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Article

Digital Transformation as a Catalyst for Sustained Innovation Input: Evidence from Chinese A-Share Listed Firms

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Abstract

As artificial intelligence, big data, and digital technologies become increasingly integrated into organizational systems, digital transformation has emerged as a key driver toward sustainable corporate development. Drawing on panel data from Chinese A-share listed firms covering 2018 - 2025, this study examines how digital transformation shapes firms' sustained innovation input. Based on a two-way fixed-effects specification, the empirical results show that digital transformation significantly promotes firms' sustained innovation input. Further mediating-effect analysis reveals that digital transformation alleviates financing constraints and thereby indirectly supports the continuity of long-term research and development activities. Heterogeneity tests demonstrate that this positive impact is particularly pronounced among non-state-owned firms and high-technology firms, while the incentive effect remains relatively weak for state-owned and non-high-tech firms. The findings highlight the role of intelligent digital technologies in strengthening firms' innovation capabilities and long-term competitiveness. This study contributes to the literature on digital transformation, artificial intelligence-enabled innovation, and sustainable development. It provides empirical evidence that digitalization acts as a vital mechanism to foster sustained innovation input and underpin corporate sustainability.

Keywords: Digital Transformation; Artificial Intelligence; Sustained Innovation Input; Financing Constraints; Sustainable Development; Digital Economy

1. Introduction

Against the backdrop where the digital economy continuously empowers the real-economy sectors, digital technologies including artificial intelligence, big data and cloud computing have gradually penetrated every link of corporate R&D, production, operation and internal management, serving as a critical lever for firms to overcome development bottlenecks. Under the innovation-driven development strategy, firms cannot consolidate their technological advantages, boost market competitiveness and achieve sustainable operation merely through short-term and fragmented innovation activities. Sustained and stable innovation input therefore becomes particularly essential. A substantial body of academic research has explored firms' continuous innovation behaviours within the digital context.

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Existing literature has investigated the determinants of sustained innovation from diverse perspectives. In terms of external conditions, government subsidies and digital inclusive finance shape the external environment for firms to carry out continuous innovation[1,2]. From an internal corporate perspective, corporate financialisation, top-management team composition and the availability of patient capital can either constrain or facilitate sustained innovation via financial-resource allocation and corporate governance mechanisms [4-6]. With the advancement of the digital economy, the effect of digital transformation on firms' innovation persistence has also drawn scholarly attention [6].

At the empirical level, there exists no unified standard for measuring sustained innovation, and different indicators are constructed with distinct emphases. Some studies adopt the ratio of the increment of intangible assets to total assets to capture innovation persistence from the perspective of accumulated knowledge assets [7]. As innovation-output data have become increasingly available, numerous studies construct multi-period rolling composite indicators based on patent data to measure sustained innovation output, which reflects the continuity of firms' innovation achievements[4]. Following the same composite-indicator logic, recent studies build metrics using multi-period R&D expenditure data to focus on sustained innovation input, which reflects the continuity of firms' inter-temporal R&D capital allocation [8]. Focusing on firms' long-term R&D spending, this paper adopts a rolling composite indicator constructed from multi-period R&D expenditure to measure sustained innovation input.

Although prior studies have gradually refined the indicator system for sustained innovation, most existing empirical works still tend to adopt short-term proxies such as current-period R&D expenditure and single-period patent output to evaluate corporate innovation. Despite advances in constructing measurement indicators for sustained innovation, few empirical studies employ inter-temporal composite indicators centred on sustained innovation input to explore the mechanisms and heterogeneous boundary conditions of digital transformation's effects on firms' stable long-term R&D investment. Addressing this research gap, this paper makes three key incremental contributions. First, instead of measuring innovation through single-period R&D spending or contemporaneous patent outputs, this study constructs a multi-period composite indicator from an inter-temporal dimension to gauge sustained innovation input, and provides new empirical evidence for corporate long-horizon R&D activities within the digital-economy context. Second, this paper investigates the mediating function of financing constraints. We find that digital transformation does not merely expand firms' current-period R&D scale. By improving external capital accessibility and easing financing pressures, it secures inter-temporal continuity in R&D spending and clarifies the transmission channel whereby digital transformation fosters sustained innovation input. Third, we categorize firms by property-right nature and industrial technological attributes. Comparing group-level disparities in the innovation incentives brought by digital transformation allows us to identify the preconditions for digital dividend release and supply micro-level evidence for differentiated policy design. On the one hand, the findings offer practical references for firms to stabilise long-term sustained innovation input through digital construction and artificial-intelligence adoption and realise sustainable operation. On the other hand, they provide decision-making support for governments to optimise digital-transformation-related policies and fully unlock firms' long-term innovation momentum.

