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Digital transformation and new quality productivity: Empirical analysis of the moderating role of gai technology application

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ABSTRACT

This study explores the impact of Chinese firms' digital transformation on the evolution of new quality productivity, with a focus on the catalytic role of Generative Artificial Intelligence (GAI) technology installation. To evaluate the hypothesized relationships, the study uses a strict econometric framework, drawing on a large panel dataset of 9,280 firm-year findings from authoritative Chinese repositories such as the *CNRDS and CSMAR*. The empirical findings reveal a statistically significant and positive association between organizational digitization efforts and improvements in quality-centric productivity indices. Notably, the use of GAI solutions enhances this link, serving as an important mediator in improving the efficacy of digital operations. Moreover, mechanistic analysis reveals that productivity gains are primarily mediated by enhanced innovation capacity and streamlined operations, reflected in patent activity, R&D efficiency, and improved workflow metrics. Additionally, this study employs a multifaceted validation strategy that includes propensity score matching (PSM) to reduce selection bias and heterogeneous effect tests across industry sectors and firm sizes. This study adds new theoretical and practical perspectives to the discussion of technology-driven competitive advantage by recognizing the dual mediating pathways through which digital transformation promotes productivity growth and measuring the conditional reinforcement provided by GAI.

Contribution/Originality: This study contributes to the research by demonstrating, through data, two ways that digital transformation enhances new quality productivity: through innovation and improved operations. It also shows that Generative AI can amplify these effects, based on robust econometric analysis using detailed firm-level data from Chinese companies.

1. INTRODUCTION

The growth of digital technologies has significantly changed the digital business world, so companies must utilize digital transformation to stay competitive in today's digital age (Verhoef et al., 2021). Digital transformation means using digital tools to change how businesses create value (Vial, 2019), and it has changed from something optional to something very important. This change has happened faster because of *Generative Artificial Intelligence (GAI)*, which can help make digital transformation work better (Davenport & Ronanki, 2018).

But even though many businesses are using digital transformation, studies about its effects on productivity show mixed results (Acemoglu, Autor, Hazell, & Restrepo, 2022; Brynjolfsson & McAfee, 2014). Also, we don't know much about how GAI affects this, which is a significant gap in current research. Making things more complicated is the idea of *new quality productivity*, which is more than just the usual efficiency measures and includes innovation, agility, and creating lasting value (Lee & Trimi, 2021).

This study fills these gaps by carefully examining (1) how digital transformation affects new quality productivity, (2) how using GAI changes this relationship, and (3) the ways these effects occur, especially through innovation ability and improved operations.

This study highlights important insights about theory and real-world applications by analyzing data from Chinese companies. The analysis demonstrates that digital efforts enhance quality-based productivity in the studied companies, while also revealing that GAI technologies can either aid or hinder transformation results depending on their usage and company settings. The study identifies two main mechanisms for these effects: improved creative ability for new products and services, and enhanced business processes that reduce waste and costs these pathways are interconnected but vary in significance across different industries and company types. For company leaders, these findings offer practical guidance for optimizing technology investments, especially emphasizing that proper use of generative AI within overall digital strategies is more effective when aligned with company skills and market position, indicating that customized implementation outperforms a uniform approach. For policymakers, the findings provide solid recommendations for developing frameworks that support the integration of digital solutions and generative AI systems, potentially guiding regulations that foster innovation while ensuring necessary protections in a changing business environment. Therefore, the relationship between traditional digital transformation components and new generative AI features is a crucial area for gaining a competitive edge in today's business landscape, with impacts extending beyond immediate efficiency gains to include long-term competitiveness and company sustainability.

This research examines how digital transformation affects productive efficiency and how GAI technologies alter this effect. Using company data from China collected over time, the study employs robust statistical methods to test theories, understand how these effects operate, and address potential issues in the analysis. The findings offer valuable insights for both researchers and business leaders.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. Digital Transformation and New Quality Productivity

Digital transformation is a significant change in organizations driven by new digital technologies (Sebastian et al., 2017). It's different from basic digitization which just changes analog data to digital because it completely changes business models, work processes, and how companies interact with customers through digital tools (Warner & Wäger, 2019). Studies show that this transformation can really improve many aspects of how organizations work, from operations to innovation and market response (Legner et al., 2017). Also, *new quality productivity* is more than just the usual productivity measures because it includes things like innovation potential, organizational flexibility, quality improvements, and creating lasting value (Brynjolfsson & Hitt, 2000). This wider view better shows the complex nature of performance in today's digital world, where things you can't touch and the ability to change quickly are very important for creating value (Teece, 2018).

