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On the Impact of Digital Transformation on Firm Profitability: Evidence from Heterogeneous Industries

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Abstract

Uncovering the heterogeneous impact of digital transformation on corporate profitability across industries is of critical importance, as it enables enterprises to avoid misguided transformation initiatives and assists governments in designing targeted industrial policies. Current literature has largely neglected the moderating role of industry-specific characteristics, limiting its capacity to inform context-specific strategies. To address this gap, this study constructs a firm-level digital transformation index using textual analysis of annual reports from A-share listed companies between 2010 and 2023, and employs a two-way fixed effects model for empirical validation. The results demonstrate that although digital transformation significantly improves the average return on assets, its effects are highly sector-dependent: it generates substantial profitability gains in the energy and information technology sectors, yet yields only marginal or even negative returns in both discretionary and consumer staples industries. These findings remain robust after controlling for endogeneity through instrumental variable estimation and undergoing a battery of robustness checks, including alternative variable specifications and sample period adjustments. This research underscores that digital transformation does not uniformly enhance profitability-its efficacy is moderated by industry characteristics-and offers empirical support for enterprises to eschew one-size-fits-all approaches and adopt context-aware transformation strategies.

Keywords

digital transformation, corporate profitability, industry heterogeneity, textual analysis, two-way fixed effects model

1. Introduction

The world is currently undergoing profound transformation driven by next-generation information technologies such as cloud computing, big data, artificial intelligence (AI), and the Internet of Things (IoT). The entry of human society into the digital economy era has accelerated.

Digital transformation is no only an optional choice for enterprises but also a core strategy concerning survival and development. Governments worldwide have elevated digital development to a national strategic level, exemplified by China's ‘Digital China’ initiative and the European Union's ‘Digital Europe Programme,’ aiming to incentivise industrial upgrading and innovation through policy guidance. Against this macro background, enterprises across traditional manufacturing, services, and emerging high-tech sectors alike confront the critical challenge of how to effectively implement digital transformation to secure sustainable competitive advantages in fiercely contested markets.

Despite the substantial investment required and its recognition as an inevitable trend, the pathways to realising value and the associated economic benefits are neither linear nor predetermined. Academic discourse has previously addressed a similar 'IT productivity paradox,' where substantial investments in information technology failed to yield commensurate productivity gains. Today, as digital transformation represents a more advanced form of IT investment, its relationship with corporate financial performance-particularly profitability-remains an area requiring deeper exploration. Many enterprises have invested heavily in digital upgrades yet failed to achieve anticipated profit returns, finding themselves trapped in a predicament of 'transformation without efficiency gains.'

This raises a fundamental question: how precisely does digital transformation impact corporate profit margins? Does its mechanism of influence vary according to industry characteristics? The existing research broadly acknowledges the positive effects of digital transformation, such as optimising operational efficiency, innovating business models, and enhancing customer experience. However, whether these positive factors ultimately translate into tangible profit growth requires validation through rigorous empirical studies. Particularly across different industries, variations in technological foundations, market structures, regulatory environments, and value chain positions may lead to significant differences in the pathways, priorities, and outcomes of digital transformation.

