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Impact of Enterprise Digital Transformation on the Efficiency of Total Factor Energy Utilization

-- From the Perspective of Differences in Enterprise Energy Efficiency

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Abstract. With the advent of the information age and the rapid progress of technology, it has become inevitable for enterprises to move towards digital transformation. Energy is one of the most vital material bases for national economic and social development, which plays a vital role in national economic growth. How to use energy efficiently has been the core factor to measure the sustainable development potential of an enterprise. Based on the data of listed companies in China, this paper empirically analyzes the impact of enterprise informatization on energy efficiency from different perspectives. Studies have shown that the degree of enterprise informatization has a direct relationship with its energy efficiency. At present, the overall informatization of enterprises in various regions of China is low. However, with the continuous popularization of digital technology and applications, it has a certain inhibitory effect on enterprise energy consumption, with the effect becoming more and more apparent. Especially during the digital transformation, the role of state-owned enterprises in promoting total factor energy consumption has been more significant. Therefore, from the perspective of digital transformation, it is of great significance to study the energy efficiency of state-owned enterprises. This research explores the significant differences in energy efficiency among various industries, and the adoption of digital transformation strategies will help narrow these differences and further promote energy efficiency improvement across the industry. In addition, through the analysis of typical cases, this topic reveals the main problems faced by enterprises in the process of digital transformation and their causes, which puts forward corresponding countermeasures and suggestions. This study can provide a solid theoretical basis for the positive role played by Chinese enterprises and related departments during the digital transformation.

Keywords: Digital Transformation; Energy Utilization Efficiency.

1. Introduction

In the current business environment, the digital transformation of enterprises has become crucial. Globally, digital transformation will be the most important driver of future economic growth. Digital transformation is reshaping the operating model, organizational structure and market competitiveness of enterprises with its all-round and far-reaching reform characteristics. With the continuous development of the social economy, energy issues have attracted widespread attention from all walks of life. How to use energy efficiently has become one of the key factors for the sustainable development of enterprises. How to improve the efficiency of energy utilization is a major problem faced by enterprises. In the current context, in-depth research on the core mechanism of how enterprises affect their energy efficiency through digital transformation not only has far-reaching significance in theory, but also has value that cannot be ignored in practice.

2. Literature Review

The core idea of enterprise digital transformation is to use the wide application of digital information technologies such as cloud computing, artificial intelligence and big data to promote the all-round and multi-level reconstruction of enterprise organizational structure, business process and business model. This can not only improve the core competitiveness of the enterprise, but also help the enterprise achieve the high-quality development of “increasing income, reducing costs, improving efficiency, and controlling risks”. According to the research of Pei Xuan et al., digital transformation has brought apparent and long-term positive effects to various types of enterprises, whether traditional or emerging [7]. In addition, enterprises can use digital transformation to gain benefits in terms of technological advantages, management advantages, and intellectual capital. As proposed by Yuan Chun et al., enterprises can achieve more efficient specialization through digital transformation, which can significantly improve total factor productivity [14], and this is supported by the research of Zhang Xueyang et al [16]. Moreover, the digital transformation of enterprises has also played a significant role in alleviating the restrictions on enterprise financing [12], which helps to reduce the ineffective investment of enterprises and improve the efficiency of capital use [17]. Meanwhile, in terms of digital technology and business model innovation, some scholars have discussed the positive or negative effects of digital transformation of enterprises on their business performance, financial risks and competitive advantages from different perspectives. Yang Zhensen and his team hold the view that by improving the enterprise ability in green innovation, it is possible to further promote the digital transformation of enterprises, so as to achieve a higher development quality [13]. Hence, for enterprises at different stages of the life cycle, their digital transformation is imperative and necessary. For those enterprises in the growth stage, digital transformation can help them formulate differentiated strategies, thereby improving their value-creation capabilities. According to Tong Ziqiang and his team, by increasing the construction of digital infrastructure, enterprises can effectively move towards the road of green innovation [9]. On this basis, this paper further explores the relationship between enterprise digital transformation and enterprise energy conservation and emission reduction. Xiao Renqiao and his team pointed out that the digital transformation of enterprises can indirectly promote the improvement of ESG performance by optimizing their structure, enhancing the ability of green innovation and reducing inefficient investment [11]. These views all emphasize the role played by enterprises in promoting the development of informatization. According to the research of Nie Shunjiang and his team, enterprises have significantly promoted their acceptance of energy-saving green innovation during the digital transformation, among which digital green R&D investment has played an intermediary role [6]. To a certain extent, these conclusions support the view that core enterprises in the digital economy era promote their green innovation and development through the implementation of digital transformation. Through digital transformation, core enterprises can use supply chain management strategies more efficiently, which not only promotes the growth of funds, but also improves the dissemination of technology, thus significantly enhancing the innovation potential of enterprises. In addition, after taking other factors into account, the above conclusion still holds. The research of Ma Wenjia et al. confirmed this finding [4]. Based on the research of Yuan Yehu and his team, the implementation of digital transformation strategies by reducing operating costs and financing restrictions as well as strengthening social supervision can effectively improve the green innovation capabilities of energy companies [14]. This theoretical model proves that digital transformation will significantly improve the production efficiency and resource utilization efficiency of enterprises. Especially for state-owned energy enterprises, new energy enterprises and mature energy enterprises, digital transformation has played a crucial role in promoting green innovation. The research of Ren Yangjun et al. found that by improving the specialization and division of labor, the energy efficiency of enterprises can be further improved [7]. This conclusion also verifies that digitalization is vital to improving the energy efficiency of state-owned enterprises [3].

