

Beyond binary: exploring the interplay of China's digital transformation and firm performance through dual mechanism analysis

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ABSTRACT

Utilizing data from Chinese A-share listed firms we explore the paradoxical effects of digital transformation on firms' financial and operational performance. Through text mining, mechanism and heterogeneity analyses, the study's findings indicate that digital transformation may inflate operational costs and compromise firm performance. When considering financial restrictions and R&D, the productivity gains emanating from digital transformation, underscores the symbiotic potential of concurrent technological and financial strategies. Heterogeneity analyses reveal a differentiated impact: larger firms and specific sectors, such as technology, witness a significant boost in productivity, whereas state-owned entities and joint ventures are less susceptible to performance downturns.

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Introduction

Over the past decade, concepts like Industry 4.0 and the Fourth Industrial Revolution have promised significant transformations in industrial manufacturing (Meindl et al. 2021). Many companies have embraced digitalization, aiming to benefit from new digital business models or to radically alter their production systems' value propositions (Holmström et al. 2019). However, the reality of digital manufacturing projects often falls short of these ambitious goals. Instead of achieving new business models, many industrial incumbents experience only incremental improvements, such as efficiency gains and cost reductions within existing processes (Gregory et al. 2015; Helo and Hao 2017). This discrepancy highlights the concept of Digital Transformation Paradoxes, which refers to the contradictory demands organizations face during their digital transformation journey. As Danneels and Viaene (2022) explain, companies must balance innovation with stability – pursuing new digital capabilities while maintaining and optimizing their current operations. Additionally, they must manage both short-term performance and long-term transformation goals, balancing external disruptive forces with internal capabilities (Vial 2019). These paradoxes create tensions that complicate decision-making, often impacting transformation and firm performance (X. Guo et al. 2023).

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These tensions are explored in several works, emphasizing the gap between ambitious goals and practical results (Gebauer et al. 2020; Guo et al. 2023), such as Bianca et al. (2021) addresses the radical changes required to manage crises and the resulting digital inequalities. However, the digital revolution has fundamentally transformed corporate production mechanisms, providing significant potential for enhancing TFP and strengthening competitive advantages (Chen, Yang, and Li 2022; Guo et al. 2023). One strand of the literature demonstrates the development of digital technologies revolutionizes organizations and promotes productivity (C. Y. Cheng, Chien, and Lee 2021; Dedrick, Kraemer, and Shih 2013; Kallal, Haddaji, and Ftiti 2021). Moreover, while incorporating external knowledge is vital for a successful digital transformation strategy, it can also result in significant costs and, in some cases, reduce efficiency in resource allocation. This misalignment can negatively impact financial performance of firms (Hwang and Lin 1999; Nambisan, Wright, and Feldman 2019).

The digital transformation paradox is also evident in China, where businesses have enhanced productivity and expanded operations (Suo et al. 2024), yet significant digital transformation outcomes remain relatively scarce, further underscoring the importance of studying the impact of digitalization on firm performance (Zhao et al. 2024). The digitalization of small businesses in China has significantly enhanced their labour productivity, facilitated new collaboration methods, and expanded their operational scope through e-commerce. Over the next decade, it is projected that the internet could contribute 7% to 22% of the overall GDP growth in China. A report by Accenture (2021) shows that the proportion of Chinese enterprises with significant digital transformation outcomes has increased from 11% to 16%. Leading enterprises have widened the gap in digital capabilities and operational performance compared to others. Accelerating effective digital transformation for sustainable development has become imperative for enterprises (Accenture 2021).

Current research on digital transformation highlights significant variations in its impact due to contextual factors such as government policies, market dynamics, and technological infrastructure. In China, the unique environment created by proactive government roles and rapid urbanization underscores these contextual differences, yet the dual impact of digital resources remains underexplored (X. Guo et al. 2023; Lu et al. 2022). Theoretical frameworks like the Resource-Based View (RBV), Dynamic Capabilities, and Technology Acceptance Model (TAM) are commonly used, but there is a pressing need to integrate these with Paradox Theory to fully understand digital transformation's dual nature. Despite the widespread use of RBV (Santhanam and Hartono 2003), few studies have comprehensively combined paradox theory with practical applications. Sector-specific research indicates varying benefits of digital transformation, particularly favouring technology-intensive industries and traditional manufacturing, yet such analyses are still limited (B. Guo and X. Huang 2024). Additionally, despite the emerging number of studies in the area, there is a lack of comprehensive understanding regarding the scope and nature of benefits that digital transformation brings across various contexts and timeframes (Gray and Rumpe 2017; C. Matt, Hess, and Benlian 2015). This has led to inconsistent findings, with limited insight into how digital transformation balances immediate operational challenges with long-term strategic gains (Svahn et al. 2017; Yeow, Soh, and Hansen 2018).

In view of the above, the motivation for this study stems from China's rapid digital transformation, driven by government policies, technological advancements, and market dynamics, which presents both opportunities and challenges for firms. There is a critical need to understand how this transformation impacts firm performance within this unique context, addressing a significant gap in the current literature. Existing research shows a positive link between digital transformation (DT) and firm performance. For instance, McKinsey's survey indicates only 20% of companies saw financial gains from DT (Presley 2023), and Scott, Van Reenen, and Zachariadis (2017) found the SWIT network boosts banks' long-term profitability; however, such outcomes remain inconsistent (Isik et al. 2024).

This study aims to resolve these inconsistencies by exploring the dual mechanisms of digital transformation, balancing immediate operational disruptions with long-term strategic benefits. Additionally, recognizing that different industries experience digital transformation differently, the study provides a detailed analysis of its impact across sectors such as technology, manufacturing, and pollution control. By examining data from 2000 to 2022, the study offers a comprehensive, longitudinal perspective on the evolution of digital transformation's impact on firm performance, essential for understanding its stages and maturity in Chinese firms.

In this context, this research paper, utilizing data from Chinese A-share listed firms covering the years 2000 to 2022, delves into the intricate complexities surrounding digital transformation, aiming to address several fundamental research questions: What factors contribute to the paradoxical outcomes observed in firms undergoing digital transformation? How do technological advancements and transition cost influence these outcomes? What is the differential impact of digital transformation across various firm types, sizes, and industries? Lastly, how do financial restrictions and R&D investments modulate the productivity gains from digital transformation?

By employing a dual mechanism approach and conducting mechanism and heterogeneity analyses, the study seeks to provide nuanced insights into the strategic implications of digital transformation. Compared to previous studies, our research offers several potential contributions. While the resource-based view (RBV) has been widely adopted in theoretical frameworks (Santhanam and Hartono 2003), many existing studies lack a comprehensive integration of paradox theory with practical applications. This research addresses this gap by utilizing Paradox Theory, Transaction Cost Theory (TCT), and the IT Productivity Paradox. It provides practical recommendations and strategic insights for businesses, exploring the root causes of paradoxes that arise during the digitalization process, thereby effectively connecting theoretical frameworks with practical complexities. Furthermore, prior research has not sufficiently considered the dual impact of digital resources (X. Guo et al. 2023; Lu et al. 2022). This study adopts a dual mechanism approach based on Paradox Theory, focusing on both technological advancements and transition cost. This dual perspective offers a more comprehensive understanding of the inherent paradoxes of digital transformation, which previous studies have not fully addressed. Finally, unlike earlier studies that often neglected the varying impacts of digital transformation across different types of firms and industries, this research includes a detailed heterogeneity analysis. It evaluates the differential impact of digital transformation across various firm types, sizes, and industries, providing a nuanced understanding of

how different organizational contexts influence the outcomes of digital transformation initiatives.

The findings suggest that digital transformation can lead to increased operational costs and a decline in firm performance, as evidenced by a negative impact on return on assets (ROA) and return on equity (ROE) through higher sales expense ratios and diminished cost and expense profit ratios and cash flow. Despite this, the study finds that in the face of financial constraints, the beneficial effects of digital transformation on productivity are enhanced, particularly when R&D spending is aligned with digital efforts, suggesting R&D's catalytic role in augmenting the positive outcomes of digital transformation. Furthermore, an analysis of firm and industry heterogeneity reveals that while digital transformation generally decreases firm performance, with a more pronounced effect on larger firms, state-owned enterprises and joint ventures are less impacted, likely due to established processes and market stability. Specifically, in the tech industry, digital transformation significantly boosts productivity. In the manufacturing sector, digital transformation gradually increases labour productivity despite initially complex effects on overall productivity whilst it variably benefits labour productivity in heavily polluting industries. This comprehensive investigation highlights the nuanced and multifaceted impacts of digital transformation, suggesting its effectiveness is contingent on strategic alignment with R&D investments and the specific firm and industry contexts.

The rest of the paper is organized as follows: Section '[Literature review and theoretical framework](#)' conducts a literature review, develops the hypotheses as well as presents the theoretical framework used in the study whilst Section '[Methodology](#)' presents the methodology and the models. Section '[Empirical results](#)' presents the empirical results, including a detailed rationale of the employed methods and Section '[Discussion](#)' discusses the key findings. Section '[Implications](#)' expounds on the theoretical and practical implications of the study whilst Section '[Conclusions](#)' provides some concluding remarks.

Literature review and theoretical framework

Paradox theory of firm performance

Paradox theory offers a way to move beyond 'either/or' thinking by embracing 'both/and' approaches (Lewis and Smith 2014; Putnam, Fairhurst, and Banghart 2016). In the context of digital transformation, this perspective shifts the focus from the binary decision of whether to transform to more nuanced considerations such as 'how to effectively transform' and 'who achieves success first'. Theoretical debates surround the productivity paradox (Brynjolfsson, Rock, and Syverson 2017; R. M. Solow 1956) and the digitalization paradox (Gebauer et al. 2020). With the advancement of digital technologies, digital transformation and productivity exhibit a 'J-shaped' curve (Brynjolfsson, Rock, and Syverson 2017). According to Gebauer et al. (2020), while increased digital investments may initially fail to yield corresponding performance improvements – a phenomenon known as the digitalization paradox – organizations that strategically manage these investments can ultimately achieve significant performance gains.

