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Green finance policy and corporate digital transformation: Evidence from China using a difference-in-differences approach

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ABSTRACT

This paper examines whether green finance policy promotes corporate digital transformation (CDT) at the firm level. Using China's Green Finance Reform and Innovation Pilot Zones (GFRIPZ), launched in 2017, as a quasi-natural experiment, we apply a difference-in-differences approach to Chinese A-share-listed firms from 2011 to 2022. The final sample contains 26,940 firm-year observations from 3,679 firms. The baseline model controls for firm-level characteristics and includes firm and industry-year fixed effects. The results show that GFRIPZ increases CDT by 0.013 units ($p < 0.01$), equivalent to about 20.6% of the sample mean. This finding remains robust after parallel trends tests, placebo tests, alternative measures of CDT, exclusion of municipalities, exclusion of other policy interference, PSM-DID estimation, and heterogeneous treatment effect estimators. Mechanism tests indicate that GFRIPZ promotes CDT mainly by easing financing constraints and increasing innovation resource input. The effect is more pronounced among non-state-owned enterprises, large firms, and firms with higher market positions. The findings suggest that green finance policy can serve not only as an environmental governance tool but also as an institutional driver of firms' digital upgrading. Policy makers should better integrate digital transformation objectives into green finance frameworks and provide differentiated support for resource-constrained firms.

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Contribution/Originality: This paper examines whether green finance policy promotes corporate digital transformation using China's GFRIPZ as a quasi-natural experiment. It identifies financing-constraint relief and innovation resource input as key mechanisms and reveals heterogeneous effects across ownership, firm size, and market position, providing firm-level evidence for improving green finance policy design.

1. INTRODUCTION

Digital technologies are reshaping how firms organize production, operations, and management. Consequently, digital transformation has become an increasingly important factor in corporate development (Wang & Shao, 2024; Wang, Xie, Zhang, & You, 2025; Yu, 2025). By applying digital technologies to production and daily operations, firms can lower operating costs, improve resource-use efficiency, and enhance profitability (Jiang, Zhang, & Wei, 2025; Rossini, Ahmadi, & Staudacher, 2024). However, firms do not always have sufficient incentives or capacity to advance digital transformation. On the one hand, digital transformation usually involves a large initial investment and a long adjustment process, while its economic returns may not appear quickly (Rongwei Zhang & Wang, 2025). On the other hand, firms need to rebuild or upgrade existing technological systems when adopting digital technologies. Because digital knowledge can generate spillovers, some firms may choose to wait and imitate rather than bear the cost of early investment. This free-riding problem weakens firms' willingness to take the lead in digital transformation (Liu, Sheng, Hu, & Tian, 2025). Therefore, market forces alone may not be sufficient to overcome the barriers to digital transformation. Policy support and incentive schemes are therefore needed to help firms move more actively toward digital transformation.

Among various policy instruments, green finance policies have attracted growing scholarly attention because they combine financial resource allocation with environmental regulation. Previous research has mostly focused on whether green finance changes firms' productivity, innovation activities, and ESG performance (Ge et al., 2026; Xu, Zhu, & Wang, 2023; Ye & Tian, 2025). However, digital transformation means that firms use digital technologies to reshape manufacturing activities, management practices, and decision-making processes. It is not a single technological outcome, but a broad organizational change that includes technology adoption, process reengineering, and internal adjustment. This makes it fundamentally different from the outcomes examined above and calls for separate investigation. Resource dependence theory suggests that organizational decisions are constrained by the conditions under which external resources are obtained. When access to key resources changes, organizations tend to adjust their behavior to maintain the availability of those resources. Although general financial support can ease financing constraints, it does not guide firms toward digital transformation. Green financial support, by contrast, links access to financial resources with environmental governance performance through explicit green compliance requirements. As a result, firms have stronger incentives to use digital tools for cleaner production.

China launched the Green Finance Reform and Innovation Pilot Zones in 2017, offering a useful setting to test how financial support for market-oriented environmental governance affects firms. The policy provides stable external funding and eases the pressure from the high upfront costs and delayed returns of digital transformation. As an instrument of green development incentives, the policy encourages firms to strengthen environmental monitoring and production upgrading, both of which depend increasingly on digital technologies. Under this policy framework, digital transformation is no longer only a way to improve operational efficiency; it also becomes an important way for firms to respond to green development requirements and strengthen their environmental governance capacity.

Although green finance policies have received increasing research attention, whether and how these policies promote corporate digital transformation (CDT) remains insufficiently examined. It also remains unclear whether their effects vary across firms with different characteristics. This paper uses a DID model to examine how GFRIPZ affects CDT. This study's main contributions can be summarised in three areas. First, this paper links green finance policy with CDT and extends firm-level research on the consequences of GFRIPZ. By treating green finance reform as an institutional driver of CDT, this study shows that GFRIPZ can facilitate firms' digital upgrading and offers new empirical evidence on how government institutional arrangements shape CDT. Second, this paper identifies the channels through which GFRIPZ affects CDT. Specifically, it tests whether financing-constraint relief and innovation-resource input explain how green finance support is converted into digital upgrading. Third, it examines heterogeneity by ownership, firm size, and market position, showing which firms benefit more from GFRIPZ.

2. LITERATURE REVIEW

Prior research has examined the internal and external drivers of CDT, with firm size, resources, human capital, managerial cognition, and governance quality often identified as key internal factors (Chen & Zhang, 2025; Ma, Zhou, & Dong, 2026; Zou, Fu, Zeng, & Huang, 2024). CDT requires sustained investment and organizational adjustment, so firms with stronger resource bases and governance capabilities are better positioned for transformation (S. Liu, 2026). External factors such as competition, digital infrastructure, industrial linkages, and institutions also matter (Chen, Huang, & Gao, 2024; Fan & Xu, 2024; Ma et al., 2026; Zou, Hao, & Zhang, 2026). Competitive pressure can force firms to improve operational efficiency, while well-developed digital infrastructure helps reduce the cost of acquiring digital technologies. However, the above studies still pay insufficient attention to policy-level institutional factors, especially whether green finance policies can promote CDT.

Recent studies show that green finance can guide capital toward cleaner projects, ease financing bottlenecks in technology upgrading, and improve green innovation and environmental performance (Li, Bu, & Liu, 2025; Yu, Wu, Zhang, Chen, & Zhao, 2021; Ruomeng Zhang & Ling, 2026). For heavily polluting firms, these policies may raise financing requirements and environmental risk costs, pushing them to adjust investment and upgrade technology (Liu, Wang, & Cai, 2019; Lu, Pan, Fan, & Guan, 2025). However, the evidence is mixed. Some studies find that green finance improves long-term performance (Jiang & Ma, 2025), while others show that it may raise short-term compliance costs and weaken operating performance (Yao, Pan, Sensoy, Uddin, & Cheng, 2021). Poor implementation, resource misallocation, and symbolic responses may weaken policy effects (Wu, Kang, & Ryu, 2025; Yi, Xia, Cheng, & Dai, 2026), so whether green finance promotes CDT remains unclear.