3. Research Hypotheses

3.1. Positive Correlation Between Enterprise Digital Transformation and Energy Utilization Efficiency

Digital transformation has injected data-centric decision-making power into enterprises, enabling enterprises to track and monitor dynamic changes in energy supply and demand in real-time, so as to obtain comprehensive and accurate data information. This batch of data not only provides enterprises with the cornerstone of a comprehensive understanding of energy utilization, but also enables enterprises to quickly identify and deal with problems encountered in energy utilization through in-depth data analysis, thereby significantly improving energy utilization efficiency. Real-time monitoring of energy utilization and timely discovery of energy waste are of great significance to reducing energy consumption. In addition, by using smart sensors and control systems, enterprises can flexibly adjust their energy allocation and utilization strategies according to actual energy demand and supply conditions, so as to maximize energy utilization efficiency. Digital transformation has also promoted the ability of collaborative optimization among various departments within the enterprise. With the support of digital technology, information can be transmitted quickly and accurately within the enterprise, enabling various departments to cooperate more closely to jointly formulate and optimize energy utilization plans, so as to achieve a more significant improvement in energy utilization efficiency as a whole. Thus, the capabilities of data-driven decision-making, intelligent energy management, and collaborative optimization brought about by the digital transformation of enterprises will have a positive impact on the energy utilization efficiency of enterprises. Based on the above analysis, the first hypothesis of this paper is put forward.

H1: There is a positive correlation between the enterprise digital transformation and energy utilization efficiency. As the transformation deepens, the efficiency will also increase accordingly.

3.2. Analysis of the Different Impact of Enterprise Nature Diversity on the Efficiency of Total Factor Energy Utilization under Digital Transformation

During the digital transformation, state-owned enterprises and non-state-owned enterprises have their unique advantages and challenges. Non-state-owned enterprises are usually more willing to enhance their competitiveness and market adaptability through digital transformation to quickly seize market share and meet customer needs. They adopt emerging technologies and innovative models faster, such as cloud computing, big data analysis, artificial intelligence, etc., so as to improve the quality, efficiency and personalization of products and services. Besides, they are more willing to break down barriers between departments, and promote the sharing and integration of information and resources. Non-state-owned enterprises are also more adventurous and prone to try emerging technologies and new business models. In contrast, state-owned enterprises have many unique advantages. The government is more likely to provide financial support for state-owned enterprises alone, such as financial subsidies, low-interest loans, technological innovation funds, etc. These financial supports are conducive to the investment and implementation of digital transformation projects, helping enterprises purchase advanced digital equipment, develop innovative digital technologies, and train employees with the skills and knowledge needed for digital transformation. State-owned enterprises may obtain digital transformation policy guidance and support from government departments, including issuing relevant documents to clarify development directions and key areas, and help them understand the significance, goals and paths of digital transformation. Meanwhile, state-owned enterprises usually have a relatively stable organizational structure and management system with more decision-making levels. Their organizational structures often go through long-term development and precipitation. The division of responsibilities between various departments and positions is clear with clarified management levels. The decision-making of digital transformation will be fully discussed and evaluated, and various possible risks and impacts will be considered, which can reduce the risk of digital transformation to a certain extent. Thus, during the digital transformation, state-owned enterprises have shown obvious advantages with relatively faster development speed. At the same time, the digital transformation of state-owned enterprises has indicated significant results in improving the efficiency of total factor energy utilization of enterprises. The second part studies the influencing factors of different ownership enterprises during the digital transformation. Based on the above analysis, the second hypothesis is proposed.

