (size), quantified by the total assets of the enterprise.

Technology intensiveness (TI), coded as 1 if the enterprise is technology-intensive, and 0 otherwise [48].

Asset intensiveness (AI), coded as 1 if the enterprise is asset-intensive, and 0 otherwise [24].

Technological innovation output (Innov_out), measured using the natural logarithm of the number of authorized patents plus one.

Control variables (CVs):

Enterprise size (Size) and number of employees (Employee), closely linked to an enterprise's technological innovation capabilities and resource allocation. By controlling for these variables, we can eliminate the influences of variations in enterprise size and employee count on technological innovation, allowing for a more precise assessment of the role of digital transformation.

Debt ratio (Lev), which reflects the enterprise's financial leverage and debt repayment capacity. Controlling for this variable helps to mitigate the potential impact of financial status on technological innovation inputs and outputs.

Additional control variables include whether the chairman and general manager are the same person (Dual), the average age of the management team (TMTAge), financial integration (FinInst), the management expense ratio (Mfee), the capital accumulation rate (RCA), financial leverage (FL), equity concentration (Top5), and the total asset turnover rate (ATO). By controlling for these aspects related to corporate governance structure, management traits, financial strategy, and operational efficiency, we can comprehensively account for the endogenous effects of these factors on technological innovation, thereby more accurately uncovering the impact of digital transformation on technological innovation.

In order to minimize the endogeneity problem when examining the effect of digital transformation on technological innovation, we incorporated the aforementioned control variables into the regression analysis (Table 1).

Table 1. Variable descriptions.

Variable Nature	Variable Name	Abbr.	Variable Definition
Dependent Variables	Technological innovation output	Innov_out	Natural logarithm using number of patents granted for inventions plus 1 [30–32].
	Technological innovation investment	Innov_inv	Enterprise's annual R&D expenditure as a percentage of total revenue [30–32].
Independent Variable	Digital transformation	Dig	Logarithmization of total digitized index, obtained from text mining methods [33,34].
Mediating Variable	Cost stickiness	CS	Weiss micro-measurement model [27,29].

Table 1. *Cont.*

Variable Nature	Variable Name	Abbr.	Variable Definition
Moderating Variables	Enterprise size	Size	Total enterprise assets.
	Technology-intensive	TI	Technology-intensive is 1; otherwise 0 [24].
	Asset-intensive	AI	Asset-intensive is 1; otherwise 0 [24].
	Level of technological innovation	LTI	Natural logarithm of number of patents granted plus 1.
Control Variables	Enterprise size	Size	Natural logarithm of annual total assets.
	Number of employees	Employee	Number of employees taken as natural logarithm.
	Gearing ratio	Lev	Total liabilities at end of year/Total assets at end of year.
	Two jobs in one	Dual	1 if the chairman and general manager are the same person; 0 otherwise.
	Average age of management	TMTAge	Average age of directors and supervisors.
	Combination of production and financing	FinInst	Whether holding shares of other financial institutions.
	Management expense ratio	Mfee	Administrative expenses/operating income.
	Capital accumulation ratio	RCA	Current year's equity/Previous year's equity − 1.
	Financial leverage	FL	(Net profit + Income tax expense + Financial expense)/(Net profit + Income tax expense).
	Equity concentration	Top5	Number of shares held by top five shareholders/Total number of shares.
	Total asset turnover ratio	ATO	Operating income/average total assets.

3.3. Research Model Construction

To test Hypothesis 1 (H1a, H1b), Hypothesis 2 (H2), and Hypothesis 3 (H3), we developed three regression models, as follows. ① In Model (2), we regressed digital transformation on enterprise technological innovation. If the coefficient was positive and statistically significant, then digital transformation enhanced technological innovation, thus supporting Hypothesis 1 (H1a, H1b). ② In Model (3), we regressed digital transformation on cost stickiness. If the coefficient was negative and statistically significant, then digital transformation could mitigate cost stickiness, thereby confirming Hypothesis 2 (H2). ③ In Model (4), we regressed technological innovation on both digital transformation and cost stickiness. If the coefficient for cost stickiness was negative and statistically significant, then cost stickiness had a detrimental effect on technological innovation, thus validating Hypothesis 3 (H3).