Government fiscal and financial support can also promote technology adoption by easing firms' funding pressure and reducing the cost of digital investment (He, Ding, & Zhou, 2025; Zhao, Zhao, Sun, & Xing, 2024). However, rent seeking and subsidy dependence may weaken policy effects, making the fit between policy resources and firm capabilities important (Yang, Deng, & Du, 2024). Thus, government support is more effective when policy resources fit firms' capabilities.

To sum up, the research that already exists provides a solid base for understanding CDT and the effects of green finance policies. However, several gaps remain in the existing literature. First, studies on the drivers of digital transformation pay insufficient attention to green finance policy as an external institutional shock. Second, prior research mainly examines how green finance policies affect green innovation and environmental performance, while CDT has received limited attention. Third, the literature on government support and technology adoption rarely examines this issue within an analytical framework in which green finance policies drive digital transformation. Accordingly, this paper links green finance policy with CDT and investigates whether GFRIPZ affects firms' digital upgrading, as well as the channels through which this effect occurs.

3. THEORETICAL ANALYSIS

3.1. GFRIPZ and CDT

Digital transformation requires a significant initial investment and takes a relatively long time to pay off. Financing constraints therefore, become an important factor limiting firms' digital transformation (Chen & Zhang, 2025; Jiang et al., 2025; Rossini et al., 2024). External institutional support can therefore ease firms' resource constraints and reduce the risks of digital transformation.

This study argues that GFRIPZ can support CDT in two ways. It improves firms' access to relevant resources while also guiding their behavior through green development requirements. In terms of resource provision, GFRIPZ supports digital transformation through credit support, tax reductions, and other incentives. In terms of behavioral guidance, GFRIPZ imposes policy constraints on pilot-zone firms through market-based environmental regulation. Firms that violate environmental rules may lose policy support and face regulatory penalties. Under this incentive and constraint mechanism, firms have stronger incentives to improve production efficiency and reduce pollution. Digital technologies support this process by improving production processes and energy efficiency. Therefore, under GFRIPZ, firms have both better resource conditions and stronger incentives to pursue digital transformation. Based on this reasoning, we propose that:

H_1: GFRIPZ can significantly promote CDT.

3.2. Mechanism Analysis

3.2.1. Financing Constraint Relief Channel

CDT requires a large investment and delayed returns, so financing constraints become a key barrier (Rongwei Zhang & Wang, 2025). In addition, information asymmetry further exacerbates this constraint, as digital projects are characterized by high uncertainty and adjustment costs (Li, Liu, & Zhao, 2026), and prior evidence shows that improved information transparency can significantly alleviate firms' information frictions and promote better investment decisions. GFRIPZ may ease financing constraints by encouraging financial institutions to expand green credit and provide risk compensation. Together, these measures improve credit access, reduce financing costs, and increase lenders' willingness to provide credit by lowering information asymmetry.

Furthermore, digital transformation is intrinsically consistent with the green development goals advocated by GFRIPZ (Tang, Cao, & Li, 2026). Intelligent manufacturing can optimize corporate energy-use efficiency, environmental data monitoring systems can improve firms' precise control over pollutant emissions, and digital supply chain management can help reduce resource waste and carbon emissions in production and circulation. Digital transformation itself constitutes an important means through which firms achieve green compliance and efficiency improvement. Therefore, the policy orientation of GFRIPZ can guide firms to allocate newly available financial resources to digital investment, thereby reducing the cost of green transformation through digital technologies. Accordingly, we conjecture.

H_{2a}: The GFRIPZ promotes CDT by alleviating firms' financing constraints.

3.2.2. Innovation Resource Input Channel

Digital transformation requires not only continuous R&D investment but also the participation of R&D personnel with specialized knowledge and technical capabilities. R&D expenditure directly determines the intensity of firms' research and development in digital technologies, while the stock of R&D personnel directly affects firms' ability to assimilate and apply digital technologies (Chen et al., 2024). Together, they constitute the core innovation resource base for CDT.

The GFRIPZ can promote the buildup of firms' innovation resources along two dimensions: financial support and human capital deepening. In terms of financial resources, the policy combines incentives with constraints and encourages firms to devote more resources to R&D activities. In terms of human resources, the pilot policy creates new opportunities for industrial development and technological upgrading within the pilot zones. This helps attract skilled R&D personnel and motivates firms to expand their R&D teams so that they can better respond to the requirements of green development and digital transformation.

The Porter hypothesis suggests that well-designed environmental regulation can stimulate innovation and partly offset compliance costs, although this view remains debated (Porter & van der Linde, 1995). By contrast, regulation may crowd out R&D, but GFRIPZ works mainly through financial incentives. By combining environmental constraints with green credit and fiscal support, GFRIPZ may reduce regulatory crowding-out and encourage R&D funding and personnel input, thereby improving the internal conditions for digital transformation. Accordingly, we conjecture:

H_{2b}: The GFRIPZ advances CDT by promoting corporate innovation resource input.

3.3. Heterogeneous Effects

GFRIPZ may affect firms differently because ownership, size, and market position shape their policy responses (Berikhanovna, Bauirzhanovna, Kudaibergenovna, Gulbagda, & Serikovna, 2023; Wang, Bian, Zhu, Lu, & Wang, 2025).

Non-state-owned enterprises are more responsive to green finance policy signals because they face tighter financing constraints and stronger market pressure. State-owned enterprises have better resource access, but weaker incentives may limit the policy effect. Large firms often have stronger technology and talent advantages. Large firms use green finance resources more effectively, whereas weaker absorptive capacity may constrain small- and medium-sized enterprises. From the perspective of market position, firms with stronger market power can access green finance resources earlier and convert them more efficiently into digital investment. The above analysis leads to the following hypotheses:

H_{3a}: GFRIPZ promotes CDT more strongly in enterprises that are not state-owned than in state-owned enterprises.

H_{3b}: GFRIPZ promotes CDT more strongly in large enterprises than in small and medium enterprises.

H_{3c}: GFRIPZ promotes CDT more strongly in firms with higher market positions than in firms with lower market positions.

4. EMPIRICAL DESIGN

4.1. DID Model Specification

To estimate the effect of the GFRIPZ on the CDT (Digital), the following regression model is specified.

$$Digital_{it} = \beta_0 + \beta_1 DID_{it} + \gamma Control + \mu_i + \theta_{j\times t} + \varepsilon_{i,t} \quad (1)$$

In the notation that follows, firm and year are indexed by i and t. $Digital_{it}$ is the outcome variable and records the extent of CDT of firm i in year t. The variable of central interest, DID_{it}, is defined by the product of $Treat_i$, an indicator equal to 1 for firms located in GFRIPZ cities, and $Post_t$, an indicator equal to 1 for years after the policy launch; DID_{it} therefore switches to 1 for observations that lie within a pilot zone city after the reform and takes the value 0 for all other firm-year observations. The coefficient β_1 identifies the average treatment effect of the GFRIPZ on CDT. The vector Control contains a set of firm-level control variables. Firm fixed effects remove all time-invariant firm heterogeneity. Industry-by-year effects go further: they net out any shock common to all firms in the same sector in a given year, whether that shock is a regulatory change, a demand swing, or a technology wave. This layered structure leaves only within-firm, within-industry-year variation to identify the policy coefficient. ε_{it} is the random disturbance term. Standard errors are clustered at the firm level across 3,679 firm clusters.