H2: During the active promotion of digital transformation, state-owned enterprises play a vital role in improving the efficiency of total factor energy utilization.

4. Experimental Design

4.1. Samples and Data Sources

This paper uses the data of listed enterprises from 2007 to 2022, which draws on the processing method of Lu Fucai et al. (2023) for the original data as follows: Exclude samples with missing total assets, main business income, and number of employees. Meanwhile, samples with less than 8 employees, total assets of enterprises less than total fixed assets, total assets less than current assets, an asset-liability ratio less than zero, and net sales margin less than 0.1% or higher than 99% are excluded. After these processes, a total of 39882 observed samples are obtained [3]. The data of listed enterprises comes from the WIND database and CSMAR database.

4.2. Measure of Key Variables

1. Explained Variable

Enterprise efficiency of total factor energy utilization is to measure the efficiency and effectiveness when using various resources. To evaluate this indicator more accurately, the environmental pollution of enterprises is taken into account with the non-radial SBM-ML index (referred to as "ML index") used to measure the enterprise efficiency of total factor energy utilization. The inputs and outputs of this indicator are measured as follows:

(1) Input factors: The labor input of an enterprise is determined by the number of employees as a variable. In terms of capital investment, the net value of fixed assets is regarded as an alternative variable. Land investment mainly refers to the funds required by enterprises for the expropriation of cultivated land and expenditures for agricultural infrastructure construction. To determine the energy input, we calculated the ratio of industrial electricity consumption in the city where the enterprise is located to the proportion of the enterprise's employees. To be specific, industrial electricity means the electric energy generated in the production process of industrial enterprises, while industrial added value refers to the value created by industrial enterprises within a certain period of time.

(2) Expected output: The expected output of an enterprise is reflected by its operating income. Considering that China is still in the middle stage of industrialization, the total industrial output value has been adjusted.

(3) Unexpected output: This is an unexpected output that converts the discharge of "three industrial wastes" (including sulfur dioxide, wastewater, and smoke and dust) into the employment ratio of enterprise employees in the cities and towns where they live.

2. Explanatory Variables

Enterprise Digital Transformation (DCG). The enterprise digital transformation is not limited to the digital storage of data, but also promotes the digitization of production materials and production processes through the utilization of digital technology and hardware systems, thus improving cooperation efficiency, reducing costs and promoting production efficiency. Referring to the quantitative measures of Wu Fei et al. (2023), this paper collects the annual reports of all A-share listed enterprises on the Shanghai and Shenzhen stock exchanges through Python, and uses the Java PDF Box to extract and save the text content to establish a database for subsequent keyword screening. After in-depth analysis and discussion, this paper selects and discusses relevant keywords around two major fields of academia and enterprises, aiming to provide a comprehensive and accurate research perspective [9].

This paper draws on Chen Chunhua et al. (2019) and Li Chuntao et al. (2020) to sort out key words of enterprise digital transformation, which figures out five categories including artificial intelligence technology, big data technology, cloud computing technology, blockchain technology and digital technology application. On this basis, the expressions of negative words before the key words are excluded. Besides, non-enterprise keywords of "digital transformation" (including the enterprise shareholders, customers, suppliers, and enterprise executives) are also excluded. Finally, based on the database formed by Python on the text content of the annual reports of listed enterprises, the word frequency is searched, matched and counted according to the above words, so as to classify and collect the word frequency of key technical directions and form the final total word frequency, thus building an indicator for the enterprise digital transformation system [1][2]. The obtained data are logarithmically processed.

3. Control Variables

In the design stage, various factors that may affect the research results are carefully considered, with effective measures taken to eliminate them to ensure the objectivity and accuracy of the research results.

We have introduced a series of control variables (as seen in Table 1), including enterprise asset-liability ratio, enterprise size, ratio of enterprise cash flow, growth ability, investment opportunities, fixed asset ratio, board size, and ratio of the independent director.

Table 1. Variables and Their Definitions

Type	Name	Symbol	Definition
Explained Variable	Enterprise Efficiency of Total Factor Energy Utilization	EE	Using non-radial SBM-ML index for measurement with details as seen above
Explanatory Variable	Enterprise Digital Transformation	DCG	Statistics on the key words of enterprise digital transformation with details as seen above
Control Variable	Asset-Liability Ratio	Lev	Total liabilities at end of period/Total assets at end of period
	Enterprise Size	Size	Natural logarithm of total assets
	Enterprise Cash Flow Ratio	Cashflow	Net cash flows from operating activities divided by total assets
	Growth Ability	Growth	(Operating income for the year/Operating income for the previous year)-1
	Investment Opportunities	TobinQ	Tobin Q
	Ratio of Enterprise Fixed Assets	FIXED	Net fixed assets at the end of the period/Total assets
	Board Size	Board	Number of board of directors taken natural logarithm
	Ratio of Independent Directors	Indep	Number of Independent Directors/Total number of Directors
	Industry Fixed Effects	Industry	Dummy variable
	Annual Fixed Benefit	Year	Dummy variable