This study examines the dual mechanisms through which digital transformation impacts firm performance, focusing on the paradoxes inherent in this process. It integrates Transaction Cost Theory (TCT), Paradox Theory, and the IT Productivity

Paradox. Digital transformation, encompassing intelligent manufacturing, information systems, internet business models, and digital technology applications, can reduce transaction costs and improve efficiency. However, the Paradox Theory highlights that while digital transformation can enhance financial and operational performance (Gupta et al. 2020), it may also introduce challenges that negate these benefits. The IT Productivity Paradox further suggests that the productivity gains from digital investments are not always immediate, influenced by factors such as R&D expenditure and financial constraints (Cui and Wang 2023; Fernández-Rovira et al. 2021). This framework aims to provide a nuanced understanding of the strategic implications of digital transformation in Chinese firms, emphasizing the complex interplay between digital investments and firm performance in the Figure 1.

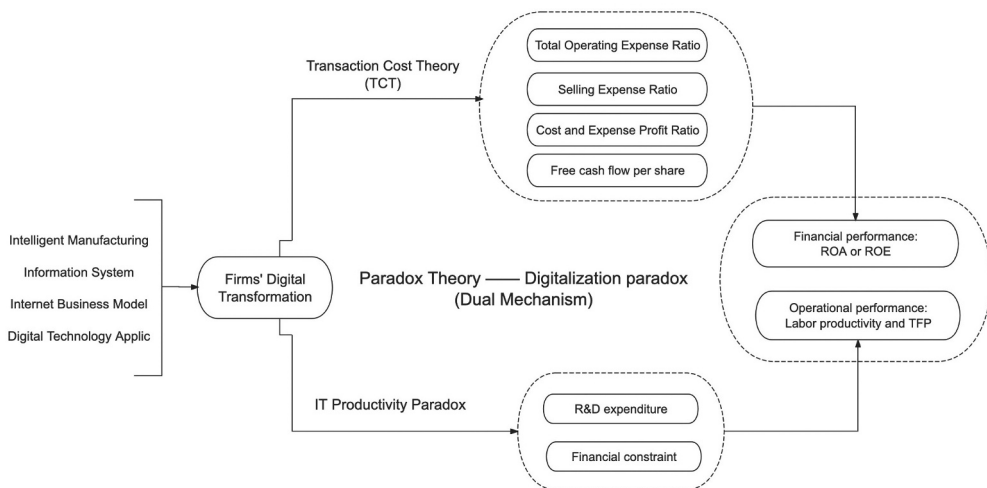


Figure 1. Theoretical framework.

Transaction cost theory of financial performance

Transaction Cost Theory (TCT), developed by Ronald Coase, elucidates the reasons for the existence of firms and the associated costs of market transactions. The theory classifies these transaction costs into search costs, negotiation costs, and enforcement costs. According to TCT, firms opt to internalize transactions when the costs of market transactions surpass the costs of managing these transactions within the organization, thereby enhancing overall efficiency (Coase 1937; Williamson 1985).

In the context of digital transformation, the adoption of technologies such as big data, cloud computing, and artificial intelligence aims to optimize business processes and management. However, this transformation introduces significant operational costs, including complexities in technology integration, substantial learning and training costs, increased expenses for system maintenance and cybersecurity, and elevated

management and coordination efforts (Barney and Hesterly 2006). These increased operational costs can negatively impact company performance, particularly in the short term. Financial metrics such as the Total Operating Expense Ratio, Selling Expense Ratio, Cost and Expense Profit Ratio, and Free Cash Flow per Share are essential in assessing this impact, as they often reflect heightened operational expenses and diminished profitability during the initial phases of digital transformation (Barney and Hesterly 1999, 2006; Coase 1937; Williamson 1985).

Digital transformation transcends mere technological adoption to encompass human factors (Tabrizi et al. 2019). The essential elements for embracing Industry 4.0 include not just digital technology but also executive leadership, workforce talent, and a variety of other resources (Bag et al. 2021). The non-physical assets are critical in adopting digital practices (Kouhizadeh, Saberi, and Sarkis 2021). This creates a significant demand for highly skilled employees, subsequently raising the costs associated with labour.

The digital transformation of an enterprise leads to lower performance through increased cost of sales ratios, mainly due to high initial investment; increased marketing and customer education costs; staff training and technical support costs; and reduced operational efficiency during the period of adaptation to the new system. The operational efficiency of the business may temporarily decrease because the business is adapting to new digital systems and processes. This reduction in efficiency may lead to longer sales cycles, which in turn increases selling expense ratio.

Digital transformation often leads to a reduction in cost and expense margins in the short term, primarily due to substantial upfront investments in new technology, system upgrades, and software acquisitions that raise immediate expenditures, with benefits that may take longer to materialize. Additionally, during the transition, firms may experience a temporary decline in operational efficiency, face a market adaptation period for new products or services, and incur risks and integration costs associated with technology adoption. These factors can place early-stage pressure on profitability, leading to a temporary dip in firm performance (Ghosh et al. 2022). However, digital transformation also requires significant investments in upgrading industry assets, such as machinery, equipment, and control systems, which cannot be fully amortized in the short term. This contributes to higher operating expense rates and lower cash flow ratios, further impacting firm performance. The path to enhancing firm performance thus lies in converting digital resources into digital capabilities, which necessitates continuous learning and incurs additional management expenses. These include salaries for highly skilled workers, digital training for managers and employees, consulting fees, and integration costs for new and existing resources (Yoo 2010). Consequently, the more enabling technologies a firm adopts, the higher its management expenses, potentially reducing performance in the short term.

Thus, the following hypotheses are proposed:

H1a: Digital transformation decrease firm performance by increasing the total operating expense rate.

H1b: Digital transformation decrease firm performance by increasing the selling expense ratio.

H1c: Digital transformation decrease firm performance by reducing cost and expense profit ratio.

H1d: Digital transformation decrease firm performance by reducing cash flow per share of firms.

IT productivity paradox theory of labor productivity and TFP

The IT productivity paradox describes the discrepancy where firms' substantial investments in IT do not translate into expected productivity gains, as discussed in Brynjolfsson and Hitt (2003). This paradox is reflected in the contradictory findings on technology investment, where some studies show improved economic growth and innovation (Kleis et al. 2012), while others suggest it may inhibit firm performance (Ho, Wu, and Xu 2011). The inconsistent results are due to the lack of rigorous theoretical models and the moderating effect of technology capability (Huang et al. 2006; Santhanam and Hartono 2003). Studies show how technology investment, infrastructure use, or human capital affects performance (Dabla-Norris et al. 2019; Grant 2024), but neglect the moderating technology capability effect and financial constraint effect (Meindl et al. 2021; Tu and He 2023). Firms' digital transformation, which aims to improve operational performance through enhanced labour productivity and total factor productivity (TFP), is significantly influenced by R&D expenditure and financial constraints.

At present, China's market economic system is still improving and developing, and financing constraints are a common problem faced by most enterprises (Chan, Dang, and Yan 2012). Different enterprises have different scale structures, organizational systems and geographical locations, etc. Financing constraints are essentially a contradiction between the demand for financing and the supply of financing. However, the digital transformation of enterprises can significantly improve their operational efficiency through the introduction of automation, data analysis, cloud computing and other technologies. For enterprises facing financing constraints, such efficiency gains are particularly important, as they can achieve higher outputs with less capital investment, thus alleviating the financial constraints to a certain extent. As financial constraints intensify, companies are driven to explore ways to boost efficiency and cut costs, with digital transformation serving as a powerful tool to achieve these goals (Kaplan and Zingales 1997). By improving operational efficiency, reducing costs, enhancing market competitiveness and risk management capabilities, digital transformation is expected to bring significant productivity gains to firms in the face of financial constraints (Kong, Huang, and Liu 2023). So, this paper proposes the following hypothesis:

H2a: Financial constraints positively moderate the impact of digital transformation on productivity, including both labour productivity and total factor productivity.

Total factor productivity (TFP) is widely influenced by R&D activities, which are thought to enhance productivity through knowledge accumulation and efficiency gains (Aw, Roberts, and Xu 2011; Dai, Zhang, and Luo 2022; H. Liu et al. 2021). However, the literature reveals inconsistencies in this relationship, as some studies confirm positive productivity impacts (Añón Higón 2007; Boeing, Mueller, and Sandner 2016), while others find

inconclusive links or note that R&D benefits vary significantly based on factors like R&D intensity and industry context (Atella and Quintieri 2001; Kancs and Siliverstovs 2016). The ‘Solow Paradox’ highlights a disconnect, where substantial R&D investments do not consistently yield expected productivity gains (Capello, Lenzi, and Perucca 2022; R. Solow 1987; R. M. Solow 1956), and recent studies attribute TFP slowdowns to a declining potential for innovation-driven growth (Pinchetti 2020). Despite extensive theoretical research, gaps remain, particularly as the Solow Paradox lacks empirical validation in the context of digital transformation, leaving a gap in understanding digital transformation application (Gregory et al. 2015; R. Solow 1987). Addressing these gaps through further empirical investigation would provide a more comprehensive perspective on the R&D-productivity relationship and its enhancement through digital transformation (Zhuo and Chen 2023).

This study posits that when a firm allocates significant funds to research and development, it is expected that the beneficial impact of digital transformation on productivity will substantially decrease and so on, thus, the following hypothesis is proposed:

H2b: A firm’s R&D expenditure positively moderates the relationship between digital transformation and productivity, encompassing both labour productivity and total factor productivity.

Digital transformation and firm heterogeneous

Several studies collectively provide a nuanced perspective on the effects of digital transformation in the business sector. Ren, Liu, and Ding (2023) emphasize the role of intergenerational dynamics, showing how the willingness of entrepreneurs to cede control and the readiness of their children to take over leadership influence a firm’s digital transformation. They also highlight the diverse impacts of digital transformation based on business type, location, and the educational level of entrepreneurs’ children. Y. Chen and J. Xu (2023) focus on specific impacts on different types of firms, noting that digital transformation disproportionately affects non-state-owned firms and affects material resource costs. Ren, Liu, and Ding (2023) further investigate industry and regional peer effects, finding that industry peer influence enhances corporate environmental performance while regional peer effects alleviate financing constraints, improving environmental performance. Lastly, Gao et al. (2023) analyse the impacts of agent heterogeneity and collaboration on innovation performance during digital transformation in manufacturing enterprises. They suggest that high digitization levels or large enterprise sizes can mitigate adverse impacts, while cooperation quality is crucial for smaller or less digitized enterprises. Collectively, these studies highlight the diverse impacts of digital transformation across firm types, sizes, and generational dynamics, offering valuable insights for navigating the challenges and opportunities of the digital economy. Therefore, the following hypotheses are proposed:

H3: The impact of digital transformation on firm performance varies according to firm heterogeneity.

