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*Research article*

# The moderate level of digital transformation: from the perspective of green total factor productivity

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**Abstract:** In the context of accelerated development of the digital economy, whether enterprises can drive green total factor productivity (GTFP) through digital technology has become the key to promoting high-quality development of the economy and achieving the goal of "dual-carbon", However, the relationship between digital transformation and GTFP is still controversial in existing studies. Based on the data of 150 listed companies in China's A-share energy industry from 2011 to 2021, this study empirically analyzes the impact of digital transformation on GTFP using a fixed-effect model. The study shows an inverted U-shaped nonlinear effect of digital transformation on enterprises' GTFP, and the conclusion still holds after a series of robustness tests. Mechanism analysis shows that enterprise investment efficiency and labour allocation efficiency play a significant mediating role in the above inverted U-shaped relationship, in which the inverted U-shaped relationship between digital transformation and GTFP mainly stems from the influence of enterprise investment efficiency. Heterogeneity analysis finds that the inverted U-shaped relationship between digital transformation and GTFP of enterprises is more significant in large-scale enterprises, new energy enterprises and enterprises in central and western regions. The study's findings provide important insights for enterprises to promote digital transformation and realize the green and high-quality development of the energy industry.

**Keywords:** energy industry; digital transformation; green total factor productivity; resource allocation efficiency; super-efficient SBM model; Global Malmquist-Luenberger index

## 1. Introduction

Global warming has caused significant damage to the natural ecological environment on which human beings depend for survival, and greenhouse gas emissions (mainly carbon dioxide emissions) from human activities have been the leading cause of global warming since the mid-20th century. According to the BP Statistical Yearbook of World Energy, China's carbon emission scale (CESC) in 2021 will be 12.04 billion tons, accounting for 30.89% of the global CESC, making China the world's largest carbon emitter. The Chinese government has set the goal of "peak carbon by 2030 and carbon neutrality by 2060". It has incorporated this goal into the overall layout of ecological civilization construction and formulated a comprehensive action plan. According to the Second Biennial Update Report on Climate Change of the People's Republic of China, carbon dioxide emissions from energy activities (referred to as carbon emissions) are the leading cause of China's high carbon emissions, accounting for an average of 98.5% over the years, and in terms of the composition of the industry, carbon emissions from the energy industry accounted for an average of up to 60% over the years. The "Guiding Opinions on Accelerating the Establishment of a Sound Green, Low-Carbon and Circular Economic System" in February 2021 puts forward the promotion of a comprehensive green transformation of the economy and society, and the rise of the realization of higher quality and more efficient development. From this, we can see that effectively improving the green total factor productivity (GTFP) of the energy industry and breaking the development model of "high input, high energy consumption and high pollution" of the energy industry have become the inherent requirements for realizing the goal of "dual-carbon", as well as the high-quality development of the economy. In the current era of the digital economy, digitalization is gradually becoming a vital breakthrough point for global enterprise innovation and change. The "14th Five-Year Plan for the development of the digital economy" proposes accelerating the application of intelligent energy construction, promoting the intelligent upgrading of energy production, transportation, consumption and other aspects, and promoting the energy industry's low-carbon transformation. In the context of data becoming a core element alongside capital, labor, land and technology, digital transformation has gradually become an important engine to promote the growth of GTFP in the energy enterprises. Then, is there a nonlinear effect of enterprise digital transformation on GTFP? Through what mechanisms does digital transformation affect enterprise GTFP? What are the differences in the relationship between digital transformation and GTFP depending on the size of the enterprise, industry, and region? The discussion of these issues is of great practical and theoretical significance for China to accelerate the process of carbon emission reduction and realize the goal of "dual-carbon" at an early date. At the same time, it also provides a valuable reference for other economies to learn low-carbon development through digital transformation.

## 2. Literature review

This study reviews existing literature in three main areas: Digital transformation, GTFP, and the impact of digital transformation on GTFP.

### *2.1. Digital transformation*

With the rise and evolution of the new round of scientific and technological revolution and industrial change, emerging digital technologies represented by artificial intelligence, cloud computing, blockchain, big data, etc. are developing rapidly and are increasingly integrated into the whole process of economic and social development in all fields. Existing literature has mainly empirically explored the economic effects of digital transformation from the micro level. Unlike pure digital technologies such as artificial intelligence, enterprise digital transformation creatively applies cutting-edge digital information technologies to production and operation systems, management models, and core business processes, resulting in disruptive innovation and change [1]. As the digitalization level of Chinese enterprises increases, many scholars have begun to pay attention to the microeconomic effects of digital transformation. By combing through the existing literature, it is found that the effects of digital transformation can be categorized as either positive or negative/uncertain. On the one hand, many scholars believe that enterprise digital transformation is beneficial for enterprises to improve innovation performance and business performance, as well as to enhance total factor productivity, etc. [2–5]. Specifically, enterprises embed digital technologies and data elements into decision-making, research and development, production, sales, service, and other business processes to improve their resource allocation capabilities by optimizing their organizational structure [6], business processes, and production operations, which in turn improves their operational efficiency and financial performance [7]. Meanwhile, Huang et al. [8] also suggested that enterprises using digital technology can play the functions of management empowerment, investment empowerment, operation empowerment, and labor empowerment, and promote the total factor productivity of enterprises. On the other hand, some scholars believe that digital transformation has a negative or uncertain impact on enterprises. Unlike informatization, digital transformation has higher requirements for enterprises. There will be problems such as the digital divide increasing the difficulty of collaboration [9] and the lag in matching the management organization system and capabilities with the digital technology architecture [10]. For example, Guo et al. [5] also found that digital transformation will reduce firm performance by increasing the operating cost ratio, decreasing total asset turnover, and increasing overhead. Overall, the existing literature has yet to reach a consistent research conclusion on the effect of digital transformation on business development.

### *2.2. GTEP*

In recent years, GTFP has received extensive attention from the academic community. Existing studies have discussed the influencing factors of GTFP from three perspectives: economic transformation, environmental factors, and digital technology. Under the path of economic transformation and upgrading, one group of studies argues that factors such as industrial agglomeration, technological progress, foreign direct investment, and urbanization will promote the transformation and upgrading of regional economic structure, optimize the allocation of regional resources and factors, and lead to technological progress and innovation, which in turn will promote GTFP [11,12]. Another category of research examines the role of environmental factors such as carbon emission trading rights, green credit policy, and environmental regulation intensity on GTFP from the perspective of environmental protection and pollution reduction [13,14]. The third type of research starts from the perspective of digital technology, and existing studies have found that the application of digital technology helps industries access knowledge and information more conveniently, improves the innovative knowledge reserve, and promotes technological upgrading, which then improves the efficiency of resource utilization, as well as accelerates the rational allocation of resource elements and the synergistic division of labor among industries, optimizes the industrial structure, and achieves the transformation of industrial greening [15,16]. For example, Lyu et al. [17] measured the level of urban GTFP based on the Global Malmquist-Luenberger (GML) index. They found that the digital economy has a significant positive U-shaped impact and spatial spillover effect on GTFP. Chen and

Wang [18] used a double difference model and found that the information benefit policy promotes the GTFP level of pilot cities but inhibits the neighboring cities' GTFP level.

### *2.3. The impact of digital transformation on GTFP*

Although there is a wealth of research on the relationship between digital transformation and GTFP, the results of existing studies are divergent and still need to be further examined and deepened. Some studies believe that digital transformation of enterprises can optimize their organizational structure, business processes, production operations, break down the information barriers within and outside the enterprise, accelerate the aggregation and optimal reorganization of green technological innovation resources, improve the production efficiency of the enterprise, and make use of digital equipment to carry out all-around intelligent monitoring of the production process of the enterprise to achieve more efficient production management, improve the efficiency of energy use, reduce pollution emissions, and play an "incentive" role in GTFP [19–22]. For example, Lee et al. [23] found that digitalization significantly boosted GTFP in the Yangtze River Delta (YRD) region of China using panel data from 2002 to 2020. Meanwhile, Zou and Ahmad [24] also pointed out that economic digitalization positively moderates energy transition and green industrial development. The higher the level of economic digitalization, the greater the influence of energy transition on green industrial development. Other studies suggest that the digital transformation of enterprises has a "crowding out" effect on GTFP [25]. First, digital transformation, as a massive and complex system engineering, involves multiple levels of enterprise production and management. Therefore, enterprises need to invest more funds to achieve digital transformation, which may lead to insufficient investment in other production factors and imbalanced internal resource allocation; Second, digital transformation will lead to an increase in energy factor inputs by reducing the cost of energy use while improving the energy utilization efficiency of enterprises, resulting in a noticeable energy rebound effect, which will hurt the GTFP of enterprises [26,27]. Lange et al. [28] found that digital transformation will lead to an energy rebound effect by improving energy use efficiency, which will lead to an increase in enterprises' energy consumption. However, some scholars have found that the relationship between digital transformation and GTFP is not purely linear, and that there is a "U," inverted "U," or other non-linear relationship between the two [29]. Digital transformation promotes GTFP by improving technological level and energy efficiency, but also inhibits GTFP by increasing energy consumption and operating costs; the relationship between digital transformation and GTFP depends on the trade-off between the two effects. For example, Liu et al. [7] found that enterprises' digitalization input and output efficiencies show an inverted U-shaped relationship. Zhang et al. [30] also pointed out that there is a positive "U" relationship between digitalization level and urban GTFP.

