Available Online: 3 August 2026 DOI: 10.54254/2977-5701/2026.35851

Research on the impact of corporate digital transformation on investment efficiency

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Abstract. Digital technologies are increasingly reshaping firms' operational processes, information management, and resource allocation practices. As digital transformation becomes more deeply embedded in business activities, its influence on corporate investment decisions has attracted growing scholarly attention. Drawing on data from Chinese A-share listed companies during 2013-2024, this study investigates the relationship between digital transformation and investment efficiency. The results show that firms with a higher level of digital transformation exhibit significantly lower inefficient investment and consequently higher investment efficiency. The estimated effect remains robust after a series of additional analyses addressing potential endogeneity and model specification issues. Further examination suggests that the positive effect of digital transformation is partly attributable to the alleviation of financing constraints and the reduction of agency costs. By improving information flows and strengthening governance mechanisms, digital transformation contributes to more efficient capital allocation within firms. The study extends existing knowledge on the economic outcomes of digital transformation and offers evidence relevant to both corporate investment management and digital economy policy design.

Keywords: digital transformation, investment efficiency, financing constraints, agency costs

1. Introduction

Driven by continuous technological innovation, digitalization has become an important force influencing corporate development and industrial upgrading. To promote the growth of the digital economy, China has implemented a range of supportive measures that encourage firms to invest in digital capabilities. Consequently, many firms have begun to embed digital tools into their organizational and operational activities. The application of technologies such as big data analytics, cloud platforms, and artificial intelligence not only changes traditional business models but also creates new opportunities for improving productivity and organizational performance.

Despite these developments, corporate investment efficiency in China remains relatively low. Financing constraints, information asymmetry, and agency conflicts continue to distort investment decisions, leading to underinvestment or overinvestment and ultimately reducing the efficiency of resource allocation. Improving investment efficiency has therefore become an important issue for both researchers and policymakers.

Against this backdrop, digital transformation provides a potential pathway for enhancing investment efficiency. By improving information collection, processing, and transmission, digital technologies increase information transparency and reduce information asymmetry, thereby improving the quality of investment decisions. In addition, digital transformation can strengthen corporate governance by enhancing managerial oversight and reducing agency costs. It may also facilitate communication between firms and financial institutions, ease financing constraints, and improve access to external capital. Through these channels, digital transformation is expected to promote more efficient resource allocation and enhance corporate investment efficiency.

Against this background, this paper takes Chinese A-share listed companies from 2013 to 2024 as the research sample to analyze the relationship between digital transformation and investment efficiency. It further investigates whether financing constraints and agency costs serve as important transmission channels. The study helps clarify the economic consequences of digital transformation at the firm level and provides evidence for understanding the role of digital technologies in improving resource allocation efficiency.

2. Theoretical analysis and research hypotheses

Digital technologies enhance information transparency and reduce information costs, thereby improving decision-making and internal control [1]. They also strengthen shareholder monitoring and curb managerial opportunism, leading to higher decision quality [2]. The foregoing discussion suggests the following hypothesis:

H1: Digital transformation of enterprises can improve investment efficiency.

Financing constraints are an important channel linking digital transformation to investment efficiency. Digitalization reduces information asymmetry and eases financing constraints by improving information processing and communication with financial institutions [2]. This effect is particularly important for Chinese SMEs [3]. By improving access to external finance, digital transformation promotes more efficient investment. The foregoing discussion suggests the following hypothesis:

H2a: Digital transformation of enterprises can alleviate financing constraints, thereby improving enterprise investment efficiency.

Agency conflicts are a key factor affecting investment efficiency [4]. By reducing information asymmetry, lowering monitoring costs, and strengthening external oversight, digital transformation mitigates managerial opportunism and improves investment decisions [5]. It also reduces incentives for resource misallocation through stronger performance-based incentives. The foregoing discussion suggests the following hypothesis:

H2b: Digital transformation improves a company's investment efficiency by reducing agency costs.