$$\mathrm{Innov}_{i,t} = a_0 + a_1\mathrm{Dig}_{i,t} + a_j\mathrm{CVs}_{i,t} + \sum a_k\mathrm{Year} + \sum a_l\mathrm{Firm} + \varepsilon_{i,t} \tag{2}$$

$$\mathrm{Mediator}_{i,t} = b_0 + b_1\mathrm{Dig}_{i,t} + b_j\mathrm{CVs}_{i,t} + \sum b_k\mathrm{Year} + \sum b_l\mathrm{Firm} + \varepsilon_{i,t} \tag{3}$$

$$\mathrm{Innov}_{i,t} = c_0 + c_1\mathrm{Dig}_{i,t} + c_2\mathrm{Mediator}_{i,t} + c_j\mathrm{CVs}_{i,t} + \sum c_k\mathrm{Year} + \sum c_l\mathrm{Firm} + \varepsilon_{i,t} \tag{4}$$

The dependent variable is technological innovation (Innov), which is measured across 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 are included to better address endogeneity in order to more accurately uncover the effect of digital transformation on technological innovation. Furthermore, to mitigate endogenous disturbances, the three models also incorporate dummy variables for time (Year) and individual firms (Firm), aiming to absorb the effects of unobservable factors at both the time and individual levels as much as possible; here, i represents the unique identifier of a specific listed enterprise (i.e., the stock code), t represents the year of data collection, and ϵ is the random error term of the model.

4. Empirical Results

4.1. Regression Results of Digital Transformation on Technological Innovation

In this study, we employed a fixed-effect model to validate the following two hypotheses: (H1a), digital transformation exerts a significant positive influence on the technological innovation output of China's manufacturing sector, implying that it enhances enterprises' R&D efficiency, thereby boosting the production of new products, technologies, and processes; and (H1b), digital transformation also positively impacts the technological innovation investment in China's manufacturing industry, indicating that it stimulates enterprises to increase their investments in technological R&D, thus fostering the sustainable development of technological innovation activities.

Columns (1) and (3) in Table 2 present the regression results based on Model 2. The regression coefficients for digital transformation on technological innovation output and investment are 0.078 and 0.002, respectively, both significant at the 1% statistical level. Consequently, Hypotheses 1a and 1b are supported by the empirical evidence.

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

Variables	(1) Innov_Out	(2) Innov_Out	(3) Innov_Inv	(4) 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
Firm	controlled	controlled	controlled	controlled
N	19,047	19,047	19,047	19,047
R^2	0.222	0.223	0.233	0.215

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

In the initial stages of digital transformation, enterprises may need to allocate substantial resources to establish the necessary infrastructure and processes, potentially hindering their technological innovation capabilities to some extent; however, as digital transformation progresses, enterprises can more effectively leverage these digital resources to enhance their technological innovation. Hence, the relationship between enterprise digital transformation and technological innovation may not be entirely linear. To further investigate this potential nonlinear relationship, we incorporated the square term of digital transformation into the fixed-effect model. Columns (2) and (4) in Table 2 display the regression results after including the square of digital transformation (Dig) in Model 2. Column (2) shows the regression outcomes for technological innovation output with the addition of the square term. The regression coefficient for digital transformation was −0.006, but this is not statistically significant. The regression coefficient for the square term of digital transformation was 0.018, which is significant at the 1% statistical level. Column (4) presents the regression results for technological innovation input after adding the square term. The regression coefficient for digital transformation was −0.002, which is significant at the 5% statistical level, while the regression coefficient for the square term of digital transformation was 0.001, significant at the 1% statistical level. These regression results indicate that digital transformation has a U-shaped effect on both technological innovation output and input; that is, as the level of digital transformation increases, enterprises' technological innovation performance exhibits a non-linear trend, initially decreasing and then increasing. From a holistic and long-term perspective, digital transformation enhances enterprises' technological innovation output and investment.