Compared with other literature, the possible marginal contributions of this study are as follows: First, in terms of indicator measurement, the enterprise digital transformation index published in the China Stock Market & Accounting Research (CSMAR) database is used to characterize the level of digital transformation of energy listed companies. Existing literature mainly adopts text analysis or regional (industry)-level digital economy indicators to construct enterprise digital evaluation indexes [3–5,22]. Still, these two metrics unilaterally focus on the digitalization level at the micro- or mid-macro level, which is biased and does not reflect the whole picture of energy enterprises' digital transformation well. The CSMAR database constructs the enterprise digitalization index from six dimensions: strategic leadership, technology drive, organizational empowerment, enterprise digitalization achievements and applications, and environmental support at the meso-macro level, which not only reflects the differences in the degree and direction of digital transformation of different enterprises, but also takes into account the influence of the meso-macro context on enterprise digital transformation and can reflect the degree of enterprise digitalization more realistically and comprehensively. Second, it enriches and expands the research literature on the economic consequences of enterprises' digital transformation and the factors influencing GTFP. It also provides empirical evidence on how digital transformation affects enterprises' GTFP. Although some of the literature has explored the relationship between digital technology advancement and corporate green development [25,28,31,32], these studies mainly take a specific technology, such as artificial intelligence and automation applied in enterprises as the entry point of the research, and they lack sufficient attention to the relationship between micro-enterprise digital transformation and GTFP. Based on solving the endogeneity problem of the model, this study systematically examines the impact of digital transformation on enterprise GTFP from a micro perspective. It provides path support for Chinese energy enterprises to achieve green, low-carbon change and high-quality development, and provides a "China solution" for other economies. Third, this study incorporates "enterprise digital transformation-enterprise resource allocation efficiency-GTFP" into a unified analytical framework, which provides systematic evidence to accurately understand the intrinsic mechanism of enterprise digital transformation and GTFP. Unlike previous literature that mainly analyzes the mechanism between digital transformation and GTFP from factors such as technological progress, energy utilization efficiency, and structural optimization [22,33–36], this study starts from the perspective of resource allocation efficiency, uses enterprise investment efficiency and labor allocation efficiency to characterize enterprise resource allocation efficiency, and further analyzes the internal mechanism of digital transformation affecting enterprise GTFP. The research findings of this article provide new ideas for understanding and evaluating the economic consequences of digital transformation in energy enterprises, as well as references for optimizing investment and labor resource structure in energy enterprises.

## 3. Theoretical analysis and research hypotheses

### *3.1. Digital transformation and GTFP*

The digital transformation of enterprises can not only empower the traditional business of enterprises through digital technology, improve the productivity and energy efficiency of enterprises, and have a "data-driven" effect on the GTFP of enterprises [5,22], but may also lead to an imbalance between information overload and the matching of management capabilities, increasing the coordination cost and energy consumption of enterprises and inducing the "curse of capability" of enterprises [26,28], which will have a "crowding out" effect on the GTFP of the enterprise. These two effects may have a trade-off at different stages of enterprise digital transformation. Based on this, this article proposes that there is an inverted U-shaped relationship between enterprise digital transformation and GTFP, and digital transformation can affect enterprise GTFP through the following main mechanisms.

Moderate digital transformation is conducive to improving enterprise GTFP. First, enterprises can break the "information barriers" between enterprise departments based on the application of an industrial Internet platform, improve the information transparency of enterprise processes, realize the integration of enterprise management and production control, and improve the efficiency of enterprise operation [1,35]; through the whole chain data communication and intelligent analysis, realize the comprehensive connection between enterprises and external user demand, innovation resources, and production capacity; at the same time, industrial internet platforms can also achieve comprehensive connections between energy enterprises and external user demands, innovative resources, and production capacity, helping enterprises adjust production plans promptly based on product demand, raw material supply, and capacity configuration, optimizing the allocation of various resources, thereby improving capacity utilization, promoting cost reduction, quality improvement, and efficiency enhancement for enterprises[22]. Second, enterprises promote the intelligent upgrading of the production process through the introduction of emerging technologies such as the Internet of Things, big data analysis, and artificial intelligence [7], improve the efficiency of equipment operation, and carry out all-around, real-time monitoring of the operating status of the equipment of each link and energy consumption to realize the exemplary management of energy consumption, improve the efficiency of energy utilization, reduce the cost of production, help the enterprise save energy and increase efficiency, and promote the enterprise GTFP [36–38]. Ultimately, enterprises put digital technology into enterprise production and operation as a production factor, which can not only play the role of technological progress contained in itself [34], but also can be superimposed and integrated with other factors of production to promote changes in the enterprise production mode and organizational process restructuring and drive the flow of technology, capital, talent, and materials with data flow [29], promote the rapid flow and efficient allocation of resource elements, help enterprises better integrate and utilize internal and external innovative technology resources, and then improve the level of enterprise GTFP [12,15].

When firms over-promote digital transformation, it may inhibit the improvement of GTFP. First of all, as the degree of digital transformation continues to increase, the energy utilization efficiency will also increase accordingly. According to the “Jevons paradox,” improving energy utilization efficiency can lower actual energy prices, increase consumer demand for energy, and for profit seeking purposes, enterprises will expand their production scale and use more energy factors to replace other input factors [26,27], leading to an increase in energy factor input and unexpected output, ultimately suppressing the increase in GTFP levels. In addition, the higher the degree of digital transformation, the stronger the systematization and complexity of internal management within the enterprise, and the more stakeholders the enterprise involves, resulting in an accelerated increase in coordination costs [7,10]. The decrease in the expenses brought about by the digital transformation will be smaller than that of digitalization inputs, which ultimately leads to a slowdown of the process of the enhancement of the GTFP of the enterprise until it declines. Based on this, this paper proposes hypothesis H1.

H1: Digital transformation has an inverted U-shaped impact on enterprises’ GTFP: “moderate” digital transformation can improve an organization’s GTFP.

### *3.2. Digital transformation and enterprise resource allocation efficiency*

As a new type of production factor, the data factor breaks the limited supply constraints of traditional elements such as land, capital, labor, etc. and has the effect of the economy of scale and economy of scope, which can comprehensively improve the allocation efficiency and level of enterprise factor resources, and has become an essential driving force for enterprises to create new value. Therefore, from the perspective of enterprise resource allocation efficiency, this paper divides enterprise resource allocation efficiency into two parts, enterprise investment efficiency, and labor allocation efficiency, to further sort out the logical mechanism of digital transformation affecting enterprise GTFP.

First, from the perspective of enterprise investment efficiency, when the degree of digital transformation is within a certain level, digital transformation will improve the GTFP of enterprises by improving their investment efficiency. Enterprises can utilize digital technologies such as the Internet, big data, and cloud computing to collect, store, analyze, and process various types of internal and external information in real-time, efficiently, and comprehensively, and encode and output the data into standardized and structured information [39], building a group level data resource pool from horizontal to edge and vertically to the bottom, assist enterprises in timely understanding of market demand and analyzing market trends [1], exploring potential investment opportunities, implementing scientific and efficient investment plans, improving investment efficiency, and ultimately enhancing the GTFP level of enterprises. At the same time, using the prediction technology of artificial intelligence and machine learning, enterprises can also carry out technological analysis of investment programs, scientifically assess the benefits and risks of investment programs [40], and formulate more scientific and suitable investment strategies, thus reducing overinvestment and underinvestment behaviors of enterprises. In addition, promotion of digital transformation in the enterprise can improve the governance level of the enterprise, improve the transparency of information in all aspects of production and operation of the enterprise [41], and internal and external stakeholders can have more real-time and efficient access to report on the enterprise's internal business decision-making, effectively supervise the investment and management behaviours of managers during their tenure of office, and suppress irrational decision-making behaviours such as excessive or insufficient investment made by managers due to personal interests, and effectively promote the improvement of GTFP of enterprises.