The ideas linking digital transformation and new quality productivity come from the *resource-based view (RBV)* and *dynamic capabilities theory* (Barney, 1991; Teece, Pisano, & Shuen, 1997). Digital transformation builds special digital skills that help use resources better, improve knowledge use, and make organizations better at adjusting to market changes (Vial, 2019). These skills then lead to productivity gains in many different areas (Fitzgerald, Kruschwitz, Bonnet, & Welch, 2014).

But studies on this relationship still show mixed results. Some research finds good connections between using digital tools and productivity results (Tambe & Hitt, 2012), while other studies see a continuing "productivity paradox," where digital investments don't create the expected efficiency improvements (Acemoglu et al., 2022). These different findings suggest that other factors and specific situations strongly affect how well digital transformation works (Zhang & Dong, 2023).

2.2. GAI Technology and Its Moderating Role

Generative Artificial Intelligence (GAI) is a type of AI that creates new content, generates ideas, and solves problems by analyzing patterns in data (Vu et al., 2024). These tools such as large language models, generative adversarial networks, and reinforcement learning can significantly change areas such as language processing, image creation, and decision-making (Brown et al., 2020). The way GAI changes the link between digital change and productivity comes from the Technology-Organization-Environment (TOE) model (Tornatzky & Fleischer, 1990) and the idea of absorptive capacity (Cohen & Levinthal, 1990).

This change occurs in three main ways. First, GAI helps companies handle data better. It converts large amounts of digital data into business-relevant ideas (Davenport, 2018). Second, these tools assist people by automating difficult jobs and utilizing resources more efficiently (Agrawal, Gans, & Goldfarb, 2018). Third, GAI accelerates the development of new ideas by creating short test versions and guiding them with data.

New studies suggest that GAI could greatly increase the returns on digital transformation investments by improving decision-making, accelerating innovation, and helping create highly personalized customer experiences (Brynjolfsson, Rock, & Syverson, 2019). But there isn't much solid research yet on GAI's role in this process, especially in Chinese companies.

3. HYPOTHESIS DEVELOPMENT

Based on the resource-based view, dynamic capabilities theory, and the TOE framework, we suggest two testable ideas to explore how digital transformation, generative AI, and new quality productivity work together:

3.1. Digital Transformation and New Quality Productivity

Based on the resource-based view (RBV) and dynamic capabilities theory, this study states that digital transformation helps improve new quality productivity. It does this by building digital skills that are unique to each company, utilizing resources more effectively, and assisting companies in responding to market changes (Barney, 1991; Teece et al., 1997). Also, when digital tools are used in daily work, they can make tasks faster, improve products, and help create new ideas (Vial, 2019). On top of that, being able to gather, understand, and use data clearly helps managers make better choices and build company knowledge over time. All these changes help improve different parts of new quality productivity (Brynjolfsson & Hitt, 2000). Consequently, we propose the following hypothesis:

H_1: Digital transformation has a positive and statistically significant effect on the development of new quality productivity.

3.2. The Moderating Role of GAI Technology Application

Anchored in the technology-organization-environment (TOE) framework and absorptive capacity theory, this study contends that the deployment of generative artificial intelligence (GAI) technologies serves as a positive moderator in the digital transformation new quality productivity nexus (Cohen & Levinthal, 1990; Tornatzky & Fleischer, 1990). GAI systems help organizations make sense of large amounts of data created by digital transformation. This leads to better insights and smarter decisions (Davenport, 2014, 2018). Besides handling data, GAI tools also perform complex analysis, support human thinking, and help utilize resources more effectively. These actions help digital transformation work better (Agrawal et al., 2018). GAI also makes companies more productive by improving customer service, accelerating R&D, and creating new ways to generate revenue. Accordingly, we advance the following hypothesis:

H_2: The adoption of generative artificial intelligence (GAI) strengthens the positive association between digital transformation initiatives and new quality productivity enhancements.