4.2. Robustness Analysis

The digital transformation of the manufacturing industry is likely to influence technological innovation within enterprises, and, conversely, technological innovation by enterprises may also impact their digital transformation; consequently, there may exist a bidirectional causal relationship, giving rise to endogeneity issues. To address these issues, the instrumental variable and propensity score matching difference-in-differences (PSM-DID) methods were employed to mitigate endogeneity concerns.

4.2.1. Instrumental Variable Method

In this study, we employed the instrumental variable (IV) method to conduct robustness tests on Hypotheses 1a and 1b. The chosen IV is the mean digital transformation level of enterprises within the same industry, excluding the target enterprise itself, denoted as IV_mean_lnd. According to its definition and the criteria for instrumental variables, an effective IV must exhibit high correlation with the endogenous independent variable, be uncorrelated with the error term, and maintain exogeneity. Given that other enterprises in the same industry operate under similar market conditions and technological trends, their levels of digital transformation tend to be comparable; consequently, the mean digital transformation level of these peer enterprises is highly correlated with that of the target enterprise, thus satisfying the first criterion. Simultaneously, the digital transformation processes of these peer enterprises are independent of the target enterprise. Furthermore, the mean indicator does not encapsulate the specific error term information pertaining to the target enterprise, thereby fulfilling the conditions of exogeneity and independence from the error term. In conclusion, the selection of the mean digital transformation level of peer enterprises within the same industry as an IV is justifiable.

Table 3 presents the regression results obtained using the IV method based on Model 2, examining the influence of digital transformation on technological innovation across two dimensions: technological innovation output (Innov_out) and technological innovation input (Innov_inv). The corresponding coefficients were 0.595 and 0.023, respectively, both of which are statistically significant at the 1% level; these findings confirm the robustness of the empirical results pertaining to Hypotheses 1a and 1b.

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

To further assess the robustness of Hypotheses 1a and 1b, we employed the propensity score matching difference-in-differences (PSM-DID) method for empirical validation.

Enterprises were categorized into experimental (treat = 1) and a control groups (treat = 0). An enterprise was assigned to the control group if the frequency of keywords pertaining to digital transformation in its annual reports remained consistently low across all years, indicating no actual digital transformation; conversely, if the frequency of such keywords was high in at least one year, the enterprise was classified into the experimental group. During the propensity score matching phase, we selected multiple covariates to construct the propensity score model, encompassing the company's initial innovation level and other covariates listed in Table 1. Through propensity score matching, we aimed to achieve a balance between the experimental and control groups on all observable characteristics, excluding the treatment variable.

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	19,043	19,043
R^2	0.304	0.283

Standard errors in parentheses. *** $p < 0.01$.

For the experimental group, the year in which the digital transformation index surpassed the predefined threshold for the first time was designated as the onset of digital transformation; this year and all subsequent years were considered as the post-experimental period (period = 1), whereas the years preceding the milestone were classified as the pre-experimental period (period = 0). Such a design accommodates variations in the starting years of digital transformation across different enterprises.

Table 4 presents the regression results based on Model 2, utilizing the PSM-DID method. Columns (1) and (2) illustrate the impact of digital transformation on technological innovation output (Innov_out) and technological innovation input (Innov_inv), with coefficients of 0.282 and 0.011, respectively, both significant at the 1% statistical level; these findings further corroborate the robustness of the empirical results for Hypotheses 1a and 1b.

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	13,831	13,829
R^2	0.301	0.290

Standard errors in parentheses. *** $p < 0.01$.

4.3. Analysis of the Mediating Effect of Cost Stickiness

4.3.1. Analysis of Regression Results of Digital Transformation on Cost Stickiness

In this study, we employed a fixed-effect model to empirically test Hypothesis H2: Digital transformation exerts a significant negative influence on cost stickiness in China's manufacturing industry, implying that digital transformation can mitigate the cost stickiness of enterprises.

