

Article

Digital Transformation and Total Factor Productivity: An Intelligent System Perspective

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Abstract

Digital technologies, including artificial intelligence, big data, cloud computing, and blockchain, are increasingly embedded in firms' production and management systems, enabling more intelligent information processing, resource allocation, and operational coordination. Against this background, digital transformation has become an important means of improving production efficiency and upgrading business systems. Using Chinese A-share listed companies from 2012 to 2025 as the sample, this study examines the effect of digital transformation on total factor productivity (TFP) and further tests the mediating role of asset utilization efficiency. The results show that digital transformation significantly increases firm-level TFP, with asset utilization efficiency serving as a partial mediator. The main findings remain valid after alternative productivity measures, adjustments to the sample, propensity score matching, and an instrumental-variable approach are employed. Heterogeneity analysis indicates that the positive effect is stronger among firms in western China and state-owned enterprises. It is significant for labor-intensive and capital-intensive firms but not for technology-intensive firms. Overall, the findings demonstrate how digital transformation can enhance firm productivity through the integration of intelligent technologies and more efficient resource utilization, providing firm-level evidence for the development of more efficient and intelligent business systems.

Keywords: Digital Transformation; Intelligent Systems; Total Factor Productivity; Asset Utilization Efficiency; Resource Allocation

1. Introduction

China's economic development is shifting from a factor-input-driven model toward high-quality growth driven by innovation and efficiency. Raising total factor productivity has therefore become essential to the high-quality and sustainable development of firms. Meanwhile, rapid advances in digital technologies have brought AI and big data into corporate R&D, production, and other business activities, improving resource allocation and reducing resource waste. Digital transformation has consequently become a major strategic choice for corporate upgrading. Whether it can be effectively converted into



productivity gains is thus an important question amid the deepening integration of digital and real economies.

Existing studies have examined the relationship between digital transformation and firm-level total factor productivity from the perspectives of technological innovation, cost reduction, and more efficient resource allocation, yet their findings remain inconclusive. Zhao et al. (2021) suggests that digital transformation and the adoption of artificial intelligence contribute to higher total factor productivity [1]. In contrast, Liu (2023) argues that firms may experience a temporary “productivity paradox” during the early stage of transformation because of adjustment costs, while Huang and Jiang (2024) find that excessive investment in digital technologies may lead to resource misallocation [2,3]. Moreover, previous studies differ in terms of sample periods, geographical coverage, ownership types, and the intensity of the industries examined. Further investigation is therefore needed to clarify the relationship between digital transformation and total factor productivity, with particular attention to firm heterogeneity.

This study uses a sample of Chinese A-share listed companies from 2012 to 2025 and applies a two-way fixed-effects model to examine the relationship between digital transformation and firm-level TFP. It then investigates the underlying mechanism from the perspective of asset utilization efficiency. Heterogeneity is analyzed along three dimensions: region, ownership, and industry factor intensity. To enhance the credibility of the findings, robustness checks employ alternative variable measures and sample restrictions, while propensity score matching and an instrumental-variable strategy are used to mitigate endogeneity concerns.

This study extends the literature in three respects. First, using A-share listed firms from 2012-2025, it provides firm-level evidence covering a period of accelerated digital-technology adoption. Second, it examines heterogeneity by industry factor intensity from a factor-endowment perspective, thereby informing differentiated approaches to corporate digital transformation. Third, it combines propensity score matching with an instrumental-variable design to assess robustness with respect to firm self-selection and reverse causality, furnishing more comprehensive empirical support for the relationship between digital transformation and TFP.

2. Literature Review or Theoretical Framework

2.1. Research on Digital Transformation

Digital technology has become an integral component of corporate strategy [4]. Digital transformation encompasses not only the adoption of AI, big data, and other technologies but also systematic changes in business processes, organizational structures, and business models [5,6].

Existing studies measure digital transformation using quantitative indicators and textual analysis. Huang and Jiang (2024) identify digital assets within fixed and intangible assets and measure transformation from the perspective of digital investment [3]. Wu et al. (2021) measure digital transformation using the frequency of digitalization-related terms in annual reports, while Yi et al. (2021) and Zhao et al. (2021) similarly construct digital indicators from corporate annual-report texts [1,7,8].