4.2. Data and Variables

Dependent variable. CDT. This paper uses the MD&A sections of listed firms' annual reports to measure CDT. After constructing a dictionary of digital transformation terms, this paper identifies digital-related expressions and calculates their word frequency at the firm-year level. The final indicator is obtained by dividing the frequency of digital terms by the total word count of the MD&A section and then multiplying the ratio by 100. The complete keyword dictionary for digital transformation is reported in Appendix Table A1. To further characterize the internal structure of CDT, this paper follows the classification system of the China Listed Firms' Digital Transformation Research Database (CLFDTRD) in the CSMAR database and describes the internal structure of CDT from four dimensions, namely strategic guidance, technical driver, organizational empowerment, and digital application. The detailed construction logic and weighting scheme for each dimension are presented in Appendix Table A2. Because text mining methods may be constrained by dictionary coverage and the accuracy of semantic recognition, this paper validates the above indicators from the perspectives of external validity and internal consistency. In terms of external validity, two graduate students independently cross-checked randomly selected annual report samples and examined the frequency of digital keywords and the appropriateness of their contexts one by one. The checking results were broadly consistent with the machine-based word frequency statistics, and no obvious systematic bias was found. In terms of internal consistency, this paper calculates Cronbach's alpha coefficient for the four dimensions above. The Cronbach's alpha is approximately 0.695, indicating acceptable internal consistency. Appendix Table A3 further shows significant positive correlations between the aggregate index and each sub-dimensional indicator, supporting the validity of the overall measure.

Control variables: Following prior studies, this paper controls for firm-level characteristics that may affect CDT (Gao, Huang, Huang, & Rao, 2026; Liang, Wang, & Li, 2025; Tian, Kim, & Park, 2026; Wang et al., 2025; Zou et al., 2024). Appendix Table B1 defines these variables.

Data sources: The study uses a sample of Chinese A-share listed firms covering the period from 2011 to 2022. Data on CDT are obtained from the CLFDTRD in the CSMAR database. Financial data, ownership data, and financial indicators are drawn from CSMAR's China Stock Market Financial Statements Database, China Listed Firms' Equity of Nature Research Database, China Stock Market Financial Database, and Financial Indices, respectively. All data were collected in April 2024. The sample period is chosen for two reasons. First, since GFRIPZ was gradually established in 2017, the period from 2011 to 2016 provides a sufficient pre-policy window for the parallel trends test. Second, the period from 2017 to 2022 captures firms' post-policy responses and forms a relatively balanced window for identifying the causal effect of GFRIPZ on CDT.

Data cleaning procedure: Starting from the CSMAR basic information table, the sample is restricted to A-share firms from 2011 to 2022. Firms ever classified in the financial or real estate sector are excluded, as are observations with abnormal trading status, ST. After matching digital transformation indicators by stock code and year and retaining only observations with complete data on all required variables, singleton observations are dropped. The final sample contains 26,940 firm-year observations from 3,679 firms. Appendix Table C1 reports the step-by-step screening process.

Appendix Table D1 reports the descriptive statistics. Digital has a mean of 0.063, which is low and suggests that most firms in the sample are still at an early stage of CDT. The standard deviation of 0.15 and a maximum of 1.053 point to wide dispersion, with some firms considerably further along than the typical firm.

5. RESULTS AND DISCUSSIONS

5.1. Baseline Model

Table 1 reports the results under different fixed-effects settings. Across all columns, the coefficient of did is positive and significant, indicating that GFRIPZ promotes CDT. Column (5), which controls for firm fixed effects and industry-by-year fixed effects, is used as the baseline specification. The estimated effect equals about 20.6% of the sample mean (0.013/0.063), suggesting a sizable policy impact.

For the control variables, Size is significantly positive, suggesting that larger firms have stronger technological and organizational capacity for CDT. ROA is negative and significant only at the 10% level. This result may reflect the forward-looking investment nature of digital transformation, whereby firms need to bear relatively high costs in the early stage of transformation, which places pressure on current profitability. In addition, firms with higher current profitability may face relatively weaker demand for digital transformation, resulting in a negative correlation between the two. The significantly negative coefficient of InsHold may be related to the greater emphasis placed by institutional investors on short-term operating performance. A higher institutional shareholding ratio may, to some extent, suppress firms' willingness to invest in digital transformation with a longer payback period. The positive and significant coefficient of Growth suggests that firms with stronger growth potential have greater expansion needs and are more willing to improve production and operating processes through digital technologies, thereby promoting digital transformation.

Table 1. Baseline results.

Variables	(1)	(2)	(3)	(4)	(5)
	Digital	Digital	Digital	Digital	Digital
DID	0.013**	0.010**	0.015***	0.014***	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Age		-0.021	-0.007	-0.006	-0.044***
		(0.018)	(0.006)	(0.006)	(0.016)
Size		0.023***	0.007***	0.007***	0.018***
		(0.003)	(0.002)	(0.002)	(0.003)
ROA		-0.059***	-0.050**	-0.042*	-0.022*
		(0.014)	(0.024)	(0.024)	(0.014)
LEV		0.003	-0.021**	-0.026***	-0.006
		(0.009)	(0.009)	(0.009)	(0.008)
Indep		0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Top1		-0.000	-0.001***	-0.001***	0.000
		(0.000)	(0.000)	(0.000)	(0.000)

Variables	(1)	(2)	(3)	(4)	(5)
	Digital	Digital	Digital	Digital	Digital
Board		0.005	-0.017	-0.017	0.002
		(0.008)	(0.011)	(0.011)	(0.007)
InsHold		-0.000***	-0.000	-0.000	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
concen		-0.002	-0.007*	-0.006	0.003
		(0.004)	(0.004)	(0.004)	(0.003)
Turnover		0.008*	0.004	0.004	0.002
		(0.004)	(0.004)	(0.004)	(0.004)
Growth		0.002	0.011***	0.011***	0.002*
		(0.001)	(0.002)	(0.002)	(0.001)
Firm FE	✓	✓	✗	✗	✓
Year FE	✓	✓	✓	✗	✗
Ind FE	✗	✗	✓	✗	✗
Ind-year FE	✗	✗	✗	✓	✓
Controls	✗	✓	✓	✓	✓
Observations	26,940	26,940	26,940	26,940	26,940
Adj.R2	0.788	0.792	0.333	0.365	0.829

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All subsequent tables follow the same convention.

