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DIGITAL TRANSFORMATION AND CORPORATE TECHNOLOGICAL INNOVATION: AN ANALYSIS BASED ON DIFFERENCES IN FIRM DEVELOPMENT STAGES

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ABSTRACT

In the current era, digital transformation has become an irresistible trend of social development. This study mainly explores the performance of technological innovation in the process of corporate digitalization.The research classifies the samples by firm age and conducts grouped regression analysis.This paper also carries out robustness tests on the main effect by narrowing the sample period and adopting alternative estimation methods. The results verify the high reliability of the research conclusions.

Based on the theoretical framework of technological innovation, this study selects Chinese A-share listed companies from 2007 to 2022 as research samples.The empirical results indicate that digital transformation can significantly promote the level of technological innovation. Furthermore, grouped regression results reveal that firms with heterogeneous resource endowments perform differently in this process.During digital transformation, mature enterprises have sufficient time to accumulate tangible and intangible resources, which are conducive to their technological innovation.Young firms, with a shorter establishment history, suffer from relative resource scarcity, which hinders their technological innovation outcomes amid digital transformation.

This study suggests that enterprises should formulate targeted digital development paths.Meanwhile, the government shall implement macroeconomic regulation and formulate differentiated subsidies for various enterprises to support their development. Future research can expand the research scope to include more types of enterprises and conduct in-depth analysis on the main effect.

KEYWORDS: Digital Transformation, Enterprise Technological Innovation, Firm Development Stages, Firm Heterogeneity.

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1.0 INTRODUCTION

With the continuous advancement of digital technologies, digitally empowered industries have emerged as a new engine of economic growth, markedly improving national industrial development and economic expansion (Tian and Li, 2022; Yi and Wang, 2021)[1]-[2]. As the main participants in economic activities, corporate digital transformation serves as a core driving force for economic development. China has vigorously promoted digital development to optimize resource allocation and stimulate corporate innovation vitality (Li and Li, 2024; Qiu and Chang, 2025)[3]-[4]. Theoretically, digital transformation can inject new momentum into technological innovation. However, its practical effects remain controversial in academic circles, which constitute the starting point of this research.

Gabriele (2024) defines digital transformation as a process in which organizations shift from IT support to taking digital resources as the strategic core [5] . Hartigh (2022) divides the process of corporate digital transformation into three consecutive and indivisible stages [6]. Michelotto (2024) emphasizes that digital transformation is driven not only by external factors, but also requires multi-dimensional internal support including organizational structure and talents [7]. While Alessia (2020) recognizes the role of digital technologies in promoting comprehensive corporate reform, she also points out that digital transformation is far from smooth [8]. A survey conducted by Alessia (2020) reveals that approximately 66% to 84% of digital transformation projects end in failure [8]. Wu et al. (2021) further note that digital components, digital platforms and other elements constitute digital transformation [9] . In terms of technological innovation, after Schumpeter laid the theoretical foundation, subsequent scholars have further enriched relevant research from multiple perspectives such as institutional environment and policies. Nambisan et al. (2017) argue that enterprise technological innovation operates as an interconnected complex system, and solid core capabilities are the prerequisite for sustained innovation growth **Error! Unknown switch argument.**.Li et al. (2024) conduct an in-depth discussion on the connotations and differences between disruptive innovation and combinatorial innovation **Error! Unknown switch argument.**.

Academics hold divergent views on whether digital transformation can facilitate corporate technological innovation. Nambisan et al. (2017) states that digital transformation fosters corporate technological innovation by establishing internal and external information channels and collaboration networks [10]. Nevertheless, the innovation effect of digital transformation is not uniform across firms. Liang and Li (2022) find that digital transformation promotes process and product innovation performance through R&D capabilities, but the effect varies across sectors and is more evident in firms with higher technological content [11].

Existing studies have not reached a consensus on the relationship between digital transformation and corporate technological innovation. Although numerous studies have been carried out, this paper argues that there are still limitations in current research on their correlation. Based on the above analysis, this paper integrates the Resource-Based View and technological innovation theory. Breaking the limitation of traditional research that focuses merely on physical resources, this paper analyzes how digital transformation drives technological innovation from the perspective of dynamic capabilities and digital resources. Using data of Chinese listed companies from 2007 to

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2022, this paper conducts empirical tests with the fixed-effects model and OLS model. The results show that digital transformation significantly promotes corporate technological innovation, and such facilitating effect is stronger in mature firms than in young ones.

