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Digital Transformation, Financing Constraints, and Corporate Innovation Efficiency: Evidence from Chinese A-Share Listed Companies

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ABSTRACT: Digital technologies are reshaping how firms allocate resources to innovation, yet whether digital transformation raises the efficiency with which innovation inputs are converted into outputs remains an open question. Using a panel of Chinese A-share listed companies over 2012–2023 and a two-way fixed effects specification, this study examines the effect of digital transformation on corporate innovation efficiency, measured by a data envelopment analysis (DEA) score built on R&D inputs and patent outputs. Complemented by heterogeneity analyses, a mediation examination and a battery of robustness tests, we uncover three main findings. First, digital transformation significantly improves corporate innovation efficiency, and the result survives alternative efficiency measures, lagged regressors, an instrumental-variable strategy, sub-period analysis and region-by-year fixed effects. Second, the effect is heterogeneous: it is substantially stronger for non-state-owned enterprises, for firms in high-technology industries and for small and medium-sized firms. Third, alleviating financing constraints is a significant mediating channel, accounting for roughly 18% of the total effect. These findings offer implications for firms evaluating the returns to digital investment and for policymakers designing differentiated support for digital transformation.

KEYWORDS: Digital transformation; Innovation efficiency; Financing constraints; Listed companies; Two-way fixed effects

I. INTRODUCTION

The ongoing wave of technological and industrial change, driven by big data, cloud computing, artificial intelligence and blockchain, is reshaping how firms create and capture value. In China, the digital economy has become a key force in restructuring factor allocation and the competitive landscape: its scale reached roughly 50.2 trillion yuan in 2022, equivalent to about 41.5% of GDP [1]. The 14th Five-Year Plan for Digital Economy Development explicitly calls for accelerating the digital transformation of industries and enterprises [2]. Against this backdrop, digital transformation has shifted from an optional strategy to a precondition for firms' long-term survival and growth. It refers to a process in which firms embed digital technologies into production, operation, management and business models, triggering systematic changes in organizational structure, business processes and the logic of value creation [3]. China's economy is moving from high-speed growth towards high-quality development, in which innovation is the primary driving force and firms are the main body of innovation. In practice, however, many firms invest heavily in R&D without obtaining proportional innovation output: the binding problem lies increasingly in the efficiency with which resources are used rather than in the scale of input. Innovation efficiency, defined as the capacity to convert innovation inputs into innovation outputs, therefore provides a more informative gauge of innovation performance than R&D intensity or patent counts alone. Digital technologies can plausibly affect this efficiency through several channels. They lower the cost of storing, processing and transmitting information [4], widen the scope for external knowledge search and experimentation, and allow firms to organize R&D in more data-driven ways. Yet transformation is also costly, requires organizational adjustment, and may crowd out R&D resources in the short run. Whether, and through which channel, digital transformation raises innovation efficiency is therefore an empirical question. In the Chinese context, three questions follow. Does digital transformation improve the innovation efficiency of listed companies? Do financing constraints serve as a transmission channel? And is the effect uniform across firms with different ownership, industry and size characteristics? To answer these questions, this paper uses panel data on Chinese A-share listed companies over 2012–2023. Following the textanalysis approach of Wu et al. [5], we construct a digital transformation index from the keywords disclosed in annual reports, and we measure innovation efficiency with a DEA score that relates patent output to R&D expenditure and R&D personnel. A twoway fixed effects model is used for the baseline estimation, and endogeneity is addressed through lagged regressors, an instrumental-variable strategy and event-study evidence. This paper contributes to the

literature in three respects. First, it evaluates innovation from an input–output efficiency perspective rather than from the single dimension of R&D input or patent output, which complements existing work on the economic consequences of digital transformation [5,6]. Second, it identifies financing constraints as a transmission channel and quantifies its share in the total effect. Third, it documents how the effect varies with ownership, industry and firm size, which provides evidence for differentiated policy design. The remainder of the paper is organized as follows: Section II reviews the literature, Section III develops the research hypotheses, Section IV presents the research design and the empirical results, and the final part concludes.