3. Research design

3.1. Data selection

The sample consists of firms listed on China's Shanghai and Shenzhen A-share markets over the period 2013–2024. Firm-level information is collected from the Wind and CSMAR databases. Financial institutions as well as firms designated ST or *ST are removed from the sample. Observations lacking essential data for the main variables are further discarded. To reduce the influence of extreme observations, all continuous variables are adjusted using 1% tail trimming.

3.2. Variable definitions

3.2.1. Dependent variables

Enterprise Investment Efficiency (Inv): Investment efficiency is measured using a regression model [6]. The absolute residual value serves as a proxy for investment inefficiency, with smaller values indicating higher efficiency and larger values indicating lower efficiency. The Richardson [6] model is employed as Equation (1):

$$Inv_{i,t} = \alpha_0 + \alpha_1 Growth_{i,t-1} + \alpha_2 Lev_{i,t-1} + \alpha_3 Cash_{i,t-1} + \alpha_4 Age_{i,t-1} + \alpha_5 Size_{i,t-1} + \alpha_6 Ret_{i,t-1} + \alpha_7 I_{i,t-1} + \sum Industry + \sum Year + \varepsilon \tag{1}$$

$Inv_{i,t}$ represents the growth investment of enterprise i in year t, measured by the ratio of net cash expenditures on the acquisition, construction, and disposal of fixed and other non-current assets to total assets. $Growth$ for business growth, Lev for debt-to-asset ratio, $Cash$ for free cash flow, Age for company age, $Size$ for asset size, Ret for earnings per share, I for new investments, $Industry$ for industry dummy variables, $Year$ for year dummy variables, ε for residual.

3.2.2. Core explanatory variable

Enterprise Digital Transformation Index (Dig): Following Wu Fei. [1], Dig is constructed from the frequency of digital-related terms. The measure is transformed as ln(1+frequency)/100, with higher values indicating a higher level of digital transformation.

3.2.3. Control variables

Control variables include Size, FirmAge, Top1, CAP, TobinQ, SOE, Dual, and Lev, representing firm size, firm age, the largest shareholder's ownership share, capital intensity, Tobin's Q, ownership type, CEO duality, and the debt-to-asset ratio, respectively.

3.2.4. Mediating variables

(1) Financing Constraints (FC): This study refers to Gu Leilei et al. selects the FC index to measure the degree of a firm's financing constraints [7].

(2) Agency Costs (ATO): Following Li Lei et al. agency costs are proxied by total asset turnover (operating revenue/total assets), with higher values indicating lower agency costs [8].

3.3. Model construction

(1) Baseline regression model: The baseline empirical framework is developed to analyze the association between digital transformation and investment efficiency. Accordingly, this study constructs the baseline regression model as shown in Equation (2):

$$Inv_{i,t} = \alpha_0 + \alpha_1 Dig_{i,t-1} + \alpha Controls_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \tag{2}$$

$Inv_{i,t}$ is inefficient investment, $Dig_{i,t-1}$ is the lagged digital transformation variable, $Controls_{i,t}$ denotes control variables, and ε is the error term. Year and industry fixed effects are included.

(2) Mediation effect model: The benchmark results establish a significant relationship between digital transformation and investment efficiency. To investigate the mechanisms behind this relationship, financing constraints and agency costs are introduced as potential mediating variables. The mediation effect is examined through the following regression models.Therefore, this study specifies the regression model for mechanism testing as Equations (3) and (4):

$$Mediator_{i,t} = \beta_0 + \beta_1 Dig_{i,t-1} + \beta Controls_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \tag{3}$$

$$Inv_{i,t} = \beta_2 + \beta_3 Mediator_{i,t} + \beta_4 Dig_{i,t-1} + \beta Controls_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \tag{4}$$

where $Mediator_{i,t}$ for mediating variables.