4. Model Construction

To deeply explore the impact of enterprise digital transformation on total factor energy efficiency, we have constructed the following baseline regression model and conducted rigorous testing:

$$EE_{\mathrm{it}} = \alpha_0 + \alpha_1 \mathrm{Digital}_{\mathrm{it}} + \alpha_2 \sum Contral_{it} + Ind + year + \varepsilon_{it} \quad (1)$$

Digital refers to the level of enterprise digital transformation; year refers to the fixed effect of time; Control refers to the corresponding control variable; EE refers to the enterprise efficiency of total factor energy utilization; Ind refers to the fixed effect of the industry with the corresponding regression coefficients of α0 and α1, and ε refers to random disturbance term.

5. Empirical Analysis

5.1. Descriptive Statistical Analysis

The descriptive statistics of each variable (as seen in Table 2) indicate that the average total factor energy efficiency (EE) of the enterprise is 0.989, and the standard deviation is 0.121, proving relatively low variability. The median is higher than the average, indicating that the data is slightly positively biased. Most businesses are more efficient, with values ranging from 0.720 to 1.176. Enterprise digital transformation (DCG) is extremely right-skewed, with an average of 1.261, a median of only 0.693, and a standard deviation of 1.386. The maximum 6.301 is well above the most observed values, indicating that there are cases of extremely high values. Other control variables are associated with regular feature symbols.

Table 2. Descriptive Statistical Analysis

VarName;	Obs	Mean	SD	Min	Median	Max
EE	39882	0.989	0.121	0.720	1.008	1.176
DCG	39882	1.261	1.386	0.000	0.693	6.301
Lev	39882	0.465	1.136	-0.195	0.440	178.345
Size	39882	22.176	1.361	15.418	21.995	28.636
Cashflow	39882	0.046	0.100	-10.216	0.045	2.222
Growth	39882	4.297	678.373	-2.733	0.106	135000
TobinQ	39882	2.201	3.703	0.609	1.637	393.013
FIXED	39882	0.218	0.167	0.000	0.184	0.971
Board	39882	2.130	0.204	0.000	2.197	2.890
Indep	39882	37.516	5.627	0.000	35.710	100.000

5.2. Correlation Analysis

Table 3. Correlation Analysis

	EE	DCG	Lev	Size	Cashflow	Growth	TobinQ	FIXED	Board	Indep
EE	1									
DCG	0.415***	1								
Lev	-0.030***	-0.032***	1							
Size	0.191***	0.088***	0.018***	1						
Cashflow	0.016***	-0.016***	-0.046***	0.082***	1					
Growth	-0.00500	-0.00500	0.00100	-0.00200	-0.00100	1				
TobinQ	-0.021***	0.00300	0.291***	-0.251***	-0.179***	-0.00100	1			
FIXED	-0.163***	-0.302***	0.016***	0.062***	0.172***	0.00200	-0.056***	1		
Board	-0.175***	-0.110***	0.020***	0.236***	0.044***	0.00200	-0.069***	0.159***	1	
Indep	0.103***	0.087***	0.00100	0.016***	-0.018***	-0.00400	0.025***	-0.059***	-0.506***	1

To explore in more depth the close relationship between enterprise equity incentive and employee stock ownership as well as their environmental, social and governance (ESG) performance, this study will conduct a comprehensive and scientific correlation analysis of the relevant main variables, with analysis results shown in detail in Table 3.

DCG and EE are positively correlated (0.415***), which may indicate that when the level of enterprise digital transformation is high, the enterprise efficiency of total factor energy utilization is also high, initially confirming H1. To further test the existence of multicollinearity between the variables, the VIF variance inflation factor is used to test. After data analysis (see Table 4 for details), the variance inflation factor (VIF) of each variable is lower than 2, far below the critical value, which fully proves that there is no significant multicollinearity problem among the selected variables. Hence, the constructed model has good stability.