2. Theoretical Analysis and Research Hypotheses

2.1. Direct Effect of Digital Transformation on Firms' Sustained Innovation Input

Sustained innovation input can directly reflect firms' long-term development plans and sustainable growth potential, acting as an important foundation for firms to build long-term core competitiveness [9]. Unlike short-term innovation oriented at quick commercialization, sustained innovation R&D features long cycles and unpredictable returns, and demands continuous supply of capital, human resources and technologies. The scale of sustained innovation input is significantly affected by firms' internal resource coordination capacity, external information environment and overall operating strength. How to resolve these practical constraints and help firms maintain stable R&D input has become a realistic problem confronted by numerous firms in operation.

Dynamic capability theory offers a theoretical lens for interpreting why many enterprises struggle to maintain adequate sustained innovation input [10]. In contexts marked by fast-paced technological renewal and erratic market shifts, companies resting solely on inherited resources and static competencies will find it difficult to preserve competitive edges over extended periods. To cope with such environmental pressures, enterprises must cultivate three core dynamic capability dimensions: opportunity sensing, opportunity seizing, and resource reconfiguration. By embedding big data, artificial intelligence and other digital tools across end-to-end R&D and administrative workflows, digital transformation creates feasible pathways for businesses to lift their sustained innovation input.

When it comes to opportunity sensing capacity, digital transformation facilitates firms' discovery of external business prospects and lessens ambiguity when making innovation-related decisions. Enterprises equipped with superior sensing competencies can promptly track industry evolution and spot promising R&D directions. Leveraging AI-driven data-mining techniques, companies are able to gather broad-ranging intelligence covering technological evolution trajectories and shifts in consumer preferences, which mitigates information asymmetries embedded within R&D operations [11]. Raw data assets constitute the groundwork for advancing sensing capabilities. Meanwhile, artificial intelligence helps unlock value embedded within large-scale datasets, supporting managers to make sound judgements regarding technological iterations and market structural transitions [12]. Boosted information-processing performance reduces firms' rigid dependence on established technological trajectories. This allows managerial teams to craft more consistent medium-and long-range R&D schemes, insuring long-term research activities against disruptions brought by short-run market swings and securing continuous innovation investment.

For opportunity seizing capacity, digital transformation streamlines the execution of innovation initiatives and elevates the overall quality of corporate resource deployment. Digital flattening of internal administrative tiers speeds up intra-firm information flows. It makes it possible to deploy R&D personnel and capital in a targeted and adjustable way, thereby easing common pitfalls under conventional operation patterns such as resource misalignment and fragmented R&D budgets [13]. Paired with real-time operational data, intelligent algorithms can forecast resource consumption for ongoing R&D programmes and carry out adaptive resource readjustment. This prevents long-cycle research projects from being halted due to inflexible resource arrangements. Rather than pursuing reckless expansion of overall resource pools, firms can secure steady provision of innovation-related factors and curtail costly trial-and-error expenditures incurred during long-horizon R&D work [14].

The last dimension corresponds to firms' resource reconfiguration capacity. Digital transformation improves organizational agility and strengthens corporate risk buffering capacity. Digital tools reinforce organizational resilience facing external market shocks, helping enterprises keep stable R&D cadences even amid turbulent market conditions. Under such circumstances, management becomes more inclined to allocate capital toward lengthy-cycle, high-risk research ventures. This gives rise to a self-reinforcing feedback loop: sustained innovation input promotes further digital upgrading; digital transformation subsequently generates value growth and motivates additional R&D spending in return [8].

Drawing on the above theoretical reasoning, this study proposes the research hypothesis outlined below:

H1: Digital transformation exerts a significant positive promoting effect on firms' sustained innovation input.

2.2. Indirect Effect of Digital Transformation on Firms' Sustained Innovation Input

The long-term development of sustained innovation input hinges heavily on stable, sufficient and continuous capital supply, and financing constraints constitute the core bottleneck restricting firms' sustained innovation input. Unlike general single-period R&D input, sustained innovation input emphasises the inter-temporal continuity of R&D activities. It requires not only R&D funds in a single year, but also resilience against external environmental fluctuations to prevent disruptions to multi-period R&D chains. Theoretically, financing constraints curb corporate innovation not merely by limiting capital availability, but more profoundly through the psychological mechanism of "short-term loss aversion". When external financing conditions tighten, management, under pressure from

performance appraisal, tends to cut long-cycle, high-uncertainty R&D projects to smooth current-period profits. Such behaviour may not eliminate firms' R&D expenditure in the given year, yet it readily breaks the inter-temporal continuity of R&D and triggers disruptions in sustained innovation input. From the perspective of information asymmetry theory, the information gap between firms and external capital markets constitutes the root cause of financing constraints. Characterised by long time horizons, high risks and lagged returns, sustained innovation input imposes high information-collection and risk-screening costs on external investors. Coupled with adverse selection and moral hazard, most firms suffer from narrow financing channels, high financing costs and insufficient credit lines, which further lead to interrupted or reduced sustained innovation input.

