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RESEARCH ARTICLE

Greening the digital revolution: assessing the impact of digital transformation on green total factor productivity in Chinese enterprises

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Abstract
The green digital revolution has changed the production mode of enterprises. This article explores the green value of digital transformation. The study calculates the digital transformation index and green total factor productivity (EGTFP) index of Chinese enterprises from 2012 to 2021 and uses a panel data model and intermediary effect to conduct empirical tests. The results show that digital transformation has a positive impact of 0.371 units on the EGTFP. This positive effect is proven to be stable after distinguishing between substantive and tactical digital transformation, where the effect of substantive digital transformation increases over time. At the same time, enterprise property rights and location affect the role of digital transformation; moreover, digital transformation performs better when grouping the nonstate-owned enterprises and the eastern region. In addition, energy efficiency, green technology innovation, and environmental responsibility are important intermediaries, as digital transformation can affect EGTFP by improving energy efficiency, promoting green technology innovation, and strengthening environmental responsibility. These research conclusions help evaluate the economic and environmental effects of digital transformation and provide empirical evidence for the high-quality development of enterprises.

Keywords Digital transformation · Enterprise green total factor productivity · Influence mechanism · Heterogeneity

Introduction

Since 1978, China has experienced explosive economic growth with an average annual growth rate of 9.25%. This growth rate has increased the scale of the Chinese economy, and its associated extensive production methods have caused a waste of resources and environmental damage (Oliveira and Lima 2022). According to the Global Environmental Performance Index 2020, China is ranked 120th out of 180 countries in environmental performance (Wendling et al. 2020). Under the dual pressures of resource depletion and environmental degradation, the sustainability of China's economy requires maintaining the coordinated development of economic growth and ecological protection. The Chinese government has formulated a series of measures to promote the green transformation of the economy. These measures include formulating strict environmental regulations, restructuring the industry, and encouraging green innovation (Magacho et al. 2023; Zhai et al. 2022). Green transformation aims to achieve coordination between the economy and the environment, and improving green total factor productivity (GTFP) is undoubtedly the fundamental method towards this goal (Khan et al. 2022). GTFP is manifested in a production capacity that considers the overall efficiency of the resources, the environment, and the economy. Research on GTFP can provide a pathway to economic and environmental sustainability (Lena et al. 2022). Capital, technology, labor, and energy are the main factors that affect GTFP. Scholars attempt to find ways to improve GTFP from the perspective of optimizing factors such as green energy, labor skills, energy conservation and emission reduction, environmental regulation, and green finance (Amesho et al. 2022; Farooq et al. 2022; Kalantzis and Niczyporuk 2022; Umar and Safi 2023). Although optimizing the allocation of production factors in a factor-driven economic growth model effectively addresses environmental and economic

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issues, the differences in resource endowments, productive capacities, and economic levels can lead to inequalities, especially for developing countries. Plundering regional development opportunities can hinder green development (Hou et al. 2022). Therefore, it is necessary to seek new ways to improve GTFP.

With the development of digital technology, the digital economy has become the core driving force of economic growth (Pradhan et al. 2019). Digital technology has optimized production processes, organizational structures, and trade and consumption patterns, breaking the boundaries of factor-driven production modes (Vial 2019). Digital transformation has become a new way to improve economic efficiency and has been deeply integrated into all aspects of economic and social production, consumption, logistics, and so on (Wang et al. 2022). It should be noted that the role of digital transformation in technological innovation, corporate finance, organizational management, and resource sharing is reflected in economic effects (Brodny and Tutak 2022; Sengupta et al. 2021; Oliveira et al. 2021). Environmental issues are negative externalities of economic development, and the comprehensive impact of digital transformation on the economy and the environment needs to attract more attention (Lee et al. 2022). Studying how digital transformation affects enterprise green total factor productivity (EGTFP) under the new economic model is a meaningful topic.

This study focuses on digital transformation and EGTFP, including whether digital transformation affects EGTFP, the path through which digital transformation affects EGTFP, and the heterogeneity of digital transformation. This paper selects Chinese Shanghai and Shenzhen A-share listed enterprises as the research sample for the following reasons. First, the China Digital Economy Development Report (2022) shows that the scale of China's digital economy will reach 45.5 trillion yuan, accounting for 39.8% of the GDP, indicating huge space for the digitalization of Chinese enterprises (Wang et al. 2022). Second, the digital transformation of enterprises has higher requirements for public digital infrastructure, and the Chinese government has strong support for infrastructure construction (Yu et al. 2021a). Third, to encourage digital transformation and green transformation, the government has provided a series of policy support mechanisms for enterprises, such as financial subsidies, tax incentives, and green credit support, which raise the level of the enthusiasm by enterprises. Finally, under the constraints of resources, the Chinese government has continuously reformed the mode of economic growth and formulated strict environmental regulations and penalties for enterprises. The transformation needs of Chinese enterprises are urgent.