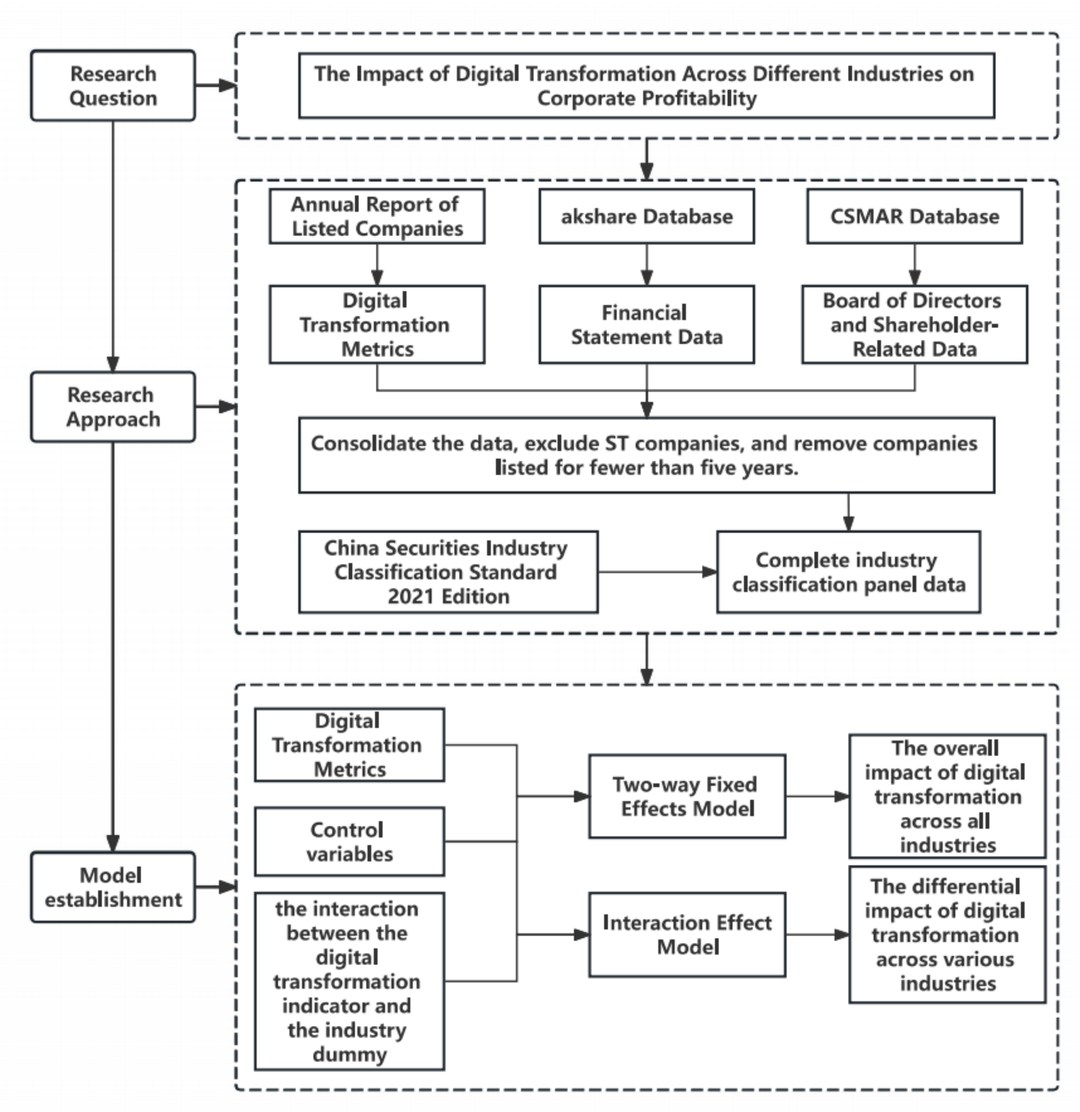
While scholars worldwide have produced substantial research in this field, gaps persist. Most studies either focus on specific industries or employ mixed regression analyses across all industries, overlooking how inherent industry attributes moderate the effectiveness of digital transformation.

This study therefore aims to address this research gap. Its core objective is to construct a systematic, cross-industry comparable digital transformation indicator system. Using multi-industry panel data, it empirically examines the impact of different digital transformation dimensions on corporate profit margins, with a particular focus on revealing and explaining the heterogeneity of this impact across sectors.

2. Research Framework

The research framework for this paper is illustrated in Figure 1.

Figure 1: Research framework



3. Current State of Research at Home and Abroad

In recent years, emerging technologies such as artificial intelligence, big data, and cloud computing have developed rapidly. While significantly enhancing social operational efficiency and public convenience, they have also raised the bar for corporate sustainable competitiveness. The iterative evolution of advanced production tools indicates that traditional production models are gradually becoming obsolete, making it imperative for enterprises to undergo digital transformation to achieve systematic upgrades in their technological infrastructure and management models, thereby navigating an increasingly complex and uncertain market environment.

Numerous scholars have explored the mechanisms through which digital transformation affects corporate performance from various dimensions (Ye and Liu, 2024, Wu et al., 2024, Gaglio et al., 2022, Li et al., 2024), with research perspectives covering areas such as optimized resource allocation and the moderating role of policy environments.