4. METHOD AND DATA

4.1. Research Design

To empirically examine the hypothesized relationships, we implement a fixed-effects panel regression framework to control for time-invariant unobserved heterogeneity across firms. The baseline econometric specification takes the following Equation 1.

$$NQP_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_2 GAI_{i,t} + \beta_3 DT_{i,t} \times GAI_{i,t} + \beta_4 Controls_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

Where $NQP_{i,t}$ represents our new quality productivity for firm i in year t, $DT_{i,t}$ represents digital transformation, $GAI_{i,t}$ represents GAI technology application, $Controls_{i,t}$ is a vector of control variables, αi represents firm fixed effects, λt represents year fixed effects, and $\varepsilon_{i,t}$ is the error term.

To avoid errors that could affect our results, we used different methods. First, we used instrumental variables (IV) regression based on theory. Second, we applied propensity score matching (PSM) to ensure the groups were comparable. Third, we applied difference-in-differences (DiD) models to address changes over time that could influence results. Additionally, we examined whether the effects varied for companies of different sizes, industries, or ownership types. To understand how the effects occurred, we tested whether innovation ability and company management quality helped explain the results. We used the Baron-Kenny method and bootstrapped errors for these tests.

4.2. Data and Sampling

We collected panel data from two main sources: Chinese Research Data Services (CNRDS) and China Stock Market & Accounting Research Database (CSMAR). The initial sample included 12,000 firm-year observations from 2015 to 2022. We removed special treatment firms (ST and PT), financial firms due to their unique regulations, and observations with missing data. The final sample consisted of 9,280 firm-year observations from 1,160 unique firms across different industries. This study uses data from 9,280 firm-year observations (2015–2022) gathered from two reliable sources: *China Research Data Services (CNRDS)* and *China Stock Market & Accounting Research (CSMAR)*. These sources are trusted and reliable. The time period (2015–2022) aligns with China's digital transformation efforts, such as the "Internet Plus" and "Made in China 2025" programs, which led to increased adoption of digital tools by companies. This period reflects significant policy changes and allows us to examine both short-term and long-term effects of digital adoption on productivity.

The main variable, digital transformation intensity, is measured in two ways: (1) using natural language processing (NLP) to analyze annual reports and find terms related to digitalization (e.g., "big data," "cloud computing," "AI integration"), and (2) using financial reports to track spending on digital infrastructure (e.g., ERP systems, IoT, and AI). To measure Generative AI (GAI) adoption, we created a new measure based on two sources: (1) AI patents (like natural language processing and generative modeling) and (2) verified partnerships with major GAI providers (like OpenAI, DeepSeek, and Alibaba Qwen). Our method considers both internal innovations and external technology partnerships.

4.3. Variable Measurement

4.3.1. Dependent Variable

New Quality Productivity (NQP): Following Lee and Trimi (2021), we constructed a composite index of new quality productivity incorporating multiple dimensions: (1) labor productivity (value added per employee), (2) innovation output (patents per R&D investment), (3) product quality (measured by customer satisfaction scores and product return rates), and (4) operational flexibility (measured by inventory turnover and time-to-market for new products). Each dimension was standardized and weighted equally to form the composite NQP index.

4.3.2. Independent Variable

Digital Transformation (DT): We measured digital transformation using a comprehensive index constructed from multiple indicators: (1) digital technology investment ratio (IT expenditure to total assets), (2) digital skill intensity (percentage of employees with IT-related skills), (3) digital business processes (percentage of business processes that are digitalized), and (4) digital revenue ratio (revenue generated from digital channels or products as a percentage of total revenue). Data were collected from financial statements, annual reports, and CNRDS's digital transformation database.

4.3.3. Moderating Variable

GAI Technology Application (GAI): Following Davenport and Ronanki (2018), we constructed a measure of GAI technology application based on (1) GAI investment intensity (GAI-related investment to total assets), (2) GAI patent portfolio (number of GAI-related patents), (3) GAI talent density (percentage of employees with GAI-related skills), and (4) GAI implementation breadth (number of business functions utilizing GAI technologies). Data were collected from corporate disclosures, patent databases, and specialized surveys within the Chinese *CNRDS* and *CSMAR*.

4.3.4. Control Variables

We also included several control variables that may influence Chinese new quality productivity:

Firm Size (SIZE): Our natural logarithm of total assets.