Digital transformation offers a technical avenue to mitigate financing constraints. Drawing on information asymmetry theory, during digital transformation, firms leverage big data, artificial intelligence and other technologies to achieve standardised and real-time disclosure of operational, financial and R&D data. This substantially reduces information asymmetry between financial institutions, external investors and firms, and effectively mitigates adverse selection and moral hazard [15]. Meanwhile, financial institutions can conduct intelligent risk control and credit evaluation based on massive data accumulated from corporate digitalisation. This breaks the traditional over-reliance on fixed-asset collateral in credit businesses and broadens financing channels for corporate innovation [7]. Alleviated financing constraints do not merely provide firms with a one-off credit facility to expand current-period R&D scale. More importantly, they improve the stability of firms' access to capital across periods. Improved expectations for external financing weaken management's short-term performance pressure and reduce incentives to slash long-term R&D amid cash-flow volatility. As a result, R&D input can be sustained across multiple fiscal years, which raises the level of sustained innovation input rather than merely boosting general single-period R&D spending [16]. Accordingly, this paper puts forward the mediating-effect hypothesis:

H2: Financing constraints exert a mediating effect between digital transformation and firms' sustained innovation input. That is, digital transformation indirectly raises the level of firms' sustained innovation input by alleviating corporate financing constraints.

3. Methodology

3.1. Sample Selection and Data Sources

This paper takes A-share listed firms from 2018 to 2025 as research samples. Financial industry firms, ST/*ST firms, samples with incomplete data and observations with asset-liability ratio exceeding 1 are excluded. All continuous variables are winsorized at the 1% level, yielding a total of 20,368 firm-year observations. The data are mainly derived from the CSMAR database and financial statements of listed firms.

3.2. Variable Definition

The explained variable is Sustained Innovation Input (SII).To capture the sustained characteristics of firms' innovation input, this paper constructs the indicator following the research method of Yang et al. [8]. The calculation formula is as follows:

$$SII_{it} = ln\left[\frac{R_{it}+R_{i,t-1}}{R_{i,t-1}+R_{i,t-2}} \times \left(R_{it} + R_{i,t-1}\right) + 1\right] \quad (1)$$

Where R_{it} denotes the R&D expenditure of firm i in year t; $R_{i,t-1}$ represents the R&D expenditure of firm i in year t-1; $R_{i,t-2}$ stands for the R&D expenditure of firm i in year t-2. SII_{it} denotes the persistent innovation input level of firm i in year t. A higher value of this indicator indicates a higher level of firms' sustained innovation input.

The core explanatory variable is Digital Transformation (DIG).Referring to Wu et al. [17], this paper adopts their digital transformation index of A-share listed firms as the core explanatory variable. Based on Python text mining technology, the index takes annual reports of listed firms as the data pool. A digital feature lexicon covering artificial intelligence, business intelligence, deep learning, natural language processing and other categories is constructed to search and count word frequencies in annual reports. The total word frequency of digital transformation is obtained by summing classified word counts, which effectively captures explicit investment of firms in digital technology application and strategic transformation. Given the obvious right-skewed distribution of the original indicator, this paper adds 1 to the raw index and takes the natural logarithm in empirical analysis to alleviate heteroskedasticity and improve estimation efficiency.

The mediating variable is Financing Constraints (FC). Following Gu et al. [18], three variables including firm size, firm age and cash dividend payout ratio are standardized by year and averaged. Listed firms are ranked according to the mean value, with the upper and lower tertiles as boundaries to define the financing constraint dummy variable QUFC. Firms below the 33rd percentile are categorized as high financing constraint group (QUFC=1), and those above the 66th percentile are low financing constraint group (QUFC=0). On this basis, a Logit model incorporating six variables (firm size, asset-liability ratio, cash dividend, market-to-book ratio, net working capital and EBIT, all divided by total assets) is constructed to fit the annual probability of firms' financing constraints, defined as the financing constraint index FC. FC ranges from 0 to 1, and a larger value means severer financing constraints faced by firms.