2.0 THEORETICAL BACKGROUND

2.1 Digital Transformation and Corporate Technological Innovation

The theory of technological innovation serves as a fundamental cornerstone for research on corporate innovative development. Schumpeter first proposed that innovation cannot be achieved without breaking through the original production function.

Existing literature mainly explores the driving mechanisms of digital transformation on corporate innovation from the following perspectives. Digital transformation broadens firms' information access channels and enhances their intelligent processing capabilities (Zhuo and Chen, 2023)[12]. The in-depth application of digital technologies breaks the constraints of traditional information collection and analysis modes, enabling large-scale gathering, in-depth analysis and trend prediction of multi-dimensional internal and external information (Lu et al., 2023)[13]. This process effectively mitigates information asymmetry in innovation decision-making and reduces the interference of environmental uncertainty on judgment. It further strengthens firms' ability to identify and seize cutting-edge technological opportunities and market innovation prospects. Digital transformation also helps improve the allocation efficiency of corporate innovation resources. The performance of corporate technological innovation relies on the efficient integration and precise matching of various innovation resources covering R&D, production and marketing (Duan and Zhang, 2025)[14].Digital empowerment effectively cuts down communication, coordination and trial-and-error costs in innovation activities. It realizes the targeted allocation and efficient utilization of innovation resources, and greatly improves resource allocation efficiency as well as input-output ratio (Jiang et al., 2025)[15]. Some scholars also argue that digital transformation enhances enterprises' capacity for knowledge integration and transformation. Digital transformation accelerates the sharing and circulation of tacit and explicit knowledge within organizations, and expands the scope of external knowledge search. It improves the absorption, integration and transformation of industrial and market knowledge, which can eventually be translated into new products, processes and technologies and deliver tangible innovation outcomes (Chen and Kim, 2023)[16].

2.2 Firm Age and Corporate Development Stages

Firm age generally refers to the length of time since a firm's establishment and serves as a key indicator to characterize its development stage. It not only reflects a firm's duration of existence, but also represents its overall capabilities embodied in resource accumulation, organizational experience, knowledge base and competence structure cultivated during long-term operation (Balasubramanian and Lee, 2008)[17].As firms grow older, they continuously accumulate experience in R&D, production and management, and gradually develop stable resource allocation approaches and behavioral patterns (Coad et al., 2016)[18]. Accordingly, firm age can reflect the evolutionary process from youth to maturity.

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Existing studies have confirmed that firm age exerts influences on innovation activities (Pellegrino and Piva, 2020)[19]. On the one hand, mature firms usually enjoy stable capital sources, sound organizational procedures, abundant technological reserves and extensive market networks, which provide solid resource support for technological innovation. On the other hand, young firms feature simpler organizational structures and shorter decision-making chains, and thus tend to be more flexible in exploring new technologies and identifying market opportunities (Hilmersson and Hilmersson, 2021)[20]. Nevertheless, young firms are commonly confronted with insufficient capital, limited technological accumulation and weak external networks, so their innovation activities are constrained by resource shortages and capability deficiencies.

In the context of digital transformation, the disparities in resources and capabilities arising from firm age deserve greater attention. Whether digital transformation can be effectively translated into technological innovation depends on firms ‘capabilities in resource absorption, knowledge assimilation and organizational integration (Li et al., 2023)[21]. Compared with young firms, mature firms possess accumulated resources, technological foundations, managerial experience and complementary assets derived from long-term operation. These advantages enable them to accurately identify application scenarios of digital technologies and embed digital tools into multiple innovation links, including R&D, production, supply chain management and market feedback (Jiang et al., 2025)[15]. Therefore, it is necessary to take into account the differences in development stages shaped by firm age when analyzing the relationship between digital transformation and corporate technological innovation.

3.0 HYPOTHESES

3.1 Digital Transformation and Firm Technological Innovation

This study argues that digital transformation promotes firms' technological innovation by improving information processing capacity, optimizing resource allocation efficiency and facilitating organizational collaboration.

First, digital transformation turns internal and external operational information into data assets, allowing firms to overcome the limitations of conventional information gathering (Li et al., 2021)[22]. Firms can capture market information in a timelier manner, which mitigates information asymmetry and environmental uncertainty in innovation decision-making, improves the accuracy of identifying technological innovation directions, and provides clear guidance for the development of new products, processes and technologies.