4. Empirical analysis

4.1. Descriptive statistics of variables

Table 4-1 presents summary statistics for the key variables. The value of Inv ranges from 0 to 1.059, with a dispersion measure of 0.054, indicating noticeable differences in investment efficiency among firms. For Dig_l1, the average value is 0.016 and the corresponding dispersion is 0.014. Its values span from 0 to 0.063, reflecting variation in the degree of digital transformation across the sample. In general, the variables exhibit reasonable distributions and are suitable for subsequent empirical analysis. Detailed statistics for the remaining variables are also provided in Table 1.

Table 1. Summary statistics

Variable	*N*	Mean	SD	Min	p50	Max
Inv	34,780	0.0380	0.0540	0	0.0240	1.059
Dig_l1	28,636	0.0160	0.0140	0	0.0140	0.0630
Size	34,780	22.37	1.296	19.52	22.20	26.45
FirmAge	34,780	3.037	0.298	1.386	3.045	4.290
Top1	34,780	0.332	0.147	0.0180	0.306	0.900
CAP	34,780	2.664	2.323	0.378	2.005	20.81
TobinQ	34,780	2.127	2.494	0.611	1.628	259.1
SOE	34,780	0.336	0.472	0	0	1
Dual	34,780	0.294	0.456	0	0	1
Lev	34,780	0.433	0.202	0.0460	0.426	0.910

4.2. Analysis of benchmark regression results

Table 2. Results of the baseline regression analysis

	(1) Inv	(2) Inv	(3) Inv
Dig_l1	-0.270***	-0.372***	-0.355***
	(0.075)	(0.079)	(0.079)
_cons	0.046***	-0.150***	-0.178***
	(0.001)	(0.047)	(0.048)
Controls	NO	YES	YES
Dual FE	YES	YES	YES
N	28,636	28,636	28,636
R^2	0.052	0.065	0.068

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

Table 2 presents the benchmark results. In Column (1), the coefficient of Dig_l1 is −0.270 and significant at the 1% level after controlling for firm and year fixed effects. The coefficient remains significantly negative in Columns (2) and (3), at −0.372 and −0.355, respectively. The consistent results across specifications suggest that digital transformation reduces inefficient investment and improves investment efficiency, supporting Hypothesis H1.

4.3. Endogeneity test

4.3.1. Instrumental variable test

To address potential endogeneity, this study employs an instrumental variable approach. Following Wu Fei [1], the lagged industry–province average level of digital transformation is used as the instrument (IV_DIG_MEAN_l1).

Table 3 presents the instrumental variable estimates. In the first stage, the coefficient on IV_DIG_MEAN_l1 is positive and statistically significant, indicating that the instrument is strongly correlated with firm-level digital transformation. In the second stage, the coefficient of Dig_l1 remains significantly negative (−0.323), consistent with the benchmark results. These findings suggest that the positive effect of digital transformation on investment efficiency is robust after accounting for potential endogeneity.

Table 3. Instrumental variables

	IV-I	IV-II
	DIG_t-1	Inv
IV_DIG_MEAN_l1	0.000***	
	(5.69)	
Dig_l1		-0.323***
		(-3.90)
Controls	YES	YES
Dual FE	YES	YES
N	23,699	23,699
R^2	0.018	0.021

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

4.3.2. Propensity Score Matching (PSM) propensity score matching

To further address potential selection bias, a propensity score matching procedure is conducted. Specifically, firms are matched on the basis of observable characteristics using a one-to-one nearest-neighbor algorithm. The post-matching estimates are reported in Table 4. Across different specifications, the estimated coefficients of Dig_l1 remain negative and statistically significant, ranging from −0.2698 to −0.3551. The consistency between the matched-sample results and the benchmark estimates suggests that the relationship between digital transformation and investment efficiency is unlikely to be driven by systematic differences between firms. Therefore, the main empirical findings remain valid after controlling for sample selection concerns.