Table 5 (1) presents the regression outcomes of digital transformation (Dig) on cost stickiness (CS) based on Model 3. The coefficient was −0.032, which is statistically significant at the 10% level; this finding indicates that digital transformation has the capacity to reduce cost stickiness. Nevertheless, in the initial phases of digital transformation, cost stickiness may not be immediately suppressed, due to factors such as initial investments, trial-and-error adjustments, and employee training; as time progresses, however, digital transformation demonstrates a significant suppressive effect on cost stickiness.

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

Variables	(1) CS	(2) 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	19,047	19,047
R^2	0.231	0.261

Standard errors in parentheses. * $p < 0.1$; *** $p < 0.01$.

To delve deeper into these dynamics, the moderating role of time was examined by incorporating the time variable as a moderator. Column (2) of Table 5 displays the regression results after including the interaction term between digital transformation and time. The coefficient for digital transformation (Dig) was 0.066, which is statistically significant at the 10% level, whereas the coefficient for the interaction term (Dig × Year) was −0.009, which is highly significant at the 1% level, suggesting that time exerts a notable moderating effect. Specifically, digital transformation initially elevates cost stickiness, but as time elapses, it transitions from increasing to suppressing cost stickiness; these findings provide support for Hypothesis 2 (H2), which posits that digital transformation suppresses cost stickiness in the long term.

4.3.2. Regression Analysis of the Mediating Effect of Cost Stickiness

In this study, we employed the three-step regression approach to examine the mediating effect of cost stickiness; specifically, we investigated how digital transformation enhances technological innovation investment in enterprises by mitigating cost stickiness.

The three-step regression method for analyzing mediation effects involves the following steps: firstly, assessing the total effect of the independent variable on the dependent variable; secondly, examining the influence of the independent variable on the mediating variable; and, finally, evaluating the significance of the direct effect of the independent variable on the dependent variable after accounting for the mediating variable, to distinguish between full and partial mediation.

In the first step, presented in column (1) of Table 6 based on Model 2, cost stickiness was excluded from the model. The regression coefficient for the impact of digital transformation on technological innovation (Innov_inv) was 0.193, indicating a significant positive effect of digital transformation on technological innovation.

The second step, shown in column (2) of Table 6 based on Model 3, reveals a regression coefficient of −0.032 for the effect of digital transformation on cost stickiness, significant at the 10% level, suggesting that digital transformation significantly reduces cost stickiness.

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

Variables	(1) Innov_Inv	(2) CS	(3) Innov_Inv
Dig	0.193 ***	−0.032 *	0.191 ***
	(0.001)	(0.017)	(0.001)
CS			−0.001 ***
			(0.000)
CVs	controlled	controlled	controlled
Year	controlled	controlled	controlled
Firm	controlled	controlled	controlled
N	19,047	19,047	19,047
R^2	0.276	0.231	0.277

Standard errors in parentheses. * $p < 0.1$; *** $p < 0.01$.

In the third step, outlined in column (3) of Table 6 based on Model 4, the regression coefficient for the effect of cost stickiness on technological innovation was −0.001, significant at the 1% level, indicating a significant negative impact of cost stickiness on technological innovation (Innov_inv).

Based on the regression results from the second and third steps, it is evident that cost stickiness acts as a mediator in the relationship between digital transformation and technological innovation (Innov_inv). The magnitude of the mediation effect can be quantified by the product of the regression coefficients of digital transformation on cost stickiness, and of cost stickiness on technological innovation.

In column (1), the regression coefficient for the effect of digital transformation on technological innovation (Innov_inv) was 0.193. In column (3), upon including cost stickiness in the model, the regression coefficient slightly decreased to 0.191, which may be attributed to cost stickiness being one of several potential mediators, indicating a partial mediation effect.

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

4.4.1. Enterprise Size Heterogeneity Analysis

Enterprises vary significantly in terms of resources, organizational structure, and market positioning, depending on their size. Large enterprises typically possess greater resources and affordability, enabling them to allocate substantial funds toward technological innovation and talent acquisition. Conversely, small- and medium-sized enterprises (SMEs) often grapple with constraints such as limited resources and financial stringency. Consequently, the impact of digital transformation on technological innovation may differ across enterprise sizes, potentially giving rise to a threshold effect. In order to investigate this, we employed a threshold effect regression model to examine the influence of enterprise size.