H3a: Digital transformation leads to a reduction in firm performance, however state-owned enterprises (SOEs) tend to be less affected by this trend.

H3b: Digital transformation leads to a reduction in firm performance, larger firms tend to be more affected by this trend.

H3c: Digital transformation leads to a reduction in firm performance, however joint ventures tend to be less affected by this trend.

Digital transformation and industry heterogeneity

Digital transformation's impact on firm performance exhibits industry-specific variances, primarily influenced by the unique characteristics of the technology, manufacturing, and pollution industries. In the technology sector, digital transformation propels innovation and adaptability by enhancing the skills of the workforce, thereby boosting productivity. In particular, Fan et al. (2024) found that informal environmental regulations significantly influence digital transformation in technology companies, promoting eco-friendly practices and enhancing overall performance (Fan et al. 2024). Similarly, Bendig et al. (2023) observed that digital orientation positively impacts environmental performance during technological changes, leading to sustainable business strategies.

In the manufacturing industry, digital transformation leads to improved operational efficiency and reduced pollution. Yadav et al. (2023) highlighted the role of digital technologies in achieving net-zero emissions and driving lean, green production processes. Additionally, X. Wu et al. (2024) demonstrated that digital transformation in the manufacturing sector enhances Environmental, Social, and Governance (ESG) performance, reducing carbon footprints and improving sustainability. Digital transformation also significantly impacts firms' environmental performance in pollution-intensive industries. L. Wang, Liu, and Xiong (2022) provided evidence from China showing that digital transformation helps reduce environmental pollution and improves corporate environmental performance (L. Wang, Liu, and Xiong 2022). Moreover, H. Li, Zhang, and Li (2023) showed that digital inputs in manufacturing enterprises contribute to pollution reduction, highlighting the role of digital transformation in promoting greener practices (H. Li, Zhang, and Li 2023). Collectively, these findings underscore the importance of tailoring digital transformation strategies to the specific needs and characteristics of each industry, thereby optimizing both performance and sustainability. Given the diverse impacts of digital transformation across different sectors, it is essential to understand how these industry-specific characteristics influence overall firm performance. Previous research highlights significant improvements in productivity and sustainability within various industries due to digital transformation. However, there remains a need to investigate the specific effects on labour productivity and total factor productivity across different industry types. So, this paper develops the following hypothesis:

H4: There are differences in the impact of digital transformation on labour productivity and total factor productivity in different types of industries.

Figure 2 provides a schematic approach of the hypotheses to be tested.

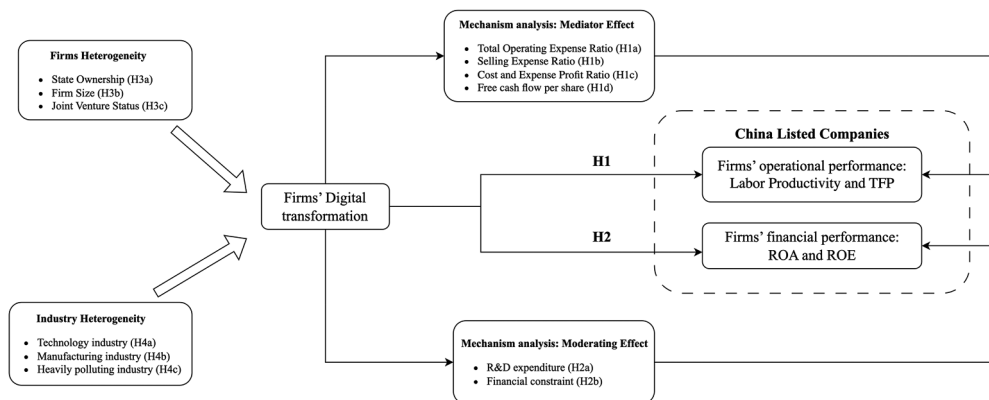


Figure 2. Hypotheses to be tested.

Methodology

In this paper, a comprehensive array of research methods was used to illuminate the underlying relationships and causal pathways of the variables in the dataset. Panel data analysis provided a robust foundation, allowing for the examination of variables over multiple time periods and across diverse units of observation. Mechanism analysis delved into the underlying processes driving observed relationships, unravelling the intricate mechanisms through which variables interact. Furthermore, the exploration of mediating effects unveiled nuanced pathways through which variables exert their influence, shedding light on the complexities of the studied relationships. Collectively, these methodological approaches not only facilitated a deeper understanding of the research questions at hand but also enriched scholarly discourse by offering nuanced insights into complex relationships.

Data sources

According to the *China Internet Development Report 2021*, China's digital economy contributed 39.2 trillion yuan in economic output in 2020, accounting for 38.6% of GDP and maintaining a high growth rate of 9.7% (ISOC 2021). The digital industrialization sector, including information and communication industries and software, had an industrial scale of approximately 7.5 trillion yuan.

In light of recent policy developments, the 14th Five-Year Digital Economy Development Plan, proposed in 2021 and released in 2022, underscores a comprehensive digital economy strategy aimed at advancing digital industrialization and promoting industrial digitalization across sectors, with essential impacts on automation, intelligence, and digital transformation in China's manufacturing sector (PRC 2022). In response to these priorities, this study utilized a dataset of A-share listed corporations from 2000 to 2022, sourced from the Wind database, China's leading economic data and software platform. To minimize potential estimation mistakes triggered by statistical variances, various data processing manipulations were implemented: (1) Exclusion of companies in the real estate, insurance, and finance industries; (2) Elimination of businesses labelled for special treatment (ST) or

delisting risk (*ST); (3) Exclusion of companies with incomplete financial records to maintain data integrity and dependability. Additionally, missing data were handled using (a) Multiple Imputation and (b) K-Nearest Neighbors Imputation (KNN). All continuous independent and control variables were winsorized at the 1% and 99% levels to mitigate the impact of potential outliers.

Model construction

The study's methodology utilizes econometric modelling to examine how digital transformation influences firm performance (Kraus et al. 2022; Zhang, Liu, and Wei 2023). It assesses various factors including asset structure (Y. Chen et al. 2023), market value, and profitability. Baseline regressions incorporating fixed effects and lagged time variables are employed (Fiss and Zajac 2006), while potential endogeneity concerns are addressed. The models are constructed as outlined below.

$$ROA_{i,t}(ROE_{i,t}) = \alpha_0 + \alpha_1 \ln DT_{i,t} + \sum a_n CV_{i,t} + \sum \beta_j Firm_{i,t} + \sum \gamma_k Year_{i,t} + \varepsilon_{i,t} \quad (1)$$

Equation (1) models' firm profitability by using Return on Assets (ROA) and Return on Equity (ROE) as potential proxies. Similar to Equation (1) it also a constant, dummy variable for time, control variables, firm and year fixed effects, and an error term.

$$LaborPro_{i,t}(TFP_{LPi,t}) = \alpha_0 + \alpha_1 \ln DT_{i,t} + \sum a_n CV_{i,t} + \sum \beta_j Firm_{i,t} + \sum \gamma_k Year_{i,t} + \varepsilon_{i,t} \quad (2)$$

Equation (2) relates firms' Total Factor Productivity ($TFP_{i,t}$) capturing productivity for company i at time t . As previously accounts for, a time dummy variable, control variables, firm and year effects, and an error term.

To ensure reliability of our results we have also conducted several robustness tests. These included addressing potential endogeneity issues through IV and 2SLS regression methods. Additionally, we employed alternative construction methods for digital transformation, with DT_A as the primary dependent variable, focusing on core technologies like blockchain and AI to enhance operational efficiency (F. Wu et al. 2021). The alternative approach emphasized business model innovation and customer engagement as well as assessed how companies integrate technologies to improve business models and foster interaction (Zhao et al. 2021). The main difference between the two measures lies in the text mining phase, where the keywords used to measure digital transformation vary between the two metrics, capturing distinct aspects of digital transformation. We also performed temporal analysis and controlled for industry and province-level variations. All these robustness tests yielded consistent results but due to word limit, detailed results are available upon request.

The variables

Dependent variable: firm performance

While return on equity (ROE) and return on total assets (ROA) are used to quantify financial performance in accordance with previous research (Maury 2022; Zhang, Liu, and Wei 2023). Labor productivity (LaborPro) and total factor productivity (TFP_LP) are used to measure operational performance (Levinsohn and Petrin 2003; Yang and Ping 2010).

Independent variable: digital transformation index

The Digital Transfer (DT) paradox has been the topic of conflicting and varied findings in prior research, which may be partially attributed to the continuous and gradual adoption of DTs. Various studies have reported either positive (European Investment Bank 2020) or negligible associations (Agarwall, Das, and Swain 2022; Santoro, Bresciani, and Papa 2020), negative relationships (Khorram Niaki et al. 2018), or insignificant relationships (Baabdullah et al. 2021; Rialti et al. 2019).

The DT index, developed by F. Wu et al. (2021), utilizes data from 55,611 listed company reports spanning from 2000 to 2022 to gauge the progression of China's digital economy. Through analysing word frequency, the metrics DT_A is calculated. DT_A measures the degree of digital transformation by evaluating enterprises' application and development in key technology sectors like blockchain, big data, cloud computing, artificial intelligence, and digital technology application. It assesses the frequency, depth, and breadth of their technology adoption, indicating progress in digital transformation and its impact on innovation and competitiveness. This metrics offer a comprehensive evaluation of Chinese listed companies' advancements in digital transformation, crucial for understanding the evolution of the digital economy within the enterprise context.

In Figure A1 in the Appendix, this six-panel plot provides a statistical overview of lnDTa. The sequence of plots suggests stability without trends, while the residuals indicate a good fit for the regression model. A boxplot points out an outlier in data that is otherwise concentrated at lower values of digital transformation, as seen in the histogram. The first difference plot shows no serial correlation, and the Q-Q plot implies a near-normal distribution with minor tail deviations, collectively offering insight into the digital transformation levels across enterprises.