The contributions of this paper are as follows. First, the paper uses text analysis to measure the enterprise internal digital transformation index, including tactical and substantive digital transformation. This approach differs from the research on GTFP that is based on macrolevel analysis and it explains the comprehensive green economic effect of digital transformation within enterprises in a scientifically objective manner. Second, this paper proposes the impact path of digital transformation on EGTFP from the three dimensions of energy efficiency, green technology, and environmental responsibility. These dimensions include the traditional path of factor optimization and reflect the role of digital innovation and digital information, providing new evidence for effectively improving EGTFP. Third, this paper studies the heterogeneity of property rights and geography in digital transformation and provides a practical basis for enterprises to formulate differentiated digital transformation policies, which is conducive to realizing enterprises' green goals.

The research outline is as follows. The second section provides a literature review. The third section presents the theoretical mechanism and research hypothesis. The fourth section presents the methodology. The fifth section presents the results and discussion. The sixth section presents the conclusion and policy implications.

Literature review

Green total factor productivity

GTFP is an indicator that evolved from total factor productivity, and it measures the quality of economic development under the constraints of resource consumption and pollutant emissions (Watanabe and Tanaka 2007). The focus of the research is on the measurement method, impact factors, and social effects. The input–output production function is the basic model to measure GTFP (Blackburn and Cruz 2021), and it is key for calculating efficiency, including expected output and unexpected output. Data envelopment analysis (DEA) and stochastic frontier analysis are the main methods for calculating production efficiencies (Tsionas 2021), such as the Super-DEA model, Malmquist–Luenberger index model, and the slack-based measure that include unexpected outputs (Aparicio et al. 2017; Sarpong et al. 2022; Keskin 2021). On this basis, the GTFP for various countries, regions, and cities has been widely measured (Rodríguez et al. 2018; Li et al. 2023; Cheng et al. 2022). In terms of impact factors, environmental regulations, financial development, industrial structure, foreign investment, marketization level, and infrastructure construction are the external factors that affect the GTFP of regions and cities (Lena et al. 2022; Sai et al. 2023; Yu et al. 2021b; Miatto et al. 2021). Energy structure, resource endowment, labor skills, and green production technology directly affect GTFP (Arin and Braunfels 2018; Farooq et al. 2022; Yasmeen et al. 2023). In terms of social effects, the role of improving GTFP is reflected in saving resources, reducing pollutants, lowering production costs, improving residents' quality of life, and promoting economic sustainability (Khan et al. 2022; Hasanov et al. 2023; Lena et al. 2022).

Digital transformation

Digital transformation involves applying digital technology to change an enterprise production, operation, and management mode (Alsufyani and Gill 2022). The role of digital transformation in economic growth has been widely explored. Enterprise production efficiency, financial risk, business models, value chain, and technological innovation all benefit from digital transformation (Brodny and Tutak 2022; Skare et al. 2023; Enrique et al. 2022; Liu et al. 2023). Compared to traditional production modes, the advantages of digital transformation are reflected in intelligent production, risk management, product upgrades, and personalized customization (Chouaibi et al. 2022; Du and Jiang 2022). Regarding the measurement of digital transformation, Skare et al. (2023) constructed an evaluation system for digital transformation from four aspects: digital technology, digital production, digital services, and digital products. Khattak et al. (2023) used the proportion of digital investment and digital value to represent digital transformation. With the application of text analysis methods in economic statistics, the frequency of keywords related to digitalization has also become one of the methods for measuring digital transformation (Cheng et al. 2023).

Currently, there is yet to be a unified opinion on the impact of digital transformation on GTFP. Regarding environmental effects, digital transformation effectively reduces carbon emissions, waste management, energy substitution, etc. (Lee et al. 2022; Ha et al. 2022). Digital energy monitoring systems facilitate full-process management of energy supply, production, transportation, and consumption, reducing excessive energy consumption (Maroufkhani et al. 2022). However, the existence of digital gaps may lead to the failure of digital transformation, increasing operational costs for businesses and reducing production efficiency (Grishchenko 2020). Additionally, digital infrastructure and products increase electricity consumption (Court and Sorrell 2020) and cause new forms of electronic pollution, which irreversibly damage the environment.

The literature on digital transformation and GTFP is extensive, but the research gaps in this literature still need to be addressed. First, the research on GTFP at the macro level of a country, region and city has been extensive, but as the core subject of the microeconomy, enterprises have yet to be addressed in this research. In a market economy, enterprises are the first participants in creating economic value and causing environmental pollution. Enterprise green total factor productivity (EGTFP) better reflects the sustainable development capability of the economy, and the research on the green development capability of microeconomies is more in line with the value goals of production efficiency and environmental protection. Second, the economic effects and the environmental impacts of digital transformation have been discussed separately, mainly focusing on the economic impact. One-dimensional effect studies cannot effectively resolve the real contradictions of sustainable development. Therefore, studying the comprehensive economic and environmental effects generated by digital transformation and analyzing the impact of digital transformation on the EGTFP is more in line with the practical requirements of high-quality economic growth. Finally, the measurement of digital transformation is a complex issue, and a single index or a subjective evaluation index system need to be more scientific. How to scientifically define the strategic behavior and substantive behavior of enterprise digital transformation is a research gap that needs to be filled.