When the degree of digital transformation is too high, it will inhibit the investment efficiency of enterprises, which will reduce their GTFP. On the one hand, enterprises will not only accumulate a large amount of information, resulting in problems such as "information overload," but also over-invest in digital infrastructure, exacerbating energy consumption and crowding out existing production resources, which in turn inhibits green total factor productivity of enterprises [20,29,42,43]. On the other hand, with the improvement of the level of enterprise digital transformation, enterprise operation, and management time, space and connectivity elements will undergo qualitative changes, there is more resistance to continuous organizational restructuring, which results in the enterprise's management and organizational systems and capabilities lagging behind the technological architecture of the digital transformation [10], and the elements of the enterprise and the organizational structure is challenging to adapt to the needs of digital transformation, thus triggering the dysfunction of the enterprise investment structure, leading to inefficient or even ineffective resource allocation, which is not conducive to the enhancement of the enterprise GTFP. Based on the above analysis, hypothesis H2 is proposed:

H2: The efficiency of enterprise investment mediates the digital transformation and GTFP of enterprises.

Second, this section provides an analysis from the perspective of the firm's labor allocation efficiency. Digital transformation increases enterprises' preference for high-skilled labor and improves the efficiency of enterprises' utilization of high-skilled labor [41]. For the digital transformation of energy enterprises as a cross-field cross-border business, enterprise staff should not only be familiar with the energy business, but also be proficient in digital technology, and need to debug, operate, and maintain the new tools and equipment, software, and hardware facilities applied in the process of digital transformation of the enterprise promptly, as well as the integration of digital technology with the business process, which puts forward a higher demand for skills of the existing employees of energy enterprises [44]. Enterprises are bound to tilt their hiring structure from the past low-end and middle-end workforce to a high-end workforce (highly skilled or highly educated), thus improving the efficiency of enterprises' utilization of advanced human capital, optimizing the structure of their workforce resources, and providing support for the improvement of their GTFP [45]. At the same time, with the digital transformation and upgrading of intelligent mines, digital pipeline networks, and other infrastructure, energy companies have realized automation and intelligence in the production process, and the traditional manual operation has been replaced by automated facilities and equipment [38,45], which is conducive to reducing the redundant workforce in the enterprise, optimizing the efficiency of the allocation of labor resources in the enterprise, and thus improving the productivity of the enterprise; the application of artificial intelligence and digital technologies such as industrial robots will reduce the pollution emissions of enterprises by improving the efficiency of energy use and prompting the enterprises to increase the sewage disposal equipment, and the robot operation instead of manual operation can achieve the required accuracy of the production process, reduce pollution generation, and improve green production efficiency [31,32]. Therefore, this paper speculates that enterprise digital transformation will enhance GTFP by improving enterprise labor allocation efficiency. To summarize the analysis, hypothesis H3 is proposed:

H3: The efficiency of enterprise labor allocation mediates digital transformation and enterprise GTFP.

## 4. Research design

### *4.1. Sample description and data sources*

This paper investigates the impact of digital transformation on GTFP and its mechanism with the listed companies in China's A-share energy industry from 2011 to 2021. The main reasons are: (1) the "12th Five-Year Plan" and "13th Five-Year Plan" are the two planning periods of China's energy development from the crude expansion to intensive and efficient accelerated gear shift period. The "Thirteenth Five-Year Plan for Energy Development," released in 2017, offers to actively promote the development of "Internet +" intelligent energy. At this time, new energy production and consumption models characterized by intelligence are emerging, and new forms of smart energy are taking shape. (2) According to the China Digital Economy Development Report (2022), China's digital economy grew slowly before 2011, while the scale of China's digital economy continued to grow after 2011, with the average annual growth rate significantly exceeding the average growth rate of GDP in the same period, becoming a new driving force for the high-quality development of China's economy. Therefore, 2011–2021 was chosen as the time study interval for the sample.

The digital conversion index, control variables, mediator variables, and input-output-related data are all from the CSMAR database. Among them, the energy input data of enterprises is sourced from the annual reports and social responsibility reports of listed companies, both of which are manually collected; the data related to the characteristics of the cities to which the enterprises belong are from the China Urban Statistical Yearbook, China Energy Statistical Yearbook, and China Price Statistical Yearbook. This article follows the Industry Classification Guidelines for Listed Companies revised by the China Securities Regulatory Commission in 2012, selecting coal mining and washing industry (B06); oil and gas mining industry (B07); mining auxiliary activities (B11); electricity, heat, gas, and water production and supply industry (D44); gas production and supply industry (D45); as well as the petroleum processing, coking, and nuclear fuel processing industry (C25) in the manufacturing industry. The chemical raw material and chemical product manufacturing industry (C26) is a traditional energy industry, and we select 64 listed companies from the concept sectors of wind power, photovoltaic, nuclear power, and biomass energy in the Tongdaxin Financial Terminal to represent the new energy industry. In addition, this paper treats the samples as follows: (1) the samples of ST and *ST type companies during the sample period and the samples of companies listed after 2011 are excluded; (2) deleting samples with missing observation values for core variables; (3) to avoid the impact of extreme values, this article applies a 1 percent Winsorize treatment to both the upper and lower levels of continuous variables. In the end, this paper obtains 1650 observations from 150 enterprises.

### *4.2. Definition of variables*

#### 4.2.1. Explained variables

The explanatory variables are enterprises' GTFP. GTFP refers to the change in output brought about by considering one or several input factors while protecting the ecological environment. Therefore, referring to Tone [46], this paper chooses the super-efficient SBM GML index model to measure the GTFP of China's A-share listed companies in the energy industry from 2011 to 2021. The measurement method is as follows:

Specifically, assuming there are K decision units (DMUs), each with N inputs $x_n$, I expected outputs $y_i$, and J unexpected outputs $b_j$, ρ represents the efficiency value. We construct the super-efficient SBM model

$$\rho = min\frac{\frac{1}{N}\sum_{n=1}^{N}\frac{x_n}{x_{n0}}}{\frac{1}{I+J}(\sum_{i=1}^{I}\frac{y_i}{y_{i0}}+\sum_{j=1}^{J}\frac{y_j}{y_{j0}})} \tag{1}$$

$$s.t.\begin{cases} \sum_{k=1}^{K}\lambda_k x_{nk} \le x_n \\ \sum_{k=1}^{K}\lambda_k y_{ik} \ge y_i \\ \sum_{k=1}^{K}\lambda_k b_{jk} = b_j \\ \sum_{k}^{K}\lambda_k = 1 \\ x \ge x_0,\ y \le y_0,\ b \ge b_0,\ \lambda_k \ge 0 \\ x_n = x_{n0} + s^- \quad (n = 1,\ 2,\ \cdots,\ N) \\ y_i = y_{i0} - s^y \quad (i = 1,\ 2,\ \cdots,\ I) \\ b_j = b_{j0} + s^b \quad (j = 1,\ 2,\ \cdots,\ J) \end{cases} \tag{2}$$

where vectors $s^-$, $s^b$, and $s^y$ denote excess inputs, undesired outputs, and insufficient desired outputs, respectively.

Furthermore, to explore the dynamic evolution trend of GTFP growth in energy listed companies, drawing on the method of Oh [47], this article constructs the GML based on Eqs (1) and (2) with the formula

$$GML^{t,\ t+1} = \frac{1+\overrightarrow{D_0^G}(x^t, y^t, b^t; y^t, -b^t)}{1+\overrightarrow{D_0^G}\ (x^{t+1},\ y^{t+1},\ b^{t+1}; y^{t+1}, -b^{t+1})} \tag{3}$$

where $GML^{t,\ t+1}$ denotes the GML index from period t to t + 1, i.e., the intertemporal dynamics of GTFP. $GML^{t,\ t+1}$ denotes an increase in GTFP, and $GML^{t,\ t+1}$ denotes a decrease in GTFP.