Referring to existing literature, this paper incorporates the following control variables into the model to avoid omitted variable bias: Asset-Liability Ratio (Lev), Return on Total Assets (ROA), Inventory Ratio (INV), Top 5 Shareholding Ratio (Top5), Tobin's Q (TobinQ), Listing Age (ListAge), Management Shareholding Ratio (Mshare), Number of Employees (Employ). The specific construction methods are shown in Table 1.

Table 1: Definition of Main Variables

Variable Category	Variable Name	Construction Method	Abbreviation
Explained Variable	Sustained Innovation Input	As previously mentioned	SII
Core Explanatory Variable	Digital Transformation	ln(Total word frequency of digital transformation keywords + 1)	DIG
Mediating Variable	Financing Constraints	As previously mentioned	FC
Control Variables	Asset-Liability Ratio	Total liabilities / Total assets	Lev
	Return on Total Assets	Net profit / Average total assets	ROA
	Inventory Ratio	Net inventory / Total assets	INV
	Top5 Shareholding Ratio	Aggregated shareholding proportion of the top five major shareholders	Top5
	Tobin's Q	(Market value of tradable shares + Non-tradable shares × Net asset per share + Book value of liabilities) / Total assets	TobinQ
	Listing Age	ln(Current year − Listing year + 1)	ListAge
	Management Shareholding Ratio	Number of shares held by management / Total shares of the firm	Mshare
	Number of Employees	Total employee headcount	Employ

3.3. Model Construction

3.3.1. Benchmark Regression Model

This paper adopts panel data and constructs a two-way fixed effect model following mainstream scholars, with the specific model specified as follows:

$$SII_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_c control_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (2)$$

Where i represents the firm, t denotes the year; SII_{it} is the explained variable referring to the sustained innovation input level of firm i in year t; DIG_{it} is the core explanatory variable measuring the digital transformation degree of firm i in year t; $Control_{it}$ stands for control variables; λ_t denotes time fixed effects; μ_i represents individual fixed effects; ε_{it} is the random disturbance term.

3.3.2. Mediating Effect Model

To further verify the existence of mediating effects, the stepwise regression method is adopted for mediating effect testing, with the models set as follows:

$$FC_{it} = b_0 + b_1 DIG_{it} + b_c control_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (3)$$

$$SII_{it} = c_0 + c_1 DIG_{it} + \ c_2 FC_{it} + c_c control_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (4)$$

Where FC_{it} is the mediating variable representing the financing constraints of firm i in year t; other variables carry the same meanings as above.

3.4. Descriptive Statistical Analysis

As shown in Table 2, the total number of observations in this paper is 20,368. The mean value of the core explained variable SII (sustained innovation input) is 19.097 with a standard deviation of merely 1.455, ranging from 15.156 to 23.080. It can be seen that the R&D expenditure scale of sample firms is generally concentrated with small inter-group differences. The mean value of the digital transformation indicator DIG is 1.993, with a standard deviation of 1.371, a minimum of 0 and a maximum of 5.069. This reflects prominent differentiation in digital construction among listed firms; some firms have not yet deployed digital transformation, resulting in a wide digital development gap across firms.

Table 2: Descriptive Statistical Analysis

Variable	Observations	Mean	Std. Dev.	Min	Max
SII	20,368	19.097	1.455	15.156	23.08
DIG	20,368	1.993	1.371	0	5.069
Lev	20,368	0.414	0.194	0.052	0.894
ROA	20,368	0.03	0.066	-0.219	0.213
INV	20,368	0.121	0.094	0.002	0.669
Top5	20,368	0.509	0.156	0.188	0.882
TobinQ	20,368	2.074	1.316	0.83	8.457
ListAge	20,368	2.287	0.72	0.693	3.434
Mshare	20,368	0.148	0.188	0	0.69
Employ	20,368	5123.34	9548.77	112	63802

3.5. Multicollinearity Test

To avoid biased parameter estimation caused by high correlation between variables, this paper adopts Variance Inflation Factor (VIF) to diagnose multicollinearity among core explanatory variables and control variables. Test results are presented in Table 3. The VIF values of all variables range from 1.04 to 1.57, with an average VIF of 1.25, far below the empirical critical value of 10. This result indicates weak correlation between explanatory variables, and there exists no systematic risk of multicollinearity in the model.