Theoretical mechanisms and research hypotheses

The direct impact of digital transformation on the EGTFP

Based on the theory of technological and economic paradigms, digital transformation can promote the establishment of a production paradigm characterized by ubiquitous perception, intelligent decision-making, agile response, global collaboration, and dynamic optimization of enterprises (Brauner and Ziefle 2022). Digital transformation has changed the enterprise production modes and organizational forms, reduced excessive dependence on resource input, enhanced resource utilization efficiency, and expanded the boundary of production (Hanelt et al. 2021; Fu et al. 2023). On the one hand, the information advantage brought by digital transformation strengthens the correlation between production, distribution, circulation, and consumption (Klingenberg et al. 2022), which is conducive to achieving fine-grained production (Cifone et al. 2021) and reducing the loss of production and energy waste. On the other hand, substituting digital production with traditional production technology can reduce negative environmental effects in the profit creation process; in particular, applying green production technology can improve the EGTFP (Wang et al. 2022). At the same time, by relying on the information platform constructed by digital transformation, enterprise cooperation and supervision relationships can be strengthened. Digital technology can help enterprises evaluate and manage the environmental and economic risks of the supply chain (Enrique et al. 2022) and can promote the construction of a green supply chain. In addition, enterprises can use the digital platform to better understand market demand and develop green production strategies. Based on this, we propose research Hypothesis 1.

Hypothesis 1: Digital transformation can improve EGTFP.

The intermediary path of digital transformation affecting the EGTFP

The EGTFP emphasizes the input−output efficiency of production factors, and reasonable resource allocation is a prerequisite for improving the EGTFP (Kranich 2020). Digital transformation has realized integrating data elements and energy elements to promote the optimization and reorganization of traditional production elements (Maroufkhani et al. 2022). The application of digitization in the energy system can be summarized into three aspects. First, through the digital service platform, enterprises can conduct data analysis and real-time monitoring of energy production, transportation, and utilization to avoid wasting resources (O'Dwyer et al. 2020). Second, digital technology not only effectively replaces traditional production technology (Loock 2020) but also generates positive external effects and improves the efficiency of the entire energy system (Zhao et al. 2022). Third, digital technology can help breakdown the "space–time barriers" in information transmission and commodity circulation, help enterprises promptly obtain accurate information on energy prices, output, and quality (Afzal et al. 2022), and strengthen the linkage between upstream and downstream industries (Mastrocinque et al. 2022). It improves the quality of raw materials and intermediate products on the supply side, reduces the energy consumption and pollution of downstream enterprises, and increases the supply of green products on the demand side.

Hypothesis 2: Digital transformation improves EGTFP by improving energy efficiency.

Technological innovation is the driving force for improving EGTFP under the constraints of ecologically limited carrying capacity (Luo et al. 2022). Enterprise green innovation is an economic activity that reduces environmental pollution, raw materials, and energy consumption at the technical level (Wang et al. 2022). Unlike general innovation activities, green innovation aims to achieve harmonious development of the economy and environment with new technology and knowledge. It requires integrating information on resource consumption and manufacturing systems, and it involves integrating knowledge in different technical fields (Conti et al. 2018). It is challenging to carry out green innovation only by relying on experience and accumulating knowledge in a single technical field (Yin et al. 2021). Digital transformation may influence green technology innovation by promoting knowledge sharing and resource integration.

On the one hand, digitization can accelerate the flow of information between different economic organizations (Müller et al. 2020), reduce internal and external transaction costs (Vatiero 2022), and increase the enthusiasm for green innovation. On the other hand, digital transformation promotes the integration of innovation resources and knowledge (Conti et al. 2018), which is conducive to transforming the traditional closed innovation model into an open and networked model (Michael et al. 2019). Open innovation provides a scenario for the effective allocation of innovation resources and improves the success rate of collaborative innovation (Roh et al. 2021).

Hypothesis 3: Digital transformation improves EGTFP by promoting green innovation.

In addition to pursuing economic returns, enterprises must undertake social responsibilities, and thus environmental responsibility is an important issue (Lopez et al. 2022). According to Porter's competitive strategy theory, taking responsibility of environmental protection will help enterprises improve their competitive advantage while solving social problems (Porter and Kramer 2006). Digital transformation endows enterprises with the development thinking of openness, cooperation, cocreation and sharing, prompting such enterprises to establish a digital participation mechanism that directly interacts with stakeholders (Wang et al. 2022). On the one hand, the disclosure of corporate environmental responsibility information helps mitigate the risk of environmental penalties and reduce the operating costs of enterprises (Zhang et al. 2022). On the other hand, undertaking social environmental responsibility sends a positive signal to the outside world and improves the social image (Meng and Zhang 2022). Enterprises that actively undertake environmental responsibilities are more likely to receive financial support such as government subsidies, bank credits, and tax incentives (Lee et al. 2017). In addition, digital transformation has bridged the gap between enterprises and customers and improved the market awareness of these customers. With the enhancement of environmental awareness, stakeholders can strengthen the management of green production through industry rules, ethics, public opinion, and public supervision (Yu and Jin 2022). The environmental management model will change from end-of-production control to preventive cleaner production. Based on this, we propose research Hypothesis 4.

Hypothesis 4: Digital transformation can improve EGTFP by enhancing environmental responsibility awareness.

