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EXPLORING THE IMPACT OF DIGITAL TRANSFORMATION ON PRODUCTIVITY: THE ROLE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY, GREEN TECHNOLOGY, AND ENERGY TECHNOLOGY

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Abstract. The aim of this paper is to explore the technological innovation mechanism by which digital transformation (DT) influences total factor productivity (TFP). We take the Chinese listed firms from 2007 to 2020 as research samples, and contribute to the above goals based on fixed-effect models, instrumental variables, mediation effect, and moderating effect models. It has been found that (1) while DT contributes positively to productivity, the enhancement of TFP in current DT is primarily attributed to artificial intelligence (AI) technology rather than other technological innovation. (2) From an innovation-directed perspective, the impact of DT on TFP may be offset by other forms of technological innovation, such as green and energy technology. Specifically, the non-AI direction of technological innovation may not align with the productivity implications of DT. (3) Intellectual property protection impedes the impact of DT on productivity and constrains the deployment of AI technology. Conversely, business strategic radicalism and corporate intangible asset have yielded favorable outcomes. This study not only verifies that the technological innovation channel of DT for enhancing TFP mainly stems from AI technology, but also implies that the current DT might exert a negative effect on other technologies.

Keywords: digital transformation, artificial intelligence technology, green technology, energy technology, total factor productivity.

JEL Classification: D24, O33, Q55.

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1. Introduction

The fundamental logic of firm productivity development is being reshaped by DT, a disruptive technological and organizational revolution (Chatzistamoulou, 2023; Peng & Tao, 2022). The promotion of sustainable global economic growth can be achieved through DT, which has become an irreplaceable source of power (Van Veldhoven & Vanthienen, 2022), and technological innovation is not only a vital part of DT, but also a core force driving productivity growth (Gong & Ribiere, 2021; Zeng & Lei, 2021). This is because DT is one of the means to optimize the allocation of resources, providing more room for technological innovation (Li et al., 2022). However, there are still studies that point to the possible negative effects of DT in productivity development of firms (McElheran & Forman, 2019), such as the Solow paradox (Brynjolfsson & Collis, 2019). Consequently, whether DT can further drive the improvement of TFP of firms on the basis of promoting technological innovation needs to be continuously discussed.

The scale of technological innovation in various sectors in China is continuing to increase as DT gradually deepens. According to the report released by the China National Intellectual Property Administration, the number of invention patents in force in China as of December 2023 is 4.991 million, and there were more than 1.6 million valid invention patents related to digital technology, and the contribution of DT to technological innovation is obvious to all (Nambisan et al., 2019). The use of green technology, AI technology, and energy technology has become a vital component of technological innovation. In particular, green technology innovation is not only a significant influence on TFP (Song et al., 2022), but also related to green development (Du & Li, 2019; Du et al., 2021), which is the crucial to balancing DT and green transformation. There has been a rise in interest in the impact of DT on green technology innovation (Xue et al., 2022; Zheng & Zhang, 2023). AI technology and DT are intimately connected (Malik et al., 2022), and the impact of DT on AI technology should be the most prominent, and how to profit from it is an urgent concern (Teece, 2018). Energy technology is not completely "green", coal, oil, natural gas, and other traditional fossil energy technology cannot be abandoned immediately (Qu et al., 2023), whether DT can play a role in energy sector remains to be seen (Du et al., 2023; Maroufkhani et al., 2022).

In addition, the imbalance in the scale and direction of technological innovation is the inevitable problem that restricts the virtuous cycle of China's economy and the improvement of industrial innovation efficiency for a long time, and it is also the root cause of the "bottleneck" of China's industrial innovation development (Qiu et al., 2023). The conclusion that there are different directions of technological change has been widely concerned by the academic circle (Hassler et al., 2021), and it is found that the change of the direction of technological change will have different impacts on TFP (Zhen et al., 2021), resulting in different economic and environmental consequences (Acemoglu et al., 2012). This reminds us that it remains to be seen whether different types of the direction of technological innovation will change the productivity effects of DT. In general, the purpose of this paper, first, is to explore the impact of DT on TFP of firms; Second from the perspective of green technology, AI technology, and energy technology, analyze what type of technological innovation can affect TFP through DT; Third, further examine how different types of the direction of technological innovation change the productivity effects of DT.

To explicitly present the similarities and differences between this paper and previous studies, we enumerate the recent studies on the impact of DT on TFP and technological innovation in Table 1. The column (2) of Table 1 presents the sources in reverse chronological sequence. The column (3) reveals the research topic of the relevant research. The column (4) presents the Main points that relevant research has concentrated on. The column (5) exhibits the methods employed in the relevant studies. Contrary to previous studies, the principal characteristic of this paper lies in exploring whether technological innovation scale and direction (AI technology, green technology, and energy technology) plays a mechanistic role in the impact of DT on TFP.

The following is the order in which this paper is organized. Section 2 is where the review of literature and hypothesis for research are presented. Data sources, variable definitions, and an econometric model are all part of the methodology shown in Section 3. The empirical results and discussion are in Section 4. In Section 5, the conclusions and implications are conferred.

Table 1. Literature about the impact of DT on TFP and technological innovation

No.	Source	Research topic	Main points	Methodology
(1)	(2)	(3)	(4)	(5)
1	Yu et al. (2024)	DT, innovation investment, and TFP	DT impacts innovation investment through TFP.	Fixed-effect model Random-effect model Instrumental variable Mediating effect model
2	Du et al. (2024)	DT and green technology innovation	The spatial spillover effect between DT and green technology innovation is mainly achieved through the transfer of high-tech industries between regions.	Spatial Durbin model Mediating effect model
3	Yang et al. (2024)	DT and TFP	Innovation capability and cost control play a crucial mechanistic role in the impact of DT on TFP.	Fixed-effect model Instrumental variable Mediating effect model
4	Teng et al. (2024)	DT and TFP	Supply chain efficiency plays a crucial mechanistic role in the impact of DT on TFP.	Fixed-effect model Instrumental variable Mediating effect model
5	Su et al. (2023)	DT and TFP	Cost stickiness plays a crucial mechanistic role in the impact of DT on TFP.	Fixed-effect model Instrumental variable PSM method
6	Cheng et al. (2023)	DT and TFP	The influence of DT on TFP has an inverted U-shaped relationship	Fixed-effect model Non-linear model
7	Wang et al. (2023b)	DT and green TFP	Structural optimization and green technology innovation effects are two critical paths through which DT affects green TFP.	Data envelopment analysis Fixed-effect model DID model Instrumental variable Mediating effect model
8	Zhang and Dong (2023)	DT and TFP	Quality of internal control plays a crucial mechanistic role in the impact of DT on TFP.	Fixed-effect model Instrumental variable Mediating effect model
9	Gaglio et al. (2022)	DT, innovation, and TPF	Innovation plays a crucial mechanistic role in the impact of DT on TFP.	Fixed-effect model Instrumental variable
10	Nambisan et al. (2019)	DT and innovation	Technological innovation plays a crucial role in DT	Meta analysis

Generally, the marginal contributions of this article are listed as follows: (1) We investigates whether DT can impact TFP via the mechanisms of the scale of technological innovation (including AI technology, green technology, and energy technology). Meanwhile, we further examine the impact of different types of the direction of technological innovation on the productivity effect of DT. (2) The development level of artificial intelligence technology of firms is measured by combining patent IPC code and easily confused keywords in patent name and patent abstract. (3) Three types of heterogeneity related to technological innovation have received attention in this paper, including the regional level of intellectual property protection, business strategic radicalism of innovation, and the size of firm intangible assets.

2. The review of literature and hypothesis for research

Before discussing the literature review, we show the research framework of this paper, as shown in Figure 1. (1) Examine whether DT can drive TFP; (2) Explain the mechanism of TFP improvement driven by DT from the perspective of the scale of technological innovation; (3) Further explain the impact of DT on TFP from the perspective of the direction of technological innovation. In addition, the heterogeneity of DT affecting TFP has also attracted attention (intellectual property protection, business strategic radicalism, and enterprise intangible assets).