The threshold effect regression model constitutes an econometric analysis technique designed to capture and elucidate the nonlinear relationships among economic variables; its core principle revolves around the notion that, when a specific variable (termed the threshold variable) attains a certain value (known as the threshold), the relationship between the independent and dependent variables undergoes a marked transformation, a shift which typically manifests as an abrupt change in the slope of the linear relationship, indicating distinct linear patterns between the variables within different threshold intervals. Grounded in structural change theory, the threshold effect regression model segments the sample data into various intervals by establishing threshold variables and critical values, and subsequently estimates the relationship between the dependent and independent variables within these intervals. By identifying the inflection points in the relationships between variables (i.e., the thresholds), the model enhances its capacity to explain more intricate economic phenomena and boosts its explanatory power; to verify the existence of this threshold effect, a threshold effect regression model predicated on enterprise size was formulated as follows:

$$\mathrm{Innov}_{i,t} = d_0 + d_1\mathrm{Dig}_{i,t}(\mathrm{size} < Y_1) + d_2\mathrm{Dig}_{i,t}\left(Y_1 \le \mathrm{size} < Y_2\right) + \ldots + d_n\mathrm{Dig}_{i,t}(\mathrm{size} < Y_n) + \sum d_m\mathrm{CVs}_{i,t} + \sum \mathrm{Year} + \sum \mathrm{Firm} + \varepsilon_{i,t} \quad (5)$$

In this model, the threshold variable is enterprise size, quantified by total assets. Y_n represents the threshold value to be estimated. A prerequisite for employing the panel threshold effect regression model is the successful passage of a threshold effect test. In order to assess the threshold effect, the Bootstrap self-sampling method was utilized to determine the critical value and subsequently obtain the threshold Y_n. When the threshold variable is below the threshold Y_1, the relationship between digital transformation and technological innovation is governed by d_1. When the threshold variable exceeds or equals Y_1, but remains below Y_2, this relationship is determined by d_2, and so forth.

Upon conducting 300 bootstrap samples, we determined the following results of the threshold effect test. Table 7 indicates a *p*-value of 0.000 for the threshold effect test, signifying a significant single threshold effect with a threshold value of 24.002; furthermore, through threshold effect regression, we examined the change in the coefficient representing the impact of digital transformation on technological innovation before and after the threshold. For enterprises with a size below the threshold of 24.002, the coefficient was 0.094 with a t-value of 3.430, indicating that digital transformation has a lesser effect on technological innovation in smaller manufacturing enterprises; conversely, for enterprises exceeding the threshold of 24.002, the coefficient was 0.425 with a t-value of 5.880, suggesting that the larger the scale of the manufacturing enterprise, the greater the impact of digital transformation on technological innovation. These results demonstrate two key points: firstly, digital transformation enhances technological innovation irrespective of the manufacturing enterprise's size; secondly, the technological innovation effect increases with the scale of the manufacturing enterprise. Overall, the impact of digital transformation in the manufacturing industry on technological innovation exhibits a threshold effect, characterized by a sudden change in the magnitude of the positive influence, rather than a shift in the direction of the influence from positive to negative or vice versa.

4.4.2. Analysis of Technology-Intensive Heterogeneity

There are significant differences between technology-intensive manufacturing enterprises and non-technology-intensive manufacturing enterprises with respect to technology content, labor productivity, resource consumption, the proportion of scientific and technological personnel, and the complexity of product technical performance, as well as economic and social benefits; as a result, the technological innovation impact of digital transformation may vary across these enterprise types. In order to investigate the existence of this heterogeneity, we employed fixed-effect tests on the following two sub-samples, based on Model 2: technology-intensive manufacturing enterprises and non-technology-intensive manufacturing enterprises. Table 8 presents the regression results, from which it can be seen that the coefficient for technology-intensive manufacturing enterprises was 0.074, with a statistical significance level of 1%. In contrast, the coefficient for other manufacturing enterprises was 0.046, which is not statistically significant, indicating that the digital transformation of technology-intensive enterprises has a more profound effect on technological innovation, attributed to their abundant technical resources, high-quality talent pool, and open innovation environment, which collectively facilitate the deep integration of digital transformation and technological innovation.