Since the GML index reflects the rate of change of GTFP, it is necessary to adjust the calculated GML index accordingly to obtain the actual value of GTFP. Specifically, assuming that the GTFP for the base period of 2011 is 1, then the GTFP for 2012 is equal to 1 multiplied by the 2012 GML index, and so on, to ultimately calculate each enterprise's GTFP. The specific input-output indicators are selected as follows:

•Input indicators. For capital investment, this paper uses the net fixed assets of the firm. Second, for labor, the number of employees at the end of the year of each company is used to measure labor input. Third, the total consumption of various types of energy converted into 10000 tons of standard coal is selected to represent energy input. The energy input data comes from the annual reports of listed companies and social responsibility reports of enterprises.

•Expected output. Measured by primary business income, with 2011 as the base period, deflated using the industrial producer price index (PPI) for the prefecture-level city where the enterprise is located, derived from the China Price Statistics Yearbook.

•Non-expected output. It is expressed by the three-waste generation of industrial enterprises, including industrial wastewater emissions, industrial sulfur dioxide ($SO_2$) emissions, and industrial smoke (dust) emissions. This paper refers to the method of Wang et al. [22] to measure the pollutant emissions of each enterprise.

First, the adjustment coefficients $W_j$, i.e., the weights, were calculated for each pollution indicator in each prefecture using

$$W_j = \frac{P_{ij}/\sum P_{ij}}{O_i/\sum O_i} \tag{4}$$

where $P_{ij}$ is the emission of pollutant j (j = 1, 2, 3) in prefecture i, $\sum P_{ij}$ is the national total emission of pollutant j, Oi is the total industrial output value of prefecture i, and $\sum O_i$ is the national total industrial output value.

Second, the weighted adjusted emissions ($EM_{ij}$) of pollutant j in prefecture i are obtained;

$$EM_{ij} = W_j \times P_{ij} \tag{5}$$

Finally, the emission of pollutant j ($EM_{kj}$) from firm k in prefecture i is obtained:

$$EM_{kj} = EM_{ij} \times \frac{Q_k}{\sum Q} \tag{6}$$

where $Q_k$ is the industrial output of enterprise k, $\sum Q$ is the total industrial output of the prefecture-level city where enterprise k is located, and the data on non-expected output are from the China Urban Statistical Yearbook and the China Energy Statistical Yearbook.

### 4.2.2. Explanatory variables

The explanatory variable is the enterprises' digital transformation level (Digi). Some scholars start from the macro level and use regional or industry-level digital economy indicators to proxy the digitalization level, while others use text analysis methods to statistically measure the frequency of words related to digital transformation in the annual reports of enterprises or measure the level of enterprises' digital transformation from a single dimension, such as information technology and Internet [3,7,9,35,39]. With the gradual deepening of the discussion on the issue of enterprise digital transformation, the CSMAR database constructs an enterprise digitalization index from six dimensions: strategic leadership, technology-driven, organizational empowerment, environmental support, digital achievement, and digital application. Compared with the above two evaluation indexes, this evaluation index has two advantages: (1) It examines the information at the mid-macro level based on the enterprises' data and constructs the measurement system of enterprise digital transformation based on the six dimensions, which can alleviate the problem of right-skewed data caused by the zero frequency of enterprise digitalization words. (2) It contains more information about enterprises' application of digital technology, not only the measurement of the word frequency of keywords related to digital transformation in the existing literature, but also more objective evaluation indexes such as digital workforce investment plan, digital capital investment, and the intensity of digital technology in the industry in which it is located, which can measure the level of digital transformation of the enterprise objectively and comprehensively, and it is pretty representative and reliable [48]. Based on this, this paper adopts the Digital Transformation Composite Index from the CSMAR database to measure the degree of enterprise digital transformation.

#### 4.2.3. Control variables

This paper selects five control variables that may affect GTFP: (1) Enterprise size (Ass), expressed as total assets at the end of the year. According to the Environmental Kuznets (EKC) hypothesis, firm size affects firm output and pollution emissions. (2) Age of the firm (Age), which is the difference between the current year and the firm's establishment date. Life cycle theory suggests that the development of enterprises will generally go through the growth, maturity, and decline stages, and there will be differences in learning ability and technology level at different stages, which all impact the GTFP level of enterprises. (3) Profitability (ROA), expressed as net profit/total asset balance. Profitability can, to a certain extent, reflect the ability of enterprises to carry out green technological innovation, which in turn affects the level of GTFP of enterprises. (4) Level of economic development (Pgdp), measured using GDP per capita. The overall level of economic development of the region will impact the residents' green consumption concepts and the industrial structure, which in turn will affect the GTFP of enterprises. (5) Environmental regulation intensity (Res): This paper calculates the environmental regulation intensity of each city based on the emissions of industrial wastewater, sulfur dioxide ($SO_2$), and industrial smoke (dust) in each city where the enterprises are located, using the entropy weight method. According to the Porter hypothesis, appropriate environmental regulation will stimulate technological innovation in firms, with the benefits of innovation offsetting or even outweighing environmental protection costs, thus ensuring or increasing enterprises' GTFP.

### 4.3. Model setting

In order to test the relationship between digital transformation and enterprise GTFP, this paper constructs the following model for regression analysis:

$$GTFP_{it} = \alpha + \beta_1 Digi_{it} + \beta_2 Digi_{it}^2 + \sum Controls_{it} + \delta_i + \eta_t + \theta^{c\times t} + \varepsilon_{it} \tag{7}$$

where subscript i denotes the firm and t denotes the year. The dependent variable $GTFP_{it}$ represents the GTFP level of enterprise i in year t. $Digi_{it}$ represents the degree of digital transformation of enterprise i in year t. Controls are a set of control variables. $\delta_i$, $\eta_t$, and $\theta^{c\times t}$ denote firm fixed effects and year fixed effects and "Region (province) where the firm is located × year" fixed effects, respectively. $\varepsilon_{it}$ is a random error term. This paper focuses on the significance of the coefficients $\beta_1$ and $\beta_2$ in model (7). According to the previous research hypothesis, if $\beta_1$ is significantly positive and $\beta_2$ is significantly negative, it implies that there is a significant inverted U-shaped relationship between corporate digital transformation and corporate GTFP.

## 5. Empirical results and analysis

### 5.1. Descriptive statistics

Table 1 shows the descriptive statistics of the main variables in this paper. Among them, the mean value of GTFP water of energy-listed companies is 1.1497, and the standard deviation is 1.0895, indicating apparent differences in the level of GTFP among different energy-listed companies. From the statistical results of enterprise digital transformation level (Digi), the mean value of enterprise digital transformation water is 32.543, the median is 29.211, and the standard deviation is 8.365, which, on the one hand, indicates that most energy-listed companies have a lower digital transformation level, and, on the other hand, indicates that there are significant differences in the digital transformation level among different types of energy listed companies. In addition, the rest of the control variables in this paper are generally consistent with the results of related literature, and no significant differences are observed.

**Table 1.** Results of descriptive statistics.

| Variables | Obs | Mean | Std | Min | Max | Median |
|---|---|---|---|---|---|---|
| GTFP | 1650 | 1.1497 | 1.0895 | 0.0000 | 6.6252 | 1.000 |
| Digi | 1650 | 32.543 | 8.365 | 23.133 | 57.160 | 29.211 |
| $Digi^2$ | 1650 | 1128.954 | 630.407 | 535.136 | 3267.243 | 853.265 |
| Ass | 1650 | 318.775 | 575.411 | 0.179 | 123.334 | 4900.685 |
| Age | 1650 | 18.668 | 5.762 | 5.000 | 32.000 | 19.000 |
| ROA | 1650 | 0.031 | 0.041 | −0.140 | 0.141 | 0.029 |
| pgdp | 1650 | 69409.795 | 33912.939 | 22195.000 | 173600.000 | 62290.000 |
| Res | 1650 | 0.028 | 0.077 | 0.000 | 0.479 | 0.002 |

### *5.2. Benchmark regression*

Table 2 shows the results of the benchmark regression of digital transformation (Digi) on enterprises' GTFP. In the regression results with only the core explanatory variable Digi in column (1), the variable Digi is not significant, indicating that there may not be a simple linear relationship between the digital transformation and GTFP of enterprises. Column (2) shows the regression results of GTFP using the variable Digi and its square term $Digi^2$ after controlling for fixed effects of the company, year, and province × year, and column (3) presents the results of regressions with further inclusion of control variables. It can be seen that, regardless of whether the control variable is added or not, the coefficient of variable Digi is positive, and the coefficient of its square term $Digi^2$ is negative, both of which are significant at the 1% level, indicating an inverted U-shaped relationship between digital transformation and GTFP. The empirical results are consistent with the findings of other scholars [49]. For example, Lange et al. [28] argued that the energy-saving effect of digital transformation is limited and that the use of digitization technologies may produce an energy rebound effect, which leads to an increase in energy consumption. Lin and Huang [29] found an inverted U-shaped relationship between digitalization and energy efficiency using data from 90 countries from 2000 to 2020. Liu et al. [7] found an inverted U-shaped effect of corporate digitalization inputs on output efficiency.

