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Digital transformation, total factor productivity, and firm innovation investment

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A B S T R A C T

In the context of the digital economy, empowering firm innovation investment through digital transformation is an important strategy for promoting innovation development in China. This study investigates the effects and mechanisms of digital transformation on firm innovation investment from the perspective of total factor productivity, using a sample of manufacturing companies listed on the A-share market in China from 2012 to 2021. The following three main findings were obtained. First, results of both fixed- and random-effects regression methods revealed that digital transformation significantly promotes firms' innovation investment. This conclusion remains robust after controlling for endogeneity issues using the instrumental variable method and replacing the explanatory variable measurement methods. Second, stepwise regression analysis revealed a negative mediating mechanism of total factor productivity (TFP) in the impact of digital transformation on the level of firm innovation investment. The main reason for this is that an improvement in TFP intensifies the competition for capital and labor input between the production and innovation departments. Third, the group regression for heterogeneity analysis found that the overall effect of digital transformation on firm innovation investment is significantly positive in groups with low financing constraints and high human capital, but not significant in groups with high financing constraints and low human capital. Moreover, the negative mediating mechanism of TFP is significantly valid in all groups, further validating the competition between the production and innovation departments for capital and labor input. Based on the findings of this study and from the perspective of governance by the Chinese government, three policy recommendations are proposed to empower firm innovation development through digital transformation.

Introduction

The current Chinese economy has entered a stage of high-quality development. The report of the 20th National Congress of the Communist Party of China also emphasizes that one of the core tasks in this development process is to promote innovative development, which inevitably relies on firms' innovation investment at the micro level. Simultaneously, with the rapid development of the digital economy and the increasingly integrated combination of digital technologies—represented by artificial intelligence, blockchain, cloud computing, and big data technologies—with the real economy has impacted the operational development process of firms as microeconomic entities (Favoretto, 2022). According to the "White Papers on Digital Economy of China's Listed Companies" (2022), the current digital penetration rate of Chinese listed companies exceeds 70 %, signifying that digital transformation has become an inevitable trend for Chinese firms. Existing research suggests that digital transformation essentially involves applying new technologies (digital technology) to the production, operation, and management aspects of firms, thereby changing the original business processes (Chen et al., 2022; Gilch & Sieweke, 2021; Ilona et al., 2018). The application of new technologies is a manifestation of technological progress that can enhance corporate operational performance in various ways (Gaglio, 2022; Li et al., 2024; Xu et al., 2022). Therefore, can the successful application of new technologies stimulate firms to pursue them further, thereby enhancing their level of innovation investment? What is the mechanism of action? In the era of digital economy, the answers to these questions are related to how the Chinese government should continue to promote the level of innovative economic development. Therefore, this study focuses on exploring the impact of digital transformation on innovation investment in Chinese enterprises and clarifying the underlying mechanism from the perspective of total factor productivity (TFP).

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The main contributions of this study are as follows. First, it provides new research perspectives. The current literature mainly discusses the impact of digital transformation on innovation performance (Li et al., 2023; Liu et al., 2023; Peng & Tao, 2022); however, little research has investigated the impact of digital transformation on firm innovation investment. Therefore, this study can supplement the existing literature and provide new explanations for the economic effects of digital transformation. Second, the current study explores new economic mechanisms. The existing literature mainly examines the impact mechanism of digital transformation on firm innovation from the perspectives of global innovation network integration, knowledge flow, human capital enhancement, and innovation mode optimization (Akter et al., 2023; Fan et al., 2024; Forman & Zeebroeck, 2019; Li et al., 2024). Meanwhile, this study provides a new explanation for the impact of digital transformation on firm innovation by clarifying the mediating effect of TFP. Third, while the existing literature mostly focuses on the positive impacts of digital transformation on firms (Vial, 2019; Wang & He, 2024); this study is the first to demonstrate that TFP negatively mediates the impact of digital transformation on firms' innovation investment, which is important for comprehensive assessment of the economic effects of digital transformation.

Literature review

What is the impact of digital transformation on innovation investments? What is the role of the TFP in this impact? This section reviews relevant literature to address these two questions.

Can firms' digital transformation enhance their levels of innovation investment? Existing literature has not addressed this question directly. Previous studies have primarily examined the impact of digital transformation on innovation performance from the perspective of innovation outcomes (Li et al., 2023; Liu et al., 2023; Peng & Tao, 2022). These studies have generally acknowledged the significant positive effect of digital transformation on innovation performance in terms of innovation output (Ghasemaghaei & Calic, 2020; Vial, 2019; Wu & Li, 2024; Zapata et al., 2020) and innovation efficiency (Gu, 2023; Wang & He, 2024). Digital transformation can enhance innovation performance by facilitating global innovation network integration, knowledge flow, human capital enhancement, and innovation mode optimization. First, digital transformation helps firms access heterogeneous and diversified new knowledge and resources through global innovation network integration, ensuring the freshness, breadth, and flexibility of knowledge, which enhances innovation performance (Andersson et al., 2005; Fan et al., 2024; Rabbiosi & Santangelo, 2013; Wu et al., 2021). Second, digital transformation strengthens firms' ability to digest, absorb, and reconstruct new technologies and knowledge, facilitates internal and external data and knowledge sharing, and improves innovation performance (Ferreira et al., 2019; Forman & Zeebroeck, 2019; Ning et al., 2023; Sun, 2024; Urbinati et al., 2020). Third, digital transformation enhances employees' ability to acquire new knowledge and master new skills, promotes the upgradation of human capital within firms, and consequently improves innovation performance (Kohli & Melville, 2019; Li et al., 2024; Smith et al., 2017). Fourth, digital transformation optimizes innovation modes and facilitates adaptive adjustments in organizational business and process management, thereby enhancing innovation performance (Akter et al., 2023; Nambisan et al., 2017).