Table 4. Analysis of PSM matching results

	(1) Inv	(2) Inv	(3) Inv
Dig_l1	-0.2698***	-0.3546***	-0.3551***
	(-3.62)	(-4.49)	(-4.50)
_cons	0.0462***	-0.1791***	-0.1778***
	(38.43)	(-3.76)	(-3.73)
Controls	YES	YES	YES
Dual FE	YES	YES	YES
N	28,633	28,633	28,633
R^2	0.0520	0.0676	0.0675

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

4.4. Robustness test

Table 5 presents several robustness checks. The coefficient of Dig_l1 remains significantly negative when using the Chen measure of investment efficiency (−0.1767), adding provincial fixed effects (−0.298), and excluding observations from 2020–2022 (−0.322). These results confirm the robustness of the baseline findings.

Table 5. Robustness test

	(1) Inv_Chen	(2) Inv_p	(3) Inv_e
Dig_l1	-0.1767***	-0.298***	-0.322***
	(0.0679)	(-3.62)	(-3.12)
_cons	-0.0283	-0.144***	-0.136***
	(0.0650)	(-3.63)	(-2.74)
Controls	YES	YES	YES
Dual FE	YES	YES	YES
N	27,486	24,350	16,772
R^2	0.011	0.060	0.063

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

4.5. Mechanism verification

Table 6 reports the mechanism tests. In Column (2), Dig_l1 is negatively associated with Financing Constraints (FC), with a coefficient of −0.444 significant at the 1% level. After FC is added to the baseline model, its coefficient is significantly positive (0.011), indicating that digital transformation improves investment efficiency by easing financing constraints, consistent with Hypothesis H2a. For Agency Costs (ATO), the coefficient of Dig_l1 in Column (4) is 0.699 and significant at the 1% level. In Column (5), ATO is significantly negative (−0.014), while Dig_l1 remains significantly negative (−0.345), suggesting that digital transformation improves investment efficiency through reducing agency costs, consistent with Hypothesis H2b.

Table 6. Mechanism test results

	(1) Inv	(2) FC	(3) Inv	(4) ATO	(5) Inv
Dig_l1	-0.355***	-0.444***	-0.350***	0.699***	-0.345***
	(-4.50)	(-3.66)	(-4.44)	(2.82)	(-4.39)
FC			0.011***		
			(3.03)		
ATO					-0.014***
					(-4.71)
_cons	-0.178***	4.065***	-0.223***	0.994***	-0.164***
	(-3.74)	(32.70)	(-4.38)	(4.22)	(-3.47)
Controls	YES	YES	YES	YES	YES
Dual FE	YES	YES	YES	YES	YES
N	28,636	28,636	28,636	28,636	28,636
R^2	0.068	0.473	0.068	0.255	0.069

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

5. Conclusion and recommendation

5.1. Conclusions

Based on a panel dataset of Chinese A-share listed companies from 2013 to 2024, this study analyzes the relationship between digital transformation and investment efficiency. The empirical findings show that firms undergoing digital transformation exhibit lower levels of inefficient investment. The estimated effect remains stable after a range of supplementary analyses designed to address potential endogeneity and model specification issues.

Further examination indicates that improvements in financing conditions and corporate governance play an important role in explaining this relationship. Digital technologies facilitate information exchange, reduce communication costs, and improve access to external financial resources, thereby easing funding pressures faced by firms. In addition, digital transformation strengthens internal and external monitoring, limits managerial discretion, and contributes to more rational investment choices. Through these channels, firms can improve the allocation of capital and enhance investment efficiency.

Overall, the findings deepen the understanding of the economic value of digital transformation and offer evidence regarding its role in promoting more efficient corporate investment behavior.

5.2. Recommendations

First, policymakers should continue to support digital transformation and digital infrastructure development to enhance firms' investment efficiency.

Second, efforts should be made to expand financing channels and improve digital financial services, thereby reducing financing constraints and financing costs.

Third, firms should strengthen digital governance mechanisms, improve information transparency, and enhance managerial oversight to reduce agency costs and curb inefficient investment.

Fundings

Shandong Province Key R&D Program (Soft Science Project)—Key Project (2026RZB0301) and Interdisciplinary Innovation Guidance Program of Qilu University of Technology (Shandong Academy of Sciences) under Grant (2026XKJC0202)

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