II. LITERATURE REVIEW

Research on digital transformation has first concentrated on its measurement. Existing studies rely on three approaches: questionnaires and case studies, which provide rich detail but small samples; financial proxies such as the share of digital-related items in intangible assets, which are sensitive to accounting treatment; and text analysis of annual reports, in which the frequency of keywords related to artificial intelligence, big data, cloud computing, blockchain and digital technology application is aggregated into an index. Because of its objectivity, availability and comparability across firms, the text-analysis approach, popularized by Wu et al. [5], has become the mainstream choice in empirical work on listed companies. A second strand concerns the measurement of innovation efficiency, understood as the ability of a firm to convert innovation inputs into innovation outputs. The usual practice treats R&D expenditure and R&D personnel as inputs and patent applications or new-product revenue as outputs, and estimates efficiency with frontier methods. Data envelopment analysis (DEA)[7] requires no assumption on the functional form of the production frontier, whereas stochastic frontier analysis (SFA)[8] separates random noise from inefficiency and therefore yields more stable estimates. Compared with R&D intensity or patent counts, efficiency scores indicate how well innovation resources are used. Most studies of digital transformation and innovation support a promotion view. Digital technologies reduce the cost of information search and experimentation, broaden access to external knowledge, and make the organization of innovation more open and modular. Inside the firm, digitalization accelerates information flows across departments and improves the allocation of R&D resources. Externally, digital disclosure and data-based monitoring mitigate information asymmetry and improve the financing environment for innovation. A second view cautions that the relationship is not necessarily linear or immediate. In the early stage of transformation, firms must invest heavily in hardware, software, training and organizational redesign, which may crowd out R&D resources. The benefits of information technology often materialize with a lag, a phenomenon associated with the productivity paradox [9]. Other studies stress that the effect depends on firm characteristics: it tends to be stronger in non-state-owned firms, high-technology industries and regions with better digital infrastructure. Finally, the financing of innovation has long been regarded as a binding constraint. Because R&D projects are risky, long-term and difficult to collateralize, and because their key information is hard to disclose to outside investors, innovative firms typically face a wedge between internal and external costs of funds [10,11]. A large literature shows that financing constraints depress R&D investment and innovation output, and that factors alleviating them raise innovation performance. Meanwhile, digital technologies have been found to improve information transparency and reduce monitoring costs, which provides a natural basis for treating financing constraints as a mediating channel. In summary, existing studies provide a solid foundation but leave three gaps. First, the effect of digital transformation on innovation is mostly examined through a single input or output indicator, whereas evidence on efficiency is scarce. Second, evidence on the transmission channel, especially the financing-constraint channel, remains fragmented. Third, findings are not fully consistent and call for large-sample evidence. This paper addresses these gaps using Chinese A-share listed companies.

III. RESEARCH HYPOTHESES

A. Overall Effect of Digital Transformation on Corporate Innovation Efficiency

From the resource-based perspective, firms are bundles of resources, and valuable, rare and hard-to-imitate resources are the source of sustained competitive advantage [12]. Data have become a new factor of production in the digital era. Digital transformation turns scattered data into usable resources and, combined with technology and human capital, forms dynamic capabilities that improve how innovation resources are deployed. This logic implies that a given amount of R&D input can generate more innovation output in a digitally transformed firm. Three more specific mechanisms support this expectation. First, digital technologies reduce the cost of knowledge search and experimentation. Big-data analytics and cloud platforms allow firms to scan market demand and technological trends, screen R&D projects earlier, and terminate unpromising projects at lower cost, which reduces wasted input. Second, digitalization improves resource allocation inside the firm. Data-driven management makes R&D progress, costs and outcomes more visible, which narrows the gap between planned and actual resource use. Third, according to transaction cost theory, the boundary and efficiency of the firm depend on the costs of searching, bargaining and monitoring [14]. Digital tools reduce these costs both within the firm and in collaboration with suppliers, customers and research institutions, which

facilitates collaborative innovation. It is also possible that transformation brings short-term adjustment costs and crowds out R&D resources. However, for listed companies, which generally have sufficient financial and managerial capacity, the efficiency-enhancing mechanisms are expected to dominate in the long run. Based on the above analysis, this paper proposes the first research hypothesis. **H1: Controlling for other conditions, digital transformation significantly improves corporate innovation efficiency.**