How does digital transformation affect firms' innovation investments in terms of TFP? Existing research has primarily focused on the impact of digital transformation on firms' TFP and has consistently found that it promotes TFP by enriching production factors (Zhao et al., 2021), improving the division of labor efficiency (Xia et al., 2022), reducing labor costs (Acemoglu & Restrepo, 2020; Kraus et al., 2022), and optimizing human capital structure (Autor & Dorn, 2013; Cheng et al., 2023). However, the impact of TFP on firms' innovation investments remains ambiguous.

In other words, extant literature does not directly clarify the impact of digital transformation on firms' innovation investments or the role of TFP. This gap can be explained by two aspects that are missing from previous studies. First, the direct impact of digital transformation on firms' innovation investments has not been explicitly discussed. Second, there is a lack of direct research on the influence of TFP on firms' innovation investment. Hence, this study aims to investigate the impact of digital transformation on firms' innovation investments and the mediating role of TFP, building upon existing theoretical and empirical analyses and providing additional insights.

Theoretical analysis

This section provides a theoretical analysis exploring the impact and mechanisms of digital transformation on firms' innovation investments from the TFP perspective.

Theoretical analysis of the impact of digital transformation on firms' innovation investments

This study posits that digital transformation significantly promotes firms' innovation investments, which can be analyzed from two aspects: innovation investment willingness and innovation investment capability.

First, digital transformation enhances innovation performance, thereby increasing a firm's willingness to invest in innovation. The ultimate goal of firms engaging in innovative activities is to gain a competitive advantage and improve operational profits. Digital transformation can promote innovation performance through various means, including global innovation network integration, knowledge flow, enhancement of human capital, and optimization of innovation modes (Akter et al., 2023; Fan et al., 2024; Li et al., 2024; Sun, 2024). This implies that by empowering digital transformation, firms can achieve more innovative outcomes with a given level of innovation investment, obtaining greater competitive advantages and operational profits. Digital transformation increases the expected returns on innovation investment, which inevitably stimulates a firm's willingness to invest in innovation.

Second, digital transformation can alleviate financial constraints, thereby enhancing firms' abilities to invest in innovation. Innovative activities are characterized by high investment, high risk, and long cycles, and rely heavily on the robustness and scale of financing. However, the high uncertainty in innovation R&D results makes it difficult to match the security requirements of traditional commercial banks' credit, leading to financial constraints for firms' technological innovations (Hajivassiliou & Savignac, 2024). Digital transformation can alleviate these financial constraints. Previous research has identified information asymmetry as a significant cause of firms' financial constraints (Stiglitz & Weiss, 1981; Xu et al., 2023). Firms accumulate large amounts of data and information during their internal production and operations (Duarte et al., 2012), which are trapped in discrete production models and cannot be effectively explored and utilized. Digital technology empowerment enables the collection and processing of accumulated data (Wu et al., 2021). With the support of digital technology, massive amounts of unstructured and non-standardized data can be transformed into easily understandable visualized data. Firms can analyze acquired internal and external information and obtain reports and forecasts regarding their business conditions (Fan et al., 2024). These processed data can help financial institutions more accurately assess the current situation and future prospects of firms, reduce the difficulty and cost of pre-loan examinations, strengthen positive market expectations, and consequently alleviate the financial constraints faced by firms (Manita et al., 2020), thereby enhancing their capability to invest in innovation.

Based on the above analysis, we can conclude that digital transformation promotes innovation performance and increases firms' willingness to invest in innovation, while alleviating financing constraints and enhancing firms' capability to invest in innovation. Therefore, we propose the following hypothesis:

Hypothesis 1. Digital transformation significantly enhances firms' innovation investment levels.

The mediating mechanism of total factor productivity

Digital transformation promotes firms' total factor productivity

Digital transformation can improve firms' TFP by enriching production factors, enhancing the division of labor efficiency, reducing labor costs, and optimizing human capital structure.

First, in terms of enriching production factors, digital transformation provides firms with valuable, diverse, and heterogeneous information (Li et al., 2022). Moreover, information theory suggests that efficient information processing enhances a firm's strategic decision-making efficiency. Second, in terms of enhancing the efficiency of the division of labor, digital transformation reduces the cost of information transmission between different departments within firms, thereby alleviating organizational management issues and improving production. For example, firms' data analysis capabilities can optimize organizational management processes and decision outcomes, thereby improving their TFP (Xia et al., 2022). Third, digital transformation decreases labor costs for firms, further enhancing production and division of labor efficiency. Digital transformation enables the automation of traditional production processes, resulting in lower labor costs per unit of output (Kraus et al., 2022). Finally, in terms of optimizing human capital structure, as the value chain in the manufacturing industry increases, the specialization of labor elements increases gradually. High-quality labor and specialized knowledge facilitate the integration of various links in the value chain, contributing to business process improvement and cost reduction in production and transactions, highlighting their role in the industrial division of labor (Acemoglu & Restrepo, 2020; Autor & Dorn, 2013). The intelligent development of firms will lead to the substitution of low-skilled labor with advanced machinery and increased demand for highly educated labor, optimizing the human capital structure of firms (Cheng et al., 2023).