Regarding its determinants, internal factors—including financial capacity, technical talent, managerial awareness, data resources, and organizational capabilities—directly shape the transformation process. External conditions, such as digital infrastructure, public policy, and the financial environment, affect both the cost of and incentives for corporate digital transformation [9].

In terms of economic consequences, prior research finds that digital transformation promotes corporate innovation, improves operating performance, increases firm value and stock liquidity, and strengthens environmental, social, and governance (ESG) performance [7,8].

2.2. Research on Total Factor Productivity

Total factor productivity captures output efficiency attributable to technological progress, managerial improvement, and optimized resource allocation beyond conventional inputs such as capital and labor. Solow (1957) attributed output growth unexplained by increases in capital and labor to technological progress, laying the theoretical foundation for TFP research [10]. Syverson (2011) further documented persistent productivity differences across firms and emphasized TFP as a key measure of operating efficiency and long-term competitiveness [11].

Existing studies primarily estimate TFP using the Olley-Pakes (OP) and Levinsohn-Petrin (LP) methods. Olley and Pakes (1996) use firm investment as a proxy for unobserved productivity, forming the basis of the OP method, whereas Levinsohn and Petrin (2003) use intermediate inputs as the proxy, forming the LP method [12,13]. Using data on Chinese industrial firms, Lu and Lian (2012) compare alternative estimation methods and provide an important reference for firm-level TFP research in China [14].

Technological progress and improvements in technical efficiency are key sources of TFP growth. Human-capital accumulation, managerial efficiency, and better resource allocation can raise TFP, whereas financing constraints, market segmentation, and factor misallocation suppress production efficiency [11].

2.3. Research on the Impact of Digital Transformation on Total Factor Productivity

The prevailing view is that digital transformation improves firm-level TFP. Brynjolfsson and Hitt (2003) find that information technology contributes more to firm output over the long run than in the short run, although complementary organizational change and human capital are required [15]. Bartel et al. (2007) show that information technology can enhance productivity through process improvements and product innovation [16]. Evidence from Chinese firms similarly indicates a significant positive effect, although its magnitude varies with the sample, the measurement of digitalization, and firm characteristics [17-19]. Regarding mechanisms, existing research highlights knowledge spillovers, corporate innovation, cost control, and labor allocation [17,18,20]. Digital transformation may raise TFP by strengthening internal controls, stimulating entrepreneurship, and improving ESG performance [21-23]. Digital technologies thus affect productivity not only by optimizing production processes but also by improving governance, resource integration, and sustainability capabilities. Although the literature has extensively examined the association, studies differ in sample coverage, indicator construction, and the mechanisms considered. Some studies suggest that the relationship between digital transformation and total factor productivity may be nonlinear. Liu (2023) notes that firms may temporarily experience a “productivity paradox” during the early stages of transformation because of adjustment costs [2]. Huang and Jiang (2024) find that excessive investment in digital technologies may result in resource misallocation [3]. These findings indicate that the digital transformation productivity relationship warrants further investigation in light of firms’ regional contexts, ownership structures, and industry characteristics.

3. Theoretical Analysis and Research Hypothesis

Information asymmetry theory implies that multiple organizational layers may impede internal information transmission, increasing decision-making errors and costs. Digital technologies such as artificial intelligence and big data strengthen firms’ capacity to collect, transmit, and analyze information. Managers can consequently track market demand, production progress, and equipment status in a timely manner, improve operating decisions and production management, and reduce redundant investment and idle assets caused by delayed information. The resulting improvement in input-output efficiency

contributes to firm-level TFP growth.

From a resource-allocation perspective, digital transformation can optimize production processes and equipment scheduling, thereby improving the use of existing assets. In production, equipment monitoring and data analytics help identify operating anomalies, optimize maintenance schedules, and increase equipment availability and production continuity. Cross-departmental data sharing also facilitates coordination among procurement, production, and sales. Along with the supply chain, digital platforms improve information sharing with upstream and downstream partners, giving firms timely access to orders, inventories, and logistics data. This strengthens supply-demand coordination, curbs excess inventory and tied-up capital, and accelerates asset turnover. Greater asset utilization is an important channel through which digital transformation improves firm performance [24]. By reducing inefficient resource occupation and improving input-output efficiency, it can further raise TFP.

Accordingly, the following hypotheses are proposed:

H1: Corporate digital transformation significantly increases total factor productivity.

H2: Corporate digital transformation increases total factor productivity by improving asset utilization efficiency.