Table 4. VIF Test

Variable	VIF	1/VIF
Board	1.500	0.669
Indep	1.380	0.724
TobinQ	1.210	0.827
Size	1.190	0.844
FIXED	1.160	0.863
DCG	1.130	0.887
Lev	1.110	0.904
Cashflow	1.060	0.939
Growth	1	1.000

5.3. Benchmark Regression

Table 5. Basic Regression Results

	(1)	(2)	(3)
VARIABLES	EE	EE	EE
DCG	0.036***	0.035***	0.032***
	(91.16)	(88.95)	(78.35)
Lev		-0.002***	-0.003***
		(-4.42)	(-5.44)
Size		0.014***	0.019***
		(34.37)	(44.61)
Cashflow		0.010*	0.028***
		(1.91)	(5.06)
Growth		-0.000	-0.000
		(-0.66)	(-0.62)
TobinQ			0.001***
			(5.93)
FIXED			-0.028***
			(-8.29)
Board			-0.115***
			(-36.15)
Indep			-0.001***
			(-6.38)
Constant	0.943***	0.638***	0.803***
	(1,264.61)	(71.81)	(69.40)
Industry Fixed	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes
Observations	39,882	39,882	39,882
r2 _ a	0.172	0.197	0.230

As for controlling year and industry fixed effects, this paper uses a stepwise regression method to test the impact of the enterprise digital transformation on the efficiency of total factor energy utilization. First, the independent variables are regressed, and then the control variables are added step by step to regress. According to Columns (1) (2) (3) in Table 5, enterprise digitalization all promotes the enterprise efficiency of total factor energy utilization, which are all significant at the level of 1%, indicating that H1 is reliable.

5.4. Endogenous Problems

1. Differences in Differences

Table 6. DID Test Results

	(1)	(2)	(3)
VARIABLES	EE	EE	EE
DID	0.111***	0.107***	0.098***
	(101.21)	(97.22)	(88.28)
Lev		-0.002***	-0.003***
		(-4.30)	(-5.25)
Size		0.012***	0.017***
		(29.75)	(40.71)
Cashflow		0.003	0.025***
		(0.54)	(4.68)
Growth		-0.000	-0.000
		(-0.48)	(-0.44)
TobinQ			0.001***
			(6.00)
FIXED			-0.044***
			(-13.40)
Board			-0.112***
			(-35.76)
Indep			-0.001***
			(-6.02)
Constant	0.923***	0.663***	0.822***
	(1,088.10)	(75.73)	(72.22)
Industry Fixed	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes
Observations	39,882	39,882	39,882
R-squared	0.204	0.222	0.257
r2 _ a	0.204	0.222	0.257
F	10243	2277	1532

Although all regression models use the lag treatment of core explanatory variables to reduce the ambiguity of causal relationships, there is still a risk of missing key variables in the model. Therefore, this paper regards the enterprise digital transformation in batches as a quasi-experiment similar to a natural experiment. Referring to the research of Zheng Jianming et al. (2018), this study selected the multi-period difference-in-differences model (DID) to further solve the endogenous problem. By conducting a secondary difference analysis between the treatment group and the control group, intrinsic differences between individuals and biases caused by time trends that are not related to the treatment group are effectively excluded, so as to evaluate the direct impact of enterprise digital transformation on total factor energy production efficiency [17]. On this basis, we constructed the difference-in-differences model, aiming to explore the specific effect of enterprise digital transformation on the enterprise efficiency of total factor energy utilization.

$$EE_{it} = \beta_0 + \beta_1 du_{it} + \beta_2 (du_{it} \times dt_{it}) + \beta_3 \sum Contral_{it} + Ind + year + \varepsilon_{it} \tag{2}$$

Where du is treated as a dummy variable of the individual. If du=1, it means that some enterprises have undergone a digital transformation during the sample period, while du=0 means that no enterprises have participated. In addition, a period dummy variable dt is also introduced, which is set to 1. When the enterprise completes digital transformation in the current year and subsequent years, it will be assigned to 1, otherwise, it will be 0.

Table 6 shows the results of the empirical test based on the difference-in-differences method. Through analysis of the stepwise regression method, it is found that the regression coefficients of du×dt are all positive and significant at the level of 1%. This indicates that after the implementation of digital transformation, enterprises can significantly improve the efficiency of total factor energy utilization. Although difference-in-differences have been performed to correct the endogenous problem, the results are still significant, which further verifies the stability of the original model.