Specifically, the scale and direction of technological innovation in this paper are determined by AI technology, green technology, and energy technology. For details, refer to Subsection 3.2. Among these, AI and green technology fall within the macroscopic classification of technological innovation, indicating their potential for integration across diverse domains. Exploring AI and green technologies helps clarify the synergy between digitalization and greenization. Energy technology belongs to the application classification of technological innovation. Referencing the research conducted by Aghion et al. (2016), examining energy technology aids in elucidating whether DT will alter the variational trajectory of technology within specific domains.

2.1. What does DT mean and how does it affect productivity

At present, the core object of DT is firms, and the content of DT is the collection of information, the use of information technology to standardize management processes, the processing of data, and the application of digital technology to assist decision-making (Buck et al., 2023; Wu et al., 2019). DT is not limited to the in-depth use of digital technology by firms but also includes the use of digital thinking to transform organizational and generative methods, to employ data or information as production factors to improve productivity (Chatzistamoulou, 2023; Kraus et al., 2021; Zhang & Dong, 2023). Consequently, DT should be the fundamental restructuring and innovation of all aspects of a business or organization using

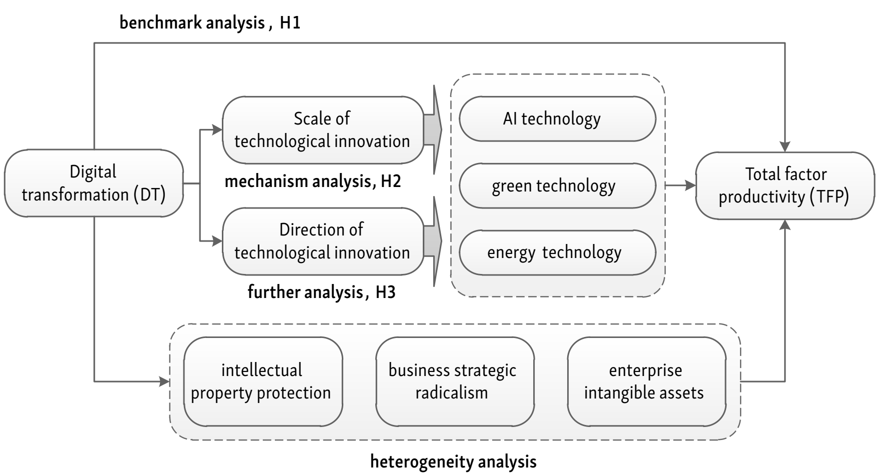

Figure 1. Research framework

relevant technologies to improve productivity, add value, and create new growth opportunities (Vial, 2019). This transformation involves not just transforming traditional paper-based processes into electronic processes, but transforming the way businesses operate, organizational structures, corporate cultures, and customer interactions by leveraging big data, cloud computing, AI, the internet of things, financial technology, and other advanced technologies (Gong & Ribiere, 2021).

DT undoubtedly has an impact on TFP (Gaglio et al., 2022; Su et al., 2023; Teng et al., 2024; Wang, 2023). Some studies have pointed out that when the DT does not match the organizational structure of the firm, the 'information technology paradox' can arise, i.e., the DT can inhibit productivity growth (McElheran & Forman, 2019). However, there is an increasing amount of research supporting the benefits of DT for productivity. Where, Nucci et al. (2023) takes Italian firms as the research samples, and believes that DT promotes the improvement of TFP, and there is a directed in the service industry and large enterprises. Picazo Rodríguez et al. (2023) argues that DT boosts productivity perceptions and is affected by technostress and work engagement. As an important engine of the world economy, the impact of China's DT on productivity is also of great concern. Lei and Wang (2023) believes that the impact of DT on TFP of Chinese listed companies is positive, and there are such impact ways as innovation effect, cost effect, and resource allocation effect. Also for Chinese listed companies, Cheng et al. (2023) found that the impact of DT on TFP is nonlinear, i.e., inhibition and promotion occur in a U-shaped pattern, and DT has the potential to enhance TFP in the long term. Even for green TFP, the stimulative effect of DT remains (Wang et al., 2023b). In reality, it is becoming more recognized that DT can have a beneficial effect on productivity.

H1: *DT can promote TFP.*

2.2. Technological innovation mechanism of DT affecting productivity

There is a complex chain of transmission among DT, technological innovation, and TFP.

First, DT is seen as a boost to technological innovation, which opens up new opportunities for innovators and stakeholders (Nambisan et al., 2019). DT can not only drive digital technology innovation (Fang & Liu, 2024), but also drive the improvement of technological innovation capability and innovation management (Gregory et al., 2019). Specifically, DT improves innovation performance (Li et al., 2023b). However, some studies also believe that DT is not a prerequisite for Chinese manufacturers to improve their innovation performance (Xing et al., 2023). Only under the state of balanced development and technology-driven, DT can exert its innovation incentive result. Specific technological innovations are examined to examine the impact of DT on green and energy technologies, and there is evidence of facilitative effects (Du et al., 2023, 2024; Zheng & Zhang, 2023). The correlation between AI technology and DT is high, so the development of related technologies is driven by DT (Ayoko, 2021).

In contrast, scholars have long valued the contribution of technological innovation to productivity and have included industry-specific studies. (Huang et al., 2019; Karafillis & Papanagiotou, 2011; Lipsey & Carlaw, 2004; Yu et al., 2024). Technological innovation is viewed as the primary driver of TFP in the digital economy (Pan et al., 2022). Not only in China, but also in other developing countries, the contribution of technological innovation to productivity is beyond doubt (Saleem et al., 2019). For green TFP, technological innovation is also considered to have a positive impact, and the positive impact is also durable, there is no specific threshold conditions (Wang et al., 2021). Studies based on spatial econometric models also found that green technology innovation significantly promoted TFP (Du & Li, 2019) and green TFP (Wang et al., 2021). TFP has been given attention not only because of green technology innovation, but also because of the impact of energy technology innovation and AI technology innovation (Wang et al., 2023a; Yang, 2022).

Furthermore, the direction of technological innovation at the enterprise micro level determines the biased technological progress at the sector macro level. It has emerged that biased technological change has an impact on TFP, but the effect of different types of biased technological progress on TFP remains uncertain (Qiu et al., 2023; Zhen et al., 2021). Consequently, we should be mindful of whether the direction of technological innovation has a moderating impact on the productivity effects of DT. To put it simply, we present the following research hypotheses.

H2: *DT can promote TFP through the channels of the scale of technological innovation such as AI technology, green technology, and energy technology.*

H3: *The promotion effect of DT on TFP is influenced by the direction of technological innovation.*

3. Methodology

3.1. Data sources

This paper utilizes Chinese A-share listed firms (Shanghai and Shenzhen stock markets) as research samples between 2007 and 2020. The China Stock Market & Accounting Research database (n.d.) is the source of the financial data for listed firms. The WinGo textual analytics database (n.d.) is used to obtain the annual report and MD&A section data for listed firms. The China National Intellectual Property Administration (n.d.-a;-b) is the source of patent data relating to green technology, AI technology, and energy technology. Additionally, to ensure the effectiveness and continuity of data, the research samples are treated as follows: (1) The list excludes samples of firms that have suffered losses (ST, ST*, and PT). (2) The financial sector's listed firms are not included as samples. (3) Listed firms with an IPO date of less than one year are not included in the sample. (4) The list of firms with discontinuous data is not included in any samples. Finally, 12544 firm-year sample data in 986 listed firms are obtained.

3.2. Variable definitions

3.2.1. Explained variables

Total factor productivity (*TFP*). According to Olley and Pakes (1996), Levinsohn and Petrin (2003), Ahmed and Elfaki (2024), Ahmed and Kialashaki (2021), Huang et al. (2019), and Nucci et al. (2023), the TFP at the micro level of the firm needs to be measured based on the theory of Cobb-Douglas production function.