5.2. Dimension of Digital Transformation

CDT covers strategic guidance, organizational empowerment, technical drivers, and digital applications. The baseline results confirm the overall effect of GFRIPZ but not its dimensional distribution. Table 2 shows that did is significantly positive across all four CDT dimensions, suggesting that GFRIPZ promotes strategic guidance, organizational support, technology input, and digital application. This finding indicates that GFRIPZ affects CDT across multiple dimensions rather than through only one aspect.

Table 2. Regression results of different dimensions.

Variables	(1)	(2)	(3)	(4)
	Strategic guidance	Organizational empowerment	Technical driver	Digital application
DID	0.001***	0.001***	0.012***	0.003**
	(0.000)	(0.000)	(0.004)	(0.001)
Firm FE	✓	✓	✓	✓
Ind-year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	26,940	26,940	26,940	26,940
Adj.R2	0.515	0.620	0.824	0.675

Note: **, and *** denote significance at the 5% and 1% levels, respectively.

5.3. Robustness Test

5.3.1. The Parallel Trend Assumption

Whether the DID approach is valid depends on whether the treatment and control groups exhibit comparable pre-policy trends. In order to assess the validity of the parallel-trends assumption, we estimate the following model (You, Cifuentes-Faura, Liu, & Wu, 2024).

$$Dig_{i,t} = \beta_0 + \beta_1 \sum_{t=-5,\, t\neq -1}^{t=5} Treat_i \times Post_t + \beta_2 Control + \delta_{Ind} + \delta_{year} + \varepsilon_{i,t} \quad (2)$$

As shown in Figure 1, there are no obvious pre-trend differences, which validates the parallel-trends assumption.

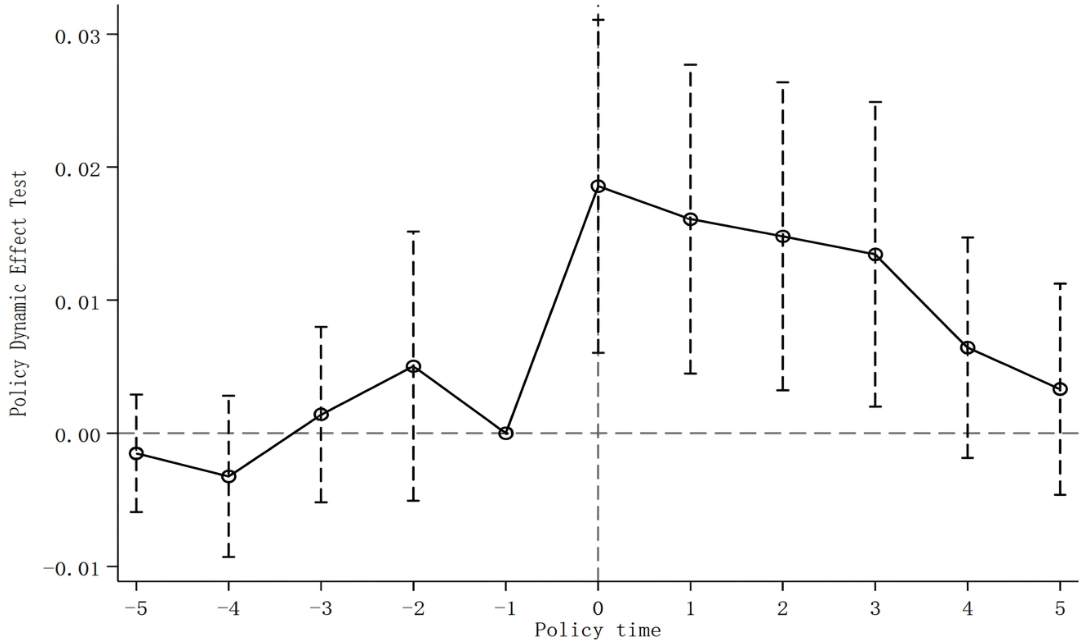

Figure 1. Parallel trend test.

5.3.2. Placebo Test

To further probe the causal link between the GFRIPZ and CDT, a placebo test is carried out. Fig. 2 displays the probability density distribution of coefficients derived from 500 randomly assigned false policy shocks. Most simulated coefficients are distributed around zero, suggesting that the placebo policy shocks do not produce significant effects. By contrast, the baseline coefficient of 0.013 is clearly located to the right of the simulated distribution. This evidence suggests that the positive effect of GFRIPZ on CDT is not likely to be explained by random factors.

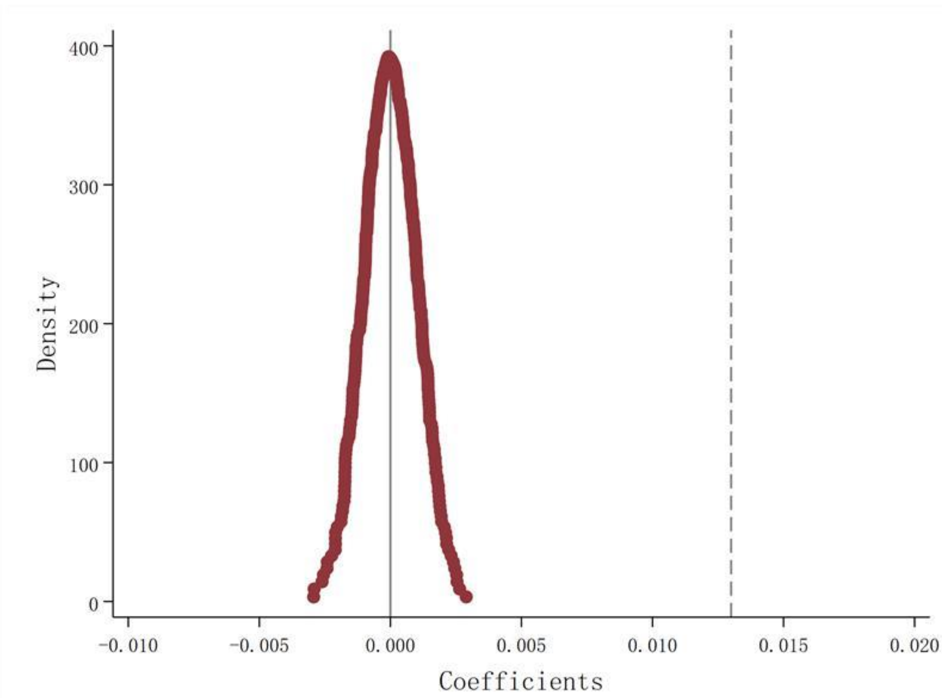

Figure 2. Placebo test.

Note: The red dots indicate the coefficients obtained from 500 randomly assigned placebo policy shocks.

5.3.3. Alternative Measures of Dependent Variable

To examine whether the findings depend on the measurement of CDT, this paper uses two alternative dependent variables. First, DG1 from the CSMAR database is adopted as a comprehensive CDT index constructed from multiple dimensions, with the results reported in Column (1) of Table 3. Second, DG2 is used, which is measured as the natural logarithm of the total frequency of digital-related terms in the MD&A sections of firms' annual reports. The results are shown in Column (2). For both alternative measures, they had a positive and significant coefficient. This result indicates that the baseline finding is robust to alternative measures of CDT.