Table 3 : Multicollinearity Test Results

Variable	VIF	1/VIF
DIG	1.06	0.944308
Lev	1.37	0.727467
ROA	1.23	0.815694
INV	1.04	0.957484
Top5	1.22	0.81652
TobinQ	1.11	0.897884
ListAge	1.57	0.636707
Mshare	1.39	0.718897
Employ	1.28	0.781335
Mean VIF	1.25	—

4. Empirical Results and Analysis

4.1. Benchmark Regression Results and Analysis

Table 4 presents baseline regression outcomes. Column (1) delivers estimation results excluding any firm-level control variables. Here, the coefficient for digital transformation equals 0.061, reaching statistical significance at the 1% threshold. This outcome points to a favourable association between digital transformation and firms' sustained innovation input. Once the full set of control variables is added for Column (2), the corresponding coefficient drops to 0.037 and still retains significance at the 1% statistical level. From an economic interpretation perspective, each one-unit rise in the digital transformation index correlates with a 0.037 growth in sustained innovation input. This finding suggests enterprises with more thorough digital deployment can better preserve the inter-temporal consistency of their R&D spending. Such favourable motivating impact persists even when firm-specific fixed effects, year fixed effects and an array of firm-level attributes are accounted for, hence confirming Hypothesis H1.

Table 4 : Benchmark Regression Results

Variables	(1) SII	(2) SII
DIG	0.061***	0.037***
	(0.009)	(0.006)
Lev		0.670***
		(0.052)
ROA		1.126***
		(0.079)
INV		0.369***
		(0.110)
Top5		0.481***
		(0.096)
TobinQ		-0.038***

Table 4 (continued)

Variables	(1) SII	(2) SII
		(0.004)
ListAge		0.126***
		(0.030)
Mshare		0.002***
		(0.001)
Employ		0.000***
		(0.000)
Constant	0.349	19.275***
	(0.438)	(0.330)
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	20,368	20,368
R-squared	0.031	0.126
Number of stkcd	4,447	4,447

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

4.2. Robustness Tests

4.2.1. Replacing the Explained Variable

To test whether benchmark regression results rely on the specific construction method of sustained innovation input indicator, this paper reconstructs a current-period sustained innovation input indicator SII_Curr following He et al. [19]. The calculation formula is:

$$\mathrm{SII_Curr_{it}} = \ln\left(\frac{\mathrm{R_{it}}}{\mathrm{R_{i,t-1}}} \times \mathrm{R_{it}} + 1\right) \quad (5)$$

Test results in Column (1) of Table 5 show that the coefficient of DIG is 0.045 and significant at the 1% level, consistent with benchmark regression results.

4.2.2. Replacing the Core Explanatory Variable

Referring to Xiao et al. [20], this paper adopts a lexicon containing 197 keywords related to digital transformation, takes annual reports of A-share listed firms as text analysis objects, and uses Python crawler technology to extract and segment annual report texts. The frequency of each keyword in each firm's annual report is counted separately, and the total word frequency plus 1 is logarithmized to obtain a new indicator DIG1 measuring digital transformation degree. Substituting DIG1 into the benchmark regression model, results in Column (2) of Table 5 show that the coefficient of DIG1 is 0.091 and significant at the 1% level, consistent with benchmark regression results.

4.2.3. Lagging the Core Explanatory Variable

Since a time lag exists between the implementation of digital transformation and its actual impacts, this paper lags digital transformation by one period following Wang et al. [21], which also alleviates endogeneity arising from reverse causality. The one-period lagged digital transformation indicator L.DIG is adopted, and test results in Column (3) of Table 5 show that the coefficient of L.DIG is 0.026, significantly positive at the 1% level, consistent with benchmark results.

4.2.4. Excluding Special Years

The outbreak of COVID-19 in 2020 generated extensive and profound exogenous shocks on firms' production and operation. Firms' digital transformation rhythms, financing environments and R&D investment decisions may deviate from long-term equilibrium during this period. To test whether benchmark results are driven by observations in this special period, all observations of 2020 are excluded for re-estimation. Results in Column (4) of Table 5 reveal that the coefficient of DIG remains significantly positive at the 1% level, proving the cross-period robustness of benchmark conclusions rather than being solely driven by pandemic shocks.

Table 5: Robustness Tests

	(1)	(2)	（3）	（4）
Variables	**SII_Curr**	**SII**	**SII**	**SII**
DIG	0.045***			0.022***
	(0.010)			(0.007)
DIG1		0.091***		
		(0.026)		
L1_DIG			0.026***	
			(0.007)	
Lev	0.831***	0.675***	0.624***	0.676***
	(0.077)	(0.052)	(0.060)	(0.057)
ROA	1.763***	1.125***	1.015***	1.008***
	(0.118)	(0.079)	(0.088)	(0.085)
INV	0.537***	0.377***	0.436***	0.441***
	(0.165)	(0.110)	(0.124)	(0.118)
Top5	0.578***	0.489***	0.573***	0.485***
	(0.144)	(0.096)	(0.116)	(0.111)
TobinQ	-0.024***	-0.038***	-0.031***	-0.026***
	(0.006)	(0.004)	(0.005)	(0.005)
ListAge	0.122***	0.137***	0.188***	0.156***
	(0.045)	(0.030)	(0.046)	(0.032)
Mshare	0.003***	0.002***	0.002**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Employ	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	18.745***	19.303***	19.204***	19.293***
	(0.494)	(0.330)	(0.423)	(0.312)
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	20,368	20,352	15,818	17,812
R-squared	0.075	0.125	0.074	0.074
Number of stkcd	4,447	4,447	4,107	4,430