Materials and methodology

Models

We constructed the benchmark model to analyze the relationship between digital transformation and EGTFP, as shown in Eq. (1). i and t represent the industry and year, respectively. $DT_{i,t}$ represents the digital transformation of enterprise i in year t, which includes $DT - sub_{i,t}$ and $DT - tac_{i,t}$. $control_{i,t}$ represents the control variables. λ_i and η_t denote time fixed effects and industry fixed effects, respectively. $\varepsilon_{i,t}$ is the residual term of the model. When $\alpha_1 > 0$ and it passes the significance test, this implies that digital transformation has a green production effect.

$$EGTFP_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \alpha_i \sum control_{i,t} + \lambda_i + \eta_t + \varepsilon_{i,t} \tag{1}$$

To test the intermediary effect of digital transformation on EGTFP, this paper constructs Eqs. (2) and (3). $Med_{i,t}$ is the mediating variable. The intermediary effect is mainly judged by the significance of β_1, γ_1, and γ_2. When all these coefficients pass the significance test and $\gamma_1 < \alpha_1$, a partial intermediary effect exists. When at least one of either β_1 or γ_2 is not significant, there may be no intermediary effect, and the approach needs further assessment using the Sobel test.

$$Med_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_i \sum control_{i,t} + \lambda_i + \eta_t + \varepsilon_{i,t} \tag{2}$$

$$EGTFP_{i,t} = \gamma_0 + \gamma_1 DT_{i,t} + \gamma_2 Med_{it} + \gamma_i \sum control_{i,t} + \lambda_i + \eta_t + \varepsilon_{i,t} \tag{3}$$

Variables

Enterprises green total factor productivity (EGTFP)

The EGTFP represents the input−output efficiency considering environmental pollution. There are parametric and nonparametric methods for efficiency measurement. The stochastic frontier approach (SFA) mainly represents the parametric method, which limits the production function and single output. The nonparametric method is represented by the data envelopment analysis (DEA), which includes constant returns to scale (CCR), variation in returns to scale (BCC), slack-based measure (SBM), and other models. DEA does not need to set a specific function form, and it can avoid the structural deviation caused by the wrong setting of the production function. Traditional DEA does not consider the impact of unexpected output. We refer to the extension of the DEA by Tone (2002) and use the super-SBM to calculate the EGTFP. The super-SBM is a nonradial DEA model, which not only makes up for the problem of ignoring slack variables in traditional radial DEA but also avoids the problem of truncation of efficiency values in empirical research. The super-SBM is calculated in Eq. (4). When resource elements are incorporated into production decisions, each decision-making unit (DMU) includes m kinds of input elements, z kinds of expected outputs and s kinds of unexpected outputs. In Eq. (4), $\lambda_{t,k}$ represents the weight vector, n represents the number of DMUs, and x represents the input production factors. y^a and y^b represent the expected and unexpected outputs, respectively. ρ is the target efficiency value.

$$\rho = \min \frac{\frac{1}{m}\sum_{i}^{m}\frac{\overline{x_i}}{x_{ik}}}{\frac{1}{z+s}\left(\sum_{\gamma=1}^{z}\frac{\overline{y^a}}{y^a_{\gamma k}} + \sum_{\upsilon=1}^{s}\frac{\overline{y^b}}{y^b_{\upsilon k}}\right)} \quad s.t. = \begin{cases} \bar{x} \geq \sum_{j=1,\neq k}^{n} \lambda_j x_{ij} \\ \overline{y^a} \leq \sum_{j=1,\neq k}^{n} \lambda_j y^a_{ij} \\ \overline{y^b} \geq \sum_{j=1,\neq k}^{n} \lambda_j y^b_{ij} \\ \bar{x} \geq x_k, \overline{y^a} \leq y^a_k, \overline{y^b} \geq y^b_k, \lambda \geq 0 \end{cases} \tag{4}$$

According to the theory of production factors and related literature (Hasanov et al. 2023; Cheng et al. 2023), the input and output indicators selected in this paper for the measurement of EGTFP are as follows. Input indicators include capital input, labor input, and energy input. The capital is calculated using the perpetual inventory method, as shown in Eq. (5). The labor force is represented by the employment of enterprises. Energy input and utilization is expressed as the annual industrial electricity consumption by enterprises. The expected output variable is represented by the enterprise annual main business income. Undesirable output variables are represented by the three types of waste generated by enterprises: industrial waste gas emissions, industrial wastewater emissions, and industrial soot emissions.

$$K_t = K_{t-1}(1 - \delta_t) + I_t / P_t \tag{5}$$

K_t and K_{t-1} are the capital quantities in period t and period $t-1$, respectively. δ_t is the depreciation rate. I_t is the investment in fixed assets in period t. P_t is the regional investment price index of enterprises in period t.

Digital transformation (DT)

Digital transformation has penetrated all production activities and is difficult to measure with a single indicator. Unlike previous studies focusing on single indicators such as digital financial inclusion, the Internet, and intelligence (Sun and Tang 2022; Ying et al. 2021), this paper evaluates digital transformation based on substantive and tactical dimensions. Substantial digital transformation is represented by the actual investment of enterprises, including hardware and software investment. The strategic digital transformation is represented by the enterprise digital management strategy and development plan. Substantial digital transformation

Table 1 The description of digital transformation indicators

Variable	Type	Indicator	Description
Digital transformation	Substantial digital transformation	Digital investment	The ratio of the market value of hardware facilities such as computers and electronic equipment to total assets
			The ratio of the sum of software development investment and market value of software facilities to total assets
	Tactical digital transformation	Digital word frequency	Statistics on the frequency of keywords such as the internet, cloud computing, big data and artificial intelligence
			Statistics on the frequency of keywords such as internet business, e-commerce (O2O, B2B)
			Statistics on the frequency of keywords such as informatization (information sharing, information management and integration)

(*DT-sub*) is expressed in terms of enterprise digital investment (hardware investment and software investment), and it is the investment that has already occurred in enterprise digitalization. It is calculated as shown in Table 1. Tactical digital transformation (*DT-tac*) takes some relatively successful enterprises as a reference and uses a Python algorithm to screen out high-frequency words in the digital transformation process for measurement. It is represented by the logarithm of the number of keywords in the annual reports of listed enterprises, as shown in Table 1.