4. Research Design

4.1. Sample Selection and Data Sources

The sample consists of Chinese A-share listed firms from 2012 to 2025. Data on corporate digital transformation are extracted from the texts of listed firms' annual reports, while all other data are obtained from the China Stock Market & Accounting Research (CSMAR) database.

The raw data are processed as follows. First, financial firms are excluded. Second, firms with abnormal operating status, including ST and PT firms, are removed. Third, observations with a debt-to-asset ratio greater than or equal to one are excluded. Fourth, observations with missing values are dropped. Fifth, to mitigate the influence of outliers, all major continuous variables are winsorized at the 1st and 99th percentiles. The final sample contains 45301 firm-year observations.

4.2. Variable Definitions

4.2.1. Dependent Variable: Total Factor Productivity (TFP)

Following Levinsohn and Petrin (2003), this study uses firm-level productivity data compiled from the CSMAR database and measures total factor productivity using the Levinsohn-Petrin (LP) method [13]. This approach employs intermediate input as a proxy for unobserved productivity shocks, thereby helping to mitigate the input selection problem in production function estimation. To assess whether the results are sensitive to the choice of estimation method, the robustness analysis re-estimates total factor productivity using the Olley-Pakes (OP) method [12].

4.2.2. Independent Variable: Digital Transformation (Dig)

Following Wu et al. (2021), this study employs textual analysis to count the occurrences of terms related to digital technologies, including artificial intelligence, big data, cloud computing, and blockchain, in the annual reports of listed firms [7]. The firm-level digital transformation measure is constructed by adding one to the aggregate frequency of these digital keywords and then taking the natural logarithm.

4.2.3. Mediating variable: asset utilization efficiency (ATO)

Following He and Liu (2019), asset utilization efficiency is measured by the total asset turnover ratio, calculated as operating revenue divided by average total assets [24].

4.2.4. Control Variables

To reduce interference from other factors, eight control variables are included: firm size (Size), debt-to-asset ratio (Lev), profitability (ROA), cash flow (Cash), growth (Growth), CEO duality (Dual), market value (TobinQ), and listing age (Age). Detailed definitions are presented in Table 1.

Table 1: Variable Definitions

Variable Type	Variable	Symbol	Definition
Dependent variable	Total factor productivity	TFP	LP and OP methods
Independent variable	Digital transformation	Dig	Ln (sum of digital-transformation keyword frequencies+1)
Mediating variable	Asset utilization efficiency	ATO	operating revenue/average total assets
Control variable	Firm size	Size	Ln (total assets)
	Debt-to-asset ratio	Lev	total liabilities/total assets
	Profitability	ROA	net income/total assets
	Cash flow	Cash	net operating cash flow/total assets
	Growth	Growth	revenue growth rate
	CEO duality	Dual	1 if the chairperson also serves as CEO; 0 otherwise
	Market value	TobinQ	Tobin's Q
	Listing age	Age	Ln (current year-listing year+1)

4.3. Model Specification

To test the effect of corporate digital transformation on TFP and the mediating role of asset utilization efficiency, the following models are specified using the three-step mediation procedure within a two-way fixed-effects framework:

$$TFP_{it} = \alpha_0 + \beta_0 Dig_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{Model (1)}$$

$$ATO_{it} = \alpha_1 + \beta_1 Dig_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{Model (2)}$$

$$TFP_{it} = \alpha_2 + \beta_2 Dig_{it} + \theta_2 ATO_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad \text{Model (3)}$$

where i and t index firms and years, respectively; TFP_{it} denotes firm-level total factor productivity; Dig_{it} denotes the degree of digital transformation; ATO_{it} represents asset utilization efficiency, and $Controls_{it}$ is the vector of control variables. α is the constant; μ_i and λ_t denote firm and year fixed effects, respectively; and ε_{it} is the idiosyncratic error term. To address within-firm correlation in the error term over time, standard errors are clustered at the firm level.