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

4.3. Mediating Effect Test

To uncover the internal transmission mechanism through which digital transformation acts on firms' sustained innovation input and test the mediating role of financing constraints, this paper adopts the stepwise regression approach for mediating-effect testing. The specific regression outcomes are presented in Table 6. Column (1) of Table 6 reports the regression of digital transformation on financing constraints. Digital transformation yields a coefficient of -0.005, which is statistically meaningful at the 1% significance threshold. This result reveals that deeper corporate digitalisation helps lower the financing constraint index. Heightened information transparency stemming from corporate digital upgrading substantially improves external financing circumstances for sample firms. Column (2) outputs regression results for the complete model specification, incorporating both the core explanatory variable

and the mediating variable simultaneously. The coefficient estimate for digital transformation keeps its positive sign and statistical significance at the 1% level, whereas financing constraints carry a significantly negative coefficient also at the 1% level. These empirical patterns illustrate that financing constraints act as a major limiting force holding back firms' sustained innovation input. By easing such financing frictions, digital transformation delivers indirect improvements to enterprises' sustained innovation input. The above empirical evidence therefore supports Hypothesis H2.

Table 6 : Mediating Effect Test

Variables	(1) FC	(2) SII
DIG	-0.005***	0.033***
	(0.001)	(0.006)
FC		-0.708***
		(0.039)
Lev	-0.487***	0.325***
	(0.010)	(0.054)
ROA	0.427***	1.428***
	(0.016)	(0.080)
INV	0.275***	0.563***
	(0.022)	(0.110)
Top5	-0.053***	0.443***
	(0.019)	(0.095)
TobinQ	-0.009***	-0.045***
	(0.001)	(0.004)
ListAge	-0.075***	0.073**
	(0.006)	(0.030)
Mshare	-0.000	0.002***
	(0.000)	(0.001)
Employ	-0.000***	0.000***
	(0.000)	(0.000)
Constant	0.638***	19.727***
	(0.067)	(0.327)
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	20,368	20,368
R-squared	0.268	0.144
Number of stkcd	4,447	4,447

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

4.4. Heterogeneity Test

4.4.1. Heterogeneity by Corporate Ownership

This section assesses how ownership attributes shape the nexus between digital transformation and corporate sustained innovation input. Using ultimate-controller characteristics as grouping criteria, the overall sample is separated into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). Baseline regression specifications are estimated individually for each group. Table 7 documents outputs derived from these subgroup regressions. The SOE subsample in Column (1) produces a digital transformation coefficient of 0.030, attaining statistical significance at the 5% threshold. By comparison, Column (2) draws on no-SOE observations and delivers a coefficient value of 0.038, which is significant at the 1% level. Positive and statistically discernible coefficients emerge within both subgroups. Such evidence suggests digital transformation can raise sustained innovation input for SOEs and non-SOEs. Even so, the real-world influence brought by digital transformation

differs in magnitude across these two firm categories. Group-specific regressions alone cannot confirm whether such coefficient differences are statistically credible. Therefore, this paper constructs an ownership dummy variable SOE, which equals 1 for state-owned enterprises and 0 for non-state-owned enterprises. An interaction term between digital transformation and ownership (DIG×SOE) is introduced into the full-sample two-way fixed-effects model for further testing. As shown in Column (3) of Table 7, the estimated coefficient of the interaction term DIG×SOE is −0.019 and statistically significant at the 5% level. This result suggests that the effect of digital transformation on firms' sustained innovation input differs significantly by firm ownership. Economically, an equivalent increase in digital transformation yields a stronger marginal boost to sustained innovation input among non-SOEs relative to SOEs. This discrepancy may arise from institutional differences: SOEs need to balance multiple operational objectives and feature multi-level approval procedures and limited organisational flexibility, which weakens the resource-allocation optimisation effect brought by digital transformation. By contrast, non-SOEs are market-profit-oriented with short decision-making chains and flexible operations. They can rapidly integrate digital tools such as big data and artificial intelligence into the full R&D workflow, so as to maximise the stimulating effect of digital transformation on sustained innovation input.