Control variables

The choice of control variables aligns with existing literature (Cai et al. 2022; Zhang, Liu, and Wei 2023). Tobin's Q value (TobinQ), cash reserves (cash), investment expenditure rate (invst), firm size (Size), and managerial structural variables such as the number of supervisors (SupervisorNumber1) and total annual compensation of supervision (SumSalary1) are explicitly incorporated (Ren, Liu, and Ding 2023; S. Wang and Esperança 2023). The definitions of variables are given in Table 1 whilst the descriptive statistics for these variables can be found in Table A1 in the APPENDIX. It should be mentioned that VIF and cross correlations were used to ensure that multicollinearity is kept at bay. Due to economy of space the respective tables were intentionally left out, but they can be provided upon requests.

Empirical results

Baseline regression

In the baseline regression, Table 2 presents findings regarding the return on assets (roaB) and return on equity (roeB) concerning the level of digital transformation (lnDTa). In model (1), a negative and significant coefficient of lnDTa indicates that as digital transformation increases, the return on assets decreases, likely due to heightened short-term costs of digitalization investment. This trend is reinforced by similarly negative and highly significant coefficients in L1.lnDTa and L2.lnDTa in model (2) and model (3). Models (4) to (6) show

Table 1. Definition of variables.

Variable type	Variable name	Variable symbol	Variable definition
Independent variable	Digital transformation	lnDTa	Natural logarithmic total of word frequencies in DT_A (F. Wu et al. 2021)
Dependent variable	Profitability of Firms	roaB	ROA, return on total asset
		roeB	ROE, return on equity
Control variable	Firms' total factor productivity	LaborPro	Labour productivity = $\ln(\text{Revenue}/10000 + 1) / \ln(\text{Number of employees} + 1)$
		TFP_LP	TFP calculated using the LP method
		size	Company scale = $\ln(\text{total asset})$
		tobin	Tobin's Q = $\text{Total Market Value of Firm} / \text{Total Asset Replacement Cost}$
		cash	Cash holdings = $(\text{monetary funds} + \text{transactional financial assets}) / \text{total assets}$
		inv	Investment expenditure rate = $\text{purchase and construction of fixed assets, intangible assets and other long-term asset payment cash} / \text{total assets}$
Mechanism analysis variable	Mediator Effect	SupervisorNumber1	Number of Supervisors-At the end of the year
		SumSalary1	Total annual salary of supervision-at the end of the year
		TOCR	Total Operating Expense Ratio; Total operating costs of the company as a percentage of total revenue or sales
		SER	Selling Expense Ratio; The ratio of the company's selling expenses divided by its sales revenue.
		CEP	Cost and Expense Profit Ratio; The ratio of a company's operating profit divided by its sales revenue.
	Moderating effect	cflow	Free cash flow per share of the business; The ratio of the number of Outside Shares in circulation to the firm's free cash flow.
		KZ	Financial constraints
		RD2	R&D expenditure as a percentage of operating revenue

Table 2. Results on firms' financial performance.

	(1) roaB	(2) roaB	(3) roaB	(4) roeB	(5) roeB	(6) roeB
lnDTa	-0.0074*** (-8.8454)			-0.0309*** (-3.7161)		
L.lnDTa		-0.0126*** (-11.3717)			-0.0383*** (-2.7013)	
L2.lnDTa			-0.0155*** (-15.2147)			-0.0483*** (-3.0911)
size	0.0092*** (6.9832)	0.0117*** (6.2836)	0.0204*** (11.3500)	0.0399*** (3.0428)	0.0962*** (4.0373)	0.0994*** (3.6211)
tobin	0.0022*** (5.8083)	-0.0044*** (-8.6438)	0.0016*** (3.0246)	0.0075** (1.9790)	0.0024 (0.3671)	-0.0085 (-1.0430)
cash	0.1534*** (21.8144)	0.1571*** (15.1386)	0.1631*** (15.7537)	0.3422*** (4.8945)	0.2642** (1.9912)	0.5686*** (3.5901)
inv	0.2406*** (13.1081)	0.2437*** (9.0379)	0.2388*** (8.9558)	0.6726*** (3.6848)	0.9153*** (2.6544)	0.8868** (2.1738)
SupervisorNumber1	0.0012 (0.8091)	-0.0005 (-0.2371)	0.0007 (0.3829)	0.0324** (2.2043)	0.0399 (1.5278)	0.0418 (1.4033)
SumSalary1	1.14e-10** (2.0286)	1.25e-10 (0.6010)	1.36e-10 (0.8526)	3.22e-10 (0.8252)	-2.10e-09 (-0.3386)	-1.46e-09 (-0.2104)
_cons	-0.2126*** (-7.1533)	-0.2425*** (-5.7378)	-0.4536*** (-11.0803)	-1.0373*** (-3.5093)	-2.2922*** (-4.2423)	-2.4054*** (-3.8398)
N	25250	21450	18195	25250	21450	18195
R ²	0.036	0.030	0.042	0.003	0.002	0.003

t statistics in parentheses.

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

similar negative and significant coefficients for InDTa regarding return equity, indicating that increasing digital transformation levels reduce ROE, potentially reflecting lower-than-expected initial returns on digital investments. Further, in Models (5) and (6), the negative and significant coefficients of L1.InDTa and L2.InDTa suggest that the negative effect of digital transformation on return on assets persists over time, aligning with previous research suggesting that not all businesses may benefit from digital transformation as expected (D. T. Matt and Rauch 2020; Paiola and Gebauer 2020; Tabrizi et al. 2019).

In terms of labour productivity as well as overall factor productivity, the empirical data strongly suggest that digital transformation has a beneficial impact on company productivity (see Table 3). Across all model settings, the coefficients for the degree of digital transformation and its delays are positive and statistically significant, indicating that businesses tend to achieve bigger productivity benefits as they advance in their digital transformation efforts. TFP development is primarily driven by technological advancement, which also has a bearing on resource allocation, industrial structure, breakthrough technology, and efficiency improvement. These gains not only manifest in the short term but also appear to amplify over time, suggesting that the benefits of digital transformation are cumulative and potentially increase as firms become more adept at leveraging digital technologies. This underscores the importance of digital transformation initiatives as a key driver of productivity growth in the modern economy.

Mechanism analysis

Mediator effect

For this type of analysis specific mediator variables have been introduced in the model so as to explore not only the direct impact of digital transformation on firm performance (X.

Table 3. Results on firms' operating performance.

	(1) LaborPro	(2) LaborPro	(3) LaborPro	(4) TFP_LP	(5) TFP_LP	(6) TFP_LP
InDTa	0.0026*** (2.6203)			0.0145*** (4.4525)		
L.InDTa		0.0059*** (5.7790)			0.0141*** (4.1391)	
L2.InDTa			0.0091*** (8.3935)			0.0076** (2.1412)
size	0.0025 (1.6441)	0.0011 (0.6282)	−0.0046** (−2.4011)	0.6194*** (120.6713)	0.6159*** (107.2774)	0.6261*** (100.6282)
tobin	0.0041*** (9.1871)	0.0045*** (9.6024)	0.0039*** (6.9158)	0.0083*** (5.5891)	0.0077*** (4.9705)	0.0075*** (4.0386)
cash	0.0658*** (7.9974)	0.0912*** (9.5121)	0.1028*** (9.3302)	0.2707*** (9.8819)	0.3751*** (11.7321)	0.3751*** (10.4430)
invt	−0.2449*** (−11.3990)	−0.2436*** (−9.7758)	−0.1877*** (−6.6165)	−0.2200*** (−3.0760)	−0.1718** (−2.0676)	0.0643 (0.6946)
SupervisorNumber1	−0.0110*** (−6.3823)	−0.0080*** (−4.2421)	−0.0073*** (−3.5485)	0.0039 (0.6825)	0.0057 (0.9029)	0.0171** (2.5363)
SumSalary1	−5.00e-10*** (−0.2808)	−4.90e-10** (0.1596)	−2.65e-10 (0.4621)	−7.61e-10*** (7.6941)	−9.53e-10*** (7.9460)	−5.33e-10 (5.8571)
_cons	1.5882*** (45.6595)	1.5958*** (40.8681)	1.7112*** (39.2771)	−5.5733*** (−48.1225)	−5.5217*** (−42.4064)	−5.7736*** (−40.6453)
N	25250	21450	18195	25250	21450	18195
R ²	0.017	0.021	0.020	0.527	0.507	0.500

t statistics in parentheses.

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

Guo et al. 2023), but also the indirect impact through operational efficiency and financial position. Mechanism analysis aims to identify how digital transformation affects firm performance by influencing the firm's operating costs (TOCR), sales efficiency (SER), Cost and Expense Profit Ratio (CEP), and cash liquidity (cflow) and thus firm performance as well as identify which mediating variables play a key role in the relationship between digital transformation and firm performance.

We first build a base regression model in which the degree of digital transformation of the firm (lnDTa) is directly predictive of firm performance indicators (ROA and ROE). This will give the direct impact of digital transformation on firm performance. Next, we set up a model using the four mediating variables (TOCR, SER, CEP, cflow) as the dependent variables and lnDTa and the rest of controls as the independent variables.

Equation (3) will test whether digital transformation affects these mediating indicators.

$$Mediator_{i,t} = \beta_0 + \beta_1 \cdot lnDT_{i,t} + \sum Controls_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \quad (3)$$

Finally, we construct regression models containing the mediating and the rest of independent variables to predict firm performance (ROA and ROE) from the literature (Baron and Kenny 1986; Zhao, Lynch, and Chen 2010). This helps us to understand the role of mediating variables in the relationship between digital transformation and firm performance in the Equation (4).

$$ROA_{i,t} (ROE_{i,t}) = \gamma_0 + \gamma_1 \cdot lnDT_{i,t} + \gamma_2 \cdot Mediator_{i,t} + \sum Controls_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \quad (4)$$

As it can be observed in Table 4, the total operational cost ratio (TOCR) is positively related to digital transformation whilst firm performance is negatively impacted by lnDTa (−0.0041 and −0.0125) in the model (2) and model (3), indicating that a higher degree of digital transformation has an adverse impact on the company's performance, hence confirming H1a. The total operating expense rate may be useful as a mediating variable, as the Sobel value was significant at the 1% level.