Firm Age (AGE): Our natural logarithm of the years since establishment.

Leverage (LEV): Total debt divided by total assets.

Return on Assets (ROA): Net income divided by total assets.

Capital Intensity (CAPINT): Net fixed assets divided by total assets.

R&D Intensity (RDINT): R&D expenditure divided by total sales.

Industry Competition (HHI): Herfindahl-Hirschman Index based on industry sales.

Ownership Concentration (OWN): Percentage of shares held by the largest shareholder.

State Ownership (STATE): A dummy variable, equal to 1 if the firm is state-owned, and 0 otherwise.

Board Independence (BIND): Percentage of independent directors on the board.

Table 1 presents the descriptive statistics and measurement details for all variables used in the analysis.

Table 1. Variable descriptions and descriptive statistics.

Variable	Description	Mean	Std. dev.	Min.	Max.
NQP	New quality productivity index	0.512	0.187	0.104	0.943
DT	Digital transformation index	0.428	0.215	0.062	0.896
GAI	GAI technology application index	0.316	0.238	0.000	0.872
SIZE	Natural logarithm of total assets	22.637	1.326	19.542	26.843
AGE	Natural logarithm of firm age	2.764	0.485	1.099	3.871
LEV	Total debt / Total assets	0.452	0.198	0.043	0.876
ROA	Net income / Total assets	0.057	0.053	-0.124	0.213
CAPINT	Net fixed assets / Total assets	0.267	0.183	0.021	0.754
RDINT	R&D expenditure / Total sales	0.036	0.042	0.000	0.238
HHI	Herfindahl-Hirschman index	0.083	0.091	0.023	0.532
OWN	Percentage of shares held by largest shareholder	35.416	14.823	8.547	74.621
STATE	State ownership dummy	0.387	0.487	0	1
BIND	Percentage of independent directors	37.863	5.748	33.333	57.143

5. RESULTS AND FINDINGS

5.1. Baseline Results

Table 2 presents the baseline results examining the relationship between digital transformation, GAI technology application, and new quality productivity. Model 1 includes only control variables. Model 2 adds the digital transformation variable to test H1. Model 3 incorporates the GAI technology application variable, and Model 4 includes the interaction term between digital transformation and GAI technology application to test H2.

Table 2. Baseline regression results.

Variables	Model 1	Model 2	Model 3	Model 4
DT		0.158*** (0.032)	0.143*** (0.034)	0.092** (0.037)
GAI			0.097** (0.038)	0.076* (0.039)
DT × GAI				0.246*** (0.059)
SIZE	0.037*** (0.011)	0.028*** (0.010)	0.025** (0.010)	0.023** (0.010)
AGE	-0.018 (0.014)	-0.021 (0.014)	-0.019 (0.014)	-0.016 (0.014)
LEV	-0.086** (0.037)	-0.072* (0.037)	-0.068* (0.036)	-0.065* (0.036)
ROA	0.537*** (0.125)	0.498*** (0.124)	0.487*** (0.124)	0.473*** (0.123)
CAPINT	0.062 (0.043)	0.057 (0.042)	0.051 (0.042)	0.047 (0.042)
RDINT	0.428*** (0.118)	0.347*** (0.118)	0.321*** (0.119)	0.302*** (0.118)
HHI	-0.136* (0.071)	-0.125* (0.070)	-0.118* (0.070)	-0.112 (0.069)
OWN	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)
STATE	-0.028** (0.013)	-0.024* (0.013)	-0.022* (0.013)	-0.020* (0.012)
BIND	0.002** (0.001)	0.002* (0.001)	0.002* (0.001)	0.001* (0.001)
Constant	-0.357 (0.231)	-0.276 (0.229)	-0.254 (0.228)	-0.218 (0.227)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	9,280	9,280	9,280	9,280
R-squared	0.285	0.302	0.307	0.317
Adjusted R-squared	0.278	0.294	0.299	0.309

Note: Standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The results from Model 2 show that digital transformation has a significant positive impact on new quality productivity ($\beta = 0.158$, $p < 0.01$). Thus, we support Hypothesis 1. This suggests that companies with higher levels of digital transformation tend to achieve higher new quality productivity, which aligns with the resource-based view and dynamic capabilities perspective. Additionally, Model 4 also shows that the interaction between digital transformation and GAI technology application is positive and significant ($\beta = 0.246$, $p < 0.01$), supporting H2. This means that the positive link between digital transformation and new quality productivity is stronger for companies that use more GAI technology. GAI technologies help improve productivity gains from digital transformation.