The reasons for the above results may lie in the fact that moderate digital transformation is conducive to enterprises changing traditional business processes and business models, realizing more efficient and flexible production operations and management models, promoting efficient allocation of production factors, and improving enterprise productivity [8,19,35]. At the same time, enterprises can use the intelligent energy management system to monitor, analyze, optimize, and schedule the operating status of equipment and energy consumption in all aspects of production and operation in real-time, helping enterprises to implement more efficient distribution schemes and production plans to improve energy efficiency, achieve energy saving and emission reduction, and provide the impetus for the enhancement of the enterprise's GTFP [20,24]. However, with the deepening of digital transformation, the "energy rebound effect" [26,27], generated by the rapid expansion of enterprise production scale, will lead to an increase in energy consumption instead of a decrease and an increase in non-desired outputs. At the same time, it also causes problems such as information overload and the imbalance between enterprise management capabilities, as well as an increase in coordination costs, which is not conducive to the continuous improvement of enterprise GTFP [5].

In order to ensure the reliability of the above results, this paper refers to the practice of Lind and Mehlum [50], using the Utest test further to identify the inverted U-shaped relationship between the two. The results of the Utest test are shown in Table 3, which shows that the extreme point of the digital transformation level is 32.27438, within the range of the value of the digital transformation level [21.7891;37.1335]. At the same time, the test results in the Slope interval have a negative value, and the original hypothesis is rejected at a significance level of 5% (p-value of 0.033), which indicates that digital transformation does have an inverted U-shaped impact on GTFP, and hypothesis H1 is supported.

**Table 2.** Benchmark regression results.

| Variables | (1)<br>GTFP | (2)<br>GTFP | (3)<br>GTFP |
|---|---|---|---|
| Digi | –0.0109 | 0.0882*** | 0.0741*** |
| | (–1.9038) | (3.1899) | (2.7397) |
| $Digi^2$ | | –0.0013*** | –0.0011*** |
| | | (–3.5327) | (–3.2133) |
| Ass | 0.0003*** | | 0.0003** |
| | (2.7508) | | (2.4320) |
| Age | 0.1407* | | 0.1511* |
| | (1.7734) | | (1.9105) |
| ROA | 3.6118*** | | 3.5984*** |
| | (6.2178) | | (6.2185) |
| Pgdp | 0.0000 | | 0.0000 |
| | (0.3949) | | (0.5232) |
| Res | 2.6531*** | | 2.6201*** |
| | (5.4184) | | (5.3704) |
| Constant | –2.2987 | –0.2557 | –4.2288 |
| | (–0.8394) | (–0.5087) | (–1.5138) |
| Firm FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Province × year FE | YES | YES | YES |
| $R^2$ | 0.7186 | 0.7003 | 0.7210 |
| Obs | 1650 | 1650 | 1650 |

Note: t-statistics in parentheses, ***, **, * indicate significance at the 1, 5 and 10% levels, respectively. The following tables are identical.

**Table 3.** Utest test results.

| | Lower bound | Upper bound |
|---|---|---|
| Interval | 23.133 | 57.1598 |
| Slope | 0.0209808 | –0.0571156 |
| t-value | 1.836538 | –3.690616 |
| extreme point | 32.27438 | |
| P > \|t\| | 0.0333 | |
| 95% Fieller interval for extreme point | [21.7891;37.1335] | |

### *5.3. Robustness tests*

#### 5.3.1. Multidimensional fixed effects

In order to verify the robustness of the results, this paper adds industry fixed effects, urban fixed effects, and "industry × year" fixed effects to the baseline regression to further reveal the relationship between digital transformation and enterprises' GTFP. The results are shown in column (1) of Table 4. The relationship between digital transformation level and enterprises' GTFP still maintains an inverted U-shape, and although the coefficient of digital transformation level changes slightly, the inflection point is almost unchanged, and the above results are consistent with the previous conclusions.

5.3.2. Replacement of explanatory variables

This paper refers to the approach of Wu et al. [39] to conduct text analysis and word frequency statistics on the annual reports of listed companies. The digital transformation level (digi) is re-measured based on the total digital word frequency obtained by summing up each enterprise's digital keyword word frequency, and the core explanatory variable Digi is replaced for regression. The regression results are reported in column (2) of Table 4. The regression results in column (2) of Table 4 indicate that the inverted U-shaped relationship between digital transformation and enterprises' GTFP persists after replacing the explanatory variables, again demonstrating the robustness of the benchmark regression results in this paper.

**Table 4.** Robustness Test Results.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Multidimensional FE | Indicator replacement | Phase 1 | Phase 1 | External policy impact | |
| variables | GTFP | GTFP | GTFP | GTFP | GTFP | GTFP |
| IV | | | 0.1233** | | | |
| | | | (7.9125) | | | |
| Brandchina | | | | | 0.1293*** | 0.5712 |
| | | | | | (3.0148) | (0.4591) |
| Digi | 0.0681** | | | 0.7252*** | | 0.0962*** |
| | (2.2695) | | | (3.6939) | | (3.5709) |
| $Digi^2$ | −0.0010** | | | −0.0094*** | | −0.0016* |
| | (−2.3783) | | | (−3.6342) | | (−1.9523) |
| Brandchina × Digi | | | | | | 0.0266** |
| | | | | | | (2.3792) |
| Brandchina × $Digi^2$ | | | | | | −0.0001* |
| | | | | | | (−1.8569) |
| digi | | 0.0076** | | | | |
| | | (2.5493) | | | | |
| $digi^2$ | | −0.0001*** | | | | |
| | | (−2.9287) | | | | |
| Control variable | YES | YES | YES | YES | YES | YES |
| Frim FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Province × year FE | YES | YES | YES | YES | YES | YES |
| Industry × year FE | YES | NO | NO | NO | NO | NO |
| Industry FE | YES | NO | NO | NO | NO | NO |
| Urban FE | YES | NO | NO | NO | NO | NO |
| Kleibergen-Paap rk LM | | | 12.81*** | | | |
| Kleibergen-Paap rk Wald F | | | 21.05*** | | | |
| Cragg-Donald Wald F | | | 13.42*** | | | |

5.3.3. Instrumental variable method

This paper uses the average value of the degree of digital transformation of other enterprises in the enterprise's industry as the instrumental variable (IV) for the level of digital transformation. On the one hand, the level of digital transformation of other firms in the same industry can influence the level of digital transformation of individual firms to a certain extent, satisfying the correlation condition; on the other hand, the digital transformation level of other enterprises in the same industry has no direct relationship with the GTFP of individual enterprises, and the digital transformation level of other enterprises in the same industry will not significantly change individual enterprises' GTFP level in the current period, which meets the exclusivity requirement. The regression results of the instrumental variable two-stage least squares (2SLS) are shown in columns (3) and (4) of Table 4. In the first stage, the coefficient of the instrumental variable (IV) is significantly positive, and the results of the unidentifiable and weak instrumental variable tests show that the problem of soft instrumental variables can be ruled out; in the second stage, the regression results show that the regression coefficients of Digi and $Digi^2$ are all significant at the 1% level, which suggests that there is still a meaningful inverted U-shape relationship between digital transformation and corporate GTFP and that the conclusions of this paper are still robust and reliable.