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta}. \quad (1)$$

A_{it} means to consider the influence of other factors besides the labor factors (L_{it}) and capital factors (K_{it}) on productivity, that is, TFP, which represents the marginal return optimization of factors. Y_{it} represents the total output of a firm i in time t under the input of factors. Measured by the total operating income of listed firm. L_{it} represents the input of labor factors. Measured by the number of employees in listed firm. K_{it} represents the input of capital factors. Measured by the net fixed assets of listed firm. The logarithmic Cobb-Douglas production function is employed to measure TFP based on econometric model (Guo & Zhang, 2023). In this case, TFP is included in the residual ε_{it}.

$$Y_{it} = \alpha L_{it} + \beta K_{it} + \varepsilon_{it}. \quad (2)$$

However, due to the difference of research samples, the TFP estimated by the above model may have simultaneity bias or selectivity bias (Zhen et al., 2021). Therefore, the residual ε_{it} is decomposed to get ω_{it} and μ_{it}. Where, ω_{it} can be observed by firms and affect the selection of current factors, while μ_{it} is the residual or TFP. ω_{it} can be discussed by a variety of methods, thus producing a variety of estimation methods for TFP (Huang et al., 2019; Karafillis & Papanagiotou, 2011; Saleem et al., 2019).

$$Y_{it} = \alpha L_{it} + \beta K_{it} + \omega_{it} + \mu_{it}. \quad (3)$$

First, the LP method, in accordance with Levinsohn and Petrin (2003), the variable of intermediate inputs (*M1*) is incorporated, and the cost is adjusted taking into account the alterations of external factors in firm production, which is specified as follows:

$$Y_{it} = \alpha L_{it} + \beta K_{it} + \gamma M1_{it} + firm + year + \mu_{it}. \quad (4)$$

Hence, the LP method enhances the reliability of the estimation of TFP based on econometric model by taking into account more influential factors. Specifically, the intermediate input (*M1*) is measured by the operating costs, selling expenses, administrative expenses, and financial expenses of listed companies. *firm* is firm fixed effect, *year* is time fixed effect.

Second, the OP method, according to Olley and Pakes (1996), the capital factor is calculated based on the perpetual inventory method and takes into account the impact of current investment[1], as follows:

$$Y_{it} = \alpha L_{it} + \beta K_{it} + \gamma I_{it} + firm + year + \mu_{it}, \ K_{it} = (1-\rho) K_{it-1} + I_{it}. \quad (5)$$

Third, the OLS method, which considers firm fixed effects, time-industry fixed effect, and time-province fixed effect, can also be used to strip TFP from residuals, as follows:

$$Y_{it} = \alpha L_{it} + \beta K_{it} + \gamma M1_{it} + firm + year \# industry + year \# province + \mu_{it}. \quad (6)$$

Fourth, the GMM method, which considers the dynamic impact caused by the capital factor of the firm in the previous period (K_{it-1}), as follows:

$$Y_{it} = \rho K_{it-1} + \alpha L_{it} + \beta K_{it} + firm + year + \mu_{it}. \quad (7)$$

[1] The variable of I is measured by cash paid for the purchase and construction of fixed assets, intangible assets, and other long-term assets. Parameter ρ is the capital depreciation rate, which is considered to be 15%.

Fifth, the ACF method, Ackerberg et al. (2015) believes that the decision of capital factors is superior to other factors, and other factors are related to human labor, so the firm labor factors are related to intermediate inputs. However, labor factors cannot be reflected only by the number of employees or labor forces, i.e., the coefficient α used to measure TFP should be reflected by intermediate inputs. Specifically, the intermediate input (*M2*) is measured by the operating costs, selling expenses, administrative expenses, and financial expenses of listed companies minus depreciation expenses and cash paid to and for employees (Nucci et al., 2023; Qiu et al., 2023), as follows:

$$Y_{it} = \alpha L_{it} + \beta K_{it} + \alpha_1 M2_{it} + firm + year + \mu_{it}. \tag{8}$$

To sum up, Eq. (4), Eq. (5), Eq. (6) and Eq. (8) get α and β by parameter estimation based on least square method, and Eq. (7) gets α and β based on generalized moment estimation. Finally, the value of α and β as well as labor factor, capital factor, and total output are respectively brought into Eq. (1) to measure TFP. In benchmark model analysis subsection, the TFP measured by the LP method is used to measure the impact of the firm's DT on it, and the TFP measured by OP, OLS, GMM, and ACF is employed to conduct the robustness test.

3.2.2. Main explanatory variables

Digital transformation (*DT*). Some studies have pointed out that DT should be premised on a shift in ideology, rather than relying solely on technological and organizational changes (Zaoui & Souissi, 2020). To measure the importance of DT, textual analysis is utilized as recommended by Li et al. (2023b), Tang et al. (2023), and Wu et al. (2022). The annual reports and MD&A sections of listed firms are used to evaluate DT by counting the frequency of keywords related to DT as a proxy indicator (Wang et al., 2023b). Keywords of listed firms in 2014 and before are screened in the board of directors' report section of the annual report, keywords of listed companies in 2015 are screened in the MD&A section of the annual report, and keywords of listed companies in 2016 and after are screened in the MD&A section of the annual report. All of keywords refer to Tang et al. (2023) and Wu et al. (2022).

In addition, the variables *DT_mda* and *DT_dummy* is employed to mitigate potential measurement errors in DT. *DT_mda* is measured by the ratio of the quantity of keywords to the MD&A section text quantity, *DT_dummy* is measured by the presence or absence of keywords in the annual report, the presence is 1, otherwise 0. In view of the non-negative characteristics of keywords, this paper performs logarithmic on related data (Wu et al. 2022).

3.2.3. Mediation variables

The scale of technological innovation, including total technological innovation (*TTI*), Green technology innovation (*GTI*), AI technology innovation (*ATI*), energy technology innovation (*ETI*), and other technological innovation (*OTI*). It is considered to have high availability and credibility when using patents to measure technological innovation (Nagaoka et al., 2010). We use the number of related patent applications from listed companies during the sample period to represent the variables related to technological innovation. The current total number of patent applications for listed companies represents the variable *TTI*, *GTI* is represented by the International Patent Classification (IPC) codes released in the IPC Green Inventory (World

Intellectual Property Organization, n.d.), and *ETI* is also represented by the IPC codes (Qu et al., 2023). The variable *ATI* is measured using a combination of IPC codes and keywords in patent name and patent abstract (Baruffaldi et al., 2020; Parteka & Kordalska, 2023, Appendix for details). In addition, the variable *OTI* is calculated by $OTI = TTI - GTI - ATI$.

It should be noted that the variable *TTI* refers to the total quantity of patents applied for by listed companies within a year. *GTI*, *ATI*, and *ETI* are mainly matched from *TTI* based on IPC codes, so *GTI*, *ATI*, and *ETI* have a unified data source. From descriptive statistics, the maximum value of *GTI*, *ATI*, and *ETI* must be less than or equal to *TTI*. Since the IPC codes that identify *GTI* and *ATI* do not overlap, there is no endogenous due to measurement errors for them. However, *GTI* and *ATI* belong to the macroscopic classification of technological innovation, that is, they may penetrate all areas, including energy technology innovation (*ETI*). In other word, the IPC codes employed to identify *ETI* may overlap with *GTI* and *ATI*, especially *GTI*. Therefore, we did not consider *ETI* when calculating *OTI*, to alleviate the overestimation of *OTI* by double counting

3.2.4. Moderating variables

The direction of technological innovation is the moderating variable of this paper (Aghion et al., 2016; Qu et al., 2023). Specifically, the direction of green technology innovation (*DGTI*) is calculated by GTI / TTI. The direction of AI technology innovation (*DATI*) is calculated by ATI / TTI. The direction of energy technology innovation (*DETI*) is calculated by ETI / TTI. The direction of other technological innovation (*DOTI*) is calculated by OTI / TTI.