B. Heterogeneity Analysis and Research Hypotheses

Under China's institutional context, firms differ systematically in ownership, industry attributes and resource endowments, so the efficiency gains from digital transformation may vary. We consider ownership, industry type and firm size. Ownership. State-owned enterprises (SOEs) typically pursue multiple objectives, including employment, stability and policy tasks, and have longer decision chains. Digital tools help most when management can use the information they generate to adjust resource allocation quickly; hierarchical decision-making and weaker performance incentives in SOEs may blunt this response. In addition, SOEs enjoy easier access to bank credit and implicit government support, so the marginal gain from improved information transparency is smaller. Non-SOEs are more market-driven and have stronger incentives to convert digital capabilities into innovation output. We therefore expect a stronger effect in non-SOEs. R&D in high-technology industries is more data-intensive and relies more heavily on knowledge integration, and these firms generally have higher absorptive capacity for digital technologies. Digital tools can therefore be embedded more deeply into the R&D process. Small and medium-sized firms are short of resources and face more severe financing constraints, so digital technologies can partly substitute for scarce physical and human resources and expand access to information and external knowledge. Large firms, by contrast, already hold abundant resources and may suffer from organizational inertia, which dampens the marginal benefit. **H2a: Compared with state-owned enterprises, the positive effect of digital transformation on innovation efficiency is more significant in non-stateowned enterprises. H2b: Compared with firms in non-high-technology industries, the positive effect of digital transformation on innovation efficiency is more significant in high-technology firms. H2c: Compared with large firms, the positive effect of digital transformation on innovation efficiency is more significant in small and medium-sized firms.**

C. Mediating Mechanism of Financing Constraints

The overall effect analysis suggests that part of the benefit comes from an improved financing environment. According to financing constraint theory, when information is asymmetric, external funds are more expensive than internal funds, and innovative firms, whose projects are risky and intangible, are particularly affected. As a result, financing constraints compel firms to cut or postpone R&D, interrupt projects and rely on short-term, low-risk activities, all of which lower efficiency. Digital transformation can alleviate financing constraints through at least two channels. First, digital information systems improve the quality, timeliness and verifiability of information that firms disclose, reducing information asymmetry between the firm and external investors and lenders and thus lowering the external finance premium. Second, digital technologies strengthen internal control and risk management, which reduces agency costs and increases creditors' confidence. Relaxed constraints in turn allow firms to maintain stable R&D investment and to allocate funds to higher-return projects, which improves the efficiency of innovation. The transmission chain of digital transformation → alleviating financing constraints → improving innovation efficiency should therefore be present. **H3: Digital transformation improves innovation efficiency by alleviating financing constraints; that is, financing constraints play a mediating role in the relationship between the two.**

IV. RESEARCH DESIGN

A. Sample Selection

The initial sample consists of all A-share companies listed on the Shanghai and Shenzhen stock exchanges over 2012–2023. The period begins in 2012 because disclosure of R&D personnel and patent information became comparatively complete from that year, and it ends in 2023, the latest year with complete annual-report text. Before and after listing, enterprises' financial data and financing constraint conditions will change significantly. The overall effect analysis suggests that part of the benefit comes from an improved financing environment. According to financing constraint theory, when information is asymmetric, external funds are more expensive than internal funds, and innovative firms, whose projects are risky and intangible, are particularly affected. Data for enterprises listed for less than one year are often incomplete and exhibit large abnormal fluctuations, so they are excluded to ensure the stability of sample enterprise data. Following common practice, the sample is screened in four steps, which are summarized in Table 1.

Table 1. Sample Selection

Screening Procedure	Screening Criteria	Initial Sample Size	Sample Reduction	Effective Sample Size	Total Obs.
1	A-share listed firms with annual reports, 2012–2023	5,020	0	5,020	41,830
2	Excluding financial-industry firms	5,020	118	4,902	40,640
3	Excluding ST, *ST and delisted firms	4,902	412	4,490	36,970
4	Excluding firms listed for less than one year	4,490	230	4,260	36,120
5	Excluding firms with seriously missing key variables	4,260	774	3,486	28,964

Note: Data were obtained from the CSMAR (China Stock Market & Accounting Research) database and the CNRDS database. Sample sizes refer to the number of firms unless stated otherwise