5.3.4. Exogenous shocks based on the "Broadband China" pilot policy

In 2013, the State Council issued the Circular of the State Council on the Issuance of the "Broadband China" Strategy and Implementation Program, and selected a total of 120 cities (clusters) as "Broadband China" demonstration sites in three batches in 2014, 2015, and 2016. On the one hand, the "Broadband China" pilot policy is considered a driving policy for optimizing and upgrading China's urban network infrastructure and developing the digital economy, and a good digital infrastructure can support enterprises in carrying out digitalization-related activities. On the other hand, it is not up to enterprises to decide whether or not to enter the "Broadband China" pilot list, which suggests that the policy is exogenous and can avoid the endogeneity problem to a certain extent. Therefore, in this paper, we refer to the approach of Huang et al. [8], use the "Broadband China" pilot policy as an exogenous shock, and adopt a multi-period double-difference approach to verify further the causal relationship between digital transformation and firms' GTFP. Based on the above, if the city where the enterprise is located is selected as a "Broadband China" demonstration city, Brandchina is taken as 1 in the year of selection and the following years, and 0 in the previous years and for the other cities that are not selected. The test results in column (5) of Table 4 show that the coefficient of Brandchina is significantly positive, which indicates that after implementing the "Broadband China" strategy, the green factors of firms in the demonstration cities are significantly improved. In column (6) of Table 4, the coefficient estimate of Brandchina × Digi is significantly optimistic at the 5% level, and the coefficient estimate of Brandchina × $Digi^2$ is significantly pessimistic at the 10% level, which means that the relationship between digital transformation and enterprises' GTFP is still inverted U-shaped, consistent with previous conclusion. After implementing the "Broadband China" strategy, the relationship between digital transformation and enterprise GTFP is still inverted, consistent with the previous findings. The above results indicate that the main conclusions of this paper are still robust after considering the exogenous shock of "Broadband China".

### 5.3.5. Sensitivity analysis

To further ensure the robustness of the research results, this article refers to Singh et al. [51] to conduct a sensitivity analysis on the relationship between digital transformation and GTFP. While studying the impact of digital change of enterprises on GTFP, other factors may also impact GTFP. Therefore, this study draws on the sensitivity analysis method of Cinelli and Hazlett [52] and uses the variance relationship between potential omitted variables, core explanatory variables, and dependent variables to estimate the strength of omitted variables. This article takes the environmental regulation intensity (Res) in the control variable as a comparison variable for potential omitted variables. The estimated results are shown in Figures 1 and 2. The results indicate that, even when the potential omitted variable is 3 times the strength of Res, the estimated coefficient of Digi is positive (as shown in the left figure of Figure 1), and the estimated coefficient of $Digi^2$ is still negative. At the same time, when the strength of the omitted variable is 3 times the strength of Res, both estimated coefficients are significant, at least at the 5% level. The results of the underlying regressions continue to hold, proving that the findings of this paper are unaffected by the omitted variable.

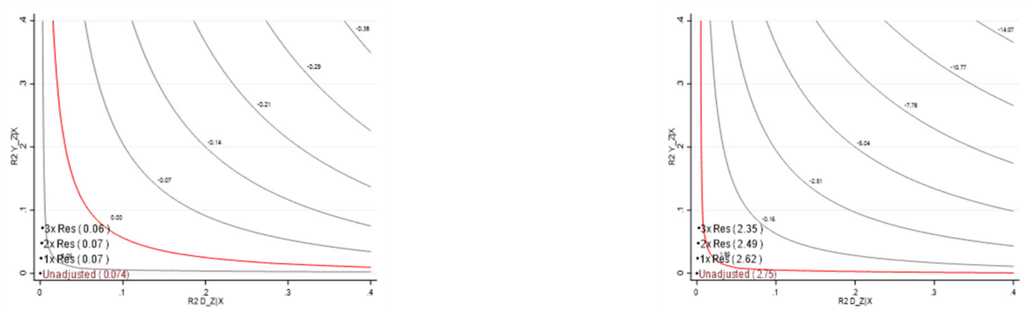


**Figure 1.** Sensitivity analysis: Digi estimated coefficients (left) and their t-values (right).

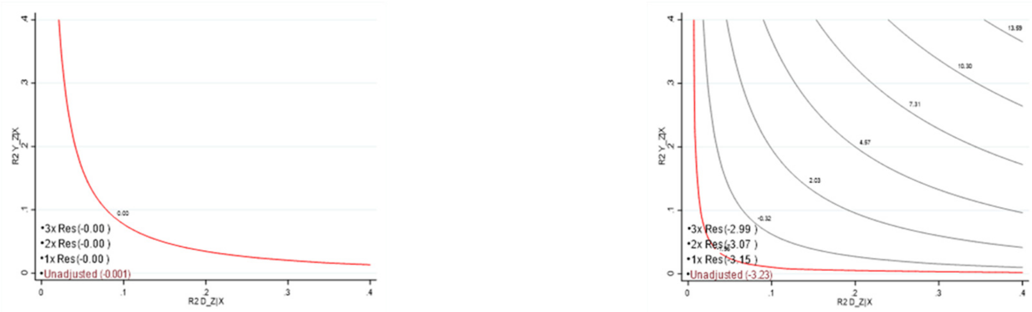


**Figure 2.** Sensitivity analysis: $Digi^2$ estimated coefficients (left) and their t-values (right).

## *5.4. Heterogeneity analysis*

### 5.4.1. Enterprise size heterogeneity

The effect of implementing digital transformation as a major structural change in enterprises varies due to differences in enterprise scale, resulting in heterogeneity in the impact of digital transformation on the GTFP of enterprises. This article divides the sample into large-scale and small-scale enterprises based on the median number of employees. It explores the impact of digital transformation on GTFP in enterprises of different scales. The test results grouped by enterprise size are reported in columns (1) and (2) of Table 5.

The results show that, among large-scale firms, the estimated coefficient of the variable Digi is significantly positive at the 5% level, and the estimated coefficient of the squared term $Digi^2$ is significantly negative at the 1% level. In small-scale firms, the estimated coefficients of the variable Digi and its squared term $Digi^2$ are insignificant. Combined with the above analysis, digital transformation requires a large amount of investment in human, material, and financial resources to gradually bring the advantages of digital transformation into play. At the same time, small-scale enterprises are limited by the lack of funds and resources, the scale of digital investment is small, and digital transformation is difficult to have a significant impact on GTFP. In contrast, the larger the enterprise scale, the greater the demand for internal and external synergy, the more shared resources accumulated, and the more significant the positive impact of digital transformation on productivity; but, with the expansion of the enterprise scale, the enterprises gradually pass the "dividend period" of digital transformation, and the process of efficiency enhancement slows down [7], ultimately exerting a restraining effect on GTFP, thereby demonstrating the inverted U-shaped impact of digital transformation on GTFP of enterprises.

#### 5.4.2. Industry heterogeneity

Due to the differences in process, product attributes, and production and management concepts, different industries have different combinations of production factors invested in their products, and such differences may also impact the relationship between digital transformation and enterprises' GTFP. This article refers to the Industry Classification Guidelines for Listed Companies issued by the China Securities Regulatory Commission 2012. It divides the sample into two parts: traditional energy industry and new energy industry for group testing. The group testing results are shown in columns (3) and (4) of Table 5. The results show that digital transformation in the traditional and new energy industries shows a significant inverted U-shape impact on enterprises' GTFP. However, relative to traditional energy enterprises, the impact of digital transformation on new energy enterprises is more significant, and the inverted U-shape inflection point of new energy enterprises is greater. The reason for the above results may be that the new energy industry, as a knowledge and technology-intensive industry, has a high level of technology and talent literacy, a fast process of digital promotion, and a significant impact of digital transformation on GTFP. In contrast, the traditional energy industry, as an energy-intensive industry, has a solidified business model, lacks the information technology talent cultivation mechanism of energy-based enterprises, lags in the construction of digital platforms, and has a lower degree of integration of digital technology and business, resulting in a minor impact of digital transformation on the GTFP of enterprises.

#### 5.4.3. Regional heterogeneity

Given the differences in economic development levels, resource endowment conditions, and the level of digital economy development among different regions, the impact of enterprise digital transformation on GTFP may vary across regions. In order to test whether the impact of digital transformation on GTFP is regionally heterogeneous, this paper divides the sample enterprises into three parts: east, central, and west. The results of the grouping test are shown in columns (5)–(7) of Table 5.