Second, digital transformation helps optimize firms' resource allocation efficiency (Duan and Zhang, 2025)[14]. According to the Resource-Based View, a firm’s competitive advantage stems not only from resource possession, but also from its capacity to identify, integrate and utilize heterogeneous resources (Freeman et al., 2021)[23]. Digital transformation establishes cross-departmental data platforms and intelligent management systems. It enhances firms’ capability to analyze and deploy operational information, and reduces information barriers and communication costs among departments. Accordingly, firms can allocate internal resources more precisely to core technology R&D, so as to raise R&D efficiency and shorten the technological innovation cycle.

Third, digital transformation facilitates organizational collaboration and knowledge sharing. Technological innovation is not an isolated activity conducted merely by the R&D department, but a systematic process involving multiple internal and external links of the firm. Digital platforms strengthen information transmission and knowledge flow across internal departments, and drive the optimization of organizational structure (Zhao et al., 2026)[24]. Meanwhile, as the digitalization level of upstream and downstream enterprises in the industrial chain improves, the capacity for information sharing and collaborative development among firms is enhanced, which further promotes cross-organizational technological cooperation and joint innovation. The improved internal and external collaboration efficiency enables firms to translate market information and technological knowledge into innovation outcomes more rapidly.

Based on the above analysis, this paper puts forward the following hypotheses:
H1: Digital transformation exerts a positive effect on firms' technological innovation.

3.2 Differences in Firm Development Stages and the Innovation Effects of Digital Transformation

This study holds that differences in firms’ development stages may affect how digital transformation influences technological innovation. Whether digital transformation can be effectively translated into innovation outcomes depends not only on digital technologies themselves, but also on firms’ existing resource base, knowledge stock and organizational capabilities. Mature firms and young firms differ substantially in these respects, so digital transformation may exert disparate impacts on their technological innovation (Coad et al., 2016)[18].

Compared with young firms, mature firms generally possess stronger capacity to absorb and utilize resources. Digital transformation usually requires substantial capital investment, sound digital infrastructure and professional talent support. Thanks to long-term operation, mature firms are better able to bear the investment costs and adjustment risks arising from digital transformation.

In contrast, young firms have a relatively weak resource base and may fail to apply digital technologies to production and operation in the short run.

Meanwhile, mature firms boast richer knowledge reserves and technological accumulation. Technological innovation cannot be achieved overnight and usually relies on the continuous accumulation of existing knowledge and experience. With abundant technologies and experience accumulated over time, mature firms can more easily identify applicable scenarios for digital technologies and integrate digital capabilities into R&D activities. By comparison, young firms have limited technological accumulation, and thus face higher costs and greater uncertainty when absorbing, integrating and converting digital resources.

Mature firms also enjoy prominent advantages in organizational collaboration capabilities and complementary assets (Helfat and Raubitschek, 2018)[25]. The impact of digital transformation on technological innovation exists not only in the R&D stage, but also requires coordination across multiple internal and external links of the firm. With clear organizational division of labor and

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standardized management procedures, mature firms can promote innovation through cross-departmental collaboration and coordination with upstream and downstream partners.
In addition, the established upstream and downstream channels and market resources of mature firms help translate R&D achievements into practical applications and commercial products. Although young firms tend to be more flexible, their organizational systems and external networks are immature, which may constrain the innovation-promoting effect of digital transformation.
Based on the above analysis, this paper proposes the following hypothesis:

H2: Digital transformation exerts a stronger positive effect on the technological innovation of mature firms than on that of young firms.

4.0 RESEARCH DESIGN

4.1 Data Source and Sample Selection

This paper selects Chinese A-share listed companies from 2007 to 2022 as research samples.This time span covers a critical period of rapid development of China's digital economy and steady advancement of corporate digital transformation, which can effectively reflect the dynamics of digital transformation and technological innovation among listed firms. Data on patent applications of Chinese listed companies are obtained from the CNRDS database. Data on digital transformation level and other control variables are retrieved from the CSMAR database. To ensure the validity and consistency of sample data, we exclude financial listed companies and firms with abnormal operating status such as ST and *ST stocks. Samples with missing values of core variables are also removed. All continuous variables are winsorized at the 1% level on both tails to eliminate the interference of outliers. After the above data cleaning procedures, we finally obtain 40,123 valid observations for the subsequent empirical analysis.