First, financial-industry firms are excluded because their capital structure and accounting standards differ fundamentally from those of non-financial firms. Second, ST, *ST and delisted firms are excluded because they usually face serious financial difficulty and abnormal operations, which makes their data unreliable. Third, firms listed for less than one year are excluded because financial data and financing conditions change sharply around the listing date. Fourth, firms with seriously missing R&D, patent or key financial data are excluded to avoid bias from large-scale imputation. After the step-by-step screening, we obtain 3,486 listed companies and 28,964 firm-year observations, which form an unbalanced panel. All continuous variables are winsorized at the 1st and 99th percentiles to limit the influence of outliers. Fourth, excluding enterprises with seriously missing data for core variables. For enterprises with serious missing data for key financial indicators or patent data, this paper excludes them to avoid estimation bias caused by large-scale imputation of missing values and to ensure the completeness of sample data. After step-by-step screening according to the above standards, this paper finally obtains 186 renewable energy listed companies, totaling 3,604 firm-year observations, forming a balanced panel data.

B. Data Sources

The data come from several authoritative databases and are all publicly available, so the results are reproducible. They fall into four categories. The first is digital transformation data, which are the core of the explanatory variable. The full texts of annual reports are obtained from the CNINFO website, and keyword frequencies are extracted with text-mining programs. The second is innovation data, used to compute the dependent variable. R&D expenditure and R&D personnel are taken from the CSMAR database and supplemented from annual-report notes, while patent applications are obtained from the CNRDS patent database and cross-checked with the official database of the China National Intellectual Property Administration. The third category is corporate financial data, used for control variables, and is mainly taken from the CSMAR financial database and the Wind terminal. These are the most widely used databases for listed-company research, and their quality has been tested by long academic use. Indicators such as firm size, leverage, profitability, growth, cash holdings, ownership concentration, firm age and ownership nature are obtained directly from them, and individual missing values are supplemented with annual reports. The fourth category is financing constraint data, used to construct the mediating variable. The SA index requires only firm size and age, which come from the same databases, so no additional data source is needed.

C. Variable Definitions

The dependent variable is corporate innovation efficiency, denoted IE. Following the mainstream practice of frontierefficiency studies, we estimate IE with an output-oriented DEA-BCC model, in which R&D expenditure and the number of R&D personnel are the inputs and the number of patent applications (invention, utility model and design patents) in the current year is the output. The model is estimated separately for each industry-year group so that firms are compared with technological peers, and the resulting score lies in the interval (0, 1]. A higher score indicates that the firm obtains more patent output from a given amount of input. Patent applications rather than grants are used because grants involve a long examination lag and cannot accurately reflect the output of the current year. In robustness tests, we re-estimate efficiency with the SFA method [8] and with a Tobit specification to account for the censored nature of DEA scores. The core explanatory variable is the degree of digital transformation, denoted

DT. Following Wu et al. [5], we count the frequency of keywords related to five technology categories (artificial intelligence, big data, cloud computing, blockchain and digital technology application) in the annual report of each firm, add one to the total and take the natural logarithm. A larger value indicates a higher degree of digital transformation. Text analysis avoids the subjectivity of questionnaires and the accounting noise of financial proxies, and it makes firms comparable across industries and years. Following the existing literature, the control variables include firm size (Size, natural logarithm of total assets), leverage (Lev, total liabilities divided by total assets), profitability (ROA, net profit divided by total assets), growth (Growth, growth rate of operating revenue), cash holdings (Cash, cash and equivalents divided by total assets), ownership concentration (Top1, shareholding of the largest shareholder), firm age (Age, natural logarithm of one plus the years since establishment) and ownership nature (SOE, equal to 1 for state-owned firms and 0 otherwise). Firm and year fixed effects are included in all regressions. The baseline model is specified as follows:

$$IE_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i denotes the firm and t the year, μ and λ are firm and year fixed effects, and ε is the error term. Standard errors are clustered at the firm level. If the coefficient on DT (α1) is significantly positive, digital transformation improves innovation efficiency, which supports H1. The mediating variable is the degree of financing constraints, denoted FC. Existing research measures financing constraints with the SA index, the KZ index and the WW index. The SA index [15] relies only on two highly exogenous variables, firm size and firm age, and is therefore less affected by endogenous financial variables. Following existing research, we use the SA index, calculated as:

$$SA = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age \quad (2)$$

where Size is the natural logarithm of total assets (in million yuan) and Age is the number of years since listing. The SA index is usually negative, and a larger absolute value indicates more severe financing constraints. We therefore take the absolute value of the SA index as FC. In the mechanism tests, we also use the KZ index, the WW index [17] and the cost of debt as alternative measures. Following the three-step mediation procedure, the mediation models are specified as follows:

$$FCit = \beta 0 + \beta 1 DTit + \beta 2 Controlsit + \mu i + \lambda t + \varepsilon it \quad (3)$$

$$IE_{it} = \gamma_0 + \gamma_1 DT_{it} + \gamma_2 FC_{it} + \gamma_3 Controlsit + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

D. Baseline Regression Analysis

Table 2 reports the descriptive statistics. The mean innovation efficiency score is 0.412 with a standard deviation of 0.236, which suggests that many firms operate far from the efficiency frontier and that there is considerable heterogeneity across firms. DT ranges from 0 to 5.198 with a standard deviation of 1.263, which indicates substantial variation in the degree of digital transformation. Roughly 31% of the observations belong to state-owned enterprises.

Table 2. Descriptive Statistics

Variable Name	Obs	Mean	Std. Dev.	Min	Max
IE	28,964	0.412	0.236	0.021	1.000
DT	28,964	1.482	1.263	0.000	5.198
Size	28,964	22.136	1.298	19.742	26.315
Lev	28,964	0.418	0.205	0.052	0.912
ROA	28,964	0.041	0.064	−0.287	0.231
Growth	28,964	0.158	0.356	−0.552	2.140
Cash	28,964	0.151	0.118	0.008	0.612
Top1	28,964	0.336	0.148	0.083	0.739
Age	28,964	2.861	0.351	1.946	3.526
SOE	28,964	0.312	0.463	0.000	1.000
FC	28,964	3.640	0.261	3.052	4.451

Table 3 reports the baseline regression results. Column (1) controls only for firm and year fixed effects, and the coefficient on DT is 0.0214 and significant at the 1% level. After adding control variables in Column (2), the coefficient is 0.0172 and remains significant at the 1% level, which indicates that digital transformation significantly improves corporate innovation efficiency. In Column (3), we further control for industry-by-year fixed effects to absorb industry-specific shocks and technological trends, and the coefficient is 0.0151 and still significant at the 1% level.

Table 3. Baseline Regression Results

Variable Name	(1)	(2)	(3)
Dependent Variable	**IE**	**IE**	**IE**
DT	0.0214***	0.0172***	0.0151***
	(0.0041)	(0.0039)	(0.0042)
Control Variables	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry×Year FE	No	No	Yes
Observations	28,964	28,964	28,964
R-squared	0.298	0.342	0.389

Note: Standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The effect is also economically meaningful. Based on Column (2), a one-standard-deviation increase in DT (1.263) raises innovation efficiency by about 0.0217, which equals roughly 5.3% of the sample mean of IE. The control variables generally exhibit the expected signs: profitability and cash holdings are positively associated with innovation efficiency, while leverage is negatively associated with it, which is consistent with the idea that internal resources support innovation and that heavy debt burdens constrain it. In summary, the baseline results provide robust evidence supporting Hypothesis 1: digital transformation significantly improves corporate innovation efficiency.This size-based heterogeneity pattern is consistent with the ownership and regional heterogeneity results. Large enterprises typically possess stronger creditworthiness, more substantial collateral, and established relationships with financial institutions, enabling them to better leverage green credit support for innovation. Collectively the heterogeneity analysis results reveal that the positive effect of green credit policy on renewable energy enterprises' green innovation is not uniform but is instead contingent upon firm-specific characteristics and external institutional environments. The policy effect is most pronounced for enterprises located in the eastern region, and large enterprises.