The effect of lnDTa on SER was found to be insignificant in model (4) but it was found to be highly significant (−0.0042 and −0.0126) in the models (5) and (6), implying that an increase in digital transformation is significantly associated with a decrease in firms' financial performance, thereby providing empirical support for H1b. Furthermore, the effect of SER on firm performance (roaB and roeB) is significant at 1% level of significance suggesting that the increase in the sales expense ratio has a negative impact on ROA and ROE.

Table 5 reports the regression results for CEP and cflow. In particular, the effect of lnDTa on CEP is negative and significant at the 5% level of significance hence, indicating that an increase in the degree of digital transformation is significantly associated with a reduction in cost and expense margins. Furthermore, the impact of lnDTa on firm performance is negative and significant on both roaB, and roeB. As for the impact of CEP on business performance it is found to be positive suggesting that an increase in cost and expense margin is significantly associated with increase in firm performance indicators hence validating H1c.

At the 5% level of significance in the model (4), the effect of lnDTa on cflow is negative and substantial, indicating that digital transformation necessitates upfront investments (e.g. acquiring new technology, software, or doing staff training). The effect of lnDTa on roaB and

Table 4. Mediator effects: regression results (TOCR, SER).

	(1) TOCR	(2) roaB	(3) roeB	(4) SER	(5) roaB	(6) roeB
lnDTa	0.0026** (0.5667)	−0.0041*** (−6.6987)	−0.0125** (−2.5201)	0.0004 (0.0938)	−0.0042*** (−6.7742)	−0.0126** (−2.5395)
TOCR		−0.0510*** (−36.4323)	−0.1195*** (−10.4844)			
SER					−0.0437*** (−5.2429)	−0.1532** (−2.3091)
size	−0.1135*** (−13.4425)	0.0006 (0.7312)	0.0189*** (3.0497)	−0.0111*** (−12.1490)	0.0018** (2.2571)	0.0211*** (3.3787)
tobin	0.0146*** (6.9428)	−0.0113*** (−30.8585)	0.0022 (0.7349)	−0.0014*** (−6.2632)	−0.0120*** (−31.9934)	0.0006 (0.2063)
cash	−0.4207*** (−11.1381)	0.1913*** (31.6014)	0.3966*** (8.0453)	0.0015 (0.3682)	0.2247*** (36.3222)	0.4790*** (9.7288)
invt	−0.5423*** (−5.4704)	0.2742*** (15.7203)	0.6179*** (4.3497)	−0.0128 (−1.1969)	0.3212*** (18.0012)	0.7242*** (5.1012)
SupervisorNumber1	0.0031 (0.3988)	−0.0013 (−1.6341)	0.0051 (0.7594)	−0.0014 (−1.6155)	−0.0018** (−2.0750)	0.0039 (0.5826)
SumSalary1	1.69e-09** (−1.9971)	1.40e-09*** (11.0044)	3.40e-09*** (3.2839)	−2.18e-11 (−0.2393)	1.51e-09*** (11.5419)	3.72e-09*** (3.5775)
_cons	3.5853*** (18.9521)	0.0479 (0.3691)	−0.3744 (−0.3539)	0.3345*** (16.4176)	−0.0331 (−0.2487)	−0.5511 (−0.5200)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Sobel Test		−0.0003*** (0.0002)	−0.0008*** (0.0003)		−0.0001*** (0.0001)	−0.0006*** (0.0003)
N	24613	25250	25250	24613	25250	25250
R ²	0.428	0.147	0.012	0.637	0.103	0.008

t statistics in parentheses.

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

Table 5. Mediator effects: regression results (CEP, cflow).

	(1) CEP	(2) roaB	(3) roeB	(4) cflow	(5) roaB	(6) roeB
lnDTa	−0.0086** (−2.4440)	−0.0004* (−0.8233)	−0.0079** (−1.5952)	−0.0014** (−2.2334)	−0.0027*** (−4.4712)	−0.0103** (−2.0638)
CEP		0.2166*** (156.5020)	0.2898*** (18.8843)			
cflow					0.3791*** (34.4839)	0.6822*** (7.6319)
size	0.0949*** (14.6158)	−0.0031*** (−5.6489)	0.0157** (2.5488)	0.0042*** (3.7472)	−0.0002 (−0.2945)	0.0185*** (2.9661)
tobin	0.0021 (1.3139)	−0.0083*** (−31.0487)	0.0054* (1.8197)	0.0025*** (8.8073)	−0.0125*** (−34.0557)	−0.0004 (−0.1209)
cash	0.5628*** (19.3820)	0.0729*** (16.2630)	0.2683*** (5.3944)	0.1098*** (21.8701)	0.1731*** (28.0351)	0.3801*** (7.5723)
invt	0.5139*** (6.7443)	0.1321*** (10.3437)	0.4779*** (3.3759)	0.0551*** (4.1824)	0.2111*** (11.8985)	0.5315*** (3.6848)
SupervisorNumber1	−0.0151** (−2.5109)	−0.0009 (−1.5137)	0.0055 (0.8171)	−0.0009 (−0.8828)	−0.0020** (−2.3659)	0.0039 (0.5778)
SumSalary1	0.0000*** (4.1398)	0.0000*** (10.6852)	0.0000*** (2.8250)	0.0000*** (4.7337)	0.0000*** (9.4587)	0.0000*** (2.9723)
_cons	−2.1190*** (−14.5720)	0.0649 (0.6834)	−0.4447 (−0.4226)	−0.0762*** (−3.0332)	0.0471 (0.3620)	−0.4261 (−0.4025)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Sobel Test		−0.0044*** (0.0002)	−0.0059*** (0.0003)		−0.0017*** (0.0001)	−0.0031*** (0.0003)
N	24613	25250	25250	24613	25250	25250
R ²	0.332	0.545	0.021	0.409	0.143	0.010

t statistics in parentheses.

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

roeB are found to be negative and significant. The impact however of cflow on firm performance is found to be positive and significant indicating that an increase in free cash flow has a significant positive effect on the ROA and ROE of the firm, implying that the higher the free cash flow, the better the financial performance of the firm typically will be, hence confirming H1d. Finally, the Sobel test suggests that the mediating variable does play a non-zero mediating role between the independent and dependent variables.

Moderating effect

In examining the relationship between firms' digital transformation and firms' labour force and total factor productivity (TFP_LP), this paper introduces two key variables: financing constraints (KZ) and the amount of firms' research and development (R&D) investment (RD) (For more on the definition and construction of the two proxies see (Aw, Roberts, and Xu 2011; Boeing, Mueller, and Sandner 2016; Griliches and Lichtenberg 1982).

Moderating effect in Equation (5):

$$\begin{aligned} LaborPro_{i,t}(TFP_{LPi,t}) = & \alpha_0 + \alpha_1 DT_{i,t} + \alpha_2 DT_{i,t} \times KZ_{i,t} (or RD_{i,t}) \\ & + \sum Controls_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \end{aligned} \quad (5)$$

The equation of moderating effect examines the influence of digital transformation on a firm's productivity, considering labour productivity ($LaborPro_{i,t}$) or Total Factor Productivity ($TFP_{LPi,t}$) as dependent variables. $DT_{i,t} \times KZ_{i,t} (or RD_{i,t})$ assesses not only the direct impact of digital transformation but also its interaction with a moderating variable, which could be knowledge intensity or R&D spending.

In Table 6, the regression analysis indicates that digital transformation (lnDTa) significantly boosts labour productivity and total factor productivity (TFP_LP), evidenced by the positive coefficients in certain models. However, financing constraints (KZ) negatively affect TFP_LP, as shown by significant coefficients in some models, which is inconsistent with research of Dabla-Norris et al. (2019). Interestingly, the interaction term (interKZ) suggests that financing constraints might enhance the positive effects of digital transformation on productivity in certain contexts, hence supporting H2a. This complexity highlights the nuanced role that financing constraints play in moderating the relationship between digital transformation and productivity.

Upon examining the regression results concerning the moderating effect of R&D Expenditure (RD2) on the relationship between labour productivity (LaborPro) and digital transformation (lnDTa), it is evident that R&D expenditure negatively affects this relationship. Specifically, the coefficient of RD2 is consistently negative across all models (ranging from -0.5847 to -4.0612) and is statistically significant in Table 7. Additionally, the interaction term (interRD2) is positive and significant in model (4) (coefficient of 0.0018 with $p < 0.01$) and model (6) (coefficient of 0.1352 with $p < 0.01$), indicating that a firm's R&D expenditure positively moderates the relationship between digital transformation and productivity, encompassing both labour productivity and total factor productivity; as such, H2b is validated.

Overall, these results suggest that while digital transformation directly contributes to increases in labour and total factor productivity, R&D expenditure seems to have an initial negative impact, which may be due to the fact that R&D investments can take time to

Table 6. Moderating effect: regression results (KZ: financial constraints).