5.3.4. Exclude Municipalities

The administrative status of municipalities directly under the central government is different from that of ordinary cities. This often means they have greater access to policy resources, financial support, and digital infrastructure. This may make it difficult to identify the policy effect. To tackle this issue, the paper removes the firms registered in these municipalities from the analysis and recalculates the model. The results can be found in Column (3) of Table 3. The main conclusion remains valid, as suggested by the coefficient of did, which is still significantly positive.

5.3.5. Exclude Other Policy Interference

The Broadband China pilot, which rolled out in several regions during our sample window, expanded digital infrastructure and may have independently improved conditions for CDT. If pilot-zone cities benefited from both programs simultaneously, our estimate could conflate the two effects. To address this, we add a dummy for Broadband China coverage to the baseline specification. Column (4) of Table 3 shows that the DID coefficient is essentially unchanged, ruling out the concern that infrastructure expansion under Broadband China is driving our result.

5.3.6. PSM-DID

As a further guard against selection bias, we match treated and control firms on observable characteristics using propensity score matching before re-estimating the DID model on the matched sample. Column (5) of Table 3 reports the output. The positive coefficient on did persists, indicating that pre-existing differences in observables between the two groups are not responsible for the baseline result.

Table 3. Robustness test.

Variables	(1)	(2)	(3)	(4)	(5)
	DG1	**DG2**	**Exclude municipalities**	**Exclusion of other policies**	**PSM-DID**
DID	0.525**	0.082**	0.014***	0.013***	0.014***
	(0.230)	(0.035)	(0.004)	(0.004)	(0.004)
Firm FE	☑	☑	☑	☑	☑
Ind-year FE	☑	☑	☑	☑	☑
Controls	☑	☑	☑	☑	☑
Observations	26,940	26,940	22,043	26,940	17,702
Adj.R2	0.871	0.801	0.820	0.829	0.822

Note: **, and *** denote significance at the 5% and 1% levels, respectively.

5.3.7. Heterogeneous Treatment Effects

One worry about staggered rollouts is that the standard two-way fixed effects estimator can be wrong when the treatment effect is not the same across groups. We therefore re-estimate the model using estimators specifically designed to accommodate such heterogeneity (Borusyak, Jaravel, & Spiess, 2024; Callaway & Sant'Anna, 2021). Table 4 shows that the positive and significant coefficient survives under both approaches, which gives us additional confidence that the baseline result is not an artifact of inappropriate weighting across treatment cohorts.

Table 4. Heterogeneous treatment effect.

Variables	(1)	(2)
	DID-imputation	CSDID
DID	1.639**	0.792**
	(0.677)	(0.376)
Firm FE	☑	☑
Ind-year FE	☑	☑
Controls	☑	☑

Note: ** denotes significance at the 5% level.

5.4. Mechanism Tests

5.4.1. Mechanism Test: Financing Constraint Relief

This paper examines whether GFRIPZ facilitates CDT by alleviating financing constraints and strengthening policy-based financial support (Jin & Gao, 2025). Table 5 reports the mechanism results. Columns (1) and (2) show significantly negative coefficients of did for the KZ and WW indices, indicating that GFRIPZ eases financing constraints. Columns (3) and (4) further show positive effects on tax rebates and credit support. These results indicate that GFRIPZ reduces the financial pressure associated with CDT by improving the external financing environment and increasing policy-based financial support. Therefore, hypothesis H2a is supported.

5.4.2. Mechanism Test: Innovation Resource Input

Columns (5) and (6) of Table 5 use R&P and R&D to measure firms' innovation resource input. Specifically, R&P denotes the proportion of R&D personnel in total employees (%), which captures the intensity of innovation-related human capital input. R&D denotes the ratio of R&D expenditure to operating revenue (%), which captures the intensity of financial input in innovation activities. The coefficients of did are significantly positive in both columns, indicating that GFRIPZ increases both R&D personnel intensity and R&D expenditure intensity. This evidence suggests that GFRIPZ facilitates the accumulation of corporate innovation resources and strengthens firms' capacity to absorb, integrate, and apply digital technologies, thereby creating favorable internal conditions for CDT. Therefore, hypothesis H2b is supported.

Table 5. Mechanism tests.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	KZ	WW	Tax	Credit	R&P	R&D
DID	-0.170***	-0.003***	0.014**	0.076*	1.008***	0.194**
	(0.041)	(0.001)	(0.006)	(0.041)	(0.255)	(0.082)
Firm FE	☑	☑	☑	☑	☑	☑
Ind-year FE	☑	☑	☑	☑	☑	☑
Controls	☑	☑	☑	☑	☑	☑
Observations	26,514	22,883	23,314	15,704	18,441	23,129
Adj.R2	0.764	0.880	0.762	0.911	0.905	0.918

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6. HETEROGENEITY TESTS

6.1. Ownership Heterogeneity

The effect of GFRIPZ on CDT may differ by ownership type. The sample is divided by ownership into state-owned enterprises (SOE = 1) and non-state-owned enterprises (SOE = 0). Table 6 shows that the effect of GFRIPZ on digital transformation is more pronounced for non-state-owned firms. This finding supports H3a.

6.2. Enterprise Scale

This paper uses asset size to classify firms into large firms (SIZE = 1) and small- and medium-sized firms (SIZE = 0), and then examines whether the policy effect differs between the two groups. The estimates reported in Columns (3) and (4) of Table 6 show that GFRIPZ has a stronger promoting effect on digital transformation among large firms. This finding supports H3b.

6.3. Enterprise Market Position

A firm's market position reflects its profitability, which is an important factor shaping its decision to undertake digital transformation. This paper uses a firm's share of industry revenue to capture its market position and classifies firms into high-market-position (MP = 1) and low-market-position (MP = 0) groups. Columns (5) and (6) of Table 6 report the corresponding split-sample estimates. The coefficient of did is positive and statistically significant only in the high-market-position subsample, suggesting that firms with stronger competitive advantages gain more from GFRIPZ.

Table 6. Heterogeneity regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	SOE=0	**SOE=1**	**SIZE=0**	**SIZE=1**	**MP=0**	**MP=1**
DID	0.018***	0.005	-0.000	0.015***	-0.003	0.020***
	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.007)
Firm FE	✓	✓	✓	✓	✓	✓
Ind-year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	17,561	9,268	13,274	13,218	13,300	13,187
Adj.R2	0.827	0.844	0.850	0.853	0.856	0.837

Note: *** denotes significance at the 1% level.