3.2.5. Instrumental variables

According to Guo et al. (2023) and Wang (2023), the instrumental variables (IV) are as follows: (1) The smart city pilot in China is an exogeneity policy shock (*SmartCity*); (2) The broadband pilot in China is another exogeneity policy shock (*BroadBand*); (3) The interaction term between the quantity of internet access ports in the province where the firm is located and the number of landline telephones per million people in each city of 1984 (*TEL*); (4) The interaction term between the quantity of internet access ports in the province where the firm is located and the number of post offices per million people in each city of 1984 (*POST*).

Both the smart city pilot in China and the broadband pilot in China are important initiatives to support the construction of digital infrastructure and are closely related to DT. Similarly, the number of landline telephones and post offices in 1984 was not only the main mode of Internet access at that time, but also the use of landline telephones and post offices in daily life has declined significantly today, so it does not directly affect the TFP of current firms.

3.2.6. Control variables

According to Wang (2023), Wang et al. (2023b), Cheng et al. (2023), Nucci et al. (2023), and Pan et al. (2022), control the following factors that may affect TFP, including firm size (*size*), listed years of firms (*age*), financial leverage (*lev*), cash flow (*cflow*), proportion of independent directors (*ind*), return on assets (*roa*), characteristic of firm property right (*soe*), total-asset-turnover (*ato*), and debt-to-assets ratio (*debt*).

3.2.7. Descriptive statistics

Based on the descriptive statistical results in Table 2, some characteristics and facts can be found. (1) There are significant differences in TFP measured by different methods; (2) From the minimum values of variables *DT*, *DT_mda*, and *DT_dummy*, not all of listed firms pay sufficient attention to DT; (3) There are great gaps in economic and financial characteristics, and productivity among listed firms; (4) From the mediation variable and its minimum values, not all of listed firms have carried out technological innovation in every time; (5) From the mean values of variables *BroadBand* and *SmartCity*, about 30% of the listed firms are located in the policy implementation areas of broadband pilot and smart city pilot in China. Table 3 presents the Pearson correlation coefficients of the pairwise variables in the benchmark model. It is observable that the absolute values of the correlation coefficients between the variables are all lower than 0.8, suggesting that there is no serious multicollinearity issue. This finding is also corroborated by the VIF test.

Furthermore, as Yang (2022), a reality is that the majority of the current burgeoning AI technologies are concentrated within computer-related listed firms. This might lead to data bias at the industrial level and thereby impact the empirical results. Therefore, in the subsection of benchmark model and mechanism analysis, we excluded the samples belonging to the computer realm, thereby mitigating the potential bias of the empirical results. Specifically, in accordance with the industrial classification guidelines released by the China Securities Regulatory Commission (n.d.), the industries to which listed firms related to computer include: Information Transmission, Software and Information Technology Services (I); Scientific Research and Technical Services (M); Computer, Communication, and Other Electronic Equipment Manufacturing (C39). Table 4 presents the annual sample industry classification. It is not arduous to discover that throughout the sample period, a total of 8258 samples pertain to the manufacturing industry (C), which has consistently been the mainstream business domain of China's listed firms.

Table 2. Descriptive statistics of variables

	Variables	Mean	Std.dev	Min	Max	Variable definition
Explained variable	*TFP_LP*	8.379	1.122	2.628	12.917	The TFP of firms calculated based on LP, OP, OLS, GMM, and ACF methods
	TFP_OP	6.712	0.977	1.079	11.418	
	TFP_OLS	10.859	1.321	5.055	14.850	
	TFP_GMM	5.630	0.933	0.009	10.638	
	TFP_ACF	11.547	1.392	5.719	15.586	
Main explanatory variables	*DT*	0.643	1.061	0	5.017	The ratio of DT keywords in annual reports, logarithmic
	DT_mda	1.513	1.221	0	5.257	The ratio of DT keywords in MD&A, logarithmic
	DT_dummy	0.455	0.498	0	1	Whether there are keywords related to DT in MD&A

End of Table 2

	Variables	Mean	Std.dev	Min	Max	Variable definition
Control variables	*size*	22.288	1.315	18.475	26.496	Total assets of a firm, logarithmic
	age	2.686	0.419	0.693	3.367	Listed years of a firm, logarithmic
	lev	0.446	0.249	0	0.933	The ratio of financial liabilities to total assets of a firm
	cflow	0.050	0.073	–0.251	0.318	The ratio of cash flow to total assets of a firm
	ind	0.369	0.053	0.222	0.600	The ratio of independent directors to total directors of a firm
	roa	0.032	0.067	–0.511	0.403	The ratio of net income to total assets of a firm
	soe	0.662	0.473	0	1	State-owned firms are 1, otherwise 0.
	ato	0.774	0.530	0.026	3.187	The ratio of business sales revenue to total assets of a firm
	debt	0.509	0.233	0.033	3.401	The ratio of total liabilities to total assets of a firm
Mediation variables	*GTI*	0.327	0.795	0	6.913	Green patent applications, logarithmic
	ATI	0.129	0.508	0	5.687	AI patent applications, logarithmic
	ETI	0.402	0.918	0	7.847	Energy patent applications, logarithmic
	TTI	1.352	1.710	0	8.890	Total patent applications, logarithmic
	OTI	1.307	1.677	0	8.730	*OTI* = *TTI* – *GTI* – *ATI*, logarithmic
Moderating variables	*DGTI*	0.026	0.075	0	0.642	The ratio of green patents in total patents, *GTI* / *TTI*
	DATI	0.006	0.031	0	0.511	The ratio of AI patents in total patents, *ATI* / *TTI*
	DETI	0.042	0.113	0	1	The ratio of energy patents in total patents, *ETI* / *TTI*
	DOTI	0.285	0.299	0	0.691	*OTI* / *TTI*
Instrumental variables	*BroadBand*	0.327	0.469	0	1	In the area of broadband pilot in China is 1, otherwise 0
	SmartCity	0.281	0.449	0	1	In the area of smart city pilot in China is 1, otherwise 0
	ln*TEL*	7.388	1.206	2.899	10.053	The number of landline telephones per million people in each city of 1984, logarithmic
	ln*POST*	11.193	1.149	6.559	14.105	The number of post offices per million people in each city of 1984, logarithmic

Table 3. Pairwise correlation statistic of variables

Variables	TFP_{LP}	DT	size	age	lev	cflow	ind	roa	soe	ato	debt
TFP_LP	1										
DT	0.262	1									
size	0.671	0.243	1								
age	0.185	0.273	0.268	1							
lev	–0.085	–0.112	0.181	–0.056	1						
cflow	0.085	–0.027	0.080	–0.064	–0.108	1					
ind	0.058	0.078	0.076	0.074	0.002	–0.041	1				
roa	0.175	0.027	0.095	–0.091	–0.191	0.363	–0.031	1			
soe	0.117	–0.046	0.145	0.101	–0.005	–0.039	–0.013	–0.080	1		
ato	0.570	0.021	0.034	–0.089	–0.246	0.088	–0.038	0.161	0.048	1	
debt	0.163	–0.042	0.147	0.011	0.258	–0.158	0.018	–0.340	0.066	0.112	1
VIF test	1.20	1.16	1.30	1.19	1.26	1.17	1.02	1.38	1.05	1.16	1.29