Total factor productivity crowds out firms' innovation investment

Improvements in TFP can suppress firms' innovation investments. TFP represents the residual value of total output after accounting for the contributions of labor and capital (Lee & Viale, 2023; Solow, 1957). An increase in TFP triggers a price effect, not only reducing the production cost and sales price per unit, but also pushing out the production possibility frontier, encouraging businesses to expand production scale, and promoting the input of capital and labor in the production department (Aghion & Howitt, 1994; Gregory, 2022). However, a firm's innovation investment also highly depends on the availability of capital and labor (Carlo et al., 2016; Honjo et al., 2014). Therefore, under limited firm resources, an increase in TFP intensifies competition between the production and innovation sectors for capital and labor investment, consequently reducing the level of firm innovation investment.

Based on the above analysis, we conclude that digital transformation can promote the improvement of firms' TFP, while TFP can crowd out the level of innovation investment. Therefore, we propose the following hypothesis:

Hypothesis 2. Regarding the impact of digital transformation on firms' innovation investment levels, a negative mediating mechanism from total factor exists. That is, digital transformation can promote a firm's total factor productivity, thereby inhibiting innovation investment.

Empirical research design

This study's empirical research design comprises three parts: variable selection, model construction, and data selection.

Variable selection

Explained variable

The explained variable in this study is a firm's innovation investment (Y). A firm's innovation investment is measured based on research and development (R&D) investment. Considering the significant differences in the total amount of R&D investment among firms of different sizes, the R&D intensity index, rather than the scale of R&D investment, better reflects the level of R&D investment appropriate for a firm relative to its size (Jeon & Jung, 2024). Following Jeon and Jung's (2024) approach, this study adopts the ratio of R&D investment to operating revenue multiplied by 100 as a measure.

Explanatory variable

The explanatory variable in this study is a firm's digital transformation (X). A firm's digital transformation (X) is measured using Wu et al. (2021)) approach. In terms of methodology, annual report textual data of Chinese A-share listed companies were collected, and the frequency of relevant keywords related to "firm digital transformation" was counted to obtain the frequency of firm digital transformation (FX). The specific keywords included artificial-intelligence technology, big-data technology, cloud-computing technology, blockchain technology, and the application of digital technology, totaling five dimensions and 76 specific terms. Furthermore, to mitigate the impact of outliers and heteroscedasticity on the empirical results, the final measure of firm digital transformation (X) was subjected to a logarithmic transformation based on the frequency of firm digital transformation (FX), as shown in Eq. (1).

$$X = ln(FX + 1) \tag{1}$$

Additionally, a robustness test was conducted by replacing the explanatory variable following the approach of Zhao et al. (2021). Specifically, based on four dimensions, namely digital technology application, Internet business models, intelligent manufacturing, and modern information systems, 99 relevant terms were selected. A new measure of a firm's digital transformation (referred to as digital transformation 2 and denoted as $X2$ in this study) was constructed based on the frequency of these terms.

Mediating variable

The mediating variable in this study is firm TFP (Z). The estimation of the sample firms' TFP (LP TFP or $LPTFP$) is based on the LP method proposed by Levinsohn and Petrin (2003). Similar to the construction of the firms' digital transformation (X) measure, the estimated LPTFP measure obtained using the LP method underwent a logarithmic transformation to mitigate the impact of outliers and heteroscedasticity on the empirical results, as shown in Eq. (2).

$$Z = ln(LPTFP + 1) \tag{2}$$

Control variables

To ensure the robustness and reliability of the empirical findings, this study included a set of control variables at both the micro and regional levels, as shown in Table 1.

Model construction

To test Hypothesis 1, we constructed a linear regression model with firm and year effects. This model is presented by Eq. (3).

$$Y_{it} = \alpha + \beta X_{it} + \chi Con_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{3}$$

Table 1
Introduction of control variables.

Variable name	Abbreviation	Construction method
Firm age	Age	Number of years since the establishment of the firm
Selling expense ratio	Ser	Selling expenses divided by total operating revenue
Tobin's Q ratio	Tobin	Market value of the firm at the end of the year divided by the asset reset cos
Current asset ratio	Lar	Total current assets at the end of the year divided by total assets
Cash asset ratio	Car	Total cash assets at the end of the year divided by total assets
Regional dependency ratio	Dr	Non-working age population to working age population ratio in the province where the firm is located, multiplied by 100
Regional retail price index	Rpi	Retail price index in the province where the firm is located (calculated based on the previous year as 100)
Proportion of tertiary industry in regional GDP	Ind3	Proportion of the tertiary industry's GDP to the total regional output in the province where the firm is located, multiplied by 100

Table 2
Descriptive statistics of the variables.