	(1) LaborPro	(2) LaborPro	(3) LaborPro	(4) TFP_LP	(5) TFP_LP	(6) TFP_LP
lnDTa	0.0026*** (2.6203)	0.0026*** (2.6188)	−0.0007 (−0.6349)	0.0145*** (4.4525)	0.0146*** (4.4974)	0.0030 (0.8170)
KZ		−0.0006 (−1.1100)	−0.0038*** (−5.3169)		−0.0145*** (−8.7062)	−0.0262*** (−10.9515)
interKZ			0.0018*** (6.3417)			0.0065*** (6.7980)
size	0.0025 (1.6441)	0.0024 (1.5320)	0.0018 (1.1915)	0.6194*** (120.6713)	0.6150*** (119.4225)	0.6131*** (119.0155)
tobin	0.0041*** (9.1871)	0.0041*** (9.1849)	0.0041*** (9.0954)	0.0083*** (5.5891)	0.0093*** (6.2869)	0.0092*** (6.1891)
cash	0.0658*** (7.9974)	0.0619*** (6.8308)	0.0627*** (6.9324)	0.2707*** (9.8819)	0.1618*** (5.3754)	0.1649*** (5.4835)
invt	−0.2449*** (−11.3990)	−0.2458*** (−11.4348)	−0.2433*** (−11.3254)	−0.2200*** (−3.0760)	−0.2462*** (−3.4452)	−0.2372*** (−3.3218)
SupervisorNumber1	−0.0110*** (−6.3823)	−0.0110*** (−6.3644)	−0.0107*** (−6.2239)	0.0039 (0.6825)	0.0047 (0.8165)	0.0056 (0.9724)
SumSalary1	−0.0000 (−0.2808)	−0.0000 (−0.2119)	−0.0000 (−0.2669)	0.0000*** (7.6941)	0.0000*** (8.2402)	0.0000*** (8.1901)
_cons	1.5882*** (45.6595)	1.5933*** (45.3745)	1.6103*** (45.7689)	−5.5733*** (−48.1225)	−5.4345*** (−46.5644)	−5.3738*** (−45.9585)
N	25250	25246	25246	25250	25246	25246
R ²	0.017	0.017	0.019	0.527	0.529	0.530

t statistics in parentheses.

p* < 0.10, *p* < 0.05, ****p* < 0.01.

translate into productivity gains. Y. Wu (2008) found that both R&D and abroad technology transfer had considerably beneficial relationships with economic productivity, but not local technology transfer in China. However, the significant interaction terms suggest that

Table 7. Moderating effect: regression results (R&D expenditure).

	(1) LaborPro	(2) LaborPro	(3) LaborPro	(4) TFP_LP	(5) TFP_LP	(6) TFP_LP
lnDTa	0.0026*** (2.6203)	0.0050*** (5.5981)	0.0047*** (4.4951)	0.0145*** (4.4525)	0.0285*** (9.2406)	0.0229*** (6.2971)
RD2		−0.5847*** (−19.2502)	−0.6037*** (−12.2778)		−3.6646*** (−34.5983)	−4.0612*** (−23.6900)
interRD2			0.0065** (0.4919)			0.1352*** (2.9422)
size	0.0025 (1.6441)	−0.0059*** (−3.8432)	−0.0059*** (−3.8344)	0.6194*** (120.6713)	0.5880*** (110.3545)	0.5883*** (110.4102)
tobin	0.0041*** (9.1871)	−0.0008* (−1.6491)	−0.0008* (−1.6557)	0.0083*** (5.5891)	0.0038** (2.3247)	0.0037** (2.2841)
cash	0.0658*** (7.9974)	0.0408*** (5.5469)	0.0412*** (5.5682)	0.2707*** (9.8819)	0.1801*** (7.0210)	0.1876*** (7.2784)
invt	−0.2449*** (−11.3990)	−0.1731*** (−8.9342)	−0.1731*** (−8.9341)	−0.2200*** (−3.0760)	−0.0930 (−1.3754)	−0.0930 (−1.3762)
SupervisorNumber1	−0.0110*** (−6.3823)	−0.0061*** (−3.6107)	−0.0061*** (−3.6115)	0.0039 (0.6825)	0.0099* (1.6753)	0.0099* (1.6702)
SumSalary1	−0.0000 (−0.2808)	0.0000*** (4.7064)	0.0000*** (4.7098)	0.0000*** (7.6941)	0.0000*** (13.4724)	0.0000*** (13.4962)
_cons	1.5882*** (45.6595)	1.7852*** (51.8045)	1.7855*** (51.8037)	−5.5733*** (−48.1225)	−4.7328*** (−39.3823)	−4.7262*** (−39.3288)
N	25250	23413	23413	25250	23413	23413
R ²	0.017	0.027	0.027	0.527	0.530	0.530

t statistics in parentheses.

p* < 0.10, *p* < 0.05, ****p* < 0.01.

R&D can act as a catalyst, amplifying the positive effects of digital transformation on productivity once it passes a certain threshold or after a lag phase. This could be indicative of synergy between digital transformation and R&D activities that becomes more apparent over time.

Heterogeneity analysis

Firm heterogeneity regression

In an attempt to capture the impact of digital transformation on firm performance across different types of firms a heterogeneity analysis is conducted. In line with Referencing (Chen, Yang, and Li 2022), the following equation serves as the model to be estimated in the Equation (6):

$$ROA_{i,t}(ROE_{i,t}) = a_0 + a_1DT_{i,t} + a_2DT_{i,t} \times SOE(orSize, JV) + \sum Controls_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \quad (6)$$

where SOE denotes State Ownership; Size is firm size, and JV stands for joint venture status.

State-owned enterprises refer to businesses where all assets are owned by the state, excluding state-owned sole proprietorships within limited liability companies (G. Liu et al. 2024). By utilizing the Wind database to classify publicly listed companies into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), we obtained the following results. According to Table 8, there is a statistically significant negative impact on the interaction term between digital transformation and state ownership (SOE), which provides support for H3a. This suggests that the performance of an SOE will be negatively impacted by digital transformation, which is consistent with the findings of L. Chen and M. Miao's (2022). State-owned enterprises typically benefit from greater access to resources and policy backing compared to their private counterparts, which provides them with a competitive edge in implementing digital technological innovations (Ai, Sun, and Kong 2023).

In the model (1), model (2) and model (4) of Table 9, the interaction term between digital transformation and large size(size) is found to have a weak and positive impact, indicating that the impact of digital transformation for a large firm will further dampen the negative effect of digital transformation on firm performance, which is in line with H3b. Furthermore, Eller et al. (2020) found that whenever it involves digitalization, small and medium-sized enterprises trail behind bigger ones. Small and medium-sized businesses' performance is adversely affected by this.

The interaction term between joint venture businesses (JVs) and digital transformation is shown to have a weak but negative influence in models (2) and (3) of Table 10, suggesting the impact of digital transformation for JVs might further negatively affect performance, thereby supporting H3b.

Industry heterogeneity regression

Table 11 reflects a significant interaction effect between the digital transformation of firms (lnDTa) and high-tech industry designation (InteraTech). Specifically, the lagged interaction term (L2.lnDTa) shows a positive and statistically significant impact on total

Table 8. Regression results with state ownership interaction.

	(1) roaB	(2) roaB	(3) roaB	(4) roeB	(5) roeB	(6) roeB
lnDTa	−0.0064*** (−6.6072)			−0.0164* (−1.6891)		
L.lnDTa		−0.0131*** (−12.6796)			−0.0299*** (−2.6666)	
L2.lnDTa			−0.0162*** (−14.3349)			−0.0414*** (−3.3205)
InteraSOE	−0.0023* (−1.8589)	−0.0023* (−1.7017)	−0.0028* (−1.8116)	−0.0391*** (−3.1020)	−0.0524*** (−3.5369)	−0.0581*** (−3.4350)
_cons	−0.2031*** (−6.7617)	−0.3217*** (−8.1915)	−0.4669*** (−9.8010)	−1.0762*** (−3.5672)	−1.7809*** (−4.1898)	−2.0194*** (−3.8347)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	24550	18843	15754	24550	18843	15754
R ²	0.036	0.039	0.042	0.003	0.004	0.004

t statistics in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.**Table 9.** Regression results with firm size interaction.

	(1) roaB	(2) roaB	(3) roaB	(4) roeB	(5) roeB	(6) roeB
lnDTa	−0.0346*** (−10.8183)			−0.1145*** (−3.5896)		
L.lnDTa		−0.0147*** (−13.0844)			−0.0371*** (−3.0799)	
L2.lnDTa			−0.0167*** (−14.7889)			−0.0461*** (−3.7015)
InteraSize	0.0280*** (8.8135)	0.0022* (1.8459)	0.0004 (0.2698)	0.0858*** (2.7148)	−0.0069 (−0.5351)	−0.0165 (−1.1475)
_cons	−0.1672*** (−5.5538)	−0.3059*** (−7.7294)	−0.4610*** (−9.5359)	−0.8981*** (−2.9940)	−1.6895*** (−3.9695)	−1.9828*** (−3.7288)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25250	19310	16076	25250	19310	16076
R ²	0.040	0.040	0.042	0.003	0.003	0.004

t statistics in parentheses.

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

factor productivity (TFP_LP), which indicates that for firms in the high-tech sector, the influence of digital transformation on productivity is notably positive.

The data in Table 12 provided indicates that digital transformation (lnDTa) has a statistically significant positive impact on labour productivity (LaborPro) in the manufacturing industry. This is shown by positive coefficients in models (1), (2), and (3), which strengthens with the introduction of lagged terms (L1.lnDTa and L2.lnDTa), implying that the impact of digital transformation on labour productivity manifests over time.

Furthermore, the interaction term (InteraMF) in Table 12 has a significant negative effect on total factor productivity (TFP_LP) in all models (4), (5), and (6). This suggests that while digital transformation positively influences labour productivity in the manufacturing sector, it may have a nuanced or potentially negative effect on overall productivity as measured by TFP in the short term. The reasons for this could be numerous, productivity slowdowns are caused by underestimating the impact of

Table 10. Regression results with joint venture interaction.

	(1) roaB	(2) roaB	(3) roaB	(4) roeB	(5) roeB	(6) roeB
lnDTa	−0.0073*** (−8.4060)			−0.0316*** (−3.6777)		
L.lnDTa		−0.0136*** (−13.6434)			−0.0398*** (−3.7200)	
L2.lnDTa			−0.0166*** (−15.0999)			−0.0493*** (−4.0803)
InteraJV	−0.0018 (−0.6448)	−0.0053* (−1.4629)	−0.0087** (−1.9443)	0.0089 (0.3163)	−0.0150 (−0.3830)	−0.0286 (−0.5819)
_cons	−0.2124*** (−7.1467)	−0.3223*** (−8.3133)	−0.4686*** (−9.9721)	−1.0382*** (−3.5122)	−1.6480*** (−3.9522)	−1.8517*** (−3.5818)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25250	19310	16076	25250	19310	16076
R ²	0.036	0.040	0.042	0.003	0.003	0.003

t statistics in parentheses.

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

Table 11. Regression results with technology industry.