The comprehensive index of enterprise digital transformation uses the entropy weight method to process digital investment and digital word frequency and calculate the comprehensive score. The entropy value method is one of the objective assignment methods. The degree of influence of low-dimensional indicators is used to determine the weight, thus reducing various human factor interference.

Mechanism variables

To study how digital transformation affects EGTFP, this paper combines the analysis of research hypotheses 2, 3, and 4 to set mediating variables (Luo et al. 2022; Zhang et al. 2022). Energy utilization efficiency (*Ee*) is the operating income to energy consumption ratio. Patents represent the innovation capability of enterprises. Green technology innovation (Gi) is represented by the logarithm of the number of green patents. The investment in environmental protection reflects the importance that the enterprise attaches to environmental responsibility (*Esr*), expressed by the ratio of the annual investment in pollution control to the enterprise total assets.

Control variables

To avoid statistical bias caused by omitted variables, this paper selects a series of other characteristic variables to control the potential factors affecting the EGTFP (Gao et al. 2022; Song et al. 2022). The economic level is expressed using the annual growth rate of regional GDP. Environmental regulation (*Er*) is expressed by the ratio of local government environmental protection expenditure to population size. The size of the enterprise (*Size*) is measured by the logarithm of the enterprise total assets. The age of the enterprise (*Age*) is represented by the number of years a company has been operating. The net profit ratio on total assets (*ROA*) measures the enterprise's financial performance. The proportion of independent directors (*Dep*) is measured by the proportion of independent directors to the total number of directors. Equity concentration ratio (*Equi*) is measured by the sum of the shareholding ratios of the second to fifth largest shareholders to the first largest shareholder. Financial leverage (*Lev*) is represented by the debt-to-asset ratio. Growth capacity (*Growth*) is expressed by the year-on-year growth rate of total operating income. In addition, time and industry dummy variables are introduced to fix the model in both directions.

Data

This paper takes China's Shanghai and Shenzhen A-share listed companies from 2012 to 2021 as the research object (Cheng et al. 2023; Liu et al. 2023), excluding data-missing companies, and excluding ST and delisted companies during the sample period, as well as financial nonentity companies. A total of 11,041 observations were obtained. The research data mainly come from the China Statistical Yearbook, WIND, and CSMAR databases.[1]

[1] Research data are available from the National Bureau of Statistics of China (https://data.stats.gov.cn/easyquery.htm?cn=C01), the CSMAR official website (https://www.gtarsc.com/), and the WIND terminal (https://www.wind.com.cn).

Table 2 The results of the descriptive statistics

Variable	Description	Means	SD	Min	Max
EGTFP	Enterprise green total factor productivity	0.171	0.192	0.002	0.975
DT	Digital transformation	0.361	0.194	0.004	1.075
DT-sub	Substantial digital transformation	0.182	0.096	0.012	0.617
DT-tac	Tactical digital transformation	1.128	1.297	0	4.832
Ee	Energy efficiency	0.762	0.871	0.229	0.913
Gi	Green innovation	0.647	0.997	0.000	4.143
Esr	Environmental social responsibility	0.168	0.129	0.000	0.375
GDP	Economic level	0.075	0.026	−0.054	0.136
ER	Environmental regulation	0.274	0.052	0.133	0.511
Size	Enterprise size	22.828	1.139	19.422	27.389
Age	Enterprise age	1.925	0.725	0.693	3.367
ROA	Return on assets	0.042	0.047	−0.131	0.189
Dep	The proportion of independent directors	0.374	0.053	0.307	0.571
Equi	Equity concentration	0.342	0.152	0.089	0.721
Lev	Financial leverage	0.429	0.211	0.049	0.872
Growth	Enterprise growth	0.298	0.624	−0.615	3.976

Results and discussions

Descriptive statistics

To avoid the errors caused by extreme values, all continuous variables were censored at the 1% and 99% levels to remove data outliers. Table 2 shows the variable descriptive statistics. Among them, the maximum value of EGTFP is 0.975, and the minimum value is 0.002. The green total factor productivity of listed companies in China is low, and the gap is large. The average value of DF is 0.361, the average value of strategic digital transformation is 1.128, and the average value of substantive digital transformation is 0.018. These figures show that the digital transformation of Chinese listed companies is still in its infancy, and that the digital transformation still needs to be substantially strengthened. Examining the impact of two different digital transformations on EGTFP is necessary.