Variables	Sample capacity	Mean value	Standard deviation	Minimum value	Maximum value
Y	21,357	4.592	3.949	0.056	24.22
X	21,357	1.223	1.283	0	6.148
Z	21,357	2.216	0.107	1.565	2.557
Age	21,357	17.50	5.782	2	63
Ser	21,357	0.080	0.095	0.002	0.502
Tobin	21,357	2.345	1.597	0.927	10.63
Lar	21,357	0.588	0.173	0.177	0.932
Car	21,357	0.164	0.130	0.008	0.631
Dr	21,357	37.38	7.170	19.27	57.79
Rpi	21,357	92.87	28.61	0	106.0
Ind3	21,357	51.23	10.25	29.70	83.90

where Y represents the explained variable indicating a firm's level of innovation investment; X represents the explanatory variable indicating the level of digital transformation of firms; the subscripts i and t denote the individual samples and years, respectively; Con represents a series of control variables at both the micro-and regional levels; μ represents individual effects; θ represents time effects; and ε represents the random error term. The relationship between Eq. (3) and research Hypothesis 1 is as follows: If the estimated coefficient of the explanatory variable (X) is significantly positive, it indicates a significant promoting effect of digital transformation on firm innovation investment, thereby supporting Hypothesis 1.

To test Hypothesis 2 and examine whether there TFP mediates the impact of digital transformation on firm innovation investment, we constructed Eqs. (4) and (5):

$$Z_{it} = \alpha' + \beta' X_{it} + \chi' Con_{it} + \mu'_i + \theta'_t + \varepsilon'_{it} \quad (4)$$

$$Y_{it} = \alpha'' + \beta'' X_{it} + \lambda'' Z_{it} + \chi'' Con_{it} + \mu''_i + \theta''_t + \varepsilon''_{it} \quad (5)$$

Eqs. (3)–(5) were used to test Hypothesis 2: In the case where Hypothesis 1 is supported, if the estimated coefficient of the explanatory variable X in Eq. (4) is significantly positive and the estimated coefficient of the mediating variable Z in Eq. (5) is significantly negative, then digital transformation inhibits firms' innovation investments by promoting TFP; this supports Hypothesis 2.

Data selection

The research sample comprised A-share listed manufacturing companies from 2012 to 2021. Financial data and annual report texts were obtained from the Guotai An database, whereas regional-level data mainly came from the statistical yearbooks of various provinces in China. After cleaning the data, 21,357 micro-level samples were obtained. Due to the lagged treatment of the samples in the empirical process, 18,513 micro-level samples were retained. The data cleaning process mainly involved the following tasks: First, identify the category of the samples based on the "Industry Classification Code of the China Securities Regulatory Commission (2012 Edition)," and select samples from the manufacturing industry. Second, to control for the impact of extreme values, the core variables of this study, including firm innovation investment, digital transformation, and TFP, underwent a 1 % winsorization process.

Table 2 presents the main descriptive statistics related to the explained variables, explanatory variable, mediating variable, and control variables in Eqs. (3)–(5). The mean, standard deviation, and maximum and minimum values of each variable were within the reasonable ranges.

Empirical analysis

Baseline regression results analysis

To test Hypothesis 1, a regression analysis was conducted using Eq. (3); the results are presented in Table 3. Both fixed effects (FE) and random effects (RE) regression methods were employed. To address potential endogeneity issues arising from simultaneous causality, a one-period lag was applied to the explanatory variable X (denoted as $L.X$). Columns (1) and (2) present the regression results using only the main explanatory variable, $L.X$. To mitigate the possible heteroscedasticity, columns (3) and (4) employed robust standard errors clustered at the firm level. Columns (5) and (6) report the regression results after introducing the control variables. P(all $\mu i=0$) represents the p-value for the F-test regarding the individual fixed effects, indicating whether FE regression is preferred over the pooled regression. The results in columns (1), (3), and (5) indicate that the FE regression outperforms the pooled regression at a significance level of 1 %. P-Wald represents the p-value for the Wald test, indicating whether the FE regression is preferred over the RE regression. The results in columns (1), (3), and (5) show that the FE regression is preferred to the RE regression at a significance level of 1 %. Therefore, the empirical analysis in this study focused primarily on the results of the FE regression, with the RE regression results used for robustness checks.

Table 3
Empirical results of the impact of digital transformation on firms' innovation intensity.

Variables	(1) FE	(2) RE	(3) FE	(4) RE	(5) FE	(6) RE
L.X	0.117*** (5.194)	0.187*** (8.716)	0.117*** (3.288)	0.187*** (5.570)	0.114*** (3.514)	0.178*** (5.821)
Control variable	No	No	No	No	No	No
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.100*** (75.409)	4.340*** (48.623)	4.100*** (66.679)	4.340*** (48.698)	−6.611 (−1.552)	−4.501 (−1.056)
Observations	18,513	18,513	18,513	18,513	18,513	18,513
R-squared	0.032	—	0.032	—	0.086	—
*F*statistics	52.28	—	21.35	—	20.33	—
P(all μi = 0)	0.000	—	0.000	—	0.000	—
P-Wald	0.000	—	0.000	—	0.000	—
Cluster	No	No	Yes	Yes	Yes	Yes

Note: The explained variable in the table is firm innovation investment (*Y*); the cluster denotes robust standard errors clustered at the firm level; values in parentheses represent *t*/*z* levels. "***," "**," and "*" represent statistical significance at the 1 %, 5 %, and 10 % levels, respectively. "*P*-Wald" represents *p*-value of Wald test.