Table 7. Regression results of the scale threshold effect test.

Category	Indicator	Value
Threshold Effect Test (bootstrap = 300)		
	RSS	2987.302
	MSE	0.592
	Fstat	33.690
	Prob	0.000
	Crit10	11.963
	Crit5	13.545
	Crit1	17.442
Threshold Estimation (level = 95%)		
	Model	Th-1
	Threshold	24.002
	Lower	23.907
	Upper	24.050
Threshold effect regression results		
Coefficient	0 (below the threshold)	0.094
	1 (above the threshold)	0.425
std. err.	0 (below the threshold)	0.027
	1 (above the threshold)	0.074
t	0 (below the threshold)	3.430
	1 (above the threshold)	5.880
P > ∣t∣	0 (below the threshold)	0.001
	1 (above the threshold)	0.000
[95% conf. interval]	0 (below the threshold)	0.040 0.148
	1 (above the threshold)	0.279 0.568

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

Variables	(1) TI	(2) TI_No
Dig	0.074 ***	0.046
	(0.020)	(0.029)
CVs	controlled	controlled
Year	controlled	controlled
Firm	controlled	controlled
N	11,198	7849
R^2	0.249	0.274

Standard errors in parentheses. *** $p < 0.01$.

4.4.3. Analysis of Asset-Intensive Heterogeneity

There are marked differences between asset-intensive (AI) and non-asset-intensive (hereinafter referred to as AI_no) manufacturing enterprises, with regards to asset investment, capital intensity, supply chain characteristics, operational complexity, technological innovation challenges, risks, and returns; consequently, the impact of digital transformation on technological innovation is likely to vary between these two types of enterprises. In order to examine the existence of this heterogeneity, we conducted fixed-effect tests on two sub-samples, based on Model 2: asset-intensive manufacturing enterprises and non-asset-intensive manufacturing enterprises. Table 9 presents the regression results; the coefficient for asset-intensive manufacturing enterprises was 0.072, which is not statistically significant, whereas the coefficient for non-asset-intensive manufacturing enterprises was 0.084, exhibiting statistical significance at the 1% level.

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

Variables	(1) AI	(2) AI_No
Dig	0.072	0.084 ***
	(0.052)	(0.018)
CVs	controlled	controlled
Year	controlled	controlled
Firm	controlled	controlled
N	3667	15,380
R^2	0.224	0.222

Standard errors in parentheses. *** $p < 0.01$.

4.4.4. Heterogeneity Analysis of Different Technological Innovation Levels

Enterprises with high levels of technological innovation typically possess stronger capabilities for technology absorption and innovation, enabling them to utilize digital technology more effectively in order to enhance their technological innovation. Conversely, enterprises with low levels of technological innovation may be constrained by limited resources, technology, and talent, making digital transformation more challenging; consequently, the impact on technological innovation may be relatively weak. In order to examine the existence of this heterogeneity, a quantile regression model was employed, based on Model 2, to assess the influence of digital transformation on technological innovation across different levels of technological innovation (10%, 25%, 50%, 75%, and 90%). Table 10 presents the quantile regression results for various technological innovation levels. For the group with the lowest level of technological innovation (q0.1), the regression coefficient was −0.000271, indicating a negative effect of digital transformation on technological innovation, albeit not statistically significant. For the groups with low (q0.25) and moderate (q0.5) levels of technological innovation, the regression coefficients were 0.157 and 0.181, respectively, suggesting a positive impact of digital transformation on technological innovation, although the effects are not statistically significant. In the groups with higher (q0.75) and the highest (q0.9) levels of technological innovation, the regression coefficients were 0.176 and 0.177, respectively, with statistical significance levels of 10% and 1%, respectively. These findings indicate that digital transformation has a strong positive effect on technological innovation. It is evident that the higher the enterprise's own level of technological innovation, the stronger the impact of digital transformation on technological innovation.

Table 10. Quantile regression results.