According to the results of the grouping test, it can be seen that the inverted U-shaped relationship between digital transformation and GTFP is significant in the eastern region, but not in the central and western regions. This indicates that the relationship does have significant differences between regions. The reason may lie in the following: On the one hand, the eastern region is an essential cluster of digital technology R&D and innovation, and its digital infrastructure level, financial development level, and human capital stock level are much higher than that of the central and western regions, which can provide more favorable external conditions for the digital transformation of enterprises, while the software and hardware foundation for the implementation of the digital transformation of enterprises in the central and western regions is relatively weak, which makes it challenging to provide enterprises with a broad digital application space, which leads to a more significant effect of digital transformation on the GTFP of energy enterprises in the eastern region. On the other hand, the central and western regions may be forced by the pressure of economic growth rate, absorbing several high-pollution, high-energy-consumption, high-emission energy industries transferred from the eastern region, and the relatively low level of economic development and income of the residents also reduces the demand for the high-quality environment of enterprises and residents. Constrained by the objective primary conditions and subjective demand awareness of the double limitations, thus leading to digital transformation, it is not easy to play a role in driving the GTFP of enterprises in the central and western regions.

**Table 5.** Heterogeneity analysis results.

| variables | (1) Large scale GTFP | (2) Small scale GTFP | (3) Traditional energy GTFP | (4) New energy GTFP | (5) Eastern part GTFP | (6) Central section GTFP | (7) Western part GTFP |
|---|---|---|---|---|---|---|---|
| Digi | 0.0916** | 0.0171 | 0.0291* | 0.0963*** | 0.0569* | 0.0153 | −0.0826 |
| | (2.4643) | (0.3456) | (1.6850) | (3.0621) | (1.6886) | (0.2366) | (−1.1996) |
| $Digi^2$ | −0.0013*** | −0.0004 | −0.0003* | –0.0014*** | –0.0009** | –0.0004 | 0.0011 |
| | (−2.7151) | (−0.6272) | (−1.7462) | (−3.4349) | (−2.0195) | (−0.4072) | (1.0984) |
| Control variable | YES | YES | YES | YES | YES | YES | YES |
| Frim FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| Province × year FE | YES | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.7706 | 0.8159 | 0.7967 | 0.6077 | 0.6498 | 0.7692 | 0.5707 |
| Obs | 884 | 766 | 942 | 708 | 884 | 454 | 312 |

## 6. Mechanism analysis

To examine whether the impact of digital transformation on the resource allocation efficiency of enterprises can lead to changes in the GTFP of enterprises, this paper will measure the resource allocation efficiency of enterprises from the aspects of enterprise investment efficiency and enterprise labor allocation efficiency, and provide supporting evidence for revealing the role of digital transformation on the GTFP mechanism 6.

### *6.1. The impact of enterprise investment efficiency*

This article draws inspiration from the research of Huang et al. [8]. First, the enterprise investment model is used to fit the expected investment scale of the enterprise. Then, the difference between the actual investment scale and the expected investment scale is used, that is, the degree to which the enterprise deviates from the optimal investment level, to characterize the enterprise investment efficiency (Absinv). The larger the Absinv value, the more severe the inefficient investment of the enterprise, and the lower the investment efficiency. The specific calculation method is shown in Eq (8):

$$Invest_{it} = \delta_0 + \delta_1 Size_{it-1} + \delta_2 LnAge_{it-1} + \delta_3 Lev_{it-1} + \delta_4 Cash_{it-1} + \delta_5 Return_{it-1} + \delta_7 \mathrm{Invest}_{\mathrm{it-1}} + \sum \mathrm{Indu} + \sum \mathrm{Year} + \varepsilon_{\mathrm{it-1}} \quad (8)$$

Among them, $Invesit_{it}$ represents the investment level of the enterprise, which is the proportion of the original price of fixed assets to the total assets at the beginning of the period. $Size_{it-1}$ is the size of the firm’s total assets, expressed as the natural logarithm of total assets. $LnAge_{it-1}$ is the number of years that the firm has been listed. $Lev_{it-1}$ is the asset liability ratio. Cashit-1 is the balance of cash and its cash equivalents as a share of total assets. $Return_{it-1}$ is measured as the annual return on individual shares taking into account the reinvestment of cash dividends. $Invest_{it-1}$ is the level of the enterprise’s investment in year t−1, calculated in the same way as above. $\sum \mathrm{Indu}$ and $\sum \mathrm{Year}$ are industry and year fixed effects, respectively. By regressing model (8), the residual obtained is used as the investment efficiency (Absinv) of the enterprise, further dividing the inefficient investment of the enterprise into two situations: overinvestment and underinvestment. When the residual is greater than 0, it indicates overinvestment (OverInv), and when the residual is less than 0, it indicates underinvestment (UnderInv).

Panel A of Table 6 explores how digital transformation (Digi) will affect enterprises’ GTFP through enterprises’ Absinv. The test results in column (1) show that the coefficient of Digi is −0.0360 and is significant at the 10% level, while the coefficient of the quadratic term $Digi^2$ is 0.0006 and is significant at the 5% level, which indicates that moderate digital transformation can effectively inhibit enterprises’ inefficient investment behaviors. However, too high a level of digital transformation in the later stage will increase the enterprises’ inefficient investment behaviors, which is not conducive to improving enterprises’ investment efficiency. In order to further examine the sources of digital transformation affecting the investment efficiency of enterprises, this paper divides the investment efficiency of enterprises into two groups, overinvestment and underinvestment, and tests them separately. Among them, columns (3) and (5) show the test results of the impact of digital transformation (Digi) on enterprises’ overinvestment (OverInv) and underinvestment (UnderInv), respectively. The results in column (3) show a significant inverted U-shaped relationship between the core explanatory variables Digi and OverInv. The results in column (5) indicate that the regression coefficient of the core explanatory variable Digi is negative but statistically insignificant, while the coefficient of the squared term is significantly positive. The reason may be that when the degree of digital transformation is below a certain level, although enterprises can alleviate information asymmetry and internal agency problems through digital transformation, thereby reducing underinvestment behavior, promoting digital management and change requires a large amount of capital investment. Most enterprises will also encounter situations such as “hesitant to transform” and “unwilling to transform” due to the high cost and long transformation period of digital transformation. As a result, there is an increase in underinvestment behavior among enterprises. The interaction between the positive and negative effects of promoting digital transformation in enterprises ultimately leads to insignificant inhibitory effects of digital transformation on the underinvestment behavior of enterprises [7]. Based on the test results in columns (3) and (5), it can be found that, in the early stages of digital transformation, digital transformation significantly reduced overinvestment behavior and improved enterprise investment efficiency. However, as digital transformation reaches a certain level, it will increase non-efficient investment behaviors such as overinvestment and underinvestment, damaging the investment efficiency of enterprises. To form a complete logical chain, columns (2), (4), and (6) further examine the effects of corporate investment efficiency, overinvestment, and underinvestment on GTFP, and find that the estimate coefficients of Absinv, OverInv, and UnderInv are all significantly negative at least at the 5% level, suggesting that inefficient investment such as corporate overinvestment and underinvestment significantly inhibit GTFP. The above results suggest that digital transformation will have an inverted U-shaped relationship with enterprises' GTFP by first promoting and then inhibiting firms' investment efficiency.

**Table 6.** Mechanism analysis.

| Panel A: Investment efficiency | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| variables | Absinv | GTFP | OverInv | GTFP | UnderInv | GTFP |
| Digi | −0.0360* | | −0.0567*** | | −0.0401 | |
| | (−1.8725) | | (−3.1321) | | (−1.6042) | |
| $Digi^2$ | 0.0006** | | 0.0009*** | | 0.0007** | |
| | (2.3236) | | (3.5484) | | (2.2493) | |
| Absinv | | −0.1007*** | | | | |
| | | (−2.7530) | | | | |
| OverInv | | | | −0.2542** | | |
| | | | | (−2.5607) | | |
| UnderInv | | | | | | −0.1882*** |
| | | | | | | (−2.8401) |
| Control variable | YES | YES | YES | YES | YES | YES |
| Frim FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Province × year FE | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.8850 | 0.5474 | 0.9120 | 0.6402 | 0.6280 | 0.5789 |
| Obs | 1650 | 1650 | 748 | 748 | 879 | 879 |
| Panel B: Efficiency of labor allocation | | | | | | |
| | (1) | | | (2) | | |
| variables | El | | | GTFP | | |
| Digi | −1.4853** | | | | | |
| | (−2.0135) | | | | | |
| $Digi^2$ | 0.0137 | | | | | |
| | (1.3844) | | | | | |
| El | | | | −0.0025** | | |
| | | | | (−2.5507) | | |
| Control variable | YES | | | YES | | |
| Frim fixed effects | YES | | | YES | | |
| Year fixed effects | YES | | | YES | | |
| Province × year FE | YES | | | YES | | |
| $R^2$ | 0.6280 | | | 0.7194 | | |
| Obs | 1650 | | | 1650 | | |