Columns (1)–(6) of Table 3 show that the estimated coefficients of the explanatory variable (*L.X*) are significantly positive at the 1 % level. This result remains unchanged when introducing control variables, altering regression methods, or employing robust standard errors clustered at the firm level. Moreover, the magnitude of the estimated coefficients for digital transformation (*L.X*) remains relatively stable in both the FE and RE regressions. These findings confirmed the robustness of our empirical results. Thus, based on the empirical results in Table 3, it can be concluded that digital transformation has a significant promoting effect on firms' innovation investment, which provides preliminary evidence supporting Hypothesis 1.

Robustness discussion

Although the empirical results in Table 3 provide a preliminary validation for Hypothesis 1, it is essential to assess the robustness and reliability of this conclusion through a robustness discussion. We examined the robustness of Hypothesis 1 based on two aspects: controlling for endogeneity issues and conducting an alternative specification regression.

Controlling for endogeneity issues

Instrumental variable methods were employed to control for potential endogeneity issues in the model specified in Eq. (1), and the empirical results are presented in Table 4.

Table 4
Empirical results of the instrumental variable approach for controlling endogeneity.

Variables	(1) IV-FE	(2) IV-RE
L.X	0.031** (2.463)	0.069*** (5.021)
Control variable	Yes	Yes
Constant	— —	−4.494 (−1.204)
Observations	18,113	18,113
R-squared	0.081	—
Individual effect	Yes	Yes
Time effect	Yes	Yes
CD-*F*statistics	55.806	—
P-HJ	0.989	—
*F*statistics	38.05	—
Cluster	Yes	No

Note: "CD-*F* Statistics" represents Cragg-Donald Wald *F* statistic. "*p*-KP" represents *p*-value of Hansen J statistic.

Two variables were selected as instrumental variables for digital transformation (*X*): the New Products Sales Income of Industrial firms above the Designated Scale in the region (IV1) and the Length of Optical Cable Lines in the region (IV2). As both instrumental variables are regional-level variables, their values are unlikely to be influenced by micro-level corporate factors, thus ensuring their degree of exogeneity. Digital transformation fundamentally involves the application of new digital technologies (Chen et al., 2022; Gilch & Sieweke, 2021). IV1, which represents the sales income of new products, effectively reflects the extent to which a company's environment accepts new technology. IV2 indicates the basic conditions required for a company to introduce digital technology. Intuitively, IV1 and IV2 are likely to positively influence a company's digital transformation level, thus ensuring the validity of the instrumental variables. Furthermore, statistical measures obtained through regression were used to test the exogeneity and validity of the instrumental variables from a statistical standpoint. In column (1), the *p*-value of the Hansen J statistic (*p*-HJ) is greater than 0.1, suggesting that the hypothesis that instrumental variables are exogenous cannot be rejected at the 10 % significance level. The CD-F statistic was greater than 19.93, indicating that the hypothesis of weak instrumental variables could be rejected, even at the strictest critical value. Therefore, the selection of instrumental variables was considered reasonable.

Table 4 reports the empirical results of the instrumental variable-fixed effects (IV-FE) regression and instrumental variable-random effects (IV-RE) regression using the instrumental variables. In columns (1) and (2), the estimated coefficients of the lagged explanatory variable (digital transformation, *L.X*) remain significantly positive at the 5 % and 1 % levels. Therefore, even after controlling for endogeneity issues using instrumental variable methods, the conclusion that digital transformation significantly promotes firm innovation investment remains robust. This finding provides further evidence that supports Hypothesis 1.

Alternate specification of the explanatory variable

To further examine the robustness of Hypothesis 1, we employed an alternative specification by replacing the core explanatory variable. Specifically, lagged one-period digital transformation 2 (*L.X2*) and lagged two-period digital transformation (*L2.X*) were used as the core explanatory variables in the regression specified in Eq. (3). The results are reported in Table 5. Both fixed effects (FE) and random effects (RE) regressions were employed, and the heteroscedasticity issues were confirmed using firm-level cluster-robust standard errors.

From the results reported in columns (1)–(4) of Table 5, it can be observed that even with the replacement of the core explanatory

Table 5
Empirical results of the robustness test using alternate specifications of the explanatory variable.

Variables	(1) FE	(2) RE	(3) FE	(4) RE
*L.X*2	0.165***	0.225***	—	—
	(4.392)	(6.508)	—	—
L2.X	—	—	0.104***	0.166***
	—	—	(2.903)	(4.928)
Control variable	Yes	Yes	Yes	Yes
Constant	−6.703	−4.762	−5.179	−3.207
	(−1.575)	(−1.120)	(−1.215)	(−0.747)
Observations	18,115	18,115	15,374	15,374
R-squared	0.086	—	0.090	—
Individual effect	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
*F*statistics	20.85	—	18.11	—
Cluster	Yes	Yes	Yes	Yes

variable, the coefficient estimates of *L.X*2 and L2.X remain significantly positive at the 1 % level. This confirms the robustness of Hypothesis 1.