Table 4. Annual sample industry classification

Industrial classification	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
A	24.0	23.0	22.0	21.0	20.0	16.0	16.0	16.0	17.0	16.0	16.0	16.0	16.0	16.0	255.0
B	15.0	16.0	19.0	23.0	26.0	28.0	27.0	28.0	30.0	31.0	31.0	32.0	32.0	30.0	368.0
C	615.0	614.0	612.0	604.0	597.0	595.0	594.0	590.0	580.0	579.0	574.0	571.0	565.0	568.0	8258.0
D	29.0	29.0	30.0	33.0	32.0	35.0	34.0	35.0	37.0	39.0	40.0	39.0	39.0	41.0	492.0
E	20.0	20.0	21.0	19.0	18.0	20.0	21.0	22.0	24.0	22.0	22.0	22.0	21.0	19.0	291.0
F	69.0	68.0	68.0	73.0	75.0	87.0	86.0	84.0	84.0	83.0	84.0	83.0	85.0	83.0	1112.0
G	26.0	27.0	28.0	28.0	28.0	31.0	31.0	31.0	30.0	30.0	31.0	32.0	31.0	31.0	415.0
H	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	42.0
I	32.0	33.0	33.0	32.0	31.0	22.0	24.0	24.0	23.0	25.0	27.0	29.0	31.0	31.0	397.0
K	0.0	0.0	0.0	0.0	0.0	15.0	14.0	15.0	17.0	15.0	14.0	16.0	17.0	18.0	141.0
L	14.0	14.0	14.0	14.0	15.0	9.0	10.0	10.0	9.0	11.0	10.0	10.0	10.0	10.0	160.0
M	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	2.0	2.0	4.0	5.0	5.0	6.0	30.0
N	7.0	7.0	4.0	4.0	4.0	11.0	11.0	12.0	11.0	11.0	11.0	11.0	13.0	14.0	131.0
O	5.0	5.0	5.0	4.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	23.0
P	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	2.0	2.0	2.0	2.0	2.0	14.0
Q	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	2.0	2.0	2.0	3.0	3.0	3.0	23.0
R	4.0	4.0	4.0	4.0	6.0	10.0	10.0	10.0	13.0	13.0	13.0	11.0	11.0	11.0	124.0
S	32.0	32.0	31.0	32.0	35.0	11.0	12.0	13.0	13.0	12.0	12.0	11.0	12.0	10.0	268.0
Total	–	–	–	–	–	–	–	–	–	–	–	–	–	–	12544.0

3.3. Econometric model

Firstly, this paper's benchmark model examines the productivity effects of DT as follows:

$$TFP_{ijpt} = \beta_0 + \beta_1 DT_{ijpt} + \sum X + firm_i + year_t + industry_j + province_p + \varepsilon_{ijpt}. \quad (9)$$

For the Eq. (9), *i* for listed firm, *t* for year, *j* for industry, and *p* for province, respectively. DT is the main explanatory variable. *TFP* is an explained variable that displays the productivity level of firms that are listed. The TFP can be affected by various control variables that are represented by *X*. *firm*, *year*, *industry*, and *province* represent 4 one-dimensional fixed effects, respectively. ε is the residual error.

Secondly, the mediation effect model is widely employed in mechanism analysis. The mediation effect model in this paper is as follows:

$$Me_{ijpt} = \beta_0 + \phi_1 DT_{ijpt} + \sum X + firm_i + year_t + industry_j + province_p + \varepsilon_{ijpt}, \quad (10)$$

$$TFP_{ijpt} = \beta_0 + \overline{\beta_1} DT_{ijpt} + \varphi_1 Me_{ijpt} + \sum X + firm_i + year_t + industry_j + province_p + \varepsilon_{ijpt}. \quad (11)$$

For the Eq. (10) and Eq. (11), *Me* represents a mediation variable, which is employed for mechanism analysis, including: (1) Total technological innovation, *TTI*; (2) Green technology innovation, *GTI*; (3) AI technology innovation, *ATI*; (4) Energy technology innovation, *ETI*; (5) Other technological innovation, *OTI*. The measurement of *TTI* is based on the total number of patent applications filed by listed firms during the current period, while *GTI*, *ATI*, and *ETI* are measured similarly to *TTI*. The *OTI* is calculated as $OTI = TTI - GTI - ATI - ETI$. When the coefficients ϕ_1 and φ_1 in Eq. (10) and Eq. (11) are statistically significant, and the coefficient magnitude or statistical significance of $\overline{\beta_1}$ is lower than β_1, then the mediation effect is recognized.

Thirdly, according to Li (2022) and Zhu et al. (2024), the moderating effect model is employed for further analysis:

$$TFP_{ijpt} = \beta_0 + \theta_1 DT_{ijpt} + \theta_2 Mo_{ijpt} + \theta_3 DT_{ijpt} \times Mo_{ijpt} + \\ \sum X + firm_i + year_t + industry_j + province_p + \varepsilon_{ijpt}. \quad (12)$$

For Eq. (12), *Mo* represents a moderating variable, which is employed for further analysis. According to Aghion et al. (2016) and Shen et al. (2022), the direction of technological innovation is reflected by the proportion of a certain patent in all patents, including: (1) the direction of green technology innovation, *DGTI*; (2) The direction of artificial intelligence technology innovation, *DATI*; (3) The direction of energy technology innovation, *DETI*; (4) The direction of other technological innovation, *DOTI*. Specifically, *DGTI* is measured by the share of green technology patents in total patents, and *DATI*, *DETI*, and *DOTI* also are measured in line with that. When the coefficients θ_1 and θ_3 in Eq. (12) are statistically significant, the moderating effect is established.

4. The analysis and discussion of empirical results

4.1. Benchmark model analysis

Table 5 shows the empirical results of the benchmark model. Specifically, the column (2) includes the control variables that may affect the TFP on the basis of the column (1). The column (3) controls the firm fixed effect and the year fixed effect on the basis of the column (2), which belongs to the two-way fixed effect method (TWFE). The column (4) further controls the industry fixed effect and province fixed effect to estimate the 4 one-dimensional fixed effect. Generally, the coefficient of the *DT* in Table 5 is significantly positive at 1% level, which indicating that DT has a positive impact on TFP. This empirical result is consistent with Cheng et al. (2023), Lei and Wang (2023), i.e., DT is good for productivity.

Table 6 presents the empirical findings of considering solely listed firms related to the computer industry and excluding those unrelated to it. Firstly, the promoting impact of DT on TFP remains. Secondly, through comparing the coefficients of column (2) and column (4) (0.0294, 0.0288), it can be observed that the promoting effect of DT on TFP does not significantly depending on whether the listed firm belongs to the computer industry or not.

In addition, according to the Li et al. (2023a)'s method, the spillover of TFP at the provincial and industrial levels is carried out. Table 7 shows the spillover effect of DT on TFP. The coefficient of the *DT* is significantly positive at 1% level from column (1) to column (4), which indicating that DT has also played a positive role in promoting the TFP of other listed companies in the same industry and the same province. It must be noted that although DT has a high statistical significance to the TFP of other listed firms in the same industry and the same province, the coefficient of the *DT* is small and its economic significance is lower than the empirical results in Table 5. Combined with the results of Table 5, 6 and 7, the H1 is confirmed.

Table 5. Empirical results of benchmark model

Variables	(1)	(2)	(3)	(4)
	TFP_LP	TFP_LP	TFP_LP	TFP_LP
DT	0.2771***	0.0581***	0.0334***	0.0326***
	(29.84)	(15.79)	(8.67)	(8.68)
Control variables	×	○	○	○
Firm FE	×	×	○	○
Year FE	×	×	○	○
Industry FE	×	×	×	○
Province FE	×	×	×	○
adj R sq	0.0686	0.8894	0.9500	0.9511
Obs	12544	12544	12544	12544

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 6. Empirical results of benchmark model for computer industries

Variables	(1)	(2)	(3)	(4)
	Computer related listed companies		non-Computer related listed companies	
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*
DT	0.0323***	0.0294***	0.0293***	0.0288***
	(2.78)	(2.60)	(6.94)	(6.85)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
Industry FE	×	○	×	○
Province FE	×	○	×	○
adj R sq	0.9538	0.9544	0.9523	0.9532
Obs	1332	1332	11212	11212

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 7. Empirical results of spillover effect

Variables	(1)	(2)	(3)	(4)
	TFP_LP_sic	*TFP_LP_sic*	*TFP_LP_prov*	*TFP_LP_prov*
DT	0.0013***	0.0018***	0.0006***	0.0006***
	(4.24)	(8.39)	(4.46)	(3.78)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
Industry FE	×	○	×	○
Province FE	×	○	×	○
adj R sq	0.8446	0.9375	0.9408	0.9410
Obs	12526	12526	12544	12544

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

4.2. Robustness and endogeneity tests

In this paper the following robustness tests are carried out: (1) By employing OP, OLS, GMM, and ACF methods to re-measure the TFP instead of the LP method. (2) To avoid the benefits of economies of scale, the sample of municipalities directly under the Central Government is eliminated. (3) Considering the systematic influence of the financial crisis in global during 2008–2009 and the crisis of Chinese stock market in 2015, the sample period ranging from 2010 to 2015 is controlled. (4) Considering the systematic impact of COVID-19 on listed companies, the sample period from 2015 to 2020 is controlled. (5) Change the clustering and the dimension of fixed effect. (6) Instrumental variable (IV) method was employed to alleviate the potential endogeneity between DT and TFP.