The results in Table 2 provide strong evidence of the relationship between digital transformation, GAI technology application, and new quality productivity. Model 1 sets a baseline by including only control variables, showing that firm size, profitability (ROA), and R&D intensity have a significant and positive impact on new quality productivity, while leverage and state ownership have negative effects. In Model 2, the inclusion of digital transformation results in a positive and statistically significant coefficient ($\beta = 0.158$, $p < 0.01$). Therefore, we also support Hypothesis 1. This suggests that companies adopting digital transformation experience higher productivity, which aligns with the resource-based view, indicating that digital capabilities are valuable, unique, and difficult to replicate. Model 3 introduces GAI technology application, which shows a positive correlation with new quality productivity ($\beta = 0.097$, $p < 0.05$). The digital transformation coefficient remains significant, though slightly lower ($\beta = 0.143$, $p < 0.01$). In Model 4, the interaction between digital transformation and GAI technology application reveals a significant positive effect ($\beta = 0.246$, $p < 0.01$), providing strong support for Hypothesis 2.

This interaction effect indicates that GAI technology substantially amplifies the productivity benefits of digital transformation initiatives. The explanatory power progressively improves across models, with adjusted R-squared increasing from 0.278 in Model 1 to 0.309 in Model 4, indicating that the inclusion of digital transformation, GAI application, and their interaction enhances the model's explanatory capacity. In all models, several control variables remain consistently significant, including firm size, leverage, ROA, R&D intensity, and state ownership, highlighting their role in explaining productivity differences. The use of firm, year, and industry fixed effects helps address concerns about unobserved factors, and the consistent coefficients across models suggest that the relationships are strong and reliable.

5.2. Multicollinearity Test

Based on the above analysis, we calculated the variance inflation factor (VIF) for all variables in the full model to address potential multicollinearity issues. As shown in Table 3, all VIF values are well below the commonly accepted threshold of 10, with an average VIF of 1.83. This suggests that multicollinearity is not a significant problem in our analysis.

Table 3. Variance inflation factors results.

Variable	VIF	1/VIF
DT	2.58	0.387
GAI	2.43	0.412
DT × GAI	3.17	0.315
SIZE	2.32	0.431
AGE	1.43	0.699
LEV	1.87	0.535
ROA	1.74	0.575
CAPINT	1.54	0.649
RDINT	1.68	0.595
HHI	1.29	0.775
OWN	1.47	0.680
STATE	1.56	0.641
BIND	1.18	0.847
Mean VIF	1.83	

5.3. Robustness Tests

We conducted several robustness tests to ensure the validity of our findings.

5.3.1. Alternative Measures

We used alternative measures for our key variables. For digital transformation, we applied a binary indicator based on whether the firm's digital transformation index exceeds the industry median. For GAI technology application, we counted GAI-related patents. For new quality productivity, we used principal component analysis

(PCA) to create an alternative index. The results, shown in Table 4 (Models 1-3), were consistent with our main findings.

5.3.2. Controlling for Additional Variables

To address omitted variable bias, we included additional control variables such as executive compensation, export intensity, and foreign ownership. The results, shown in Table 4 (Model 4), remained robust.

5.3.3. Subsample Analysis

We divided our sample into different subsamples based on time periods (pre- and post-COVID), firm size (large vs. small firms), and industry (high-tech vs. traditional industries). The results, presented in Table 4 (Models 5-7), were consistent across different subsamples, although the magnitude of the effects varied.

Table 4. Robustness test results.