Variables	(1) 0.1	(2) 0.25	(3) 0.5	(4) 0.75	(5) 0.9
Dig	−0.000	0.157	0.181	0.176 *	0.177 ***
	(0.043)	(1.200)	(0.214)	(0.096)	(0.046)
N	19,047	19,047	19,047	19,047	19,047
R^2					

Standard errors in parentheses. * $p < 0.1$; *** $p < 0.01$.

5. Discussion

5.1. Implications of the Findings

Based on the aforementioned research results, we are convinced that the digital transformation of manufacturing enterprises can enhance both the output and input of technological innovation, a finding that aligns with the resource-based theory, which underscores the pivotal role of efficient allocation and utilization of internal resources in strategic execution and performance enhancement. In our study, digital transformation emerged as a crucial mechanism for optimizing resource allocation, transcending the limitations imposed by traditional cost structures and facilitating a more flexible redirection of resources toward high-value technological innovation domains. Secondly, cost stickiness serves as a mediator in the relationship between digital transformation and technological innovation; specifically, digital transformation mitigates cost stickiness, enabling enterprises to allocate more resources toward technological innovation activities, thereby boosting their technological innovation output. Furthermore, the results of the heterogeneity test revealed that the impact of digital transformation on technological innovation varies according to enterprise characteristics. Larger enterprises, technology-intensive enterprises, non-asset-intensive enterprises, and those with robust technological innovation capabilities are better positioned to enhance their technological innovation through digital transformation. Smaller enterprises often struggle to bear the high costs associated with digital transformation due to limited financial resources; non-technology-intensive enterprises possess relatively weak technical foundations and lack the necessary technical framework and professional talent pool for digital transformation; asset-intensive enterprises tend to prioritize the operation and management of physical assets, exhibiting a relatively low reliance on and application of digital technologies; and enterprises with weaker technological innovation capabilities encounter difficulties in absorbing and applying new technologies during the digital transformation process, and find it challenging to rapidly adapt to and integrate these new technologies. These enterprises are constrained by limited resource conditions which, in turn, hinders the role of digital transformation in promoting technological innovation. Thus, our research objectives have been successfully accomplished.

In this study, we used Python to extract digital transformation-related keywords from corporate annual reports and quantify their frequency to measure the extent of corporate digital transformation, a method which improves the measurement of the extent of digital transformation and fills the gap in micro-evidence in existing research.

Based on these findings, we propose the following policy recommendations: Firstly, the government should increase its support for the digital transformation of manufacturing enterprises, particularly for small-scale, capital-constrained, and non-technology-intensive enterprises. Through implementing policy measures such as financial subsidies and tax incentives, the barriers to digital transformation can be lowered, aiding enterprises in overcoming the issue of high initial investment. Secondly, in response to the challenges of weak technical foundations and talent shortages, the government should promote the establishment of a digital transformation training system and talent acquisition mechanism. Through academia–enterprise collaboration, professional training, and other avenues, the digital transformation capabilities of enterprise technicians can be strengthened, providing a talent pipeline for digital transformation. Simultaneously, the government should guide asset-intensive enterprises to shift their operational paradigms and enhance their understanding and application of digital technology. Enterprises should be encouraged to integrate digital technology into the management of physical assets, thereby improving operational efficiency and innovation capabilities. Finally, for enterprises with weak technological innovation capabilities, the government should offer technical support and consulting services to facilitate their rapid adaptation to and integration of new technologies.

Enterprises should devise differentiated digital transformation strategies tailored to their unique characteristics. Large-scale enterprises should leverage their resource advantages to deepen digital transformation and increase technological innovation inputs and outputs. Technology-intensive enterprises should strengthen the integration of digital technology with their existing technologies, thereby enhancing their technological innovation capabilities. Non-asset-intensive enterprises should actively explore new avenues for digital transformation, reduce their dependence on physical assets, and improve operational efficiency and innovation capabilities. Small-scale, non-technology-intensive, and asset-intensive enterprises, as well as those with weak technological innovation capabilities, should actively seek government support to utilize policy benefits and financial subsidies to lower the cost of digital transformation; concurrently, they should strengthen school–enterprise collaboration, recruit and cultivate digital talents, and bolster their technical foundations. Enterprises should shift their operational paradigms, prioritize the application of digital technology, mitigate cost stickiness through digital transformation, free up more resources for technological innovation, and promote high-quality enterprise development.