4.2.1. Robustness tests

Table 8 presents the results of the robustness test for the alternative TFP measurement method. The coefficients of the *DT* are significantly positive at 1% level in column (1) to column (4), which means that the promotion of DT still plays a promote effect on TFP even if the calculation methods of TFP (OP, OLS, GMM, and ACF) are changed.

Table 8. The robustness tests of replace *TFP_LP*

Variables	(1)	(2)	(3)	(4)
	TFP_OP	*TFP_OLS*	*TFP_GMM*	*TFP_ACF*
DT	0.0212***	0.0200***	0.0295***	0.0185***
	(4.96)	(6.20)	(6.47)	(5.71)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
Industry FE	○	○	○	○
Province FE	○	○	○	○
adj R sq	0.9078	0.9708	0.8917	0.9733
Obs	12544	12544	12544	12544

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 9 presents the influence of DT on TFP after the exclusion of the sample of municipalities directly under the central government and accounting for the global financial crisis in 2008–2009, the China stock market crash in 2015, and COVID-19 in late 2019. The empirical results in the column (1) show that the promotion of DT to TFP is established regardless of the comparative advantages gained by Chinese capital cities. The empirical results in the column (2) exclude the samples during the global financial crisis from 2008 to 2009 and the samples after the China stock market crash in 2015.The column (3) displays empirical results after considering the systematic impact of COVID-19 on listed companies. The column (4) shows the empirical results after considering high-dimensional fixed effect (industry-year fixed effect and province-year fixed effect) and clustering to Industry-Province. Generally, the coefficients of the *DT* in columns (1) to (4) is significantly positive, which shows that the promotion of DT to TFP is stable.

4.2.2. Endogeneity tests

The endogeneity issues faced in this paper can be listed as: (1) The measurement of DT is still a difficult point in related research, so there may be measurement errors in DT. (2) There might exist reverse causality between DT and TFP since digital level serves as an important criterion for measuring the performance of firms. Table 10 shows the results of endogeneity test of measurement error. The variables of *DT_mda* and *DT_dummy* is significantly positive in 1% or 10%, in other words, even when the level of DT is measured differently, DT still contributes to productivity gains.

Table 9. The robustness tests of other

Variables	Exclude municipalities	From 2010 to 2015	From 2015 to 2020	Change fixed effects and clustering
	(1)	(2)	(3)	(4)
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*
DT	0.0359***	0.0293***	0.0140***	0.0296***
	(8.48)	(4.16)	(2.84)	(4.70)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	×
Industry FE	○	○	○	×
Province FE	○	○	○	×
Industry-Year FE	×	×	×	○
Province-Year FE	×	×	×	○
Cluster to Industry-Province	×	×	×	○
adj R sq	0.9493	0.9616	0.9643	0.9520
Obs	10264	5376	5376	12526

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 10. The endogeneity tests of measurement error

Variables	(1)	(2)	(3)	(4)
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*
DT_mda	0.0204***	0.0174***		
	(5.68)	(4.95)		
DT_dummy			0.0090** (2.32)	0.0060* (1.88)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
Industry FE	×	○	×	○
Province FE	×	○	×	○
adj R sq	0.9498	0.9508	0.9496	0.9507
Obs	12544	12544	12544	12544

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 11 and Table 12 show the results of the IV method based on 2SLS. Specifically, the coefficients of the instrumental variables in the stage I are significantly positive, and those of the *DT* in the stage II are still significantly positive[2]. This result implies that DT can still

[2] Columns (1) and (3) in Table 8 and Table 9 are stage I, and columns (2) and (4) are stage II.

promote productivity improvement even after the IV method is employed to mitigate the potential endogeneity issue between DT and TFP. It should be pointed out that the coefficient of the *DT* in the second-stage regression of IV method is larger than the empirical result of the benchmark model in column (3) and column (4). According to the research of Jiang (2017), the amplification of the estimated coefficient in Table 11 and Table 12 may be caused by the 'local average processing effect', i.e., the IV method may only capture the average processing effect of some individuals in the sample rather than all individuals.

Table 11. The endogeneity tests of reverse causality (*BroadBand* and *SmartCity* as IV)

Variables	(1)	(2)	(3)	(4)
	DT	*TFP_LP*	*DT*	*TFP_LP*
DT		0.2376*** (4.89)		0.3708*** (2.74)
BroadBand	0.2483*** (8.08)			
SmartCity			0.0846*** (3.43)	
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
adj R sq	0.2219	0.8661	0.1412	0.8124
Obs	11690	11690	11690	11690

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 12. The endogeneity tests of reverse causality (*TEL* and *POST* as IV)

Variables	(1)	(2)	(3)	(4)
	DT	*TFP_LP*	*DT*	*TFP_LP*
DT		0.4377*** (10.63)		0.3897*** (8.37)
ln*TEL*	0.1328*** (13.64)			
ln*POST*			0.1022*** (9.04)	
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
adj R sq	0.2293	0.7836	0.2228	0.8085
Obs	11130	11130	11130	11130

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

4.3. Mechanism analysis

The purpose of the mechanism analysis in this paper is to explore the technological innovation channels that DT can promote productivity improvement. Specifically, Table 13 shows the mediation effect of total technological innovations (*TTI*) of the enterprise, as well as other technological innovations (*OTI*) excluding green technology, AI technology. The coefficients of the *DT* in column (1) and column (3) are not statistically significant, which shows that DT cannot enhance the technological innovation ability of firms. Furthermore, upon screening the samples of listed firms within the computer industry (the empirical results are presented in Table 14), the results of the mechanism analysis remained unaltered. In other words, the technological innovation mechanism through which DT influences TFP did not change on account of the industry specificity of listed firms.

Table 15 focuses on AI technology innovation that highly related to DT and green and energy technology that highly related to green transformation. In concrete terms, the coefficient of the *DT* in column (1) and column (3) is significantly positive, while the coefficient of the *DT* in column (5) is not significant, i.e., DT can improve green technology innovation and AI technology innovation. Further combining the empirical results in column (2) and column (4) in Table 15, it is found that the coefficient of the *GTI* is not significant and the coefficient of the *ATI* is significantly positive and the coefficient of the *DT* is smaller than the regression coefficient in column (4) in Table 5. Consequently, the mediation effect of AI technology innovation is established, but the mediation effect of green technology and energy technology does not exist. Generally, although DT has a positive impact on TFP, the current DT can only affect TFP through AI technology. In other words, for the time being, DT is incapable of enhancing TFP through non-AI technological innovations. Meanwhile, Table 16 and Table 17 present the analysis results of the technological innovation mechanism regarding the impact

Table 13. The mechanism analysis of *TTI* and *OTI*

Variables	(1)	(2)	(3)	(4)
	TTI	*TFP_LP*	*OTI*	*TFP_LP*
DT	0.0047	0.0326***	0.0014	0.0326***
	(0.42)	(8.68)	(0.13)	(8.68)
TTI		–0.0011 (–0.38)		
OTI				–0.0003 (–0.09)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
Industry FE	○	○	○	○
Province FE	○	○	○	○
adj R sq	0.7883	0.9511	0.7871	0.9511
Obs	12544	12544	12544	12544

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

of DT on TFP after controlling for listed firms within the computer industry. Specifically, the coefficients of columns (3) and (4) are significantly positive. In other words, irrespective of whether listed firms in the computer industry are considered separately, DT can merely enhance TFP by promoting AI technology. The H2 is confirmed and the H3 is not valid.