4.2 Variables setting and measurement

Patents are the most commonly used and widely recognized indicators for measuring innovation, and their reliability and robustness have been verified in empirical research(Acs et al., 2002)[26].This paper takes corporate technological innovation as the dependent variable and evaluates it across three dimensions (Yuan et al., 2023)[27]. The number of invention patent applications (PatentInv) reflects firms 'breakthroughs in core technological fields. The number of utility model patent applications (PatentUti) represents the innovative optimization of existing product structures. The total number of patent applications (PatentAll) captures both major technological innovations and partial technical improvements of enterprises. We add one to the number of the three types of patent applications and then take the natural logarithm. To account for the time lag between digital transformation and innovation output, this paper uses patent applications in year t+1 as the dependent variable.

Next, we introduce the core independent variable of this study, corporate digital transformation. Referring to the text analysis method adopted in existing literature, we measure the level of corporate digital transformation by the word frequency of digitalization-related terms in annual reports. Following Wu Fei et al., we classify relevant terms into two categories: underlying digital technologies and digital applications. The word frequency of these terms in annual reports is calculated to quantify digital transformation intensity (Hu et al., 2025)[28].

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To avoid confounding bias, we add control variables following prior literature. First, we control for firm basic characteristics. Firm size (Size) is measured as the natural logarithm of operating revenue. Firm age (Age) refers to the number of years since the firm's establishment. Ownership nature (SOE) is a dummy variable, which equals 1 for state-owned enterprises and 0 otherwise. Second, we control for firm financial indicators. Leverage (LEV) is the ratio of total liabilities to total assets. The proportion of property, plant and equipment (PPE) is calculated as fixed assets divided by total assets. Return on assets (ROA) equals net profit divided by total assets. Cash flow (Cash) is net cash flow from operating activities over total assets. Book-to-market ratio (BM) is total shareholder equity divided by market capitalization. Third, we control for corporate governance variables. Board size (Boardsize) is the natural logarithm of the number of directors. Independent director ratio (Indboard) is the proportion of independent directors on the board. CEO duality (Dual) is a dummy variable, taking the value of 1 if the chairperson and CEO are the same person and 0 otherwise. Finally, we include year fixed effects and firm fixed effects to control for common time shocks and unobserved firm-level heterogeneity.

4.3 Model construction

To examine the impact of digital transformation on corporate technological innovation, we establish the following two-way fixed-effects model:

$$Innovation_{i,t+1}=\alpha_0+\alpha_1 Lndgt_{i,t}+\sum_{i=2}^{12}\alpha_i Controls_{i,t}+\mu_t+\lambda_i+\varepsilon_{i,t} \quad (1)$$

Here the dependent variable $Innovation_{i,t+1}$ denotes the technological innovation performance of firm i in year $t+1$. Given the potential time lag in the effect of digital transformation on innovation, we use the next-period innovation level as the dependent variable to mitigate simultaneous reverse causality. The independent variable $Lndgt_{i,t}$ represents the digital transformation level of firm i in year t, measured as the natural logarithm of one plus the frequency of digitalization-related words in annual reports. $Controls_{i,t}$ refers to a set of control variables. λ_i stands for firm fixed effects, capturing time-invariant individual characteristics of each firm. μ_t denotes year fixed effects, accounting for the common impacts of macroeconomic conditions and policy changes across years. $\varepsilon_{i,t}$ is the random error term.

5.0 REGRESSION RESULTS

5.1 Descriptive Statistical Analysis

Table 1 presents the descriptive statistics for the core variables in this study.

The total number of patent applications has a mean value of 1.093, a standard deviation of 0.626, a minimum value of 0 and a maximum value of 2.053. This reveals that sampled firms generally carry out technological innovation activities, while obvious gaps exist in innovation performance across individual enterprises. The mean values of invention patent applications and utility model patent applications are 0.881 and 0.880, with standard deviations of 0.610 and 0.651 respectively, indicating highly similar distribution characteristics for the two indicators. The minimum value of the three patent indicators equals zero, meaning that a subset of firms filed no corresponding patent applications during the sample period.

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Digital transformation has a mean of 1.278, a standard deviation of 0.374, a minimum of 0 and a maximum of 1.922. Such statistics reflect sizable disparities in the disclosure frequency of digital transformation keywords in annual reports. Some firms have not launched tangible digital transformation initiatives, whereas others have reached a relatively high transformation level.