	(1) LaborPro	(2) LaborPro	(3) LaborPro	(4) TFP_LP	(5) TFP_LP	(6) TFP_LP
lnDTa	−0.0012 (−0.8832)			0.0195*** (4.5343)		
L.lnDTa		0.0020* (1.7355)			0.0190*** (4.7194)	
L2.lnDTa			0.0025** (1.9720)			0.0129*** (3.0854)
InteraTech	−0.0004 (−0.2392)	−0.0013 (−0.9535)	−0.0003 (−0.1688)	−0.0020 (−0.4061)	0.0089* (1.9058)	0.0150*** (2.9317)
size	−0.0208*** (−10.3864)	−0.0193*** (−8.5862)	−0.0223*** (−8.7298)	0.6040*** (92.5597)	0.6111*** (79.1573)	0.6194*** (72.3604)
tobin	0.0036*** (7.3832)	0.0016*** (2.6430)	0.0034*** (4.7104)	0.0107*** (6.7798)	0.0121*** (5.9829)	0.0165*** (6.8916)
cash	0.0588*** (6.5681)	0.0823*** (8.0890)	0.0802*** (6.8051)	0.2187*** (7.5115)	0.3339*** (9.5492)	0.3654*** (9.2402)
inv	−0.1605*** (−6.8158)	−0.1792*** (−6.5393)	−0.1132*** (−3.6510)	−0.3144*** (−4.1019)	−0.2201** (−2.3361)	−0.0041 (−0.0395)
SupervisorNumber1	−0.0063*** (−3.4459)	−0.0020 (−0.9793)	0.0002 (0.0796)	0.0110* (1.8557)	0.0076 (1.0898)	0.0169** (2.1741)
SumSalary1	−0.0000** (−2.3931)	−0.0000 (−1.1018)	−0.0000 (−1.3599)	0.0000*** (7.3426)	0.0000*** (6.1313)	0.0000*** (4.7994)
_cons	2.1365*** (46.5060)	2.0758*** (40.2831)	2.1272*** (36.1597)	−5.2189*** (−34.9076)	−5.4058*** (−30.5238)	−5.6366*** (−28.5586)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	22607	17141	14209	22607	17141	14209
R ²	0.053	0.045	0.043	0.549	0.517	0.502

t statistics in parentheses.

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

the digital economy (Aeppel 2015). For example, the short-term costs of integrating new digital technologies which may temporarily offset the productivity benefits, or it may reflect a lag before full benefits of digital transformation are realized in TFP measures.

Table 13 results highlight the impact of digital transformation (lnDTa) on labour productivity (LaborPro) and total factor productivity (TFP_LP) within the context of heavy pollution industries. When considering the lagged impact (L2.lnDTa), there's

Table 12. Regression results with manufacturing industry.

	(1) LaborPro	(2) LaborPro	(3) LaborPro	(4) TFP_LP	(5) TFP_LP	(6) TFP_LP
lnDTa	0.0035** (2.4822)			0.0315*** (6.9135)		
L.lnDTa		0.0033*** (2.8319)			0.0197*** (4.8993)	
L2.lnDTa			0.0027** (2.2035)			0.0116*** (2.7539)
InteraMF	−0.0081*** (−5.4438)	−0.0080*** (−6.2240)	−0.0062*** (−4.2812)	−0.0392*** (−8.0867)	−0.0240*** (−5.3937)	−0.0148*** (−3.0267)
size	−0.0215*** (−10.7129)	−0.0190*** (−8.4847)	−0.0218*** (−8.5748)	0.4533*** (69.3241)	0.4622*** (59.7420)	0.4674*** (54.3083)
tobin	0.0036*** (7.5372)	0.0016*** (2.7690)	0.0034*** (4.7709)	0.0087*** (5.5310)	0.0091*** (4.5007)	0.0131*** (5.4423)
cash	0.0597*** (6.6802)	0.0823*** (8.1024)	0.0805*** (6.8384)	0.2304*** (7.9153)	0.3527*** (10.0661)	0.3784*** (9.5164)
inv	−0.1590*** (−6.7560)	−0.1777*** (−6.4919)	−0.1118*** (−3.6113)	−0.4688*** (−6.1124)	−0.4432*** (−4.6931)	−0.2106** (−2.0132)
SupervisorNumber1	−0.0062*** (−3.4058)	−0.0019 (−0.9195)	0.0003 (0.1391)	−0.0038 (−0.6352)	−0.0012 (−0.1751)	0.0097 (1.2411)
SumSalary1	−0.0000** (−2.2950)	−0.0000 (−0.9862)	−0.0000 (−1.2266)	0.0000*** (4.7318)	0.0000*** (4.5234)	0.0000*** (3.2991)
_cons	2.1507*** (46.7894)	2.0752*** (40.3332)	2.1240*** (36.1455)	−3.3431*** (−22.3215)	−3.5810*** (−20.1707)	−3.7498*** (−18.8893)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	22607	17141	14209	22607	17141	14209
R ²	0.055	0.047	0.045	0.464	0.424	0.406

t statistics in parentheses.

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

a positive and statistically significant effect on labour productivity, indicating that the benefits of digital transformation accrue over time. This lagged effect is more pronounced for total factor productivity, where the initial and lagged (L1.lnDTa and L2.lnDTa) effects of digital transformation are both positively significant, suggesting that digital transformation has a robust positive influence on overall productivity in the long run.

The interaction term (InteraPU) represents the additional effect of being in a heavy pollution industry on the relationship between digital transformation and productivity (Table 13). The positive coefficients for the interaction term in the LaborPro models significant in the model (1) to (3) and TFP_LP model in the model (4), which suggest that in heavy pollution industries, digital transformation may have a distinct, albeit small, positive impact on labour productivity, which is consistent with the result of Z. Li and Wang (2022). Overall, while digital transformation appears to benefit productivity, the effect is nuanced by industry characteristics such as the level of pollution, in line with H4.

Discussion

As it emerges from this study, digital transformation has a dual nature: it enhances labour and total factor productivity (TFP_LP) while potentially decreasing firm performance. While digital initiatives drive efficiencies and innovation, leading to positive effects on productivity metrics, they can strain firm performance, particularly impacting financial metrics like ROA and ROE. Investments in technology adoption and restructuring can increase operational costs in the short term, reducing profitability and efficiency. Effective

Table 13. Regression results with polluting industry.

	(1) LaborPro	(2) LaborPro	(3) LaborPro	(4) TFP_LP	(5) TFP_LP	(6) TFP_LP
lnDTa	0.0020* (−1.7522)			0.0219*** (5.9505)		
L.lnDTa		0.0017 (1.5148)			0.0208*** (5.2765)	
L2.lnDTa			0.0026** (2.1095)			0.0140*** (3.3531)
InteraPU	0.0044* (1.9110)	0.0052** (2.0422)	0.0091*** (3.1307)	0.0239*** (−3.1664)	−0.0064 (−0.7331)	0.0102 (1.0377)
size	−0.0207*** (−10.2998)	−0.0194*** (−8.6247)	−0.0222*** (−8.7315)	0.6032*** (92.4256)	0.6117*** (79.2788)	0.6208*** (72.6129)
tobin	0.0035*** (7.3357)	0.0015** (2.5416)	0.0034*** (4.7390)	0.0107*** (6.8426)	0.0122*** (6.0547)	0.0166*** (6.9519)
cash	0.0583*** (6.5239)	0.0818*** (8.0484)	0.0802*** (6.8084)	0.2201*** (7.5666)	0.3361*** (9.6146)	0.3690*** (9.3325)
inv	−0.1608*** (−6.8261)	−0.1799*** (−6.5663)	−0.1128*** (−3.6415)	−0.3137*** (−4.0943)	−0.2166** (−2.2990)	0.0018 (0.0172)
SupervisorNumber1	−0.0062*** (−3.3980)	−0.0018 (−0.9115)	0.0004 (0.1793)	0.0106* (1.7922)	0.0072 (1.0377)	0.0171** (2.1905)
SumSalary1	−0.0000** (−2.4224)	−0.0000 (−1.1605)	−0.0000 (−1.4457)	0.0000*** (7.3738)	0.0000*** (6.1999)	0.0000*** (4.8874)
_cons	2.1328*** (46.4067)	2.0748*** (40.2704)	2.1223*** (36.0921)	−5.2016*** (−34.7851)	−5.4098*** (−30.5437)	−5.6589*** (−28.6622)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	22607	17141	14209	22607	17141	14209
R ²	0.054	0.045	0.044	0.549	0.516	0.502

t statistics in parentheses.

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

management is crucial to leverage productivity benefits while mitigating adverse impacts on performance, emphasizing a balanced approach to implementation. This paradox underscores the need for companies to concurrently fulfil opposing requirements in digital transformation, striking a balance between exploring new opportunities and leveraging existing resources, while prioritizing quickness, innovation, and stability (X. Guo et al. 2023; Haffke, Kalgovas, and Benlian 2017; Z. Li and Wang 2022).

The organizational paradox inherent in digital transformation involves a continuous conflict between interdependent elements (Schad et al. 2016). This paradox leads to a hindrance in short-term company performance indicators like Return on Assets (ROA) and Return on Equity (ROE). Investments in new technologies, digital infrastructure, and marketing efforts necessary for adapting to a digital business model surge total operating expenses and selling expense ratios, impacting profitability and liquidity in the short term. Despite laying the groundwork for long-term competitive advantage, these expenditures strain current financial metrics, evidenced by a decrease in the Cost and Expense Profit Ratio and cash flow per share. This financial trade-off highlights the complexity of balancing investments in intangible assets for future growth with addressing immediate economic challenges prompted by digital initiatives. The organizational paradox reflects conflicting demands from diverse internal and external stakeholders during digital transformation, as described by Donaldson and Preston (1995).

The interplay between digital transformation and productivity, particularly labour productivity and total factor productivity (TFP), is influenced by financial constraints and R&D spending levels. Financial limitations paradoxically may drive firms to innovate

and utilize digital technologies more efficiently, leading to significant short-term productivity gains. Conversely, heavy investments in research and development (R&D) may initially obscure the productivity benefits of digital transformation. This highlights the need for a balance between achieving immediate operational efficiencies through digital methods and investing in R&D for sustainable innovation and long-term growth. Financial institutions can play a role by swiftly identifying reliable companies and offering lower cost lending due to reduced information risk. Additionally, firms can leverage digital information-sharing advantages to access financial information quickly and mitigate funding limitations (Lu et al. 2022).