The impact of digital transformation on EGTFP

The Hausman test was carried out in this paper to assess the applicability of the random and fixed effects, and the results (Prob > chi2 = 0.0001) showed that the fixed effects are more suitable. In addition, this paper uses the variance inflation factor (VIF) to test multicollinearity, and the maximum VIF value is 1.98, which is less than the critical standard of 10, indicating no multicollinearity problem. Table 3 shows the estimation results of the benchmark Eq. (1). Column (1) provides the result without any control variables and fixed effects. The estimated coefficient for the explanatory variable is 0.374 and is statistically significant at the 1% level. In columns (2) and (3), this paper further adds control

Table 3 The results of benchmark regression

Variables	EGTFP		
	(1)	(2)	(3)
DT	0.374*** (4.82)	0.353*** (3.79)	0.371*** (3.48)
GDP		0.117** (2.36)	0.121** (2.38)
ER		0.029** (2.11)	0.024** (2.09)
Size		0.172*** (3.27)	0.168*** (2.91)
age		0.003** (2.10)	0.002** (2.11)
ROA		0.022* (1.89)	0.024* (1.90)
Dep		0.011* (1.79)	0.012* (1.78)
Equi		−0.001* (-1.71)	−0.001* (−1.70)
Lev		−0.192** (−2.22)	−0.188** (−2.16)
Growth		0.019** (1.98)	0.018** (1.97)
Constant	0.062*** (3.66)	0.071*** (3.61)	0.059*** (3.54)
Industry	No	No	Yes
Year	No	No	Yes
R^2	0.130	0.215	0.319
N	11041	11041	11041

***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively (same as the table below)

Table 4 Dynamic effects of different digitization types

Variables	EGTFP					
	(1)	(2)	(3)	(4)	(5)	(6)
$DT\text{-}sub_{t-1}$	0.274*** (3.14)					
$DT\text{-}sub_{t-2}$		0.313*** (2.74)				
$DT\text{-}sub_{t-3}$			0.386*** (3.01)			
$DT\text{-}tac_{t-1}$				0.328*** (3.36)		
$DT\text{-}tac_{t-2}$					0.305** (2.33)	
$DT\text{-}tac_{t-3}$						0.289 (1.48)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.297	0.298	0.297	0.340	0.340	0.339
N	11041	11041	11041	11041	11041	11041

Table 5 Robustness test

Variables	(1) Replace variable	(2) Combined fixed	(3) Instrumental variable	(4)
DT	0.512*** (3.65)	0.301*** (2.97)	0.083** (2.26)	0.291*** (2.74)
Control	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Year × Industry	No	Yes	No	No
Kleibergen−Paap rk LM				117.28***
Kleibergen−Paap rk Wald F				163.73
R^2	0.265	0.296	0.252	0.460

variables and fixed effects of regions and enterprises, and the coefficients of the digital transformation are 0.353 and 0.371, and these values are still significant at the 1% statistical level. Digital transformation improves the EGTFP after adding relevant control variables, and research Hypothesis 1 is confirmed.

To more accurately evaluate the impact of digital transformation on the EGTFP, this paper divides digital transformation indicators into substantive digital transformation (*DT-sub*) and tactical digital transformation (*DT-tac*). Table 4 shows the impact of the two "substantive-tactical" digital strategies on the EGTFP. At the same time, this paper pays attention to the dynamic superposition characteristics of the impact of digital transformation on EGTFP in the time dimension, hence adding to the verification of testing Hypothesis 1.

The results in Table 4 show that from lag 1 to lag 3 of the digital transformation, the coefficient of *DT-sub* has always been significant in improving the EGTFP and shows a dynamic increase in the time series. The improvement effect of *DT-tac* exists in lag period 1 to lag period 3. Hypothesis 1 was further confirmed. However, *DT-tac* did not pass the significance test in lag 3 period, and its impact on the EGTFP tended to decay in the long run. These results can infer that substantial digital transformation is the key to improving EGTFP in the long run. Providing long-term support for EGTFP will be easier only if tactical digital transformation is carried out and the substance is addressed.

Robustness and endogeneity tests

To confirm the scientificity of the benchmark results, this paper adopts strategies such as replacing explanatory variables, controlling the joint fixed effect of "year × industry," and the instrumental variable method, as shown in Table 5. First, according to the median value of the digital

Table 6 The heterogeneity of enterprise property rights

Variables	SOEs			Non-SOEs		
	(1)	(2)	(3)	(4)	(5)	(6)
DT	0.357*** (2.74)			0.402*** (3.29)		
Dt-sub		0.261** (2.24)			0.363** (2.36)	
Dt-tac			0.382** (2.11)			0.247** (2.21)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.280	0.288	0.275	0.329	0.320	0.314

transformation index, this paper divides the sample group into a higher degree of transformation (DT = 1) set and another set with a lower degree of transformation (DT = 0) and the benchmark model regression is re-estimated. The coefficient of the digital transformation variable is 0.512, which is consistent with the baseline conclusion. Second, this paper changes the fixed-effects setting and re-estimates the benchmark model using the combined fixed effects of industry and year. The coefficient of the digital transformation is 0.291, which verifies the robustness of the benchmark conclusions. Finally, this paper selects the number of fixed telephones per 10,000 people in prefecture-level cities in 1984 as an instrumental variable for enterprise digitization (Li and Wang 2022). The communication methods used in the past development process will affect enterprises' application and acceptance of information technology in the sample period from the aspects of technical level and social preference, indicating that the instrumental variables meet the correlation conditions. At the same time, the telephone mainly provides communication services for the public and does not directly affect the production process of enterprises, which shows that the instrumental variables meet the exogenous conditions. In the validity test of the instrumental variables, the results of LM statistics and Wald F statistics show that there are no unidentified problematic and weak instrumental variables. The regression results of the instrumental variables show that the impact of digital transformation is still significant.