Table 14. The mechanism analysis of *TTI* and *OTI* for computer industries

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Computer related listed companies				non-Computer related listed companies			
	TTI	*TFP_LP*	*OTI*	*TFP_LP*	*TTI*	*TFP_LP*	*OTI*	*TFP_LP*
DT	0.0157	0.0295***	0.0081	0.0294***	0.0009	0.0288***	0.0018	0.0288***
	(0.49)	(2.61)	(0.26)	(2.60)	(0.33)	(6.85)	(0.61)	(6.85)
TTI		−0.0042 (−0.40)				−0.0050 (−0.40)		
OTI				−0.0032 (−0.30)				−0.0051 (−0.42)
Control variables	○	○	○	○	○	○	○	○
Firm FE	○	○	○	○	○	○	○	○
Year FE	○	○	○	○	○	○	○	○
Industry FE	○	○	○	○	○	○	○	○
Province FE	○	○	○	○	○	○	○	○
adj R sq	0.8425	0.9543	0.8374	0.9543	0.7757	0.9532	0.7756	0.9532
Obs	1332	1332	1332	1332	11212	11212	11212	11212

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 15. The mechanism analysis of *GTI*, *ATI*, and *ETI*

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GTI	*TFP_LP*	*ATI*	*TFP_LP*	*ETI*	*TFP_LP*
DT	0.0244***	0.0325***	0.0335***	0.0319***	0.0020	0.0326***
	(3.48)	(8.67)	(6.31)	(8.46)	(0.27)	(8.68)
GTI		0.0015 (0.34)				
ATI				0.0208*** (3.21)		
ETI						0.0001 (0.03)
Control variables	○	○	○	○	○	○
Firm FE	○	○	○	○	○	○
Year FE	○	○	○	○	○	○
Industry FE	○	○	○	○	○	○
Province FE	○	○	○	○	○	○
adj R sq	0.6759	0.9511	0.6582	0.9511	0.6949	0.9511
Obs	12544	12544	12544	12544	12544	12544

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 16. The mechanism analysis of *GTI*, *ATI*, and *ETI* for computer industries

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GTI	*TFP_LP*	*ATI*	*TFP_LP*	*ETI*	*TFP_LP*
DT	0.0390	0.0289**	0.0683***	0.0282**	–0.0306	0.0295***
	(1.60)	(2.58)	(3.31)	(2.49)	(–1.30)	(2.59)
GTI		0.0131 (1.05)				
ATI				0.0180* (1.93)		
ETI						0.0038 (0.30)
Control variables	○	○	○	○	○	○
Firm FE	○	○	○	○	○	○
Year FE	○	○	○	○	○	○
Industry FE	○	○	○	○	○	○
Province FE	○	○	○	○	○	○
adj R sq	0.7154	0.9544	0.7486	0.9544	0.7336	0.9543
Obs	1332	1332	1332	1332	1332	1332

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 17. The mechanism analysis of *GTI*, *ATI*, and *ETI* for non-computer industries

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GTI	*TFP_LP*	*ATI*	*TFP_LP*	*ETI*	*TFP_LP*
DT	0.0078	0.0288***	0.0124***	0.0285***	0.0042	0.0288***
	(1.12)	(6.85)	(2.84)	(6.78)	(0.53)	(6.85)
GTI		0.0009 (0.18)				
ATI				0.0211*** (2.78)		
ETI						0.0025 (0.58)
Control variables	○	○	○	○	○	○
Firm FE	○	○	○	○	○	○
Year FE	○	○	○	○	○	○
Industry FE	○	○	○	○	○	○
Province FE	○	○	○	○	○	○
adj R sq	0.6578	0.9532	0.5215	0.9532	0.6864	0.9532
Obs	11212	11212	11212	11212	11212	11212

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

4.4. Further analysis

The purpose of further analysis is to explore how other types of technological innovation are affected when DT affects TFP through AI technological innovation. The coefficients of the *DT* in column (1) to column (4) in Table 18 are significantly positive, which shows that DT can still promote the TFP even if the moderating effect of the direction of technological innovation is considered. The coefficients of the *DT×DATI* and the *DT×DETI* in column (2) and column (3) in Table 18 are not statistically significant, and there is no moderating effect. It must be noted that the coefficients of the *DT×DGTI* and the *DT×DOTI* in column (1) and column (4) are significantly negative, which indicates that it will hurt the productivity effect of DT with the proportion of green technology and other types of technological innovation (*DOTI*) in total technological innovations increase. In Table 19, we employ the number of patent applications to construct the interaction term between DT and technological innovation, to test the empirical results in Table 18. The coefficient of the *DT×OTI* in Table 19 of column (4) is significantly negative, which also indicates that increasing the scale of other technological innovations (*OTI*) will adversely affect the productivity effects of DT. Promoting green technology and other types of technological innovation may have adverse effects on the productivity effects of DT. In other words, DT has a crowding out effect on other types of technological innovation.

Table 18. The moderating effect of the direction of technological innovation

Variables	(1)	(2)	(3)	(4)
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*
DT	0.0344***	0.0321***	0.0337***	0.0211***
	(8.56)	(8.28)	(8.33)	(6.67)
DT×DGTI	–0.0171* (–1.77)			
DT×DATI		0.0078 (0.66)		
DT×DETI			–0.0105 (–1.16)	
DT×DOTI				–0.0169*** (–2.83)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
Industry FE	○	○	○	○
Province FE	○	○	○	○
adj R sq	0.9511	0.9511	0.9511	0.9511
Obs	12544	12544	12544	12544

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 19. The moderating effect of technological innovation

Variables	(1)	(2)	(3)	(4)
	TFP_LP	*TFP_LP*	*TFP_LP*	*TFP_LP*
DT	0.0344***	0.0318***	0.0342***	0.0392***
	(8.37)	(8.02)	(8.37)	(8.28)
DT×*GTI*	–0.0045 (–1.54)			
DT×*ATI*		0.0031 (0.92)		
DT×*ETI*			–0.0042 (–1.55)	
DT×*OT*I				–0.0063*** (–3.04)
Control variables	○	○	○	○
Firm FE	○	○	○	○
Year FE	○	○	○	○
Industry FE	○	○	○	○
Province FE	○	○	○	○
adj R sq	0.9511	0.9511	0.9511	0.9511
Obs	12544	12544	12544	12544

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

4.5. Heterogeneity analysis

The heterogeneity analysis in this paper is based on the mechanism analysis, which purposes to explore the impact of intellectual property protection, business strategic radicalism, and enterprise intangible assets ratio on the channels of green technology, AI technology, and energy technology. Table 20 shows the heterogeneity analysis of intellectual property protection. Specifically, the power of intellectual property protection is measured in this paper by the median of the proportion of the number of concluded patent infringement cases in cities to the total number of such cases in the country (Hao et al., 2021). The results in columns (3) and (4) show that the mediation effect of AI technology is still valid, but its coefficient scales of the *DT* and *ATI* are lower than the results in Table 13, which indicates that the DT in regions with strong intellectual property protection has less impact on AI technology. To sum up, intellectual property protection inhibits the channel role of AI technology.

Table 21 and Table 22 present the results of the heterogeneity analysis regarding the degree of business strategic radicalism and the proportion of intangible assets. Bentley-Goode et al. (2017)'s method is used to measure the business strategic radicalism, and the proportion of intangible assets of enterprises is measured by the proportion of intangible assets in total assets, and the level of both is also measured by the median. Specifically, in Table 21 and Table 22, the coefficient of variable *AIT* in column (4) is greater than that of *AIT* in Table 5. It is not difficult to find that under the background of the digital economy, the higher the degree of business strategic radicalism, the more prominent the channel role of AI technology, i.e., the current enterprise with a higher degree of business strategic radicalism is more suitable for DT. In addition, the higher the proportion of intangible assets, the more AI technology will help DT. Consequently, compared with intellectual property protection, the impact of business strategic radicalism and the proportion of enterprise intangible assets on the role of AI technology channels is opposite.