5. Empirical Results

5.1. Descriptive Statistics

Table 2 reports descriptive statistics for the main variables. The sample contains 45301 firm-year observations. The mean TFP is 9.064, with a standard deviation of 1.105. Differences in technological capabilities, resource-allocation efficiency, and management practices generate substantial variation in firms' ability to convert production factors into output. Digital transformation has a mean of 1.658, a standard deviation of 1.407, a minimum of 0, and a maximum of 5.198, indicating pronounced differences across firms. Some firms have integrated digital technologies into R&D, production, and management, whereas others lag because of constraints in finance, technology, and talent. Among the control variables, the standard deviation of Growth is 0.352, reflecting considerable differences in firms' development stages and operating environments. TobinQ has a mean of 2.054 and a maximum of 8.564, indicating large differences in capital-market assessments of firms' future growth opportunities and investment value. Firm size, profitability, and financial leverage also exhibit meaningful variation.

Table 2: Descriptive Statistic

Variables	N	Mean	SD	Min	Max
TFP	45301	9.064	1.105	6.817	12.08
Dig	45301	1.658	1.407	0	5.198
Size	45301	22.32	1.292	19.99	26.37
Lev	45301	0.423	0.204	0.058	0.900
ROA	45301	0.032	0.065	-0.225	0.210
Cash	45301	0.047	0.066	-0.152	0.238
Growth	45301	0.123	0.352	-0.567	1.999
Dual	45301	0.303	0.459	0	1
TobinQ	45301	2.054	1.326	0.829	8.564
Age	45301	2.231	0.783	0.693	3.434

5.2. Baseline Regression

Column (1) of Table 3 reports a coefficient of 0.0252 on Dig, significant at the 1% level. Given the standard deviation of Dig (1.407), a one-standard-deviation increase in digital transformation is associated with an increase of approximately 0.0355 in TFP. This magnitude is equivalent to about 0.39% of the sample mean of TFP (9.064), or 3.21% of its standard deviation (1.105). In column (2), the coefficient on Dig is 0.0107 and significant at the 1% level. When Dig and ATO are jointly included in column (3), the coefficient on ATO is 0.777 and significant at the 1% level, while the coefficient on Dig falls from 0.0252 to 0.0169 but remains positive and significant.

Table 3: Digital Transformation, Total Factor Productivity, and the Mediating Mechanism

Variables	(1) TFP	(2) ATO	(3) TFP
Dig	0.0252***	0.0107***	0.0169***
	(0.0044)	(0.0034)	(0.00320)
ATO			0.777***
			(0.0659)
Size	0.585***	-0.0533***	0.626***
	(0.0117)	(0.0109)	(0.00961)
Lev	0.338***	0.251***	0.143***
	(0.0422)	(0.0340)	(0.0328)
ROA	1.620***	0.951***	0.882***
	(0.0674)	(0.0545)	(0.0926)
Cash	0.628***	0.272***	0.416***
	(0.0460)	(0.0416)	(0.0418)
Growth	0.206***	0.144***	0.0938***
	(0.0072)	(0.0068)	(0.00919)
Dual	-0.0097	-0.0064	-0.00475
	(0.0087)	(0.0081)	(0.00628)
TobinQ	0.0125***	0.0142***	0.00148
	(0.0032)	(0.0027)	(0.00232)
Age	0.0223	0.0301***	-0.00110
	(0.0140)	(0.0107)	(0.0103)
cons	-4.358***	1.601***	-5.602***
	(0.247)	(0.231)	(0.220)
N	45301	45301	45301
R²	0.599	0.131	0.756

*** p < 0.01, ** p < 0.05, * p < 0.1

After accounting for years and firm fixed effects and observable controls, digital transformation is therefore positively associated with TFP, with part of this association operating through improved utilization of existing assets. Digital technologies can optimize inventory management, production scheduling, and business coordination, reduce idle assets, and allow firms to generate more operating output from a given asset base.

5.3. Heterogeneity Analysis

Firms across regions, ownership types, and industries with different factor intensities vary in their digital foundations, financing capacity, and human capital endowments. This study therefore further examines the heterogeneity in the relationship between digital transformation and firm-level total factor productivity. Industry factor intensity is classified following the industry classification proposed by Yin et al. (2018) and matched according to each sample firm's industry affiliation [25]. If a firm changes industries, its factor-intensity category is reassigned from the year of the change onward. Regional classification is based on the province of the firms registered address in each year. If the registered address moves across regions, the firm is reclassified from the year of relocation onward.