5.5. Robustness Test

1. Replace Core Explanatory Variables

Table 7. Replace Core Explanatory Variables

	(1)	(2)	(3)
VARIABLES	EE	EE	EE
Dig	0.044***	0.044***	0.040***
	(84.80)	(87.42)	(77.90)
Lev		-0.007***	-0.009***
		(-9.45)	(-10.86)
Size		0.018***	0.023***
		(45.03)	(54.40)
Cashflow		0.012**	0.033***
		(2.20)	(5.98)
Growth		-0.000	-0.000
		(-0.66)	(-0.61)
TobinQ			0.001***
			(8.70)
FIXED			-0.035***
			(-10.12)
Board			-0.112***
			(-34.83)
Indep			-0.001***
			(-5.27)
Constant	0.948***	0.543***	0.699***
	(1,281.61)	(59.97)	(59.20)
Industry Fixed	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes
Observations	38,919	38,919	38,919
R-squared	0.156	0.200	0.234
r2 _ a	0.156	0.199	0.234
F	7192	1940	1320

To ensure the reliability and stability of the basic regression results, we have adopted a variety of scientific methods to verify and evaluate the model again.

In the basic regression, we referred to the method of Wu Fei et al. (2023) and used the enterprise digital transformation as an explanatory variable, to calculate the enterprise digital transformation [9].

To test whether the results are affected by different calculation methods, referring to the practice of Yuan Chun et al. (2021) in the robustness test, we built a relatively complete digital dictionary with the help of national policy semantic expressions related to the digital economy and used machine-based learning for text analysis to construct an indicator that comprehensively reflects the digitalization of Chinese listed companies. Besides, the micro-enterprise digitalization index is constructed based on the text analysis of machine learning [13]. After rigorous regression analysis, we obtained detailed data results shown in Table 7. In the process of replacing the core explanatory variables and adding control variables, we found that the coefficient of enterprise digital transformation remained positive all the time, which indicated a significant impact at a significance level of 1%. This research result provides strong support and further confirms the key role of enterprises in their sustainable development during the digital transformation.

2. Data Tailing Processing

Table 8. Data Tailing Test

	(1)	(2)	(3)
VARIABLES	EE	EE	EE
DCG	0.037***	0.034***	0.031***
	(91.51)	(84.83)	(74.79)
Lev		-0.083***	-0.077***
		(-28.96)	(-27.42)
Size		0.020***	0.025***
		(44.12)	(51.64)
Cashflow		-0.019**	0.001
		(-2.45)	(0.15)
Growth		-0.015***	-0.017***
		(-13.14)	(-14.94)
TobinQ			0.002***
			(5.91)
FIXED			-0.025***
			(-7.16)
Board			-0.121***
			(-37.50)
Indep			-0.001***
			(-8.41)
Constant	0.943***	0.545***	0.717***
	(1,264.14)	(57.62)	(55.99)
Industry Fixed	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes
Observations	39,882	39,882	39,882
R-squared	0.174	0.218	0.252
r2 _ a	0.174	0.218	0.251
F	8374	2224	1489

We standardized the data to eliminate the impact of extreme values on the accuracy of regression analysis and ensured that the research results were scientific and credible. On this basis, this paper uses panel data of China's industrial sectors to empirically examine the impact of different levels of digitalization on the total factor productivity of enterprises, and then further explores its mechanism. As shown in Table 8, after the robustness test, the degree of enterprise digitalization still has a positive effect on the total factor energy efficiency of enterprises, which is consistent with the previous research results.

3. One-Phase-Lagged Core Explanatory Variables

Table 9. Test of Lagged Core Explanatory Variables

	(1)	(2)	(3)
VARIABLES	EE	EE	EE
L.DCG;	0.035***	0.034***	0.031***
	(85.40)	(83.74)	(74.42)
Lev		-0.002***	-0.002***
		(-3.76)	(-4.59)
Size		0.012***	0.016***
		(28.57)	(37.75)
Cashflow		0.015**	0.031***
		(2.35)	(4.83)
Growth		-0.000	-0.000
		(-0.78)	(-0.73)
TobinQ			0.001***
			(4.75)
FIXED			-0.023***
			(-6.62)
Board			-0.108***
			(-33.04)
Indep			-0.001***
			(-7.39)
Constant	0.957***	0.700***	0.862***
	(1,296.80)	(77.62)	(72.94)
Industry Fixed	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes
Observations	35,109	35,109	35,109
R-squared	0.172	0.192	0.222
r2 _ a	0.172	0.192	0.222
F	7294	1664	1113

On the one hand, the core explanatory variables of the last phase can neutralize the causal relationship between the digital transformation of some enterprises and the efficiency of total factor energy utilization. The performance of energy investment and other aspects is largely the result of the impact of the previous enterprise digitalization. On the other hand, based on the previous phases, this paper further studies the total factor productivity of different types of enterprises and their correlation, which draws corresponding conclusions and suggestions. After regression analysis of the core explanatory variables in the final period, the details are shown in Table 9. After analysis, it can be seen that the level of enterprise digital development in the previous year played a positive role in promoting the efficiency of total factor energy utilization in the following year, and this role is still significant.