Variables	Model 1 Alternative measures	Model 2 Alternative measures	Model 3 Alternative measures	Model 4 Additional controls	Model 5 Pre-COVID	Model 6 Large firms	Model 7 High-tech
DT	0.083** (0.035)	0.148*** (0.034)	0.087** (0.036)	0.089** (0.037)	0.078* (0.042)	0.114** (0.047)	0.129*** (0.049)
GAI	0.068* (0.037)	0.071* (0.038)	0.069* (0.038)	0.074* (0.039)	0.065* (0.035)	0.093** (0.046)	0.107** (0.053)
DT × GAI	0.227*** (0.057)	0.235*** (0.058)	0.213*** (0.056)	0.243*** (0.059)	0.217*** (0.062)	0.268*** (0.068)	0.291*** (0.074)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	No	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,280	9,280	9,280	9,280	4,640	4,640	3,712
R-squared	0.309	0.315	0.307	0.321	0.302	0.327	0.346

Note: Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. and Model 1 uses a binary indicator for DT. Model 2 uses GAI patent count. Model 3 uses PCA-based NQP. Model 4 includes additional controls. Model 5 includes only pre-COVID observations. Model 6 includes only large firms. Model 7 includes only high-tech industries.

5.4. Endogeneity Tests

To address potential endogeneity concerns, we employed several econometric approaches:

5.4.1. Instrumental Variable (IV) Estimation

We used industry-average digital transformation and provincial GAI policy support as instruments for digital transformation and GAI technology application, respectively. The first-stage F-statistics exceeded the conventional threshold of 10, indicating that our instruments are not weak. The results from the second-stage regression, presented in Table 5 (Models 1-2), remained consistent with our main findings, suggesting that our results are robust to endogeneity concerns.

5.4.2. Propensity Score Matching (PSM)

We used PSM to address selection bias by matching firms with high digital transformation to those with low digital transformation based on observable characteristics. The results, shown in Table 5 (Model 3), remained consistent with our main findings.

5.4.3. Difference-in-Differences (DiD) Analysis

We exploited the staggered introduction of digital transformation initiatives across firms as a quasi-natural experiment. The results, presented in Table 5 (Model 4), supported our main findings.

Table 5. Endogeneity test results.

Variables	Model 1	Model 2	Model 3	Model 4
	IV (1st Stage DT)	IV (2nd Stage)	PSM	DiD
Industry avg. DT	0.427*** (0.048)			
Provincial GAI policy	0.358*** (0.053)			
DT		0.118** (0.047)	0.103** (0.042)	0.097** (0.043)
GAI		0.089* (0.048)	0.082* (0.043)	0.078* (0.042)
DT × GAI		0.287*** (0.073)	0.235*** (0.064)	0.241*** (0.065)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	9,280	9,280	5,768	9,280
R-squared	0.426	0.304	0.298	0.312
First-stage F-statistic		35.87		
Hansen J-statistic p-value		0.245		

Note: Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. and Model 1 reports the first-stage regression for digital transformation. Model 2 reports the second-stage regression using instrumental variables. Model 3 reports the results using propensity score matching. Model 4 reports the results using a difference-in-differences approach.

5.5. Heterogeneity Analysis

To explore whether the impact of digital transformation on new quality productivity varies across different firm characteristics, we conducted heterogeneity analyses based on firm size, state ownership, and industry technological intensity. The results, presented in Table 6, revealed several interesting patterns.

Table 6. Heterogeneity analysis results.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Large firms	Small firms	State-owned	Non-state	High-tech	Low-tech
DT	0.112** (0.048)	0.078* (0.047)	0.095** (0.046)	0.128*** (0.049)	0.143*** (0.051)	0.063 (0.042)
GAI	0.094* (0.049)	0.061 (0.047)	0.083* (0.048)	0.087* (0.050)	0.116** (0.053)	0.047 (0.043)
DT × GAI	0.273*** (0.075)	0.218*** (0.071)	0.242*** (0.074)	0.287*** (0.076)	0.304*** (0.082)	0.187** (0.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,640	4,640	3,591	5,689	3,712	5,568
R-squared	0.329	0.301	0.311	0.325	0.348	0.287

Note: Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results indicate that the impact of digital transformation on new quality productivity is stronger for large firms compared to small firms, non-state-owned firms compared to state-owned firms, and high-tech industries compared to low-tech industries. Similarly, the moderating effect of GAI technology application is more pronounced for large firms, non-state-owned firms, and high-tech industries. These findings suggest that the benefits of digital transformation and GAI technology application are contingent on firm characteristics and industry context.