Table 4: Heterogeneity Analysis

Variables	TFP							
	Western	Central	Eastern	Non-SOE	SOE	Labor intensive	Tech intensive	Capital intensive
Dig	0.046***	0.0174	0.0237***	0.0169***	0.0371***	0.0319***	0.0010	0.0243***
	(0.0132)	(0.011)	(0.005)	(0.00512)	(0.00781)	(0.0079)	(0.005)	(0.0075)
Size	0.535***	0.579***	0.594***	0.593***	0.564***	0.594***	0.585***	0.510***
	(0.0368)	(0.0295)	(0.0139)	(0.0138)	(0.0225)	(0.0228)	(0.0142)	(0.0271)
Lev	0.192*	0.347***	0.355***	0.374***	0.193**	0.299***	0.427***	-0.0820
	(0.116)	(0.111)	(0.0487)	(0.0508)	(0.0830)	(0.0802)	(0.0460)	(0.0725)
ROA	1.900***	1.858***	1.515***	1.381***	2.189***	1.517***	1.761***	1.180***
	(0.210)	(0.196)	(0.0755)	(0.0741)	(0.149)	(0.120)	(0.0828)	(0.139)
Cash	0.949***	0.508***	0.581***	0.668***	0.512***	0.557***	0.618***	0.673***
	(0.136)	(0.112)	(0.0538)	(0.0557)	(0.0807)	(0.0774)	(0.0556)	(0.0903)
Growth	0.176***	0.226***	0.214***	0.211***	0.21***	0.233***	0.193***	0.198***
	(0.0162)	(0.0189)	(0.0088)	(0.0087)	(0.0120)	(0.0116)	(0.0105)	(0.0164)
Dual	-0.0254	0.0062	-0.0133	-0.0184*	0.00710	-0.0279*	-0.0054	0.0181
	(0.0259)	(0.0209)	(0.01)	(0.0103)	(0.0161)	(0.0160)	(0.0103)	(0.0170)
TobinQ	0.00317	0.0246***	0.011***	0.0141***	0.00516	0.0133**	0.0148***	0.0211**
	(0.0086)	(0.0094)	(0.0036)	(0.0035)	(0.0079)	(0.0065)	(0.0031)	(0.0083)
Age	0.0633	0.0274	0.0186	-0.0284	0.0386	0.0419	0.0042	0.0236
	(0.0437)	(0.0342)	(0.0164)	(0.0180)	(0.0323)	(0.0284)	(0.0158)	(0.0280)
cons	-3.454***	-4.286***	-4.516***	-4.528***	-3.769***	-4.410***	-4.436***	-2.552***
	(0.767)	(0.631)	(0.292)	(0.288)	(0.487)	(0.487)	(0.297)	(0.579)
N	4986	7321	32951	30904	14397	14804	21902	7765
R²	0.606	0.618	0.596	0.613	0.574	0.499	0.662	0.636

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The regional subsample results show that the coefficients on digital transformation are 0.0460 and 0.0237 for firms in western and eastern China, respectively, and both are statistically significant at the 1% level. By contrast, the coefficient is insignificant for firms in central China. A bootstrap test of cross-group coefficient differences yields a p-value of 0.046 for the difference between the western and eastern subsamples, indicating that the two estimated coefficients differ significantly. Eastern China has relatively well-developed digital infrastructure and more mature applications of digital technologies, which may limit the marginal association of additional digital investment with productivity. In western China, where the digital foundation remains comparatively underdeveloped, the adoption of digital technologies may be more readily accompanied by improvements in information transmission, production management, and resource allocation efficiency. Central China may still be upgrading its digital infrastructure: its facilities lag those in the east, while its firms lack the strong policy incentives available in the west. Some digital investments may therefore not yet have translated fully into production efficiency, leaving no discernible short-run effect on TFP.

The results by ownership type show that the coefficients on digital transformation are 0.0169 for non-state-owned enterprises and 0.0371 for state-owned enterprises, both of which are statistically significant at the 1% level. The bootstrap test produces a p-value of 0.048 for the difference between the two coefficients, suggesting a statistically significant difference across the ownership groups. This difference may be related to the advantages enjoyed by state-owned enterprises in access to finance, skilled personnel, and technology.

The results by factor intensity indicate that the coefficients on digital transformation are 0.0319 and 0.0243 for labor-intensive and capital-intensive firms, respectively, with both estimates statistically

significant at the 1% level. The coefficient for technology-intensive firms, however, is not statistically significant. The bootstrap test yields a p-value of 0.402 for the coefficient difference between the labor-intensive and capital-intensive subsamples, indicating that the two estimates do not differ significantly. Labor-intensive firms may improve labor efficiency through automation and digital management, while capital-intensive firms may use intelligent technologies to increase equipment utilization. Technology-intensive firms, in contrast, generally have a higher initial level of digitalization and may therefore have less scope for further marginal productivity gains from additional transformation.