Mediating mechanism of total factor productivity

Research Hypothesis 2 proposes a negative mediating effect of TFP in the relationship between digital transformation and firm's innovation investment. Specifically, digital transformation promotes the enhancement of TFP, which leads to a crowding-out effect on a firm's innovation investment. To test Hypothesis 2, Eqs. (3)–(5) were regressed sequentially to examine the impact of digital transformation on firms' innovation investments, the impact of digital transformation on TFP, and the crowding-out effect of TFP on firms' innovation investment. The promotion effect of digital transformation on a firm's innovation investment has already been validated in the baseline regression specified in Eq. (3) and is reported in Table 3. Therefore, in this section, Eqs. (4) and (5) were further regressed in a step-wise manner to differentiate between the impact of digital transformation on TFP and the crowding-out effect of TFP on firms' innovation investment. The results are summarized in Table 6. Both fixed effects (FE) and random effects (RE) regressions were employed for cross-validation, and robust standard errors were clustered at the firm level. To ensure comparability of the empirical results, the regression results of Eq. (3) primarily refer to columns (5) and (6) of Table 3.

The regression results of Eq. (4) are reported in columns (1) and (3) of Table 6. It is evident that in both the FE and RE regressions, the coefficient estimates of the explanatory variable *L.X* are significantly positive at the 1 % level, indicating a significant promotional effect of digital transformation on firms' TFP. The regression results of Eq. (5)

Table 6
Empirical results of the mediating mechanism of TFP.

Variables	(1)	(2)	(3)	(4)
	FE		RE	
	Z	*Y*	*Z*	*Y*
L.X	0.005***	0.189***	0.005***	0.269***
	(5.600)	(5.693)	(7.209)	(8.525)
Z	—	−15.085***	—	−14.839***
	—	(−15.207)	—	(−18.474)
Control variable	Yes	Yes	Yes	Yes
Constant	1.902***	23.642***	1.957***	25.747***
	(20.807)	(5.065)	(21.948)	(5.604)
Observations	16,634	15,908	18,128	17,394
Individual effect	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes

are reported in columns (2) and (4) of Table 6. Consistent results were observed in both the FE and RE regressions, as the coefficient estimates of TFP (*Z*) were significantly negative at the 1 % level when considering the joint impact of digital transformation and TFP on firms' innovation investment. This finding suggests the presence of a crowding-out effect between TFP and firms' innovation investment. Therefore, based on the empirical results reported in Table 6, combined with Hypothesis 1, it can be concluded that digital transformation inhibits a firm's innovation investment by promoting TFP. This finding validates Hypothesis 2.

Furthermore, after considering the mediating mechanism of TFP, the coefficient estimates of the explanatory variable *LX* in columns (2) and (4) of Table 6 remain significantly positive at the 1 % level and show a noticeable improvement compared with columns (5) and (6) in Table 3. This indicates that the mediating mechanism of TFP partially constrains the promotional effect of digital transformation on a firm's innovation investments.

Heterogeneity analysis

Based on the analysis of mediating mechanisms, we believe that while digital transformation generally promotes firms' innovation investment, there exists a negative mediating mechanism stemming from TFP. The theoretical analysis suggests that this is primarily due to competition for labor and capital resources between the production and innovation departments when a firm's resource base is limited. This also implies that when a company's resource base is weak, competition for funds and labor between its production and innovation departments becomes more intense. Therefore, we conducted a heterogeneity analysis from the perspectives of financial constraints and human capital to provide more empirical evidence for the negative mediating mechanism of TFP.

Heterogeneity of financial constraint

When firms face high financial constraints, their limited ability to obtain external financing may intensify resource competition between the production and innovation departments. This strengthens the negative mediating mechanism of TFP, leading to variations in the impact of digital transformation on innovation investments. This study first measured the level of financial constraint using the SA index and divided firms into high and low financial constraint groups. The impact of digital transformation on a firm's innovation investment and the mediating mechanism of TFP are then examined for heterogeneity between the two groups. Regarding the heterogeneity analysis of the impact of digital transformation on firms' innovation investment, regressions were conducted separately on the high- and low-financing constraint groups using Eq. (3). The results are reported in columns (1) and (4) of Table 7. Regarding the heterogeneity analysis of the mediating mechanism of TFP, regressions were performed separately on the high- and low-financial constraint groups using Eqs. (4) and (5). The results are reported in columns (2), (3), (5), and (6) of Table 7. Fixed effects (FE) regression was employed and robust standard errors clustered at the firm level were utilized.

Columns (1) and (4) of Table 7 show that the coefficient estimate of the explanatory variable *L.X* is significantly positive at the 1 % level in the low financial constraint group, while it is not significant in the high financial constraint group. This indicates that the promotion effect of digital transformation on a firm's innovation investment mainly exists in the low financial constraint group, but is not significant in the high financial constraint group. Further analysis suggests two reasons for this heterogeneity.

First, the degree of the mediating effect differs, and the negative mediating effect of TFP is higher in the high financial constraint group than in the low financial constraint group. Based on the coefficient estimates of the main variables in columns (2), (3), (5), and (6), it can be seen that the negative mediating mechanism of TFP is significant

Table 7
Empirical results of the heterogeneity analysis from the perspective of financial constraints.