Other researchers have focused on how digital transformation influences corporate Return on Assets (ROA) (Wang et al., 2023a, Zhou and Guo, 2023, Peng and Tao, 2022, Li et al., 2023, Zeng et al., 2024). By constructing different models and selecting diverse variables, they have conducted in-depth analyses of whether digital transformation can comprehensively improve corporate operational performance and overall performance levels. Most studies suggest that digital transformation enhances ROA, though some scholars point out that it entails significant hidden costs, which may adversely affect certain firms (Qi and Cai, 2020).

However, there remains a lack of systematic research on "which types of enterprises are more likely to experience negative effects due to digital transformation."

Regarding the differential impact of digital transformation across industries, as early as 2021, scholars noted that existing research often failed to examine the issue of digital empowerment in different industries from the perspective of technological paradigms (Li and Lv, 2021). Since then, most related studies have been limited to analyzing the impact of digital transformation on specific industries (Dang et al., 2021, Wang et al., 2023b, Wu et al., 2021a, Zhou et al., 2024, Gan et al., 2023, Homburg and Wielgos, 2022), with no systematic comparison or explanation of the variations in digital transformation effects across industries and the underlying logic.

4. Research Hypotheses

The core determinants of corporate Return on Assets (ROA) include production efficiency, sales performance, and cost structure. The digital marketing capabilities enabled by digital transformation-such as data analytics, AI-powered forecasting, and channel integration-can significantly enhance marketing effectiveness, thereby improving overall corporate profit margins (Xu and Pan, 2022). Furthermore, digital transformation contributes to increased production efficiency (Zhao et al., 2021).

In terms of costs, digital transformation may lead to cost savings through the adoption of advanced production technologies, yet it may also incur substantial hidden costs. These include organizational resistance to change, technical compatibility issues, system restructuring expenditures, and high initial investments. At the same time, systematic differences across industries-such as in technological foundations, market structures, asset attributes, and competitive dynamics-collectively shape a distinctly industry-specific "benefit–cost" structure of digital transformation. In industries characterized by strong technology absorption capacity and rapidly changing market demand, digital technologies tend to generate synergistic effects, allowing benefits to be realized more smoothly. By contrast, in sectors with high asset specificity and rigid production processes, transformation may entail high disruptive costs, which could fully offset potential gains in the short run. As a result, the net impact of digital transformation on ROA manifests through complex and varied pathways across different industries.

Based on the above analysis, this study proposes the following hypotheses:

H1: At the full-industry level, the extent of a firm's digital transformation has a significant positive effect on its profitability.

H2: The impact of digital transformation on corporate profitability varies significantly across industries, specifically in terms of both the direction (positive or negative) and the magnitude of the effect.

5. Data Sources, Processing and Model Specification

5.1 Data acquisition and Processing

The data utilized in this study are derived from the income statements and balance sheets of A-share listed companies spanning the period 2010–2023, with all financial indicators sourced from the akshare database. Additionally, corporate governance and basic characteristic variables, such as board size and firm age, were supplemented from the CSMAR database. During the data preprocessing phase, the following steps were undertaken: samples with missing core financial indicators were excluded; stocks designated with Special Treatment (ST) status, companies listed for less than five years, and records lacking clear and critical industry classification information were removed; and the Return on Assets (ROA) variable was winsorized at the 1% level.

The degree of corporate digital transformation was measured following the methodology established by Wu et al. (2021a). This involved text crawling of corporate annual reports, calculating the frequency of keywords based on a predefined dictionary, and constructing the digital transformation indicator by taking the natural logarithm of the total word frequency.

Upon completion of the above data processing, financial data, the digital transformation indicator, and other control variables were matched and merged according to company code and fiscal year. Furthermore, this study adopts the CSI Industry Classification Standard (2021 Edition) for sector categorization. All listed companies are classified into 11 primary industries: Energy, Raw Materials, Industrial, Consumer Discretionary, Consumer Staples, Health Care, Financial, Information Technology, Communication Services, Utilities, and Real Estate.