5.4. Robustness Tests

Table 5: Robustness Test Results

Variables	TFP			
	(1)	(2)	(3)	(4)
Dig	0.0178***	0.0125***	0.0219***	0.0267***
	(0.0044)	(0.0045)	(0.0048)	(0.0046)
Size	0.393***	0.571***	0.585***	0.587***
	(0.0110)	(0.0135)	(0.0121)	(0.0128)
Lev	0.266***	0.275***	0.323***	0.299***
	(0.0412)	(0.0470)	(0.0444)	(0.0459)
ROA	1.598***	1.603***	1.582***	1.533***
	(0.0661)	(0.0785)	(0.0795)	(0.0734)
Cash	0.562***	0.673***	0.630***	0.622***
	(0.0469)	(0.0530)	(0.0531)	(0.0491)
Growth	0.201***	0.206***	0.203***	0.206***
	(0.0074)	(0.0093)	(0.0085)	(0.0082)
Dual	-0.0113	-0.0015	-0.0085	-0.0092
	(0.0085)	(0.0095)	(0.0099)	(0.0099)
TobinQ	0.0099***	0.0143***	0.0167***	0.0158***
	(0.0031)	(0.0034)	(0.0040)	(0.0036)
Age	0.0098	0.0035	0.0311**	0.0172
	(0.0136)	(0.0148)	(0.0152)	(0.0153)
Cons	-2.324***	-4.024***	-4.366***	-4.406***
	(0.231)	(0.282)	(0.253)	(0.268)
N	45301	30936	34057	36435
R²	0.501	0.656	0.609	0.610

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 reports the robustness tests. In column (1), digital transformation remains significant at the 1% level when TFP is re-estimated using the OP method, indicating that the conclusion does not depend on a specific productivity estimator. In column (2), the coefficient remains significant at the 1% level when the sample is restricted to manufacturing firms. Digital technologies improve resource allocation through intelligent production and equipment monitoring, thereby increasing manufacturing firms' TFP. In column (3), the coefficient on digital transformation remains significant at the 1% level after observations from 2020-2022 are excluded. During this period, firms' production and operations, supply chains, and labor mobility were subject to unusual shocks; excluding these years does not change the conclusion. In column (4), digital transformation remains significant at the 1% level after firms located in the four centrally administered municipalities—Beijing, Shanghai, Tianjin, and Chongqing—are excluded. These municipalities have clear advantages in digital infrastructure, talent, resources, and policy support, yet the conclusion remains unchanged when they are omitted.

The coefficients on digital transformation are positive and statistically significant in all four tests, demonstrating that the positive effect of digital transformation on firm-level TFP is robust.

5.5. Endogeneity Tests

5.5.1. Propensity score matching

To mitigate potential sample-selection bias, this study uses propensity score matching (PSM) as an endogeneity test. Using the median of the digital transformation index as the threshold, firms at or above the median are assigned to the treatment group and coded as one, while firms below the median are assigned to the control group and coded as zero. A logit model is used to estimate propensity scores with the eight control variables as covariates, and one-to-one nearest-neighbor matching is then implemented.

Table 6: Covariate Balance Test for Propensity Score Matching

Covariate	Unmatched U Matched M	Mean		Standardized bias (%)	t-statistic	p-value
		Treatment	Control			
Size	U	22.399	22.231	13.0	13.84	0.000
	M	22.399	22.404	-0.4	-0.39	0.697
Lev	U	0.41963	0.42663	-3.4	-3.64	0.000
	M	0.41965	0.41855	0.5	0.57	0.572
ROA	U	0.03081	0.03393	-4.8	-5.11	0.000
	M	0.03082	0.03106	-0.4	-0.38	0.706
Cash	U	0.04632	0.04764	-2.0	-2.11	0.035
	M	0.04633	0.04626	0.1	0.11	0.914
Growth	U	0.12216	0.12454	-0.7	-0.72	0.471
	M	0.12218	0.11695	1.5	1.60	0.109
Dual	U	0.34172	0.26338	17.1	18.21	0.000
	M	0.34169	0.33623	1.2	1.23	0.219
TobinQ	U	2.1091	1.9982	8.4	8.91	0.000
	M	2.1088	2.1143	-0.4	-0.41	0.682
Age	U	2.2089	2.2533	-5.7	-6.03	0.000
	M	2.2089	2.2115	-0.3	-0.35	0.729