Heterogeneity test

Benchmark regression and robustness tests can confirm the effectiveness of digital transformation. The new question is the study of heterogeneity. From the perspective of property rights, as an important part of China's market economy, state-owned enterprises' (SOEs) political relations have brought more policy advantages to enterprises (Lian et al. 2022) and have had an impact on the digitalization and green production of enterprises. In addition, regional differences exist in the development of Chinese enterprises, and the geographical location of enterprises leads to heterogeneity. This paper matches the location of enterprise registration with China's regional division and studies the heterogeneity of digital transformation in the eastern, central, and western regions. Based on Eq. (1), we further studied the heterogeneity of enterprise properties using subsampled regression methods, and the results are shown in Tables 6 and 7.

Table 6 shows that in the sample of nonstate-owned enterprises (non-SOEs), digital transformation has a stronger effect on the improvement of EGTFP, and its influence coefficient is larger. It is important to note that substantive digital transformation has a greater effect on non-SOEs than on SOEs, while tactical digital transformation has the opposite effect. This is perhaps because SOEs have political connections and greater bargaining power over the market and local governments. Adequate resource supply and weak environmental regulation lead to a relatively weak effect of digital transformation on the EGTFP. In addition, due to the endorsement of government credit, the tactics of digital transformation proposed by SOEs can attract more market resources, which provides support for the digital transformation of SOEs. Nevertheless, the intervention of administrative forces and the motivation to pursue stable development lead to the low efficiency of digital transformation. The improvement of production efficiency is the only goal for the digital transformation of non-SOEs. Under the pressure of market competition and environmental penalties, non-SOEs are more motivated to implement digital applications to improve production efficiency.

The results in Table 7 show that geographic location influences the role of digital transformation. Comparing the coefficients of digital transformation, the performance of enterprises in the eastern region is the strongest, while that in the western region is weaker. It should be noted that the substantive digital transformation of enterprises in the eastern region is greater than the strategic digital transformation,

Table 7 The heterogeneity of enterprise locations

Variables	Eastern			Central			Western		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DT	0.425*** (3.11)			0.347** (2.23)			0.286* (1.79)		
Dt-sub		0.482** (2.17)			0.311** (2.09)			0.247 (1.55)	
Dt-tac			0.393** (2.25)			0.379** (2.32)			0.372* (2.13)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.314	0.317	0.310	0.282	0.285	0.279	0.289	0.291	0.271

Table 8 The results of the intermediary effect

Variables	(1) *Ee*	(2) *EGTFP*	(3) *lnGi*	(4) *EGTFP*	(5) *Esr*	(6) *EGTFP*
DT	0.480*** (3.19)	0.307*** (3.10)	0.746*** (4.25)	0.281*** (2.79)	0.258** (2.19)	0.328** (2.37)
Ee		0.133*** (2.96)				
lnGi				0.121*** (2.83)		
Esr						0.448* (1.86)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.529	0.416	0.613	0.402	0.425	0.394

and the opposite characteristics exist in other regions. The reason for this is that the digital infrastructure in the developed eastern regions is better, and sufficient capital support makes digital transformation more efficient. Enterprises in the developing areas of the central and western regions need more digital investment, and the pressure of transformation costs is relatively high. This is similar to the U-shaped relationship proven by some scholars (Cheng et al. 2023).

Mechanism analysis

The above research results show that digital transformation can improve the EGTFP. To verify the influence mechanism in this relationship, this paper combines Eq. (1) to construct recursive Eqs. (2) and (3) to analyze the path effects of energy utilization efficiency, green technology innovation, and environmental social responsibility and hence verify hypotheses 2, 3, and 4. Table 8 lists the results of the intermediary effect test. Columns (1) and (2) present the mechanism tests for energy efficiency. Columns (3) and (4) present the mechanism tests of green technology innovation. Columns (5) and (6) present the mechanism tests of environmental responsibility.

The results in Table 8 support hypotheses 2, 3, and 4. First, the coefficients of *DT* on energy efficiency, green technology innovation, and environmental responsibility are 0.480, 0.746, and 0.258, respectively, and they all pass the 1% significance test. This shows that the role of digital transformation in improving energy efficiency, promoting green technology innovation and strengthening environmental responsibility is significant. Second, the influence coefficients of digital transformation and the three mechanism variables on EGTFP are also significantly positive, indicating a partial intermediary effect of the mechanism variables. The advantages of digitalization have strengthened the correlation between enterprise production efficiency and environmental benefits. The digital management of energy, the open innovation of knowledge sharing, and the active responsibility for environmental governance have improved energy efficiency, improved production technology, shaped green image, and finally brought high-quality green efficiency to enterprises. Therefore, digital transformation can improve the EGTFP by improving energy efficiency, promoting green technology innovation, and strengthening environmental responsibility.