The main reason for this is that, benefiting from the cross-border connectivity attributes of digital technology, enterprises' information acquisition and application efficiency in the investment process have been gradually improved, helping them understand market demand, analyze market trends promptly, and make efficient decisions. At the same time, with the help of modern advanced network technology and information technology, enterprises can scientifically assess the benefits and risks of investment programs, effectively monitor and constrain the self-interested behavior of the management in investment decision-making, realize the scientific and rationalized investment decision-making [40,41], guide the flow of capital to the projects with good prospects for development and high rates of return on investment, improve the investment efficiency of the enterprise, and then enhance the GTFP level of the enterprise [18,39]. However, when enterprises do not take into account their actual situation and excessively promote digital transformation, enterprise elements and organizational structure are difficult to adapt to the needs of digital transformation, resulting in a weak correlation between digital strategy and business development, which leads to an increase in inefficient investment behaviors of the enterprise and inhibits the GTFP of the enterprise [53]. The above analysis proves that the core mechanism of "digital transformation→investment efficiency→GTFP" does exist and verifies the content of hypothesis H2.

### *6.2. The impact of enterprise labor allocation efficiency*

This article draws on the research of Ni and Wang [54] to construct a labor investment model to calculate the optimal labor allocation amount for enterprises. Then, the labor allocation efficiency of enterprises is measured by comparing the difference in labor quantity between the optimal allocation state and the actual state. This is done using the following model (9):

$$Empolyee_{it} = \delta_0 + \delta_1 Siize_{it-1} + \delta_2 Growth_{it-1} + \delta_3 Capital_{it-1} + \sum \gamma Indu + \sum \lambda year + \varepsilon_{it} \quad (9)$$

Here, $Empolyee_{it}$ represents the number of employees of the enterprise, measured by the number of employees of the enterprise at the end of the year as a proportion of the total assets; the calculation method for enterprise size $Size_{it-1}$ and primary business income growth rate $Growth_{it-1}$ is the same as above; capital intensity $Capital_{it-1}$ is measured by the proportion of fixed assets to the total assets of the company; and $\sum$ Indu and $\sum$ Year are represented as industry and year fixed effects, respectively. By regressing model (9), the residual obtained is the efficiency of labor allocation. The larger the residual, the more inefficient the labor allocation of the enterprise.

Panel B of Table 6 examines how digital transformation (Digi) will affect enterprises' GTFP through enterprises' labor allocation efficiency (El). The results in column (1) show that the coefficients of Digi are significantly negative at the 5% level. The coefficients of $Digi^2$ are positive, but statistically insignificant. Column (2) further examines the impact of corporate excess employees on GTFP and finds that the coefficient of El is significantly negative at the 5% level, indicating that corporate excess employees have a negative impact on GTFP. The above results suggest that labor allocation efficiency plays a mediating role between digital transformation and enterprise GTFP, and its mediating position mainly occurs in the stage of positive correlation between the two. The main reason behind this may be that the technological progress brought about by the digital transformation of enterprises and the widespread application of intelligent equipment can reduce the demand for medium- and low-skilled labor in the production chain, increase the employment of high-skilled and highly educated labor, and thus optimize the human capital structure of enterprises [44]. At the same time, the application of digital technology also reduces the cost of communication between managers and employees, which helps to alleviate the information asymmetry within the enterprise, optimize the efficiency of labor allocation, and thus improve the GTFP of the enterprise [8]. However, the substitution of labor by machines will not continue indefinitely [45], and large-scale machine applications will drive down production costs, incentivize enterprises to expand the scale of production, and provide incentives and conditions for enterprises to extend the industrial chain, which in turn creates more new demand for labor, and ultimately achieves dynamic equilibrium in the total employment [55]. The above results corroborate the content of hypothesis H3.

## 7. Conclusions, policy implications, and limitations

### *7.1. Conclusions and policy implications*

Based on the theoretical basis of clarifying the relationship between digital transformation and GTFP, this paper uses the relevant data of A-share energy industry listed companies in China from 2011–2021 to measure the GTFP of energy listed companies using the super efficiency SBM-GML index model. It systematically examines the impact of enterprise digital transformation on GTFP and its logical mechanism. This study shows an inverted U-shaped impact of enterprise digital transformation on GTFP, and the conclusion still holds after robustness tests. Heterogeneity analysis indicates that the inverted U-shaped relationship between digital transformation and GTFP of enterprises is more significant in large-scale enterprises, new energy industries, and eastern region enterprises. At the mechanism analysis level, digital transformation will improve GTFP by promoting enterprise investment efficiency and labor allocation efficiency when digital transformation is below the inflection point. In contrast, the negative impact of digital transformation on enterprise GTFP begins to be highlighted as enterprise investment efficiency turns favorable to negative after the level of digital transformation crosses the inflection point. Based on the above findings, the following policy implications are proposed:

First, the study found that moderate digital transformation facilitates the GTFP of energy enterprises. Therefore, energy enterprises should actively use digital technology to reconstruct energy business and systems, use data to drive enterprise process optimization and lean management, use the Internet as a medium to promote the digital empowerment of the entire energy business, promote the formation of an intelligent energy regulation system, improve the level of accurate and efficient allocation of resources, and achieve enterprise cost reduction and efficiency and management improvement. However, energy enterprises should also grasp the degree of digitalization and not blindly invest in technology. They should combine their own development positioning and market actual needs, scientifically plan and coordinate to promote, and avoid blind reform like sports.

Second, energy enterprises should not only pay attention to the role of digital transformation in improving investment efficiency, deeply integrate digital technology into different aspects of investment, and realize the application of digital technology in the whole cycle of investment to provide adequate impetus for optimizing the enterprise' investment decision-making behavior and human capital structure, but energy companies should also invest prudently based on their own needs and risk-bearing ability and continuously optimize their factor resources and organizational capacity so that the depth of digital transformation corresponding to the highest investment efficiency is continually shifted to the right. At the same time, the government should also mobilize the enthusiasm of enterprises to carry out skills training through financial subsidies and tax exemptions, and at the same time, increase the construction of digital training service platforms, significantly expand the scale and intensity of digital talent training, enhance the digital literacy and skills of workers, and mitigate the adverse impact of the digital transformation of energy enterprises on the low-end labor force.

Third, accurately help all kinds of energy enterprises to implement digital transformation smoothly and orderly. This paper finds that the inverted U-shaped effect of digital transformation on enterprise GTFP will be heterogeneous due to the differences in enterprise scale, industry, and regional characteristics. Therefore, the government should follow the principle of differentiation and implement the direction of "one policy for one place," "one policy for one enterprise," and "one policy for one line," according to the transformation of varying energy enterprises based on the qualities of various industries and resource endowment conditions in regions, with differentiated, targeted policies to better promote the balanced and coordinated inter-regional, inter-industry, and inter-enterprise digital development. It also encourages industry leaders and digital platform enterprises to open up their platforms, technologies, data, and other resource elements under the premise of guaranteeing security, and guides large enterprises with sufficient resources and conditions to build industrial communities, innovation consortia, and other characteristic carriers of integration and innovation that are shared, symbiotic, co-sharing, and win-win to drive the green and high-quality development of traditional energy enterprises and small and medium-sized micro-enterprises.

### *7.2. Limitations and future recommendations*

Although this paper provides a detailed exploration of the intrinsic links and influence mechanisms between digital transformation and GTFP of enterprises, there are still areas for improvement. First, since the CSMAR database of the corporate digital transformation index has been measured since 2011, our research sample is also limited to the period from 2011 to 2021. To further enhance the credibility and persuasiveness of the findings, it may be more meaningful to study the impact of digital transformation on the GTFP of energy enterprises in other countries, which cannot be achieved based on data availability. In the future, we will further analyze the impact of digital transformation on enterprises' GTFP using the latest sample once updated data are available. Second, this paper focuses on analyzing the mechanism of digital transformation's impact on enterprises' GTFP from the perspectives of investment efficiency and labor allocation efficiency, and future research could explore other microenterprise-level means.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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## Conflict of interest

The authors declare there is no conflict of interest.

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