5.2 Variable Specification

5.2.1 Dependent Variables

Return on Assets (ROA): This study employs ROA as a core indicator to measure corporate profitability and resource allocation efficiency. A higher ROA value signifies superior performance in cost control and operational efficiency, thereby reflecting stronger input-output effectiveness.

$$\mathrm{ROA} = \frac{\text{Net Income}}{\text{Asset}} \times 100\%$$

Return on Equity (ROE): ROE reflects the efficiency of a company's capital utilization. In this study, it is employed as a measure for robustness checks.

$$\mathrm{ROE} = \frac{\text{Net Income}}{\text{Shareholder's Equity}} \times 100\%$$

5.2.2 Explanatory Variables

Enterprise Digital Transformation Indicator (DT): Through text analysis, keywords related to digital transformation were identified and counted within the annual reports of sample enterprises over successive years, and their total word frequency was calculated. To further smooth data fluctuations and mitigate heteroscedasticity, the word frequency data were increased by one, and then the natural logarithm was taken, ultimately constructing a proxy variable for the degree of enterprise digital transformation.

$$\mathrm{DT} = \ln(\text{Frequency of Terms Related to Digital Transformation in Annual Reports} + 1)$$

5.2.3 Control Variables

The following variables are selected as control variables in this study: firm size (Size), debt-to-asset ratio (LEV), firm age (Age), number of board directors (Board), proportion of independent directors (Indep), ownership concentration (Cent1), and net cash flow (Cash).

Table 1: Variable definition

Variable category	Variable name	Symbol	Variable definition
Dependent variables	Return on Assets	ROA	Net Income/Assets×100%
	Return on Equity	ROE	Net Income/Shareholder’s Equity×100%
Explanatory Variables	Enterprise Digital Transformation Indicator	DT	The log-transformed word frequency (plus one) of digital transformation terms from annual reports.
Control Variables	Enterprise Scale	Size	The logarithm of a company's total assets at year-end
	Debt-to-asset Ratio	LEV	Total liabilities at year-end / Total assets at year-end
	Company Age	Age	ln(Current Year - Founding Year + 1)
	Number of Directors	Board	The logarithm of the number of directors at year-end
	Proportion of Independent Shareholders	Indep	Number of independent shareholders / Total number of shareholders
	Concentration of Shareholding	Cent1	Shareholding ratio of the company's largest shareholder
	Net Cash Flow	Cash	Net cash flow after Min-Max normalisation