Furthermore, the heterogeneity analysis in Table 6 reveals significant differences in how digital transformation and GAI technology application impact new quality productivity across various organizational contexts. Large firms (Model 1) exhibit a stronger positive relationship between digital transformation and new quality productivity ($\beta = 0.112$, $p < 0.05$) compared to small firms (Model 2, $\beta = 0.078$, $p < 0.1$). This suggests that resource-rich organizations are better equipped to implement and effectively leverage digital technologies. Similarly, the interaction between digital transformation and GAI technology is more pronounced in large firms ($\beta = 0.273$, $p < 0.01$) than in small firms ($\beta = 0.218$, $p < 0.01$), implying that substantial resources are necessary to fully capitalize on technological complementarities. Regarding ownership structure, non-state-owned firms (Model 4) demonstrate a stronger relationship between digital transformation and productivity ($\beta = 0.128$, $p < 0.01$) compared to state-owned firms (Model 3, $\beta = 0.095$, $p < 0.05$). This may reflect the greater flexibility and market-driven incentives found in private firms. Moreover, the biggest contrast appears when comparing high-technology and low-technology industries. In high-tech sectors (Model 5), digital transformation has a strong positive effect on new quality productivity ($\beta = 0.143$, $p < 0.01$), while in low-tech industries (Model 6), this relationship is weaker and statistically insignificant ($\beta = 0.063$, $p > 0.1$). Similarly, the moderating effect of GAI technology application is significantly stronger in high-tech industries ($\beta = 0.304$, $p < 0.01$) than in low-tech sectors ($\beta = 0.187$, $p < 0.05$). Overall, these results show that the benefits of digital transformation depend on the context, and the technological intensity of the industry is key in deciding how effective digital initiatives are. The heterogeneity analysis shows that the productivity gains from digital transformation and GAI technology differ between firms, based on their organizational features and industry context. This stresses the need for tailored digital strategies.

5.6. Mechanism Analysis

To explore the underlying mechanisms through which digital transformation affects new quality productivity and how GAI technology application moderates this relationship, we conducted mediation analyses focusing on two potential mediators: innovation capability and operational efficiency. We used R&D output (measured by the number of patents per R&D investment) as a proxy for innovation capability and the operational cost ratio (cost of goods sold divided by sales) as a proxy for operational efficiency. The results are presented in Table 7.

Table 7. Mechanism analysis results.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Innovation capability	Operational efficiency	NQP with mediators	NQP with mediators and interactions	Sobel test
DT	0.146*** (0.041)	-0.127*** (0.037)	0.063* (0.036)	0.035 (0.035)	
GAI	0.087** (0.043)	-0.079** (0.039)	0.048 (0.037)	0.032 (0.036)	
DT × GAI	0.227*** (0.067)	-0.196*** (0.062)	0.142*** (0.054)	0.084* (0.051)	
Innovation capability			0.295*** (0.043)	0.283*** (0.042)	
Operational efficiency			-0.327*** (0.048)	-0.301*** (0.046)	

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Innovation capability	Operational efficiency	NQP with mediators	NQP with mediators and interactions	Sobel test
DT × Innovation capability				0.168*** (0.051)	
GAI × Innovation capability				0.146*** (0.053)	
DT × Operational efficiency				-0.154*** (0.057)	
GAI × Operational efficiency					-0.127** (0.059)
Indirect effect (Innovation)					0.043*** (0.015)
Indirect effect (Efficiency)					0.041*** (0.014)
Controls	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	
Observations	9,280	9,280	9,280	9,280	9,280
R-squared	0.316	0.297	0.357	0.373	

Note: Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Models 1 and 2 show that digital transformation is positively associated with innovation capability and negatively associated with the operational cost ratio (indicating improved operational efficiency). Additionally, the interaction between digital transformation and GAI technology application has a significantly positive effect on innovation capability and a significantly negative effect on the operational cost ratio.

In Models 3 and 4, after adding the mediators, the direct effect of digital transformation on new quality productivity becomes smaller and less significant, while the mediators show significant effects on new quality productivity. Model 5 presents the results of Sobel tests for mediation effects, confirming that both innovation capability and operational efficiency significantly mediate the relationship between digital transformation and new quality productivity.

All in all, our findings suggest that Chinese firms' digital transformation boosts new quality productivity by improving innovation capability and operational efficiency. Also, the use of GAI technology strengthens these mediating pathways, increasing the positive impact of Chinese firms' digital transformation on new quality productivity.

6. DISCUSSION

Our empirical analysis provides robust evidence supporting both hypotheses. Digital transformation positively influences new quality productivity (H1), and GAI technology application positively moderates this relationship (H2). These findings have important theoretical and practical implications.