Table 7 Heterogeneity Test : State-owned vs. Non-state-owned Firms

	(1)	(2)	(3)
Variables	**State-owned Enterprise**	**Non-state-owned Enterprise**	**Difference**
DIG	0.030**	0.038***	0.042***
	(0.015)	(0.007)	(0.007)
DIG×SOE			-0.019**
			(0.009)
Lev	0.597***	0.749***	0.671***
	(0.131)	(0.054)	(0.052)
ROA	1.727***	0.991***	1.128***
	(0.231)	(0.078)	(0.079)
INV	0.010	0.574***	0.367***
	(0.250)	(0.118)	(0.110)
Top5	0.908***	0.258**	0.486***
	(0.225)	(0.104)	(0.096)
TobinQ	-0.063***	-0.034***	-0.038***
	(0.013)	(0.004)	(0.004)
ListAge	0.100	0.239***	0.125***
	(0.098)	(0.031)	(0.030)
Mshare	0.014***	0.001**	0.002***
	(0.004)	(0.001)	(0.001)
Employ	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Constant	17.416***	19.232***	19.277***
	(0.489)	(0.294)	(0.330)
Firm fixed effects	yes	yes	yes
Year fixed effects	yes	yes	yes
Observations	5,456	14,912	20,368
R-squared	0.135	0.142	0.127
Number of stkcd	1,194	3,484	4,447

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

4.4.2. Heterogeneity by Industrial Technology Attribute

To test whether the effect of digital transformation on firms' sustained innovation input differs according to industrial technological attributes, this paper splits the full sample into two subsamples of high-tech firms and non-high-tech firms and conducts baseline regressions separately. Grouped estimation results show that the coefficient of digital transformation is 0.042 and statistically significant at the 1% level for high-tech firms, whereas the coefficient amounts to 0.015 and remains insignificant for non-high-tech firms. Simple group-by-group comparison cannot verify the statistical reliability of coefficient differences. This paper further constructs an industry dummy variable HT, which takes the value of 1 for high-tech firms and 0 for non-high-tech firms. The interaction term DIG×HT, generated from the industry dummy and digital transformation, is incorporated into the full-sample two-way fixed-effects model for regression. Column (3) of Table 8 demonstrates that the coefficient of the interaction term DIG×HT is 0.051 and statistically significant at the 1% level. This indicates that digital transformation exerts a stronger promoting effect on sustained innovation input among high-tech firms, while non-high-tech firms can hardly rely on digitalisation to boost long-term innovation. It suggests that the empowering effect of digitalisation on long-run R&D input is not homogeneous, and industrial technological foundations determine the extent to which digital dividends can be realised. Such heterogeneity may stem from industrial characteristics. High-tech firms are knowledge-intensive with stronger technological absorptive capacity, and their R&D activities attach great importance to information quality and resource-allocation efficiency. Deployed artificial intelligence and big data can complement firms' existing technologies and human capital, improving the accuracy of R&D decisions and the efficiency of knowledge integration. By contrast, non-high-tech firms generally have weak technological foundations and infrequent regular R&D activities. They possess limited applicable scenarios for intelligent-technology adoption and lack sufficient knowledge stock to absorb data-driven and algorithm-based applications, which ultimately makes it difficult to achieve a noticeable rise in sustained innovation input.

Table 8 : Heterogeneity Test: High-tech vs. Non-high-tech Firms

Variables	(1) High-tech firms	(2) Non-high-tech firms	(3) Difference
DIG	0.042***	0.015	0.003
	(0.007)	(0.014)	(0.009)
DIG×HT			0.051***
			(0.010)
Lev	0.548***	0.947***	0.671***
	(0.052)	(0.125)	(0.052)
ROA	1.101***	1.259***	1.129***
	(0.079)	(0.189)	(0.079)
INV	0.477***	0.326	0.383***
	(0.116)	(0.254)	(0.110)
Top5	0.418***	0.634***	0.485***
	(0.102)	(0.207)	(0.096)
TobinQ	-0.036***	-0.042***	-0.038***
	(0.004)	(0.012)	(0.004)
ListAge	0.153***	-0.032	0.121***
	(0.030)	(0.070)	(0.030)
Mshare	0.001**	0.006***	0.002***
	(0.001)	(0.002)	(0.001)
Employ	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Constant	19.655***	16.842***	19.281***
	(0.283)	(0.596)	(0.329)

Table 8 (continued)

Variables	(1) High-tech firms	(2) Non-high-tech firms	(3) Difference
Firm fixed effects	yes	yes	yes
Year fixed effects	yes	yes	yes
Observations	14,038	6,330	20,368
R-squared	0.166	0.094	0.128
Number of stkcd	3,125	1,439	4,447