The common-support and balance tests show substantial overlap in propensity scores between the two groups after matching. The standardized bias of each covariate decreases markedly and remains below 10%. A two-way fixed-effects regression based on the matched sample yields a coefficient of 0.0245 on digital transformation, significant at the 1% level and consistent with the baseline result. Thus, after controlling for observable differences between high-digital-transformation and low-digital-transformation firms, a stable positive relationship remains between digital transformation and firm-level TFP. This method improves the comparability of the two groups of firms in terms of observable characteristics but cannot fully rule out the influence of unobserved factors.

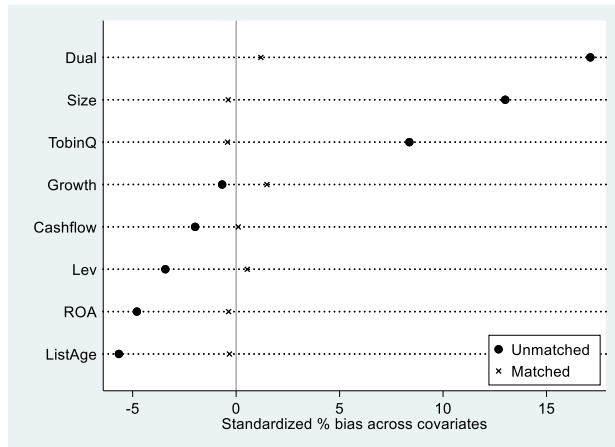


Figure 1: Standardized Bias Plot

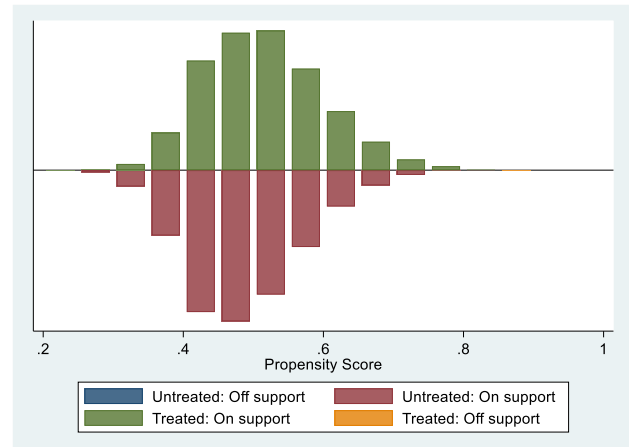


Figure 2: Common Support of Propensity Scores

Table 7: Propensity-Score-Matched Regression Results

Variables	TFP
Dig	0.0245***
	(0.0051)
Size	0.580***
	(0.0136)
Lev	0.361***
	(0.0497)
ROA	1.504***
	(0.0880)
Cash	0.743***
	(0.0620)
Growth	0.209***
	(0.0107)
Dual	-0.0053
	(0.0106)
TobinQ	0.0132***
	(0.0041)
Age	0.0280*
	(0.0167)
Cons	-4.293***
	(0.286)
N	24,250
R²	0.604

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.5.2. Instrumental-variable approach

Although the analysis controls for firm and year fixed effects and a range of firm characteristics, endogeneity may persist. First, more productive firms may possess a greater capacity to undertake digital transformation, creating reverse causality and upward bias. Second, difficult-to-observe factors may jointly affect digital transformation and TFP, producing omitted-variable bias.

To address these concerns, this study follows Jia and Li (2024) and uses the mean digital-transformation index of other firms in the same industry as an instrument [26]. The transformation choices of industry peers may influence a focal firm through demonstration, imitation, and competition, satisfying the relevance condition. At the same time, the peer mean is determined by many firms and is unlikely to be affected by managerial adjustments within the focal firm. Excluding the focal firm from the calculation further reduces the possibility that its productivity directly affects the instrument, supporting the exclusion restriction.