Variable	Low financial constraint group			High financial constraint group		
	(1) *Y*	(2) *Z*	(3) *Y*	(4) *Y*	(5) *Z*	(6) *Y*
L.X	0.114***	0.004***	0.186***	0.054	0.005***	0.136***
	(2.929)	(3.372)	(4.569)	(1.188)	(3.866)	(2.912)
Z	—	—	−15.288***	—	—	−17.370***
	—	—	(−9.858)	—	—	(−11.683)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−8.788*	1.760***	18.803***	1.324	2.014***	37.425***
	(−1.691)	(15.596)	(3.005)	(0.188)	(14.329)	(5.242)
Observations	9085	9085	9085	9030	9030	9030
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes

Table 8
Empirical results of the heterogeneity analysis from the perspective of human capital.

Variable	Low human capital group			High human capital group		
	(1) *Y*	(2) *Z*	(3) *Y*	(4) *Y*	(5) *Z*	(6) *Y*
L.X	0.024	0.005***	0.062**	0.116**	0.004***	0.136***
	(0.895)	(4.093)	(2.341)	(2.330)	(3.322)	(2.912)
Z	—	—	−8.266***	—	—	−22.770***
	—	—	(−7.741)	—	—	(−15.971)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.346***	2.069***	19.806***	4.553***	2.038***	51.113***
	(5.601)	(122.713)	(8.278)	(5.822)	(130.073)	(16.759)
Observations	8408	8408	8408	8752	8752	8752
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes

in both the low and high financial constraint groups. Even after controlling for the influence of TFP, the promotional effect of digital transformation on a firm's innovation investment remained significant in the high financial constraint group. This indicates that in the high financial constraint group the contradiction between TFP and innovation investment in terms of fund allocation is more intense because of weaker financing capacity, which leads to a more pronounced negative mediating effect of TFP. Specifically, for each unit increase in digital transformation, the negative impact on innovation investment through the TFP channel is approximately 0.061 (i.e., 0.004×15.288) units in the low financial constraint group and approximately 0.087 (i.e., 0.005×17.370) units in the high financial constraint group.

Second, the degree of the direct promotion effect differs; after controlling for the influence of TFP, the direct promotion effect of digital transformation on a firm's innovation investment is lower in the high financial constraint group than in the low financial constraint group. From the empirical results in Columns (3) and (6), the coefficient estimate of the explanatory variable *L.X* is 0.186 in the low financial constraint group and 0.136 in the high financial constraint group. This indicates that after controlling for the influence of TFP, the direct promotion effect of digital transformation on firms' innovation investment in the low financial constraint group is approximately 1.37 times higher than that in the high financial constraint group, which also contributes to the insignificant impact of digital transformation on firms' innovation investments in the high financial constraint group.

The empirical findings indicate that from the perspective of financial constraints, there is competition for capital between the production and innovation departments. When the level of financial constraints is high, this competition intensifies, strengthening the negative mediating mechanism of TFP, and rendering the overall impact of digital transformation on firms' innovation investment insignificant. By contrast, when the level of financing constraints is low, firms have sufficient ability to obtain financial support, which can alleviate this competition. Therefore, in the low financial constraint group, the overall impact of digital transformation on firms' innovation investments is significantly positive.

Heterogeneity of human capital

There is competition for labor between the production and innovation departments within firms. The dependence of firm innovation activities on labor mainly involves highly educated personnel, specifically those with higher levels of human capital, such as employees with a bachelor's degree or higher (Carlo et al., 2016). Therefore, this study measures the level of a company's human capital using the proportion of employees with a bachelor's degree or higher. Companies are divided into two groups: those with high and those with low human capital. This division allows us to examine the impact of digital transformation on firms' innovation investment and the heterogeneous performance of the mediating mechanism of TFP between the two groups of samples. To analyze the heterogeneity of the effect of digital transformation on firm innovation investment, samples from the high and low human capital groups were subjected to regression analysis based on Eq. (3). The results are reported in columns (1)–(6) of Table 8.

Columns (1) and (4) of Table 8 reveal that in the high human capital group, the estimated coefficient of the explanatory variable *L.X* is significantly positive at the 5 % level. By contrast, in the low human capital group, the estimated coefficient of the explanatory variable *L.X.* was not significant. This indicates that the promotional effect of digital transformation on firms' innovation investments is primarily present in the high-human-capital group. This difference can be explained in two ways, similar to financial constraints.

First, there was a difference in the degree of the mediating effects. The negative mediating effect of TFP is greater in the low human capital group than in the high human capital group. Based on the coefficient estimation results for the main variables in columns (2), (3), (5), and (6), it is evident that the negative mediating mechanism of TFP is significantly valid in both the high and low human capital groups. In the low-human capital group, even after controlling for the impact of TFP, the promotional effect of digital transformation on firms' innovation investments remains significant. Second, there was a difference in the degree of direct promotional effects. After controlling for the impact of TFP, the direct promotional effect of digital transformation on firms' innovation investment in the low-human capital group was lower than that in the high-human capital group.

Therefore, the empirical findings suggest that from the perspective of human capital, there is competition for resources between the production and innovation departments. When the level of human capital is low, owing to the relative scarcity of higher-level human capital, this competition intensifies, reinforcing the negative mediating mechanism of TFP, which in turn makes the overall impact of digital transformation on firm innovation investment insignificant. When human capital is high, competition is effectively alleviated.