In terms of control variables, the average leverage ratio stands at 0.422, suggesting that the overall debt burden of sampled firms remains at a moderate level. The mean ROA reaches 0.0386, demonstrating positive overall profitability for the full sample. The dummy variable for state-owned enterprises (SOE) has a mean of 0.141, corresponding to an SOE share of approximately 14.1% in the sample. The mean value of CEO duality is 0.285, implying that around 28.5% of the sampled firms have the same person serving as both board chair and general manager. Firm age averages 10.59 years, ranging from 1 year to 28 years. The diversified development stages of sampled firms create suitable conditions for the subsequent sub-sample heterogeneity tests.

Table 1: Descriptive statistics of samples.

Variable	*Obs*	*Mean*	*Std.*	*Min*	*Max*
PatentAll	40,123	1.093	0.626	0	2.053
PatentInv	40,123	0.881	0.610	0	1.965
PatentUti	40,123	0.880	0.651	0	1.955
Lndgt	40,123	1.278	0.374	0	1.922
Size	40,121	3.062	0.067	2.908	3.242
LEV	40,123	0.422	0.211	0.051	0.940
PPE	40,123	0.216	0.161	0.002	0.703
ROA	40,123	0.038	0.064	-0.259	0.206
Cash	40,123	0.172	0.137	0.010	0.673
SOE	40,123	0.141	0.348	0	1
Boardsize	40,122	0.751	0.096	0.476	0.996
Indboard	40,123	37.41	5.277	30	57.14
BM	40,123	0.618	0.244	0.115	1.170
Dual	40,123	0.285	0.451	0	1
Age	40,123	10.59	7.500	1	28

5.2 Baseline Regression Results

Table 2 reports the baseline regression results for the impact of digital transformation on corporate technological innovation. Columns M(1) to M(3) take total patent applications, invention patent applications and utility model patent applications as dependent variables, respectively. The results reveal that the coefficients of digital transformation are 0.076, 0.087 and 0.063, all significantly positive at the 1% statistical level. This finding indicates that digital transformation exerts a significant positive effect on corporate technological innovation after controlling for firm fixed effects, year fixed effects and a set of control variables.

Further analysis shows that digital transformation not only increases the total volume of patent applications, but also significantly promotes both invention patents and utility model patents,

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implying that its innovation-enhancing effect is robust across different types of technological innovation outputs. The above results fully support Hypothesis 1 of this study. And throughout this paper, t-statistics are reported in parentheses, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Baseline Regression Results

	M(1)	*M(2)*	*M(3)*
	PatentAll	PatentInv	PatentUti
Lndgt	0.076***	0.087***	0.063***
	(6.249)	(7.660)	(5.338)
control variables	Yes	Yes	Yes
_cons	-6.301***	-5.787***	-6.096***
	(-6.215)	(-7.179)	(-5.308)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	40123	40123	40123
R-squared	0.360	0.313	0.313
Adj. R-squared	0.360	0.313	0.312
F-statistic	204.006	145.082	169.900
F_p	0.000	0.000	0.000

5.3 Sub-sample Regression Results across Different Firm Development Stages

To examine whether the effect of digital transformation on technological innovation differs across firm development stages, this study conducts sub-sample regressions for young and mature firms. Following Coad et al. (2016), firms with an operating history of less than 10 years are defined as young firms, while those with an operating history of 10 years or more are classified as mature firms. Tables 3 and 4 report the regression results for the young-firm and mature-firm subsamples, respectively.

For the young-firm subsample, the coefficients of digital transformation are 0.034, 0.052, and 0.025 when total patent applications, invention patent applications, and utility model patent applications are used as dependent variables, respectively. These coefficients are significantly positive at the 5%, 1%, and 10% levels. For the mature-firm subsample, the corresponding coefficients are 0.083, 0.090, and 0.071, all of which are positive and statistically significant at the 1% level. Compared with young firms, mature firms exhibit larger coefficients and higher significance levels, indicating that digital transformation has a stronger innovation-promoting effect among mature firms.

These results suggest that mature firms are better able to transform digitalization into innovation outputs, likely because they have accumulated more resources, technical experience, and organizational capabilities over time. Overall, the sub-sample regression results support Hypothesis 2.