The increasing pace of digitization raises concerns such as job displacement and skill mismatches, with heterogeneity analysis revealing varying impacts of digital transformation across different firms and industries. State-owned enterprises, firms with longer histories, or joint ventures demonstrate resilience to negative performance effects due to established structures and collaborative strengths. Technology firms experience immediate benefits, while non-tech industries, particularly manufacturing, face complex and delayed advantages. The classification of European economies into four sets based on DIH services highlights different digitalization statuses and strategies (Gavkalova et al. 2024). A systematic review and field study in Brazilian pulp and paper companies show that only one digital technology, cloud computing, was relevant, suggesting that emerging countries need to develop technologies to meet SDGs (Costa et al. 2022). Digital strategy plays a significant role in improving manufacturing companies' ESG performance, moderated by total factor productivity, information transparency, and investor stickiness (H. Wang et al. 2023). In heavily polluting industries, public environmental concerns significantly promote digital transformation, particularly in non-state-owned, green image, and high-tech enterprises, enhancing energy consumption and productivity (Y. Wu et al. 2023). Sector-specific strategies are essential for optimizing digital transformation benefits across industries (Ciarli et al. 2021; Tian et al. 2023).

Implications

Implications for theory

Existing research underscores the potential of digital transformation to enhance firm performance, yet significant gaps remain. Past studies have often overlooked how technology capability moderates the relationship between technology investments, infrastructure use, and firm performance, particularly in developing economies (Grant 2024). Additionally, while Paradox Theory suggests that digital transformation can yield both benefits and challenges, limited research addresses the negative impacts on firm internationalization when specific conditions are unmet (Feliciano-Cestero et al. 2023). Moreover, the IT Productivity Paradox reveals that productivity gains from digital investments are often inconsistent, with few studies offering practical insights into overcoming these inefficiencies (Brynjolfsson and Hitt 2003).

This study advances our theoretical understanding by providing a more comprehensive explanation of the Productivity Paradox, revealing that the delayed or inconsistent productivity gains often stem from contextual factors such as R&D intensity, financial constraints, and industry-specific challenges. By integrating Paradox Theory, Digitalization

Theory, and TCT, this research demonstrates how digital transformation impacts firms' performance negatively, influenced by these contextual moderating factors. This nuanced analysis not only explains the underlying causes of the Productivity Paradox but also extends Paradox Theory by showing how strategic adjustments, such as enhancing technology capability, can mitigate potential negative effects. By addressing these complexities, this study enriches theoretical perspectives in strategic management, innovation, and organizational change, especially in the context of emerging economies, thereby fostering a deeper understanding of how firms can navigate the multifaceted impacts of digital transformation.

Implications for practice and policy

For practitioners, this research provides valuable insights into how digitalization strategies can be leveraged to enhance firm performance in the rapidly evolving Chinese market. By identifying the specific mechanisms through which digital transformation influences organizational outcomes, such as through increased efficiency, innovation, or market reach, practitioners gain actionable knowledge to inform strategic decision-making and resource allocation. Additionally, understanding the differential impacts of digital transformation across industries and organizational contexts enables practitioners to tailor their digital strategies effectively to maximize performance gains.

This study also offers critical insights for policy makers as they can design targeted interventions and policy frameworks to foster a conducive environment for digital innovation and adoption. This may involve initiatives to support digital infrastructure development, enhance digital literacy and skills training, or streamline regulatory processes to facilitate digital entrepreneurship and investment. Moreover, by recognizing the nuanced dynamics between digital transformation and firm performance, policymakers can develop evidence-based policies to promote sustainable and inclusive economic development in the digital era. In sum, this research serves as a valuable resource for both practitioners and policymakers seeking to navigate and capitalize on the transformative potential of digitalization in China's evolving business landscape.

It should be stressed that although this study is focused on China, the insights and findings offer valuable contributions that extend to businesses in other countries and different cultural contexts. The integration of Paradox Theory, Transaction Cost Theory (TCT), and the IT Productivity Paradox in analysing digital transformation offers a robust theoretical framework applicable across various national contexts. These theories are not confined to a specific region and can help businesses worldwide understand the dualities and complexities of digital transformation. Firms can learn about the potential pitfalls and the importance of strategic alignment between digital investments and organizational capabilities. This understanding can help businesses globally navigate similar challenges and optimize their digital transformation strategies. Companies in different sectors, whether technology, manufacturing, or pollution-intensive industries, can apply these findings to tailor their digital strategies according to their specific industry characteristics and needs.

Conclusions

The study explores the complex relationship between digital transformation and firm performance, uncovering both immediate challenges and long-term benefits. In the short term, higher levels of digital transformation correlate with decreased returns on assets and equity due to initial investment costs and lower-than-expected digital investment returns. However, digital transformation significantly boosts company and overall factor productivity, with benefits accruing as firms improve their use of digital technologies. The research highlights the intermediary impact of digital transformation on financial performance, showing it leads to higher operational costs and negatively affects firm performance metrics like ROA and ROE by altering cost structures and cash flow. The study also identifies a moderating effect where the positive impacts of digital transformation on productivity are enhanced under financial constraints and how R&D expenditure, when aligned with digital transformation efforts, can positively influence productivity. Firm heterogeneity analysis reveals that state-owned enterprises, larger firms, and joint ventures experience varying impacts from digital transformation, with SOEs being less affected. Industry heterogeneity analysis indicates that digital transformation has a significant positive impact on productivity in tech industries and heavy pollution industries, highlighting the sector-specific outcomes of digital strategies.

Furthermore, our research demonstrates that digital transformation, while offering unparalleled opportunities for innovation and efficiency, also presents a unique set of challenges and paradoxes for firms. The capability curse, as identified, highlights the complex scenario where firms' existing competencies can both facilitate and hinder digital adaptation. The findings suggest that a strategic balance between leveraging existing capabilities and embracing new digital opportunities is crucial for sustainable transformation.

For practitioners, this study underscores the importance of a nuanced approach to digital transformation that considers both technological and managerial dimensions. Firms are encouraged to adopt a holistic view of transformation, recognizing the critical role of middle management, the need for a flexible approach to technology adoption, and the importance of aligning digital initiatives with broader business strategies.

On the whole, our research highlights that digital transformation is a multifaceted process, fraught with paradoxes and challenges. By acknowledging and strategically navigating these complexities, firms can harness the full potential of digital innovation. As the digital landscape continues to evolve, it is imperative for both scholars and practitioners to continuously explore, adapt, and innovate, ensuring that digital transformation efforts are not just about survival but about thriving in the new digital era.

Finally, this study opens several avenues for future research. Future research should validate these findings by analysing different stages within the 2000–2022 timeframe. Comparing periods with low digital transformation (pre-2010) to high digital adoption (post-2010) can reveal differential impacts and provide insights into the digitalization paradox. This approach will enhance our understanding of the complex dynamics between digital transformation and firm performance in China, highlighting long-term challenges and opportunities.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

Data is available upon request from the corresponding author.

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Appendix

Table A1. Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
TFP LP	25729	8.347	1.114	3.491	13.096	5.988	11.199	0.373	3.406
LaborPro	25728	1.623	0.2	0	5.272	1.301	2.309	2.855	24.242
roaB	25729	0.032	0.148	-14.586	6.477	-0.335	0.225	-34.081	3902.16
roeB	25729	0.026	1.126	-85.647	24.265	-0.921	0.387	-52.857	3343.243
lnDTa	25729	1.89	1.404	0	6.304	0	5.303	0.438	2.445
TOCR	25729	0.987	0.83	-35.247	81.067	0.57	2.078	43.819	3905.514
SER	25729	0.08	0.103	0	4.843	0	0.478	7.506	224.902
CEP	25729	0.089	0.507	-21.895	36.148	-1.101	0.945	11.283	1448.323
cflow	25729	.045	0.082	-2.516	1.127	-1.166	0.248	-2.883	89.359
KZ	25246	1.622	2.312	-11.976	26.825	-4.514	7.351	.245	8.239
RD2	23773	0.046	0.053	0	0.436	0	0.244	2.39	11.058
size	25729	22.256	1.365	14.158	28.607	19.735	26.363	0.768	4.216
tobin	25250	2.16	2.394	0.641	126.951	0.841	8.898	21.195	834.985
cash	25729	0.206	0.145	0	0.998	0.016	0.679	1.369	5.076
inv	25729	0.047	0.047	0	0.642	0	0.22	2.167	10.404
SupervisorNumber1	25729	3.49	1.052	0	15	2	7	2.369	11.477
SumSalary1	25729	6660000	7410000	0	1.526e+ 08	578800	37044500	5.965	65.388

Sixplot for InDTa

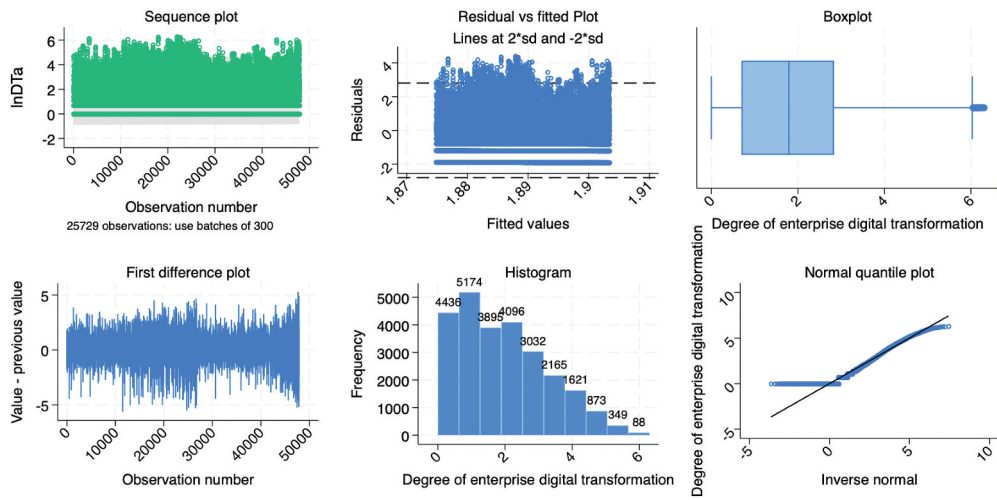


Figure A1. Sixplot for InDTa.