E. Robustness Analysis

Table 4 reports the results of five alternative specifications designed to address concerns about measurement, endogeneity, sample period and omitted variables. Column (1) replaces the DEA score with the efficiency score estimated by SFA. The coefficient on DT remains positive and significant at the 1% level (0.0153), which confirms that the result is not driven by the choice of the efficiency measure. Column (2) uses the one-period lagged DT to mitigate reverse causality, since firms with higher innovation efficiency may also be more inclined to adopt digital technologies. The coefficient is 0.0141 and significant at the 1% level. Column (3) addresses endogeneity with an instrumental-variable strategy. We use the average DT of other firms in the same industry and year (leave-one-out) as the instrument. Peer digital adoption affects a firm's own transformation through demonstration and technology diffusion, but it is unlikely to affect the firm's own innovation efficiency through other channels once industry-year conditions are controlled for. The Kleibergen–Paap F-statistic is 62.35, well above the conventional threshold of 10, which indicates that the instrument is not weak, and the second-stage coefficient is 0.0289 and significant at the 1% level. Column (4) excludes the COVID-19 period (2020–2022) to ensure that the results are not driven by this extraordinary shock, and the coefficient is 0.0129, significant at the 5% level. Column (5) includes region-by-year fixed effects to absorb time-varying regional shocks and policies, and the coefficient remains positive and significant at the 1% level (0.0138).

Table 4. Heterogeneity Results

Variable Name / Dependent Variable	(1)	(2)	(3)	(4)	(5)
	Alt. Dep. Var.	Lagged DT	IV (2SLS)	Excl. COVID-19	Region FE
	IE (SFA)	IE	IE	IE	IE
DT	0.0153***	0.0141***	0.0289***	0.0129**	0.0138***
	(0.0036)	(0.0041)	(0.0097)	(0.0053)	(0.0040)
Control Variables	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	No	No	No	No	Yes
First-stage F-statistic	—	—	62.35	—	—
Observations	28,964	25,478	28,964	21,718	28,964
R-squared	0.358	0.349	—	0.351	0.402

Note: Standard errors clustered at the firm level are reported in parentheses. Column (2) uses the one-period lagged DT. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

This section examines how the effect of digital transformation varies with firm characteristics. The analysis covers three dimensions: ownership structure, industry type and firm size. The results are reported in Table 5. In terms of ownership, the coefficient on DT is 0.0231 and significant at the 1% level for non-SOEs, whereas the coefficient for SOEs is 0.0074 and statistically insignificant, and the difference between the two groups is significant (p = 0.032). This supports H2a and is consistent with the view that market-oriented incentives and flatter decision-making help non-SOEs turn digital capabilities into innovation output, while SOEs face multiple objectives and have easier access to credit, so the marginal gain is smaller.

Table 5. Heterogeneity Results

Variable Name	Ownership Structure		Industry Type		Firm Size	
	(1) SOE	(2) Non	(3) High-tech	(4) Non-H.T.	(5) Large	(6) S/Medium
DT	0.0074	0.0231***	0.0259***	0.0098*	0.0113*	0.0224***
	(0.0061)	(0.0047)	(0.0052)	(0.0054)	(0.0060)	(0.0049)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Between-group difference (p-value)		0.032		0.018		0.087
Observations	9,037	19,927	14,330	14,634	14,482	14,482
R-squared	0.371	0.329	0.352	0.327	0.344	0.338

Note: Firms are classified as large or small/medium according to the sample median of total assets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Regarding industry type, the coefficient is 0.0259 and significant at the 1% level for high-technology firms, compared with 0.0098 (significant only at the 10% level) for non-high-technology firms, and the between-group difference is significant (p = 0.018), which supports H2b. High-technology firms conduct more data-intensive R&D and have stronger absorptive capacity, so digital tools can be embedded more deeply into the innovation process. Regarding firm size, the coefficient is 0.0224 and significant at

the 1% level for small and medium-sized firms, versus 0.0113 (significant at the 10% level) for large firms, with a between-group difference significant at the 10% level (p=0.087). This supports H2c: smaller firms, which are scarcer in resources and more financially constrained, benefit more from the information and knowledge access provided by digital technologies. Collectively, the heterogeneity results show that the positive effect of digital transformation on innovation efficiency is not uniform. It is most pronounced for non-SOEs, high-technology firms and small and medium-sized firms, findings underscore the importance of differentiated policy design that takes ownership, industry and firm size into account.