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Table 3: Regression Results for Young Firms

	M(1)	*M(2)*	*M(3)*
	PatentAll	PatentInv	PatentUti
Lndgt	0.034**	0.052***	0.025*
	(2.331)	(3.758)	(1.738)
control variables	Yes	Yes	Yes
_cons	-6.498***	-6.572***	-5.800***
	(-8.842)	(-9.757)	(-8.344)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	20,488	20,488	20,488
R-squared	0.272	0.232	0.228
Adj. R-squared	0.272	0.231	0.227
F-statistic	118.949	86.351	95.251
F_p	0.000	0.000	0.000

Table 4: Regression Results for Mature Firms

	M(1)	*M(2)*	*M(3)*
	PatentAll	PatentInv	PatentUti
Lndgt	0.083***	0.090***	0.071***
	(4.467)	(5.421)	(3.995)
control variables	Yes	Yes	Yes
_cons	-6.921***	-5.888***	-5.916***
	(-9.709)	(-8.906)	(-8.750)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	19635	19635	19635
R-squared	0.341	0.294	0.297
Adj. R-squared	0.340	0.293	0.296
F-statistic	82.443	57.635	72.532
F_p	0.000	0.000	0.000

5.4 Robustness Tests

Considering that the 2008 global financial crisis and the post-2020 COVID-19 pandemic may disrupt firms' operating environment and innovation activities, we exclude observations from 2007–2008 and 2020–2022 and re-estimate the model using the sample covering 2009 to 2019. These two external shocks may interfere with the causal relationship between digital transformation and corporate innovation, thus interfering with the accuracy of the benchmark regression results. The results show that the coefficients of digital transformation for the three types of patent applications are 0.050, 0.064 and 0.037, all significantly positive at the 1% level. This result remains robust. Table 5 reports the regression results after adjusting the sample period.

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Table 5: Robustness Test: Adjusted Sample Period

	M(1)	*M(2)*	*M(3)*
	PatentAll	PatentInv	PatentUti
Lndgt	0.050***	0.064***	0.037***
	(3.802)	(5.206)	(2.892)
control variables	Yes	Yes	Yes
_cons	-6.301***	-5.787***	-6.096***
	(-6.215)	(-7.179)	(-5.308)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	25,484	25,484	25,484
R-squared	0.302	0.279	0.255
Adj. R-squared	0.302	0.279	0.255
F-statistic	144.403	118.395	112.709
F_p	0	0	0

To further ensure the robustness of research conclusions, we re-estimate the model using the Ordinary Least Squares (OLS) method. The regression coefficients of digital transformation are 0.227, 0.234 and 0.148, all significantly positive at the 1% level. Table 6 presents the regression results based on the alternative estimation method.

Table 6: Robustness Test: Alternative Estimation Method

	M(1)	*M(2)*	*M(3)*
	PatentAll	PatentInv	PatentUti
Lndgt	0.227***	0.234***	0.148***
	(13.459)	(15.126)	(9.063)
control variables	Yes	Yes	Yes
_cons	-9.994***	-9.684***	-8.672***
	(-20.656)	(-20.949)	(-18.729)
N	40123	40123	40123
R-squared	0.293	0.282	0.252
Adj. R-squared	0.293	0.282	0.252
F-statistic	233.252	174.326	188.621
F_p	0	0	0

6.0 CONCLUSIONS

Using Chinese listed companies from 2007 to 2022 as the research sample, this paper explores the impact of digital transformation on corporate technological innovation and further analyzes its heterogeneity between young and mature firms. The results show that the coefficients of digital transformation are significantly positive when technological innovation is measured by total patent applications, invention patent applications and utility model patent applications. This indicates that digital transformation can effectively improve firms' technological innovation output. Robustness tests further confirm the above findings. Sub-sample regression results reveal that digital

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transformation exerts a more prominent promoting effect on the technological innovation of mature firms than that of young firms.

Based on the above conclusions, firms should formulate digital transformation strategies in accordance with their own development stages and refrain from blind investment. Mature firms should leverage their advantages in resources and industrial chains to integrate digital technologies into practical business scenarios. In contrast, young firms are advised to actively pursue external cooperation and strengthen talent cultivation and technological accumulation. The government needs to improve the construction of digital infrastructure and formulate differentiated supporting policies tailored to the development characteristics of various types of enterprises.

This study has several limitations First, the sample only consists of Chinese listed companies, excluding non-listed firms and enterprises from other economies. Second, this paper mainly examines the direct effect of digital transformation and the heterogeneity across firm development stages, while the mediating mechanisms have not been fully explored. Future research can expand the sample scope and conduct in-depth analysis on the specific paths through which digital transformation affects corporate technological innovation.

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