Discussions

This study proves that digital transformation can increase EGTFP, and the marginal growth effect of 0.371 is significant. Compared with regional and city-level studies, we find that digital transformation has a greater effect on enterprises (Gu et al. 2022; Li and Liao 2022). This proves that the role of digital transformation is an economic influencing factor transmitted from microenterprises to the macroeconomy (Brodny and Tutak 2022), and that enterprise-level research can better reflect the role of digital transformation. The role of substantive digital transformation is incremental, while that of strategic digital transformation is the opposite. This is similar to the research conclusions of some scholars who found that there is a nonlinear U-shaped relationship (Cheng et al. 2023). Nevertheless, our research extension explains the reason for the existence of nonlinear characteristics. The role of strategic digital transformation is unsustainable. With the deepening of substantive digital transformation, EGTFP has a growing trend. In addition, the effect of digital transformation on EGTFP is heterogeneous. The coefficients of digital transformation are 0.402 and 0.425 in the samples of the nonstate-owned enterprises and the eastern regions, respectively; these coefficients are larger than those of state-owned enterprises and enterprises in the central and western regions. The heterogeneity test results align with the realistic characteristics of China's market-oriented reform and regional green economic development (Du and Jiang 2022). Finally, compared to studies that only consider factors of production, carbon emission efficiency, and environmental institutions (Amesho et al. 2022; Farooq et al. 2022), we analyze the intermediary role of digital transformation in terms of improving energy efficiency, promoting green innovation, and enhancing environmental responsibility. These factors demonstrate the advantages of element configuration, technological innovation, and information disclosure of digital transformation and are discoveries that use digital transformation to enhance EGTFP. Overall, our research not only fills the research gap of EGTFP in terms of microeconomic digital transformation but also provides a basis for the sustainable development of enterprises in the era of the digital economy.

Conclusions and policy implications

This paper assesses the impact of digital transformation on EGTFP. First, the study uses the text analysis method and the super SBM model to measure Chinese enterprise digital transformation and EGTFP. Second, we constructed a panel data model and an intermediary effect model to test the effects of digital transformation on EGTFP. Finally, the study examines the heterogeneous role of enterprise property rights and enterprise location. The research conclusions are as follows.

First, digital transformation positively impacts EGTFP by 0.371 units. The positive effects of substantive digital transformation are time-increasing, while the opposite is true for tactical digital transformation. Therefore, the digital transformation of enterprises only stays at the strategic stage, and continuous substantive digital transformation is more conducive to the realization of the green development of enterprises. Second, there is heterogeneity in the impact of digital transformation on EGTFP. The role of digital transformation in the sample of nonstate-owned enterprises is stronger, while tactical digital transformation does the opposite. Compared with the central and western regions, the digital transformation of enterprises in the developed eastern regions is more efficient. The role of strategic digital transformation in the central and western regions is greater than that of substantive digital transformation. This shows that the green effect of digital transformation needs the support of effective market conditions. In addition, a good economic foundation can provide more favorable conditions for realizing the green production value of digital transformation. Finally, energy utilization, green technology and environmental responsibility are key intermediary paths. Digital transformation can improve EGTFP by improving energy efficiency, promoting green technology innovation, and enhancing environmental responsibility. This shows the role importance of the optimal allocation of resource factors in the upgrading process of EGTFP, and it is also necessary to raise the attention of enterprises to green technology and environmental awareness.

Enterprises should pay attention to the role of digital transformation in promoting EGTFP. On the one hand, enterprises need to combine digital technology with their basic advantages and they need to strengthen digital transformation in equipment technology, system platforms, organizational management, etc., such as building smart factories and digital factories. On the other hand, it is necessary to properly handle the relationship between substantive digital transformation and tactical digital transformation. Substantive digital transformation is sustainable. Using digital transformation as a policy arbitrage is strictly forbidden to reduce the moral hazard of digital transformation slogan trumping actions.

Due to the heterogeneity of property rights and regions, it is necessary to implement differentiated development policies according to local conditions and enterprises. State-owned enterprises and the central and western regions need effective markets and sustained investment in digitalization. Therefore, the government should support the digital transformation of enterprises. On the one hand, it should continuously accelerate the process of market-oriented transformation in China and reduce administrative intervention. On the other hand, it should invest more in digital technology and digital public infrastructure to provide developing regions with opportunities to catch up.

In addition to the traditional path of improving resource efficiency, it is necessary to focus on the role of green innovation and environmental responsibility. It is important to take advantage of digital information and build a digital energy management platform, an open green innovation system, and an environmental information disclosure system. On the one hand, enterprises should strengthen their resource investment and knowledge sharing for green technology innovation. On the other hand, enterprises should improve the quality of environmental information disclosure, actively assume environmental and social responsibilities, and establish a green social image.

This paper studies the impact and path of digital transformation on EGTFP. A robustness test series supports the research conclusions, but limitations exist. For example, in measuring digital transformation indicators, we use substantive and tactical digitalization to represent these indicators. Nevertheless, business digitalization and management digitalization are not strictly distinguished, which is a direction that needs to be expanded. In addition, we analyzed the paths from the perspective of resources, technology, and social responsibility, and they may need to be more overarching. For example, corporate finance and consumer preferences may affect digital transformation and green production, hence we need to explore more impact paths in the future.

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