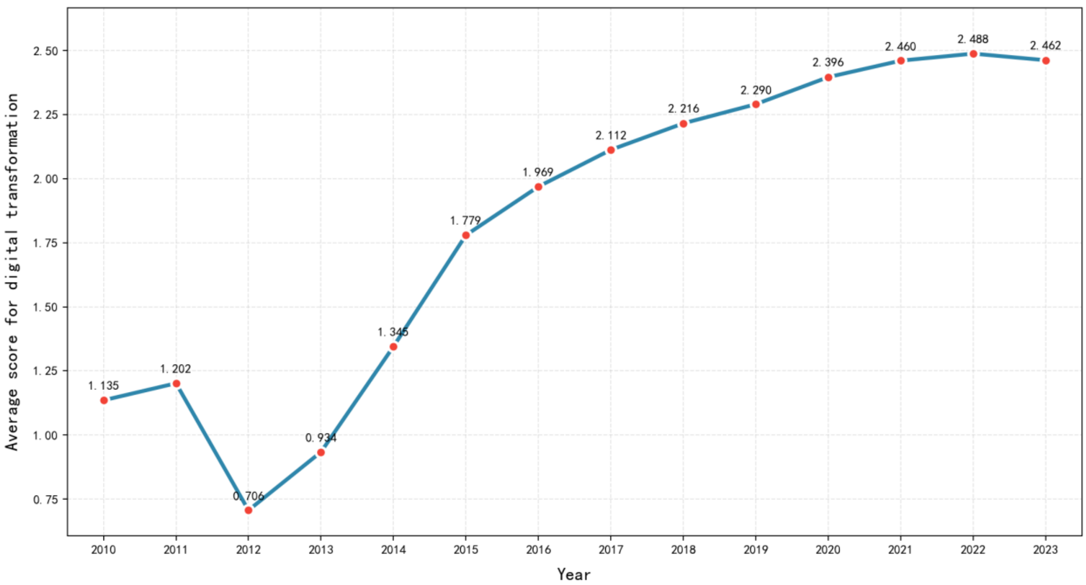
5.3 Descriptive Statistical Analysis

The descriptive statistics of the relevant variables in this study are presented in Table 2. The dependent variable, ROA, has a mean of 0.03 and a standard deviation of 0.08, with minimum and maximum values of -2.1 and 4.84, respectively. The standard deviation exceeding the mean, coupled with the wide range between extremes, indicates significant disparities in profitability across firms, with some enterprises experiencing substantial losses. The core explanatory variable, DT, displays a mean of 1.45 and a standard deviation of 1.43, ranging from 0 to 6.31. The pronounced dispersion of this variable reveals an uneven landscape in the progression of digital transformation among firms and industries within the sample. Furthermore, to examine temporal trends, the annual mean values of DT were plotted. The results demonstrate a clear upward trajectory from 2010 to 2023, corroborating the overall advancement of digital transformation among Chinese enterprises during this period.

Table 2: Statistical analysis

Variable name	Sample size	Mean	Standard Deviation	Minimum value	Maximum value
ROA	36433	0.03	0.08	-2.1	4.84
ROE	36433	0.03	1.06	-150.61	19.38
DT	36433	1.45	1.43	0	6.31
Size	36433	22.23	1.36	14.94	29.95
LEV	36433	0.43	0.21	0.01	1.94
Age	36433	2.91	0.36	0	4.19
Board	36433	2.28	0.26	1.39	3.4
Indep	36433	0.38	0.07	0.17	0.8
Cent1	36433	0.22	0.18	0	0.89
Cash	36433	0.01	0.01	-0.43	0.29
ROA	36433	0.03	0.08	-2.1	4.84

Figure 2: Annual Average Trend in Digital Transformation Indicators



5.4 Model Establishment

To address the hypotheses proposed in this study, the following model is established:

$$ROA_{it} = \beta_0 + \beta_1 DT_{it} + \sum[\gamma_j \times (DT_{it} \times Industry_j)] + \theta \times Control_{it} + \mu_{it} + \lambda_{it} + \varepsilon_{it}$$

Here, ROA_{it} is the dependent variable, representing the Return on Assets of firm i in the year t. DT_{it} denotes the digital transformation indicator of the firm. $Industry_j$ is the industry dummy variable, with one industry serving as the baseline. γ_j represents the key coefficients, indicating the differential impact of digital transformation on ROA in industry j relative to the baseline industry. $Control_{it}$ is the set of control variables. μ_i denotes firm fixed effects, controlling for time-invariant firm characteristics. λ_{it} represents time fixed effects, accounting for macroeconomic shocks. ε_{it} is the idiosyncratic error term.

Table 3: Baseline regression results

	(1)ROA	(2)ROA	(3)ROA	(4)ROE	(5)ROE
DT	0.0010*** (3.1478)	0.0059*** (3.3382)	0.0058** (2.3835)	0.0029*** (4.1702)	0.0192*** (3.6930)
Cent1		-0.0129*** (-7.3595)	-0.0181*** (-7.8158)		-0.0129*** (-3.2097)
Cash		0.0903*** (3.1231)	0.0820*** (2.7380)		0.2436*** (3.5526)
LEV		-0.1207*** (-41.879)	-0.1424*** (-37.833)		-0.1941*** (-24.194)
Size		0.0095*** (14.055)	0.0151*** (15.798)		0.0282*** (16.608)
Age		-0.0104*** (-3.5909)	-0.0349*** (-5.9223)		0.0002 (0.0261)
Board		-0.0070*** (-5.5178)	-0.0077*** (-5.0601)		-0.0181*** (-5.8715)
Indep		0.0120*** (3.3008)	0.0126*** (2.9760)		0.0289*** (3.4167)
DT_Raw Material		-0.0015 (-0.7578)	-0.0015 (-0.5698)		-0.0103* (-1.8653)
DT_Industrial		-0.0053*** (-2.9472)	-0.0054** (-2.1693)		-0.0180*** (-3.4294)
DT_Consumer Discretionary		-0.0071*** (-3.7728)	-0.0068*** (-2.6464)		-0.0211*** (-3.9236)
DT_Consumer Staples		-0.0066*** (-3.1508)	-0.0090*** (-3.1063)		-0.0214*** (-3.6868)
DT_Healthcare		-0.0054*** (-2.7229)	-0.0053** (-1.9726)		-0.0179*** (-3.2045)
DT_Financial		-0.0060*** (-3.0545)	-0.0068*** (-2.6109)		-0.0187*** (-3.2999)
DT_Information Technology		-0.0042** (-2.2138)	-0.0014 (-0.5587)		-0.0155*** (-2.9002)
DT_Telecommunications Services		--0.0047** (-2.3730)	-0.0040 (-1.4990)		-0.0182*** (-3.2355)
DT_Public Utilities		-0.0048** (-2.4047)	-0.0063** (-2.3750)		-0.0163** (-2.8866)
DT_Real Estate		-0.0057*** (-2.7048)	-0.0046 (-1.5895)		-0.0148** (-2.4168)
Year Fixed Effects	Y	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y	Y
Total Number of Records	36433	36433	28218	36433	36433