5.6. Heterogeneity Analysis

1. Heterogeneity Analysis of the Enterprise Equity Nature

State-owned enterprises and non-state-owned enterprises will face certain differences in resource factor endowments. Compared with non-state-owned enterprises, state-owned enterprises, especially when responding to national digitalization policies, will implement earlier with more complete digital transformation than non-state-owned enterprises. After classifying the sample enterprises according to the equity nature and applying group regression analysis, the results are shown in Table 10. According to the data in the table, we can observe the role played by state-owned enterprises during the digital transformation. Compared with other types of enterprises, their performance in improving the efficiency of enterprise total factor energy utilization is more significant.

Table 10. Heterogeneity Analysis of Equity Nature

	State-owned Enterprises	Non-state-owned Enterprises
VARIABLES	EE	EE
DCG	0.041***	0.025***
	(53.34)	(51.15)
Lev	-0.055***	-0.001***
	(-14.78)	(-2.60)
Size	0.026***	0.022***
	(37.94)	(37.05)
Cashflow	-0.044***	0.030***
	(-4.16)	(4.83)
Growth	0.000	-0.000**
	(0.04)	(-2.45)
TobinQ	0.003***	0.001***
	(5.34)	(4.40)
FIXED	-0.013***	-0.001
	(-2.75)	(-0.15)
Board	-0.096***	-0.092***
	(-19.62)	(-21.59)
Indep	-0.001***	-0.000**
	(-4.07)	(-2.53)
Constant	0.590***	0.686***
	(32.36)	(39.42)
Industry Fixed	Yes	Yes
Year Fixed	Yes	Yes
Observations	15,478	23,780
R-squared	0.287	0.193
r2 _ a	0.287	0.192
F	692.4	630.1

2. Regional Heterogeneity

To further test the impact of enterprise digitalization in different regions on the enterprise efficiency of total factor energy utilization, and whether it is affected by the inconsistent development of local economic and other factors, the sample enterprises are divided into three groups according to the region, with results shown in Table 11. It can be seen that the coefficient in the eastern region is 0.030, 0.038 in the central region, and 0.034 in the western region, all of which are significant at the level of 1%. It proves that in the central region, enterprise digitalization has the greatest impact on improving energy efficiency, followed by the western region and then the eastern region. The possible reason is that in the central and western regions with relatively backward economic development, enterprise digitalization is relatively low, so they have more room for digitalization improvement. Such an improvement has a greater impact on promoting enterprise energy efficiency. In the economically developed eastern regions, due to the relatively high enterprise digitalization, its effect on improving energy efficiency is relatively small. With comprehensive consideration, enterprise digitalization has a significant effect on its total factor energy utilization efficiency, and this effect shows differences in various regions, which may be intertwined with the economic development of the region and the enterprise digitalization development.

Table 11. Regional Heterogeneity Analysis

	East	Middle	West
VARIABLES	EE	EE	EE
DCG	0.030***	0.038***	0.034***
	(63.87)	(36.39)	(23.77)
Lev	-0.007***	-0.001	-0.091***
	(-8.36)	(-0.96)	(-13.85)
Size	0.017***	0.026***	0.032***
	(33.54)	(24.89)	(22.34)
Cashflow	0.031***	0.012	-0.063***
	(4.79)	(0.92)	(-3.05)
Growth	-0.000**	-0.000***	-0.000
	(-2.38)	(-2.73)	(-0.14)
TobinQ	0.001***	0.003***	0.008***
	(4.98)	(6.98)	(9.01)
FIXED	-0.015***	-0.064***	-0.011
	(-3.55)	(-8.65)	(-1.11)
Board	-0.116***	-0.111***	-0.133***
	(-29.50)	(-16.18)	(-13.39)
Indep	-0.001***	-0.000	-0.002***
	(-5.41)	(-1.13)	(-4.86)
Constant	0.854***	0.611***	0.618***
	(61.05)	(22.26)	(16.71)
Industry Fixed	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes
Observations	27,579	7,384	4,323
R-squared	0.215	0.279	0.278
r2 _ a	0.215	0.278	0.276
F	838.6	316.6	184.2