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

5. Conclusions and Implications

5.1. Main Research Findings

Drawing upon panel-level observations for Chinese A-share listed firms spanning 2018 to 2025, this work explores how digital transformation shapes firms' sustained innovation input. It further pinpoints underlying transmission mechanisms and captures heterogeneous outcome patterns under different firm contexts. Key empirical takeaways are laid out below. Digital transformation delivers meaningful improvements to sustained innovation input, and this positive association holds up against a battery of robustness diagnostic checks. By easing corporate financing frictions, digital transformation creates favourable conditions for firms to sustain R&D spending over longer time horizons. The innovation-promoting effects from digital transformation show clear disparities conditional upon firm ownership and industrial attributes: such empowering impacts exert stronger influence among non-state-owned and high-tech enterprises relative to their state-owned and non-high-tech counterparts.

5.2. Practical and Policy Implications

Derived from the above empirical evidence, this study yields actionable insights for firm management as well as public policy design.

Progress toward broader digital adoption should proceed in gradual phases so as to fully unlock digitalisation's value for sustained innovation investment. Policymakers ought to keep advancing next-generation digital infrastructure, including computing capacity and network facilities. These measures help bring down upfront transformation costs faced by small-and medium-sized enterprises. Multiple instruments including subsidies, tax incentives and special industrial funds can be adopted to promote the in-depth implementation of digital technologies across firms' full business chains. Given the rapid iteration of artificial-intelligence technologies, authorities may guide firms to deploy intelligent systems for R&D optimisation, production scheduling and technical-file management. Artificial intelligence should serve not only cost control, but also act as a critical pillar for firms to maintain long-term innovation rhythms.

Linkages between digital technologies and financial services should be established to alleviate financing pressure for long-term R&D via digitalisation. Deep integration between digital finance and supply-chain finance should be promoted. Financial institutions may leverage intelligent algorithms and massive operational data to build credit systems that better reflect firms' real-world conditions, narrow information gaps between banks and enterprises, and ease corporate financing constraints. Local governments can launch special credit facilities for firms undergoing digital upgrading, supplemented by innovation support funds, to provide sustainable financial backing for firms' consecutive and stable R&D activities.

Differentiated industrial guidance policies should be implemented to deliver targeted support matching firm characteristics. For non-state-owned firms, governments can scale up support in fiscal-tax instruments, finance and digital platforms to offset capital shortcomings and facilitate steady digital transformation. For state-owned firms, innovation-tolerance mechanisms and scientific-research

incentives should be improved to address insufficient innovation motivation. For high-tech firms, their technology-spillover effects should be further amplified; demonstration benchmarks integrating digital transformation and artificial-intelligence innovation can be built to form replicable practical models. For non-high-tech firms, digital transformation can hardly drive the growth of sustained innovation input directly. Accordingly, policymakers should avoid over-estimating digitalisation's empowering effect on long-term R&D. Priority should be given to fostering firms' basic digital capabilities, carrying out digital retrofitting of production and management workflows, reducing transformation and technology-adaptation costs, consolidating operational foundations, and cultivating sustained innovation capacity in a gradual manner. Unrealistic expectations that digital transformation will yield immediate continuous growth in R&D input should be avoided.

5.3. Research Limitations and Future Research Directions

This study has several limitations. First, the digital-transformation indicator is constructed based on text-mining of annual reports, which mainly reflects firms' publicly disclosed digital-strategy orientations, and cannot precisely capture the real implementation level of digitalisation within internal business processes. Second, regarding mechanism analysis, this paper only verifies the mediating role of financing constraints. In reality, digital transformation may influence sustained innovation input through multiple alternative channels such as organisational-structure adjustment, human-capital allocation and industrial-chain collaboration, which are not empirically examined in this paper. Third, the sample is restricted to A-share listed firms and excludes numerous small-and medium-sized unlisted enterprises. Therefore, the conclusions cannot be directly generalised to unlisted SMEs.

Against these limitations, future research can be advanced along three avenues. First, concerning the measurement of digital transformation, future studies may combine on-site enterprise questionnaires and micro-level operational data to assess the actual implementation degree of corporate digitalisation. Cross-validation with annual-report word-frequency indicators can optimise variable measurement performance. Second, to address the limited scope of transmission mechanisms, future work can further explore potential mediating and moderating factors such as top-executive individual characteristics, firms' industrial-chain status and digital-talent stock, so as to obtain a more comprehensive understanding of the preconditions under which digital transformation boosts firms' long-term R&D input. Third, regarding sample restrictions, unlisted small- and medium-sized enterprises can be incorporated into research samples. Comparisons of digital-transformation effects between listed and unlisted SMEs can be conducted to expand the generalisability of research conclusions.

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