*Figures in parentheses are t-values. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The same convention applies hereafter.*

6. Empirical Findings

6.1 Overall Data Regression Analysis

The baseline regression results are presented in Table 3. In columns (1) and (4), the core explanatory variable DT is directly regressed on the dependent variables, Return on Assets (ROA) and Return on Equity (ROE), while controlling for year and firm fixed effects. In columns (2), (3), and (5), control variables and the interaction terms between the industry dummies and the digital transformation indicator are further incorporated. Using the energy sector-the industry with the highest digital returns-as the baseline category, separate regressions are performed for ROA and ROE. The coefficient of the core explanatory variable DT is significantly positive at the 1% level across all specifications, indicating that, across the full sample, an increase in the degree of digital transformation significantly enhances both ROA and ROE. Column (3) excludes data from 2010–2013 and uses only the ten-year data from 2014–2023 for regression; the results continue to show a significant positive effect of the digital transformation indicator on corporate ROA. These findings suggest that digital transformation effectively improves corporate profitability overall, thereby providing support for theoretical Hypothesis 1.

To more intuitively present the specific impact of digital transformation in each industry, this study calculates the "total digital effect" for each sector based on the following equation and summarizes the results in Table 4.

$$Total\ \ DT\ \ Effect\ \ on\ \ ROA = Baseline\ \ ROA\ \ Effect + Interactive\ \ ROA\ \ Effect$$

$$Total\ \ DT\ \ Effect\ \ on\ \ ROE = Baseline\ \ ROE\ \ Effect + Interactive\ \ ROE\ \ Effect$$

Columns (1) to (3) report the total effects of DT on ROA across industries for 2010–2023, the total effects of DT on ROA for 2014–2023, and the total effects of DT on ROE for 2010–2023, respectively. The results reveal a distinct stratification of profitability enhancement effects from digital transformation across industries.

High-Return Industries: The energy sector exhibits total effects of digital transformation on both ROA and ROE that far exceed those of other industries. This may stem from the asset-intensive nature of the energy industry, where digital technologies generate substantial economies of scale and cost savings by optimizing exploration, extraction, supply chain management, and energy efficiency.

Medium-Return Industries: Sectors such as information technology, communication services, raw materials, and utilities show significantly positive total effects. These industries are either inherently aligned with digital technologies as providers or enablers, or their operational processes are naturally compatible with digitalization, allowing them to effectively absorb and translate digital dividends.

Low- or Negative-Return Industries: The consumer discretionary and consumer staples sectors display negative total effects from digital transformation. Meanwhile, industries including industrial, health care, financial, and real estate show positive but marginal total effects, close to zero, indicating limited marginal returns on their digital transformation initiatives.

It is noteworthy that the ranking of total digital effects across industries and their significance patterns remain highly consistent, regardless of whether the dependent variable is changed from ROA to ROE or the sample period is adjusted. This finding strongly supports Hypothesis H2 and demonstrates considerable robustness.

Table 4: Total Effects of Digital Transformation on ROA and ROE by Industry

Industry Name	(1)Total DT Effect on ROA	(2)Total DT Effect on ROA	(3)Total DT Effect on ROE
Energy	0.0059	0.0058	0.0192
Raw Materials	0.0044	0.0043	0.0089
Industrial	0.0006	0.0004	0.0011
Consumer Discretionary	-0.0012	-0.0010	-0.0020
Consumer Staples	-0.0007	-0.0032	-0.0032
Health Care	0.0004	0.0005	0.0012

Industry Name	(1)Total DT Effect on ROA	(2)Total DT Effect on ROA	(3)Total DT Effect on ROE
Financial	-0.0001	-0.0010	0.0005
Information Technology	0.0017	0.0044	0.0037
Communication Services	0.0012	0.0018	0.0010
Utilities	0.0011	-0.0005	0.0029
Real Estate	0.0001	0.0013	0.0043

6.2 Endogeneity Analysis

To address potential reverse causality between digital transformation and corporate Return on Assets (ROA), this study employs a two-stage least squares (2SLS) estimation with an instrumental variable. Following the approach of Larcker et al. (Larcker and Rusticus, 2010), the instrumental variable is constructed as the mean digital transformation level of other firms in the same industry and same year.