7. CONCLUSION

7.1. Conclusions

First, GFRIPZ significantly advances digital transformation among firms located in the pilot zones. This finding remains robust after multiple checks, including tests of parallel trends, placebo analysis, alternative dependent-variable measures, exclusion of firms registered in municipalities, controls for other policy shocks, PSM-DID estimation, and heterogeneous treatment-effect tests. Dimension-specific tests indicate significant improvements across all four dimensions of CDT, namely strategic guidance, technical driver, organizational empowerment, and digital application, suggesting a systematic promoting effect. Second, the mechanism analysis shows that GFRIPZ promotes CDT through two pathways, namely alleviating corporate financing constraints and promoting corporate innovation-resource input. Specifically, the policy reduces corporate financing constraints by expanding green credit supply and increasing policy-based financial support. Meanwhile, it promotes firms' investment in R&D funding and R&D talent through the dual mechanism of incentives and constraints. Third, the heterogeneity analysis shows that the effect of GFRIPZ is more significant among non-state-owned enterprises, large firms, and firms with higher market positions.

7.2. Policy Implications

First, the spatial expansion of green finance reform pilots should be advanced in an orderly manner, and differentiated promotion schemes should be developed according to local conditions. On the basis of systematically summarizing the experience and implementation outcomes of existing pilots, GFRIPZ should be steadily extended to non-pilot regions. The expansion should avoid simply copying existing pilot models and instead adopt locally tailored strategies to make policy effects more sustainable and replicable.

Second, digital transformation objectives should be included in the green finance policy framework. The current green finance policy system mainly focuses on traditional green indicators such as energy conservation, emission reduction, pollution control, and carbon emission control, while paying relatively insufficient attention to digital transformation. In subsequent policy design, the supporting effect of financial resources on the enhancement of firms' digital capabilities should be incorporated into policy objectives and evaluation systems. Specifically, in the allocation of green credit, green funds, and related fiscal and financial support instruments, priority may be given to projects that combine green transformation and digital upgrading, such as intelligent manufacturing, digital energy management, environmental data monitoring, and green supply chain platform construction, thereby promoting a positive synergy between green finance and CDT.

Third, precise and classified policy design should be implemented based on firm heterogeneity. GFRIPZ has a more significant promoting effect on the digital transformation of non-state-owned enterprises, large firms, and firms with higher market positions, according to the heterogeneity analysis. This implies that targeted policy design is needed. For non-state-owned enterprises, green finance access should be expanded and financing thresholds reduced. For state-owned enterprises, performance assessment and internal incentives for digital transformation should be strengthened. For small and medium-sized enterprises and firms with weaker market positions, inclusive green finance tools, public digital service platforms, and technical assistance should be improved to prevent policy benefits from concentrating among resource-advantaged firms.

7.3. Future Research Directions

This paper still leaves room for further extension. First, this paper focuses on Chinese listed firms. Future research may examine whether the effect of green finance policies on CDT varies across countries with different institutional and financial systems. Second, this paper mainly reveals the mechanisms through which green finance policies affect CDT from the perspectives of financing-constraint alleviation and innovation-resource input. Future research may further examine firms' internal decision-making processes and investigate firm-level mechanisms such as managerial cognition, organizational capabilities, and technological absorptive capacity.

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REFERENCES

Berikhanovna, C. M., Bauirzhanovna, B. A., Kudaibergenovna, N. G., Gulbagda, B., & Serikovna, Y. G. (2023). The influence of green credit policy on green innovation and transformation and upgradation as a function of corporate diversification: The case of Kazakhstan. *Economies*, *11*(8), 210. https://doi.org/10.3390/economies11080210

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting event-study designs: Robust and efficient estimation. *The Review of Economic Studies*, *91*(6), 3253-3285. https://doi.org/10.1093/restud/rdae007

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200-230. https://doi.org/10.1016/j.jeconom.2020.12.001

Chen, W., & Zhang, Q. (2025). Can corporate climate risk drive digital transformation? Evidence from Chinese heavy-polluting enterprises. *Technological Forecasting and Social Change*, *212*, 123990. https://doi.org/10.1016/j.techfore.2025.123990

Chen, X., Huang, Y., & Gao, Y. (2024). Can urban low-carbon transitions promote enterprise digital transformation? *Finance Research Letters*, *59*, 104807. https://doi.org/10.1016/j.frl.2023.104807

Fan, J., & Xu, M. (2024). The power of competition: Unveiling China's digital transformation through product market dynamics. *Economics Letters*, *234*, 111479. https://doi.org/10.1016/j.econlet.2023.111479

Gao, R. T., Huang, J., Huang, C., & Rao, X. (2026). From information to liquidity: How industry-level transparency shapes corporate cash holdings. *Pacific-Basin Finance Journal*, *98*, 103187. https://doi.org/10.1016/j.pacfin.2026.103187

Ge, T., Yang, J., Hu, Y., Zhu, T., Wu, Y., & Hu, G. (2026). Do green financial policies enhance firms' TFP? Evidence from China's green finance pilot zones. *Sustainability*, *18*(6), 3121. https://doi.org/10.3390/su18063121

He, W., Ding, Q., & Zhou, T. (2025). How fiscal policy drives corporate digital transformation: An analysis of the synergistic effects of tax incentives and special subsidies. *International Review of Economics & Finance*, *103*, 104496. https://doi.org/10.1016/j.iref.2025.104496

Jiang, M., & Ma, J. (2025). Policy, investment, and growth: How green finance drives corporate sustainable development? *International Review of Economics & Finance*, *102*, 104326. https://doi.org/10.1016/j.iref.2025.104326

Jiang, Q., Zhang, C., & Wei, Q. (2025). Digital technology adoption and enterprise investment efficiency. *Finance Research Letters*, *72*, 106623. https://doi.org/10.1016/j.frl.2024.106623

Jin, J., & Gao, B. (2025). Going with the flow or standing by: Managerial climate risk perception bias and corporate green transformation—Evidence from China. *Energy Economics*, *148*, 108694. https://doi.org/10.1016/j.eneco.2025.108694

Li, C., Bu, W., & Liu, S. (2025). The synergistic impact of green credit policy and government subsidies on green innovation of heavily polluting firms. *Discover Sustainability*, *6*(1), 1080. https://doi.org/10.1007/s43621-025-01969-1

Li, Y., Liu, S., & Zhao, B. (2026). Government data sharing and corporate green transformation: A test based on corporate news text data. *Applied Economics Letters*, 1-5. https://doi.org/10.1080/13504851.2026.2676728

Liang, Q., Wang, C., & Li, Y. (2025). How does green finance influence enterprise greenwashing tendencies? Theoretical and empirical evidence from China. *International Review of Financial Analysis*, *106*, 104574. https://doi.org/10.1016/j.irfa.2025.104574

Liu, C., Sheng, Z., Hu, X., & Tian, C. (2025). Hand in hand or left behind: The dual impact of leading firms' digital technologies on industry digital transformation. *The North American Journal of Economics and Finance*, *75*, 102305. https://doi.org/10.1016/j.najef.2024.102305

Liu, S. (2026). Artificial intelligence industrial agglomeration and innovation in key green technologies: Evidence from China. *Journal of Environmental Management*, *412*, 130161. https://doi.org/10.1016/j.jenvman.2026.130161