Table 20. The heterogeneity analysis of intellectual property protection

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GTI	TFP_LP	ATI	TFP_LP	ETI	TFP_LP
DT	0.0256*** (2.77)	0.0327*** (6.41)	0.0288*** (4.07)	0.0322*** (6.30)	0.0015 (0.16)	0.0327*** (6.42)
GTI		0.0018 (0.30)				
ATI				0.0179** (2.19)		
ETI						0.0020 (0.37)
Control variables	○	○	○	○	○	○
Firm FE	○	○	○	○	○	○
Year FE	○	○	○	○	○	○
Industry FE	○	○	○	○	○	○
Province FE	○	○	○	○	○	○
adj R sq	0.7053	0.9526	0.7178	0.9526	0.7267	0.9526
Obs	7341	7341	7341	7341	7341	7341

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 21. The heterogeneity analysis of business strategy radicalism

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GTI	*TFP_LP*	*ATI*	*TFP_LP*	*ETI*	*TFP_LP*
DT	0.0235*** (3.17)	0.0340*** (8.95)	0.0330*** (5.83)	0.0333*** (8.74)	–0.0011 (–0.14)	0.0340*** (8.95)
GTI		–0.0004 (–0.08)				
ATI				0.0224*** (3.09)		
ETI						–0.0016 (–0.40)
Control variables	○	○	○	○	○	○
Firm FE	○	○	○	○	○	○
Year FE	○	○	○	○	○	○
Industry FE	○	○	○	○	○	○
Province FE	○	○	○	○	○	○
adj R sq	0.6813	0.9536	0.6564	0.9537	0.6999	0.9536
Obs	11886	11886	11886	11886	11886	11886

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

Table 22. The heterogeneity analysis of proportion of intangible assets

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GTI	TFP_LP	ATI	TFP_LP	ETI	TFP_LP
DT	0.0178* (1.94)	0.0279*** (5.96)	0.0297*** (4.44)	0.0272*** (5.80)	–0.0022 (–0.22)	0.0278*** (5.95)
GTI		–0.0012 (–0.21)				
ATI				0.0228*** (2.79)		
ETI						–0.0014 (–0.29)
Control variables	○	○	○	○	○	○
Firm FE	○	○	○	○	○	○
Year FE	○	○	○	○	○	○
Industry FE	○	○	○	○	○	○
Province FE	○	○	○	○	○	○
adj R sq	0.6996	0.9564	0.6927	0.9564	0.7071	0.9564
Obs	8011	8011	8011	8011	8011	8011

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-value obtained from the robust standard error of clustering is shown in parentheses. FE means fixed effect.

5. Conclusions and policy implications

DT is not only the vital path for many sectors to achieve high-quality development, but also has become the vital to leading a new productivity revolution. Meanwhile, technological innovation has also played an irreplaceable supporting effect in DT. From 2007 to 2020, A-share listed firms in Shanghai and Shenzhen have financial, annual report text, and patent data used to base this paper. Initially, examine the impact of DT on TFP; The second aspect of the investigation is the technological innovation mechanism of DT that affects TFP, with a focus on green technology, AI technology, and energy technology; Third, analyze the indirect impact of technological innovation direction on the productivity effect of DT.

The study found that (1) although DT can promote TFP, mechanism analysis shows that this promotion effect is only realized through AI technology innovation which is highly related to DT, rather than other technological innovation such as green technology and energy technology. The productivity effects of DT are limited to specific technological innovations, such as AI technology. (2) The productivity effects of DT will be undermined by increasing the proportion of green technology and other types of technology innovation within the total technology innovation. To put it differently, unless there is a highly relevant technological innovation for DT, other types of technological innovations like green technology and energy technology should be reduced, etc., will have an undesirable effect on the productivity effect of DT. (3) Promoting TFP improvement through AI technology during DT in regions with strong intellectual property protection is hard compared to other regions. The DT has a positive impact on productivity through business strategic radicalism and a high share of corporate intangible assets.

Policy implications relevant to the conclusions can be listed:

- Firstly, targeted promotion of the deep integration of DT and technological innovation is necessary. Although DT has a positive impact on TFP, it can only be accomplished through technological innovations closely associated with it, such as AI technology. However, DT is not prominently promoted among other types of technological innovations. To maximize the leading role of DT in technological innovation, a firm should integrate its current DT requirements with its technological innovation advantages. Be proactive in seeking solid support for DT in technological innovation.
- Secondly, firms ought to reorganize the direction of technological innovation in light of the background of DT. If the first policy implication delineates the compatibility of DT with old technologies, then the second policy implication articulates the convergence of old technologies towards DT. Currently, technological innovation ought to be grounded on DT, and more digital attributes should be imparted to traditional technological innovation. This can be achieved by increasing the training of traditional technical talents, especially in skills related to DT such as data analysis, software design, network security, etc. Furthermore, enhance digital infrastructure to guarantee the accessibility and reliability of high-speed Internet as well as other indispensable technological infrastructure in support of DT.
- Thirdly, manufacturing constitutes the core business domain of listed firms in China. Thus, DT should prioritize promoting artificial intelligence technology in this field, facilitating a more seamless integration of AI technology into the manufacturing industry, such as intelligent manufacturing systems, supply chain management, robot production automation, and product design and development. Moreover, the DT should also strive to advance green technological innovation in manufacturing, thereby aiding the manufacturing industry in achieving green transformation.

Limitations of the study and suggestions for further expansion. (1) The measurement approaches of TFP, DT, and AI technology, particularly AI technology, can be further discussed. The utilization of patent data for measuring technological innovation at the firm level possesses a robust theoretical foundation, i.e., in accordance with the principle of profit maximization, firms safeguard the potential monopoly profits brought about by technological innovation through patents. However, other research institutions such as universities are also major contributors to patent output, and papers and research projects, as same as patents, can also reflect the power of technological innovation in a specific field. Hence, how to render the measurement of technological innovation more precise is an issue that cannot be disregarded. (2) Explore more comprehensively the technological innovation channels driven by DT for TFP, such as technology spillovers, technology trading markets, etc. (3) Employ a more comprehensive research sample at the firm level to further alleviate the restraint caused by the listed company sample only.

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APPENDIX

Table A1. The IPC codes of AI technology

AI patents (IPC code)			
G01R31/367	G06F17/ (20-28, 30)	G06F19/24	G06K9/00
G06K9/ (46-52, 60-82)	G06N7	G06N10	G06N99
G06Q	G06T7/00-20	G10L15	G10L21
G16B40/ (00-10)	G16H50/20-70	H01M8/04992	H04N21/466

Table A1 shows the IPC codes that may be involved in AI technology, according to Baruffaldi et al. (2020), Parteka and Kordalska (2023), some keywords are considered somewhat general in identifying whether they belong to AI technology, so they must be employed together with the IPC code. Consequently, we highlight the keywords that are easy to confuse in Table A2, and other keywords can refer to Baruffaldi et al. (2020).

Table A2. The keywords of AI technology (confused)

No.	AI patents (keywords)			
1.	ambient intelligence	autonomous vehicle	autonomic computing	cognitive insight system
2.	brain computer interface	community detection	computational pathology	cyber physical system
3.	data mining	dynamic time warping	firefly algorithm	Takagi-Sugeno fuzzy systems
4.	gravitational search algorithm	image processing	image segmentation	intelligence augmentation
5.	Markovian	neuromorphic computing	non negative matrix factorisation	obstacle avoidance
6.	rough set	robot	biped robot	humanoid robot
7.	human-robot interaction	industrial robot	legged robot	quadruped robot
8.	service robot	social robot	wheeled mobile robot	semantic web
9.	sensor fusion	sensor data fusion	multi-sensor fusion	text mining
10.	unmanned aerial vehicle	visual servoing		