Conclusion and policy recommendations

This study uses a sample of manufacturing companies listed on China's A-share market from 2012 to 2021 to investigate the impact and mechanisms of digital transformation on firms' innovation investments from the perspective of total factor productivity (TFP). Based on the theoretical and empirical research, this study makes the following three findings: First, digital transformation promotes firms' innovation investments significantly. This indicates that digital transformation has become an important driving force for promoting China's economic innovation and development level. Second, TFP has a negative mediating effect in the relationship between digital transformation and the level of a firm's innovation investment. Specifically, digital transformation can promote a firm's TFP, which, in turn, suppresses innovation investments. The primary reason for the phenomena observed in the empirical findings is that an improvement in TFP intensifies competition for capital and labor inputs between the production and innovation departments of a company. This finding indicates that firms face the problem of directional decision-making in the process of digital transformation. Third, heterogeneity studies found that the impact of digital transformation on firms' innovation investment varies significantly with different levels of financing constraints and human capital. From the perspective of financing constraints, the overall impact of digital transformation on a firm's innovation investment is significantly positive in the low financial constraint group, but not in the high financial constraint group. This is explained by two reasons: the higher negative mediating effect of the TFP in the high financial constraint group compared to the low financial constraint group, and the lower promotion effect of digital transformation on firms' innovation investment in the high financial constraint group compared to the low financial constraint group. From the perspective of human capital, the overall effect of digital transformation on firm innovation investment is significantly positive in the high human capital group but not significant in the low human capital group. There are two reasons for this finding. The negative mediating effect of the TFP mediation mechanism is greater in the low human capital group than in the high human capital group. The direct promoting effect of digital transformation on firms' innovation investment was lower in the low human capital group than in the high human capital group. The heterogeneity analysis further confirms the resource competition between the production and innovation departments. Simultaneously, it also demonstrates that reducing financing constraints and improving human capital level are effective approaches for alleviating resource competition and strengthening the role of digital transformation in promoting enterprise innovation investment.

The main contributions of this study are as follows. First, it provide new research perspectives. While the current literature mainly examines the impact of digital transformation on innovation performance (Li et al., 2023; Liu et al., 2023; Peng & Tao, 2022), few studies have explored the impact of digital transformation on firm innovation investment. Therefore, this study can supplement the extant literature and provide new explanations for the economic effects of digital transformation. Second, it investigates new economic mechanisms. The existing literature mainly explores the impact mechanism of digital transformation on firm innovation from the perspectives of global innovation network integration, knowledge flow, human capital enhancement, and innovation mode optimization (Akter et al., 2023; Fan et al., 2024; Forman & Zeebroeck, 2019; Li et al., 2024). Meanwhile, this article provides a new explanation for the impact of digital transformation on firm innovation by clarifying the mediating effect of TFP. Third, while the existing literature mostly focuses on the positive impacts of digital transformation on firms (Vial, 2019; Wang & He, 2024), this study is the first to find that TFP negatively mediates the effect of digital transformation on firms' innovation investment, which is important for comprehensive assessment of the economic effects of digital transformation. Nevertheless, this study had certain limitations. First, the research object of this study is manufacturing firms; meaning, it does not consider non-manufacturing firms. Therefore, it does not compare the similarities and differences in the impact of digital transformation on firm innovation investment across different industries. Second, this study explored the mediating mechanism of TFP on the impact of digital transformation on firms' innovation investments. However, digital transformation involves various aspects of enterprise production, operations, and management and its economic impacts are inevitably diverse. Considering only TFP's mediating mechanism may introduce limitations from a research perspective. Therefore, future research could expand on the basis of this study in terms of research subjects and impact mechanisms.

Based on the conclusions of this study, we propose three policy suggestions from the perspective of Chinese government governance to empower firm innovation development through digital transformation. First, the study clarifies the policy orientation and encourages firms to engage in digital transformation. This study suggests that digital transformation promotes innovation investments in firms. Therefore, the government should clarify its policy direction, and the formulation of related policies should be conducive to firms undertaking digital transformation. For firms engaged in digital transformation, it is important to strengthen related infrastructure, establish a scientific evaluation system, and introduce targeted subsidy policies. Second, the government should introduce supporting financing policies and improve the financing environment for digital transformation. The intermediary mechanism and heterogeneity analysis show that competition for capital between production and innovation departments can weaken the facilitating effect of digital transformation on firm innovation investment. The government should formulate supporting policies from the perspective of corporate financing to reduce the financial constraints firms face during digital transformation. For example, establishing special credit subsidy funds for firms' digital transformation behaviors and accelerating the formulation of policies for issuing corporate bonds related to digital transformation. Third, policy makers should formulate talent policies to enhance the supply of higher human capital. The intermediary mechanism and heterogeneity analysis also highlighted competition for labor, especially higher human capital, between production and innovation departments. Therefore, the government should also improve the corporate human capital structure through policy means, such as strengthening investment in higher education in areas where digital transformation is more intensive and providing employment subsidies for positions related to digital transformation.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

CRediT authorship contribution statement

Jiaju Yu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ye Xu:** Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jian Zhou:** Data curation, Methodology. **Wei Chen:** Writing – original draft, Methodology, Conceptualization.

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