Table 8 reports the instrumental-variable estimates. In the first stage, IV is significant at the 1% level, confirming its relevance for the focal firm's digital transformation. The Kleibergen-Paap rk Wald F-statistic is 576.21, exceeding the critical value of 16.38, and the p-value of the Kleibergen-Paap rk LM test is below 0.01, supporting instrument validity. In the second stage, the coefficient on Dig is 0.2373 and significant at the 1% level; the main result therefore remains robust.

Table 8: Instrumental-Variable Estimates

Variables	First stage	Second stage
	Dig	TFP
IV	0.3705*** (24.0044)	
Dig		0.2373*** (9.7223)
Size	0.2342*** (21.7062)	0.5311*** (57.8755)
Lev	-0.2021*** (-5.0178)	0.3798*** (14.7767)
ROA	-0.0979 (-1.2226)	1.6461*** (30.2272)
Cash	-0.1984*** (-3.0914)	0.6703*** (16.4284)
Growth	0.0334*** (3.0445)	0.1995*** (26.5632)
Dual	0.0035 (0.2995)	-0.0107* (-1.7194)
TobinQ	0.0160*** (3.7173)	0.0085*** (3.4769)
Age	0.1394*** (8.3712)	-0.0070 (-0.7493)
N	45099	45099
R ²	0.816	0.375
Kleibergen-Paap rk Wald F	576.21	
Kleibergen-Paap rk LM	P=0.000	

*** p < 0.01, ** p < 0.05, * p < 0.1

6. Conclusions and Policy Recommendations

6.1. Conclusions

Using Chinese A-share listed companies from 2012 to 2025, this study examines the effect of digital transformation on firm-level TFP. Firms with a higher degree of digital transformation exhibit higher TFP, suggesting that the application of artificial intelligence and related digital technologies supports production efficiency. Asset utilization efficiency serves as a partial mediator. The main findings remain valid when TFP is re-estimated using the OP method, the sample is modified, PSM is applied, and an instrumental-variable specification is used. The effect varies across firms: it is significantly stronger in western than in eastern China and is insignificant in central China; it is significantly stronger among state-owned enterprises than among non-state-owned enterprises; and it is significant for labor-intensive and capital-intensive firms but not for technology-intensive firms.

6.2. Policy Recommendations

First, corporate digital infrastructure should be improved. The government should continue to develop the industrial internet, computing-power networks, and data-service platforms to reduce the cost of digital transformation. Firms should apply AI, big data, and cloud computing to relevant business activities according to operational needs, while strengthening data integration and talent development to achieve deeper integration between digital technologies and core business processes.

Second, digital transformation should be promoted through region-specific strategies. Western China should continue to strengthen digital infrastructure and the supply of specialized talent and technical services to fully realize its digital advantages. Central China should focus on bridging the disconnect between digital facilities and corporate operations and strengthen the practical application of digital technologies. Eastern China should improve the quality of digital applications, with particular emphasis on AI, intelligent supply chains, and data-driven innovation.

Third, support for the digital transformation of non-state-owned enterprises should be strengthened. Governments and financial institutions can provide targeted loans and technological-upgrading subsidies to alleviate financing and technical constraints faced by private firms. State-owned enterprises should be encouraged to open digital platforms and supply-chain application scenarios to upstream and downstream small and medium-sized enterprises. Digital-project performance evaluation should also be strengthened to prevent redundant construction and inefficient investment.

Fourth, firms should select digital transformation pathways that match their industry characteristics. Labor-intensive firms should promote production automation and employee digital-skills training to reduce repetitive work and improve labor efficiency. Capital-intensive firms should strengthen the application of AI to improve asset utilization. Technology-intensive firms should avoid simply expanding digital investment and instead integrate digital technologies more deeply with R&D, knowledge management, and the commercialization of research outcomes.

6.3. Research Limitations and Future Directions

This study has several limitations. First, its digital-transformation indicator is constructed from annual-report text and does not fully capture actual technology use, report length, or strategic disclosure practices. Second, although PSM and an instrumental-variable approach mitigate endogeneity concerns, reverse causality and unobserved confounders cannot be ruled out completely. Third, the mechanism analysis focuses on asset utilization efficiency and does not identify other channels. Future research could improve measurement by combining textual indicators with data on actual digital-technology investment; exploit exogenous policy shocks to reduce endogeneity and strengthen causal inference; and

investigate additional channels as well as the long-run dynamic effects of digital transformation on firm-level TFP.

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