The role of digital transformation in manufacturing enterprises as a catalyst for technological innovation is universally applicable worldwide. In both developing and developed countries, manufacturing enterprises are confronting the challenges of intensified market competition and diversified customer demands. As a pivotal factor in enhancing corporate competitiveness, digital transformation can optimize production processes, improve operational efficiency, and foster product and service innovation. Although there are variations in the pace of digital transformation and policy support among different countries, the positive impact of digital transformation on technological innovation transcends national borders; therefore, manufacturing companies across various countries should actively embrace the trend of digital transformation and formulate transformation strategies aligned with their unique characteristics to enhance their technological innovation capabilities and market competitiveness in order to meet global challenges.

5.2. Potential Limitations and Future Research Directions

5.2.1. Potential Limitations

In this study, we utilized microdata and employed a variety of statistical regression analysis techniques, including the fixed-effect model, instrumental variable method, difference-in-differences method, threshold effect model, and quantile regression, to ensure the reliability and robustness of the research findings; however, this study has certain limitations concerning sample coverage and data time span. We only used data from Chinese A-share listed companies as samples, a choice that was mainly based on the availability and openness of the data. As an important part of Chinese enterprises, the financial data and market performance of A-share listed companies are relatively transparent and easy to obtain, providing a solid foundation for empirical research; however, we also realize that there may be certain representative limitations in selecting only A-share listed companies as samples. In order to evaluate the representativeness of the sample and reduce the impact of selection bias, future research can consider expanding the sample range to include more types of companies, such as non-listed companies. At the same time, neural network models, random forest models, and so on, can be used to further test the robustness of the research results. Additionally, due to the limited time range of the data, we found it challenging to conduct in-depth observations and analyses of long-term trends in this study; to obtain more detailed and long-term conclusions, further research is warranted.

5.2.2. Future Research Directions

Future research efforts will concentrate on the core domain of technology transfer and delve deeply into the application and development of digital technology to explore effective methods to optimize each aspect of technology transfer, including enhancing the speed and efficiency of knowledge dissemination, improving the accuracy of technology evaluation, refining the partner matching mechanism, and streamlining the transaction process. In particular, our future research will focus on analyzing how the digitalization process of enterprises can inject new vitality into the overall process of technology transfer and enhance its practical effectiveness, while simultaneously delving into how digital methods can facilitate the acceleration of technology transfer and promote its broader application. During research implementation, we will rigorously assess the specific role of digital technology in the effectiveness of technology transfer, elucidate the pivotal position and core functions of digital platforms in this process, and actively seek out specific digital tools or strategies that can effectively boost the success rate of technology transfer, with the aim of establishing a solid scientific theoretical foundation for the rapid advancement and widespread application of technology and providing practical, actionable guidance.

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Institutional Review Board Statement: This study was focused on the impact of enterprise digitalization on technological innovation. All the data used were obtained from public databases, such as the China Securities Market and Accounting Research Database (CSMAR) and the China Research Data Service Platform (CNRDS), and did not involve human or animal experiments. Specifically, the frequency of keywords related to enterprise digitalization were extracted for the purposes of this study through text mining of the annual reports of A-share listed manufacturing companies, and their degrees of enterprise digitalization were quantified and analyzed for their impacts on technological innovation. As this study was completely based on public data, and does not involve any sensitive information or activities that require ethical review (such as personal privacy, medical records, animal experiments, etc.), according to internationally accepted ethical review principles and standards, this study does not require ethical review. In addition, the research methods and analysis process used in this study were conducted according to the basic principles of academic integrity and scientific research ethics to ensure the objectivity and accuracy of the research results. Summary: This study did not involve human or animal experiments, and all data and analyses are based on public information, so no ethical review is required.

Informed Consent Statement: Not applicable.

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