Liu, X., Wang, E., & Cai, D. (2019). Green credit policy, property rights and debt financing: Quasi-natural experimental evidence from China. *Finance Research Letters*, *29*, 129-135. https://doi.org/10.1016/j.frl.2019.03.014

Lu, H., Pan, Y., Fan, R., & Guan, W. (2025). Green credit policy and heavily polluting enterprises' green transition. *International Review of Financial Analysis*, *103*, 104162. https://doi.org/10.1016/j.irfa.2025.104162

Ma, H., Zhou, M., & Dong, Y. (2026). The antecedent configurations of digital transformation in manufacturing firms and their impacts on green innovation performance. *Journal of Engineering and Technology Management*, *80*, 101964. https://doi.org/10.1016/j.jengtecman.2026.101964

Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, *9*(4), 97-118. https://doi.org/10.1257/jep.9.4.97

Rossini, M., Ahmadi, A., & Staudacher, A. P. (2024). Applying a process-centric approach to the digitalization of operations in manufacturing companies: A case study. *Procedia Computer Science*, *232*, 1141-1150. https://doi.org/10.1016/j.procs.2024.01.112

Tang, L., Cao, S., & Li, K. (2026). Does digital transformation enhance carbon reduction? New evidence from micro-enterprises and listed enterprises in China. *Environmental Impact Assessment Review*, *118*, 108255. https://doi.org/10.1016/j.eiar.2025.108255

Tian, E., Kim, S. H., & Park, S. O. (2026). Does CEO green experience influence corporate response to the environmental protection tax? Evidence on disclosure and boundary conditions. *Sustainability*, *18*(8), 3852. https://doi.org/10.3390/su18083852

Wang, D., & Shao, X. (2024). Research on the impact of digital transformation on the production efficiency of manufacturing enterprises: Institution-based analysis of the threshold effect. *International Review of Economics & Finance*, *91*, 883-897. https://doi.org/10.1016/j.iref.2024.01.046

Wang, Y., Xie, F., Zhang, B., & You, J. (2025). How can AI application affect the enterprise carbon reduction performance? *Journal of Environmental Management*, *395*, 127777. https://doi.org/10.1016/j.jenvman.2025.127777

Wang, Z., Bian, B., Zhu, C., Lu, Y., & Wang, J. (2025). Green credit policy's impact on polluting firms' market performance: The role of financing constraints. *Frontiers in Environmental Economics*, *4*, 1611379. https://doi.org/10.3389/frevc.2025.1611379

Wu, X., Kang, H.-G., & Ryu, D. (2025). Green finance reform and reshaping firm-banking relationships: Evidence from China. *Global Finance Journal*, *68*, 101200. https://doi.org/10.1016/j.gfj.2025.101200

Xu, A., Zhu, Y., & Wang, W. (2023). Micro green technology innovation effects of green finance pilot policy—from the perspectives of action points and green value. *Journal of Business Research*, *159*, 113724. https://doi.org/10.1016/j.jbusres.2023.113724

Yang, G., Deng, F., & Du, M. (2024). Research on the asymmetric influence of non-R&D subsidy and R&D subsidy on digital enterprises performance: Empirical evidence from China's digital industry. *Journal of the Knowledge Economy*, *15*(3), 14749-14786. https://doi.org/10.1007/s13132-023-01682-2

Yao, S., Pan, Y., Sensoy, A., Uddin, G. S., & Cheng, F. (2021). Green credit policy and firm performance: What we learn from China. *Energy Economics*, *101*, 105415. https://doi.org/10.1016/j.eneco.2021.105415

Ye, X., & Tian, X. (2025). Green finance and ESG performance: A quasi-natural experiment on the influence of green financing pilot zones. *Research in International Business and Finance*, *73*, 102647. https://doi.org/10.1016/j.ribaf.2024.102647

Yi, J., Xia, Z., Cheng, P., & Dai, S. (2026). Cleaner but less efficient? Green finance, resource misallocation, and supply chain spillovers in China. *Energy Economics*, *158*, 109333. https://doi.org/10.1016/j.eneco.2026.109333

You, C., Cifuentes-Faura, J., Liu, X., & Wu, J. (2024). Can the government environmental vertical reform reduce air pollution? A quasi-natural experiment in China. *Economic Analysis and Policy*, *81*, 947-963. https://doi.org/10.1016/j.eap.2023.12.009

Yu, C.-H., Wu, X., Zhang, D., Chen, S., & Zhao, J. (2021). Demand for green finance: Resolving financing constraints on green innovation in China. *Energy Policy*, *153*, 112255. https://doi.org/10.1016/j.enpol.2021.112255

Yu, Y. (2025). Research on the influence of enterprises digital transformation on inventory turnover. *International Review of Economics & Finance*, *103*, 104544. https://doi.org/10.1016/j.iref.2025.104544

Zhang, R., & Ling, S. (2026). The synergistic effect of environmental tax and green finance policy on corporate green technology innovation: Empirical evidence from Chinese listed firms. *Sustainability*, *18*(9), 4502. https://doi.org/10.3390/su18094502

Zhang, R., & Wang, S. (2025). Can the development of the digital economy reduce industrial solid waste pollution? *Journal of Environmental Management*, *386*, 125775. https://doi.org/10.1016/j.jenvman.2025.125775

Zhao, X., Zhao, L., Sun, X., & Xing, Y. (2024). The incentive effect of government subsidies on the digital transformation of manufacturing enterprises. *International Journal of Emerging Markets*, *19*(11), 3892-3912. https://doi.org/10.1108/IJOEM-05-2022-0766

Zou, M., Hao, G., & Zhang, X. (2026). The spillover of digital transformation in supply chain innovation. *Systems*, *14*(1), 41. https://doi.org/10.3390/systems14010041

Zou, Z., Fu, J., Zeng, Y., & Huang, Y. (2024). Do young CEOs matter for corporate digital transformation? *Economics Letters*, *237*, 111636. https://doi.org/10.1016/j.econlet.2024.111636

Appendix.

Appendix A. Construction Details of the Corporate Digital Transformation Index.

Appendix A presents the construction details, keyword dictionary, sub-dimensional weights, and validation results of the corporate digital transformation index.

The dependent variable, CDT (Digital), draws on text mining of the MD&A sections of listed firms' annual reports. A keyword dictionary covering artificial intelligence, big data, cloud computing, blockchain, and adjacent fields is first compiled (see Table A1). For each firm-year, the total count of matched terms in the MD&A text is divided by the section's overall word count and scaled by 100. Higher values indicate more intensive disclosure of digitalization-related activities. In addition, to capture the structural features of digital transformation, this paper further constructs four-dimensional indicators based on the classification system of the CLFDTRD, namely strategic guidance, technical driver, organizational empowerment, and digital application. The weighting scheme for each dimension is presented in Table A2.