In the first-stage regression, the coefficient of the instrumental variable is 0.9867 and is highly significant at the 1% level, indicating a strong positive correlation between the instrumental variable and the endogenous variable, thereby satisfying the relevance condition. The F-statistic of 2548.88 substantially exceeds the conventional threshold of 10, confirming the absence of a weak instrument and supporting the validity of the instrumental variable.

In the second-stage regression, the predicted value of digital transformation from the first stage is regressed on ROA. The estimated coefficient of the digital transformation indicator is 0.0011 and remains highly significant at the 1% level. This result demonstrates that, even after controlling for endogeneity, digital transformation continues to exert a statistically significant positive effect on corporate ROA.

Table 5: Regression results using the instrumental variables method

	Stage 1(DT)	Stage 2(ROA)
Instrumental Variable	0.9867*** (137.56)	
Predicted DT		0.0011*** (4.83)
Control Variables	Y	Y
F-statistic	2548.88	1004.33
Firm Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
Total number of Records	36433	36433

6.3 Robustness Checks

6.3.1 Alternative Measure of the Dependent Variable

In the baseline regressions, Return on Assets (ROA) serves as the primary proxy for corporate profitability. To further verify the robustness of the findings, this study repeats the regression analysis using Return on Equity (ROE) as an alternative measure. As shown in Columns (4) and (5) of Table 3, the coefficient of the digital transformation indicator remains significantly positive. Furthermore, the significance patterns of the industry interaction terms are highly consistent with those observed when ROA was the dependent variable. This confirms that the core findings are robust to the choice of profitability metric.

6.3.2 Adjusted Sample Period

To mitigate potential concerns regarding the influence of the sample period selection, the analysis is repeated using a restricted sample spanning the ten-year period from 2014 to 2023, with ROA re-estimated as the dependent variable. As presented in Column (3) of Table 3, the coefficient of the digital transformation indicator (DT) for the baseline industry (Energy) remains statistically significant and positive, with a magnitude similar to the full-sample estimate. Additionally, the total effects of digital transformation on ROA across industries, reported in Column (2) of Table 4, align closely with the estimates derived from the full 2010–2023 sample. These findings collectively indicate that the study's conclusions maintain strong stability and reliability across different sample periods.

7. Conclusion

Based on data from A-share listed companies from 2010 to 2023, this study constructs a corporate digital transformation indicator using textual analysis and employs a two-way fixed effects model to systematically examine the impact of digital transformation on corporate profitability and its variation across different industries. The findings reveal that digital transformation significantly enhances corporate profitability overall. In the full-sample regressions, the digital transformation indicator exerts a significantly positive effect on both Return on Assets (ROA) and Return on Equity (ROE). Moreover, the impact of digital transformation varies substantially across sectors: the energy industry exhibits the highest returns from digitalization, followed by sectors such as information technology and communication services, while consumer discretionary and consumer staples industries experience negative or near-zero marginal benefits. The core conclusions remain robust after a series of checks, including substituting the dependent variable, adjusting the sample period, and addressing endogeneity through instrumental variable estimation, indicating the reliability of the findings.

The results of this study offer important implications for both corporate practices and policy formulation. At the corporate level, firms should develop differentiated digital transformation strategies tailored to their industry characteristics. High-return industries may intensify digital investments, while low-return sectors should carefully evaluate the costs and benefits of transformation, emphasizing path optimization and risk control. At the policy level, governments should design industry-specific digital support policies rather than adopting a one-size-fits-all approach. For industries with low marginal returns from digital transformation, policy measures such as tax incentives, technical training, and public platform development could help reduce transformation costs and enhance implementation efficiency.

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Conflicts of Interest

The authors declare no conflict of interest.

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