6.1. Theoretical Implications

Our study adds to the literature on digital transformation and productivity in several ways. First, we extend the resource-based view and dynamic capabilities theory by showing how digital transformation creates value through increased new quality productivity. Our findings suggest that digital capabilities are valuable, rare, hard to imitate, and non-substitutable resources that help firms achieve better productivity outcomes (Barney, 1991).

Second, we improve the understanding of technology-enabled organizational transformation by identifying GAI technology application as a key factor in the digital transformation-productivity relationship. This finding supports the technology-organization-environment framework, emphasizing the role of technology complementarity in improving organizational performance (Tornatzky & Fleischer, 1990).

Third, our mechanism analysis shows that innovation capability and operational efficiency are important ways digital transformation boosts new quality productivity. This contributes to the innovation and efficiency literature by showing how digital technologies help firms balance both exploration (innovation) and exploitation (efficiency) activities (March, 1991).

Finally, our heterogeneity analysis offers insights into the contextual factors that affect the success of digital transformation efforts. Additionally, our findings suggest that the financial benefits of digital transformation and GAI technology use vary across firms, depending on factors such as firm size, ownership structure, and industry technological intensity.

6.2. Practical Implications

The study provides practical advice for business leaders and regulators. First, the clear link between digital transformation and higher productivity suggests that businesses should invest in digital infrastructure to enhance efficiency and market position. Leaders should see digital transformation not just as upgrading IT systems but as a key strategy to reshape value creation and competitive advantage (Cui, 2024).

Additionally, the strong influence of Generative Artificial Intelligence (GAI) adoption shows that companies should include GAI solutions in their digital strategies to fully realize productivity gains. In practical terms, decision-makers should look at how GAI can improve predictive analytics, streamline labor-intensive tasks, and optimize decision-making processes (Zhang & Dong, 2023). The mediating paths identified in this study highlight the need to align digital transformation with two key goals: promoting innovation and improving cost-effectiveness. Business leaders should utilize digital tools to enhance R&D (e.g., virtual prototyping) and process efficiency (e.g., intelligent automation and lean management).

Lastly, the differences in outcomes show that the success of digital transformation depends on the context. Instead of using a one-size-fits-all approach, management teams should customize their digital plans to meet their company's specific needs, such as size, management structure, and industry factors.

7. CONCLUSION

This research examines the effect of digital transformation on next-generation productivity metrics, focusing on the role of Generative Artificial Intelligence (GAI) adoption, using a comprehensive longitudinal dataset of Chinese enterprises. The results strongly support two key points: (1) digital transformation has a statistically significant positive effect on advanced productivity measures, and (2) this effect is greatly enhanced when organizations adopt GAI technologies. Additionally, mediation analysis shows that innovation capacity and process optimization are key pathways through which these effects occur.

Our research contributes to the literature on Chinese firms' digital transformation and new quality productivity in two ways. First, by combining the resource-based view, dynamic capabilities theory, and the technology-organization-environment framework, we offer a more complete understanding of how digital transformation creates value and how emerging technologies like GAI boost this value. Second, our empirical analysis offers valuable insights for managers who want to use digital technologies to improve productivity outcomes (Cui, 2024).

However, our study has some limitations. First, the sample is limited to Chinese companies, and the relatively small sample size may reduce the generalizability of our findings to other settings. Future research could explore these relationships in different institutional and cultural environments to improve external validity. Second, while our measurement of GAI technology application is comprehensive, it may not capture all dimensions of GAI implementation. Future studies could develop more detailed indicators to measure GAI use across various organizational functions. Finally, although we have addressed potential endogeneity concerns, the cross-sectional design of our study limits our ability to draw strong causal conclusions. Longitudinal research that follows digital transformation efforts and productivity outcomes over time would offer more robust evidence of causal relationships.

In conclusion, our study emphasizes the role of digital transformation and GAI technology application in boosting new quality productivity. As Chinese firms navigate the challenges and opportunities of Chinese digital innovation technologies, meanwhile, our study also aims to understand the factors that influence the success of digital transformation initiatives. Our research offers valuable insights for scholars and practitioners looking to leverage digital technologies to improve productivity and competitiveness in the digital age.

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