To verify the reliability of the text mining approach and the coherence of the indicator framework, this paper conducts two types of validation. In terms of external validity, two graduate students independently cross-checked randomly selected annual report samples and examined the occurrence frequency and contextual suitability of digital keywords one by one. The checking results were broadly consistent with the machine-based word frequency statistics. In terms of internal consistency, Cronbach's alpha coefficient for the four sub-dimensional indicators is approximately 0.695. Table A3 further reports the Pearson correlation coefficient matrix between the overall digital transformation indicator and the four sub-dimensional indicators.

Table A1. Digital Transformation Key Word Database.

Artificial Intelligence	Smart Contract	Heterogeneous Data	Digital Lab	Digital Marketing
Business Intelligence	Distributed Computing	Credit Reporting	Digital Platform	Unmanned Retail
Image Understanding	Decentralization	Augmented Reality	Digital Community	Unmanned Factory
Investment Decision Support System	Bitcoin	Mixed Reality	Digital Patent	Mobile Payment
Intelligent Data Analysis	Consortium Blockchain	Virtual Reality	Digital Network	Third-party Payment
Intelligent Robot	Differential Privacy Technology	Text Scraping	Digital Facilities	NFC Payment
Machine Learning	Consensus Mechanism	AI Lab	Digital Equipment	Human-Computer Interaction
Deep Learning	In-Memory Computing	AI Platform	Digital Infrastructure	Social Network
Semantic Search	Cloud Computing	AI Facilities	Digital Terminal	Smart Agriculture
Biometric Technology	Stream Computing	AI Devices	Digital Information System	Intelligent Transportation
Face Recognition	Graph Computing	AI Infrastructure	Digital Technology System	Smart Healthcare
Voice Recognition	IoT	Multi-party Secure Computation	3D Printing Equipment	Smart Home
Identity Verification	Brain-like Computing	Smart Terminal	Digital Twin	Robo-advisor
Autonomous Driving	Green Computing	Cloud Lab	Virtual Human	Smart Environmental Protection
Natural Language Processing	Cognitive Computing	Cloud Platform	3D Printing	Smart Grid

Artificial Intelligence	Smart Contract	Heterogeneous Data	Digital Lab	Digital Marketing
Supervised Learning	Converged Architecture	Cloud System	5G Technology	Smart Energy
Machine Translation	Billion-level Concurrency	Cloud Equipment	Mobile Internet	Internet Healthcare
OCR Technology	Exabyte-level Storage	Cloud Facilities	Industrial Internet	Internet Finance
Computer Vision	Cyber-Physical System	Cloud Terminal	Digital Technology	Digital Finance
Machine Vision	Mobile Computing	Cloud Community	Nano Computing	Fintech
Robot	Cloud Storage	Cloud Technology System	Intelligent Planning	Financial Technology
Intelligent Q&A	Edge Computing	Big Data Lab	Intelligent Optimization	Quantitative Finance
Expert System	Cloud Technology	Big Data Platform	Smart Wearables	Open Banking
Neural Network	Big Data	Big Data Facilities	Smart Manufacturing	Connected Vehicles
Learning Algorithm	Data Mining	Big Data Equipment	Intelligent Customer Service	Internet Plus
Automated Reasoning	Text Mining	Big Data Information System	Smart Marketing	Data Visualization
Big Data Technology System	–	–	–	–

Table A2. Measurement Weights for the Subdimensions of CDT.

Strategic guidance	Digital-related management positions established	0.2382
	Forward-looking orientation toward digital innovation	0.2788
	Continuity of digital innovation orientation	0.1879
	Breadth of digital innovation orientation	0.1283
	Intensity of digital innovation orientation	0.1668
Technical driver	Artificial intelligence	0.5504
	Blockchain	0.1298
	Cloud computing	0.1832
	Big data	0.1366
Organizational empowerment	Digital capital input	0.5022
	Digital human resource input	0.2553
	Digital infrastructure	0.1206
	S&T innovation base	0.1219
Digital application	Technological innovation	0.6342
	Process innovation	0.2378
	Business innovation	0.1280

Note: Each dimensional score is the weighted sum of its standardized components. Weights are derived from the CLFDTRD classification system in CSMAR.

Table A3. Correlation Matrix Between the Corporate Digital Transformation Indicator and Its Sub-dimensional Indicators.

Variables	Digital	Strategic guidance	Technical driver	Organizational empowerment	Digital application
Digital	1.000				
Strategic guidance	0.312^{***}	1.000			
Technical driver	0.996^{***}	0.305^{***}	1.000		
Organizational empowerment	0.540^{***}	0.231^{***}	0.467^{***}	1.000	
Digital application	0.471^{***}	0.350^{***}	0.459^{***}	0.363^{***}	1.000

Note: Cronbach's alpha is 0.695. *** denotes significance at the 1% level, respectively.

Appendix B. Variable Definitions.

Appendix B presents the definitions of the variables used in this study.

Table B1. Variable definition.

Variables	Definition
Digital	See Section 4.2 and Table A1 for details.
Age	The natural logarithm of the number of years of the business establishment
Size	The natural log of total assets
ROA	Net profit divided by total assets
LEV	Total liabilities divided by total assets
Indep	The proportion of independent directors
Top1	The proportion of the largest shareholder
Board	Board size
InsHold	Sum of the shareholding ratios of institutional investors
concen	The proportion of the 2-5 largest shareholders divided by the proportion of the largest shareholders
Turnover	Operating income divided by total assets
Growth	Revenue growth rate

Appendix C. Sample Selection Procedure.

Appendix C presents the step-by-step sample selection procedure.

Table C1. Sample selection.

Step	Sample restriction	Obs.	Firms	Dropped obs.	Dropped firms
1	Initial sample from 2011 to 2022 and retention of A-share listed firms	40,099	5,021	383	29
2	Exclusion of firms in the financial and real estate industries	36,108	4,645	3,991	376
3	Excluding firms classified as ST, *ST, PT, or in the delisting period, as well as observations with missing trading status	34,995	4,642	1,113	3
4	Matching of the digital-transformation indicator and retention of the final sample used in the main estimation	26,940	3,679	8,055	963

Note: *ST denotes firms subject to delisting risk warnings.

Appendix D. Descriptive Statistics.

Appendix D presents the descriptive statistics of the final sample.

Table D1. Descriptive statistics.

Variables	N	Mean	Sd.	Min.	Max.
Digital	26,940	0.063	0.150	0.000	1.053
DID	26,940	0.205	0.404	0	1
Age	26,940	2.924	0.317	1.946	3.526
Size	26,940	22.216	1.241	19.920	26.071
ROA	26,940	0.042	0.062	-0.255	0.228
LEV	26,940	0.416	0.197	0.051	0.899
Indep	26,940	37.590	5.306	33.330	57.140
Top1	26,940	34.141	14.504	9.180	73.980
Board	26,940	2.121	0.195	1.609	2.639
InsHold	26,940	42.983	24.858	0.277	91.208
concen	26,940	0.734	0.596	0.032	2.836
Turnover	26,940	0.635	0.409	0.089	2.499
Growth	26,940	0.266	0.628	-0.701	4.082