5.7. Mean Difference Test between Groups

For most variables, the average value of enterprises undergoing digital transformation is higher or lower than that of enterprises that have not undergone digital transformation. After careful and in-depth research and analysis, when evaluating the total factor energy efficiency (EE) of enterprises, it is observed that there are obvious differences in data between traditional non-digital transformation enterprises and enterprises undergoing digital transformation. This finding is of great importance in promoting the enterprise digital transformation and improving energy efficiency. Among enterprises that have not implemented digital transformation, their EE average is 0.92, while among enterprises that have completed digital transformation, this value increases to 1.03. Their difference is -0.11, which indicates that the performance of digitally transformed enterprises in terms of application environment has improved significantly. It is worth emphasizing that this difference is statistically significant, especially at 1% confidence. Therefore, through the research of this paper, it provides a reference for other enterprises in the industry to improve energy efficiency. Through comparative research, we found obvious differences in energy efficiency among enterprises in the same industry, especially the difference in efficiency is as high as 28 percentage points. However, by actively implementing digital transformation strategies, enterprises have the potential to narrow this efficiency gap, thereby promoting the overall improvement of energy utilization efficiency. Digital transformation can not only help enterprises optimize resource allocation and improve management efficiency, but also reduce energy consumption and improve energy utilization efficiency, providing strong support for enterprises to achieve green and sustainable development.

Table 12. Mean Difference Test Between Groups

Variable Name	Without Digital Transformation	Mean1	With Digital Transformation	Mean2	MeanDiff
EE	16223	0.92	23659	1.03	-0.11***
DCG	16223	0.00	23659	2.13	-2.13***
Lev	16223	0.51	23659	0.44	0.07***
Size	16223	21.96	23659	22.33	-0.37***
Cashflow	16223	0.05	23659	0.05	-0.00
Growth	16223	9.95	23659	0.42	9.53
TobinQ	16223	2.27	23659	2.16	0.11***
FIXED	16223	0.26	23659	0.19	0.07***
Board	16223	2.15	23659	2.11	0.04***
Indep	16223	36.98	23659	37.88	-0.90***

6. Conclusion and Policy Recommendations

6.1. Research Conclusion

The degree of enterprise digitalization has a significant positive effect on the efficiency of their total factor energy utilization, and enterprise informatization has also a significant role in promoting their energy efficiency. According to the analysis of historical data, the informatization process of enterprises has produced a significant promotion effect on improving the TFP of enterprises. Especially in state-owned enterprises, thanks to the efficient integration of technology and resources, digital transformation can significantly enhance the overall energy efficiency of enterprises. In addition, this study found that the degree of enterprise digitalization in the previous year still significantly improved the TFP in the following year. It indicates that digital transformation can not only produce immediate results, but also arouse long-term sustainable effects, providing a sustainable impetus for enterprises to save energy and increase efficiency.

Overall speaking, enterprise digitalization has a vital and positive effect on its total factor energy efficiency. The research results can have important theoretical value and practical significance for Chinese enterprises to formulate and implement digital transformation strategies, make related industrial development strategies, design related industrial policies and support measures. Through the continuous improvement of digital technology, enterprises can better improve the efficiency of energy utilization, thereby promoting the sustainable development of enterprises. On this basis, a new energy-saving model is proposed. In other words, based on digital technology, the goal of improving enterprise energy efficiency is established. Subsequent research can further explore the impact of digital transformation from other aspects and the differences in enterprise performance under different digitalization.

6.2. Policy Recommendations

First of all, it is necessary to strengthen support and guidance for the transformation of the digital economy, especially for state-owned enterprises. Through the introduction of corresponding policies and regulations, preferential treatment will be given in finance, taxation, technology, etc., and state-owned enterprises will be encouraged to actively participate in digital transformation and improve their efficiency. At the same time, the government should strengthen cooperation with enterprises to promote the application and innovation of digital technology in the power industry. Secondly, to promote the enterprise digital transformation in various industries, the government should implement appropriate strategies and measures. For those industries with low energy efficiency, the government needs to provide comprehensive and in-depth training and guidance to help them understand the importance and benefits of digital transformation. Meanwhile, enterprises should be encouraged to carry out digital transformation activities in various ways to improve their competitiveness. Moreover, to achieve digital transformation faster, we need to obtain the necessary financial and technical assistance. What’s more, promoting inter-industry cooperation and exchanges as well as enhancing cross-border applications and innovation is a crucial step. Finally, the country needs to increase its efforts in digital technology research, development and innovation. In the meantime, the government should issue relevant policies to support the construction and development of industrial technology innovation alliances. By increasing capital investment in enterprises, we can encourage enterprises to conduct research and development in multiple fields, and further promote the continuous innovation and progress of digital technology, thus providing more advanced and reliable technical support for improving the overall energy efficiency of enterprises.

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