F. Mechanism Test

This section tests whether financing constraints serve as a mediating channel through which digital transformation affects innovation efficiency. Following the three-step mediation procedure of Baron and Kenny [18], complemented by the Sobel test and by the cautions of Jiang [19] on mediation analysis in causal inference, we evaluate the role of financing constraints. Step one examines the total effect: the coefficient on DT in Column (1) of Table 6 is 0.0172 and significant at the 1% level. Step two investigates the effect of DT on financing constraints measured by the absolute value of the SA index: the coefficient in Column (2) is −0.0211 and significant at the 1% level, which indicates that digital transformation significantly alleviates financing constraints. Step three includes DT and FC simultaneously: in Column (3), the coefficient on DT decreases to 0.0141 but remains significant at the 1% level, and the coefficient on FC is −0.1468 and significant at the 1% level. The reduction in the coefficient on DT from 0.0172 to 0.0141 suggests that financing constraints partially mediate the effect, which supports H3.

Table 6. Mechanism Test Results

Variable Name	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**IE**	**FC**	**IE**	**KZ Index**	**WW Index**	**Debt Cost**
DT	0.0172***	−0.0211***	0.0141***	−0.0387***	−0.0074***	−0.0021***
	(0.0039)	(0.0049)	(0.0038)	(0.0098)	(0.0021)	(0.0006)
FC	—	—	−0.1468*** (0.0310)	—	—	—
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,964	28,964	28,964	28,964	28,964	28,964

Note: Standard errors clustered at the firm level are reported in parentheses. Debt Cost is the ratio of interest expenses to interest-bearing debt. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

To ensure the robustness of the mediation results, Columns (4)–(6) replace the SA index with the KZ index, the WW index [17] and the cost of debt. Across all three alternatives, the coefficient on DT is negative and significant at the 1% level, which corroborates the finding that digital transformation alleviates financing constraints regardless of how they are measured. The indirect effect, computed as the product of the coefficient in Column (2) and the coefficient on FC in Column (3), is about 0.0031, and the Sobel statistic is 3.19 ($p < 0.01$). A bootstrap with 1,000 replications gives a 95% confidence interval of [0.0013, 0.0051] that excludes zero. The financing-constraint channel therefore accounts for approximately 18.0% of the total effect, while the remaining 82% operates through other mechanisms, such as better resource allocation within the R&D process and lower costs of knowledge search and collaboration. These findings carry several implications. For firms, digital investment should be evaluated over a sufficiently long horizon and combined with organizational adjustment.

CONCLUSIONS

This study provides empirical evidence on the relationship between digital transformation and corporate innovation efficiency, addressing a gap in the literature, which has focused mainly on innovation input or output rather than on the efficiency with which the two are linked. Using a panel of Chinese A-share listed companies over 2012–2023, we measure digital transformation by text

analysis of annual reports and innovation efficiency by a DEA score, and we estimate the relationship with a two-way fixed effects model. The results show that digital transformation significantly improves corporate innovation efficiency, and that a one-standard-deviation increase in the degree of transformation raises efficiency by about 5.3% of its sample mean. The result is robust to alternative efficiency measures, lagged regressors, an instrumental-variable strategy, exclusion of the COVID-19 period and region-by-year fixed effects. Beyond the average effect, the heterogeneity analysis shows that the benefit is not uniform. It is stronger for non-state-owned enterprises, for firms in high-technology industries and for small and medium-sized firms, which suggests that market-oriented incentives, absorptive capacity and resource scarcity shape how effectively digital capabilities are converted into innovation output. The mechanism analysis shows that alleviating financing constraints is a significant but partial channel, accounting for roughly 18% of the total effect, and the event-study evidence indicates that the effect accumulates gradually and then stabilizes. These findings carry several implications. For firms, digital investment should be evaluated over a sufficiently long horizon and combined with organizational adjustment, since the efficiency gains materialize with a lag. For policymakers, support for digital transformation should be differentiated: deepening governance and incentive reforms in state-owned enterprises, providing targeted technical and financial support to small and medium-sized firms, and encouraging financial institutions to use digital information in credit assessment so that better information translates into easier access to finance. Finally, the study has limitations. The keyword-based index may not fully capture the true depth of transformation, patents do not cover all forms of innovation output, and although several strategies are used to address, omitted variables cannot be completely ruled out. Future research could use firm-level survey data or measures of actual digital investment, could examine additional channels such as human capital and organizational structure.

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