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RESEARCH ARTICLE

Digital economy and industrial energy efficiency performance: evidence from the city of the Yangtze River Delta in China

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Abstract

Industry dominates energy consumption and carbon emissions in China, and industrial energy efficiency is critical for the achievement of energy transformation and carbon emission reduction. With the rapid development of the digital economy, its impact on energy efficiency is gradually emerging, and it is necessary to clarify the influencing mechanism on industrial energy efficiency. Based on the panel data of industrial sectors in 41 cities in the Yangtze River Delta from 2011 to 2019, the main objectives of this study are to more accurately measure the industrial total factor energy efficiency in each city by using the Super-Dynamic-SBM model. It analyses the influence mechanism of the digital economy and other influencing factors on industrial total factor energy efficiency with different methods. The research results indicate that, first, the total factor energy efficiency of the industrial sector in the Yangtze River Delta urban agglomeration generally showed a steady upward trend. Second, the digital economy and environmental regulation play a significant role in promoting total factor energy efficiency. In addition, industrial energy efficiency and the digital economy show an inverted "U" shaped relationship. With the improvement of the digital economy, its marginal contribution to total factor energy efficiency gradually weakens. Finally, technological progress is an important transmission channel for the impact of the digital economy on total factor energy efficiency.

Keywords Digital economy · Industrial total factor energy efficiency · Super-Dynamic-SBM Model · Tobit model · Threshold model

Introduction

Background information

China's carbon dioxide emissions reached 10.24 billion tons (including Taiwan and Hong Kong, China), accounting for 31.7% of global carbon dioxide in 2020 emissions (BP 2021). Industry is the backbone in China, accounting for 39% of the national domestic output, consuming 70% of the energy, and contributing 80% of the carbon dioxide emissions (Fu et al. 2021). To cope with global climate change, China has taken the initiative to assume the responsibility of a major country and formulate a strong emission reduction plan. In 2020, China clearly put forwards the ambitious goal of "carbon peak in 2030 and carbon neutrality in 2060" at the UN Climate Conference. The IEA report points out that low-carbon technologies are of great significance for the achievements of "double carbon" commitment in China's industrial sector (IEA 2021). The World Resources Institute also predicts that improving energy efficiency could contribute to 21.2% of the total emissions reductions in the industrial sector (Xi et al. 2022). At the same time, since China's accession to the WTO, China's foreign trade has grown rapidly. Currently, China is the world's largest trading country. However, there is a large amount of embodied carbon emissions in the foreign export trade. The embodied carbon of the secondary industry accounts for more than 90% of the total embodied carbon in export trade (Yang et al. 2022b). The optimization of export structure and enhancement of the share of the tertiary sector in exports is critical to reducing trade embodied carbon(Yang et al. 2022a). Therefore, there is no doubt that the improvement

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of energy efficiency of the industrial sector and optimization of industrial structure directly affects the overall energy transition and the achievement of national emission targets. Therefore, it is necessary to study industrial energy efficiency and its influential factors. In recent years, the development of China has decelerated and shifted gears, traditional industries have slowed down, and new economies, such as the digital economy, have flourished. According to a report about the development of China's digital economy, the proportion of China's digital economy in GDP increased from 10.0% to 38.6% during 2002–2020. At the same time, a large number of studies have pointed out that the development of the digital economy plays a critical role in the improvement of production efficiency (Chen and Zhang 2022; Li 2021), industrial chain optimization (Chen and Yang 2021; Yang et al. 2022d) and industrial upgrading (Zhang and Ma 2022) in China. Meanwhile, it is an important driving force for economic development (Chen et al. 2022). However, these studies mainly focus on the correlation between the digital economy and the overall regional economy or production efficiency, and few studies have explored its impact on industrial energy efficiency. The development of the digital economy impacts conventional production and consumption patterns. New developments in the digital era, such as the industrial Internet, intelligent manufacturing, and industrial digitization, will dramatically affect the performance of industrial energy efficiency. With the continuous expansion of the application field and depth of digital technology, its impact on industrial energy efficiency will inevitably strengthen. Therefore, exploring the effect of the digital economy on industrial energy efficiency and clarifying the corresponding mechanism are of great significance for promoting the high-quality development and upgrading of traditional industries.

Importance of the Yangtze River Delta urban agglomeration

Accordingly, to fill these gaps, this study will examine the industrial total factor energy efficiency in Yangtze River Delta cities and analyse how the digital economy influences energy efficiency. According to relevant data, in 2020, the industrial added value of the Yangtze River Delta urban agglomeration reached 8,160 billion yuan, with a population of 235 million, accounting for 26.1% and 16.7% of the national total, respectively. This region has become one of the three most important urban agglomerations in China. Moreover, the region is also one of the urban agglomerations with the most complete digital economy infrastructure and the richest application scenarios in China. On the other hand, this urban agglomeration plays an important role in national energy consumption and carbon emissions (Xiao et al. 2019). According to energy statistics, in 2019, the industrial energy consumption in the region reached 520.86 million tons of standard coal equivalent (tce), accounting for 16.2% of the national industrial energy consumption. Therefore, it is important to take the Yangtze River Delta cities as a sample to evaluate industrial total factor energy efficiency and explore the relevant influencing factors. This study not only provides a helpful basis for the evaluation of China's energy transition but is also conducive to formulating policies related to China's high-quality economic development and carbon emission reduction.

Objectives of the study

To study the impact of the digital economy on total factor energy efficiency, we collect the industrial data of the 41 cities in the Yangtze River Delta region from 2011 to 2019. Then, we conducted a series of analyses by applying the Tobit model, threshold model, and DID model. The main objectives of the study are as follows.

The main objectives of this study are (i) to more accurately measure the industrial total factor energy efficiency of each city based on Super-Dynamic-SBM model in the Yangtze River Delta urban agglomeration, (ii) to identify the impact of the digital economy on industrial total factor energy efficiency at the city level, (iii) to study the nonlinear relationship of the impact of the digital economy on industrial total factor energy efficiency, (iv) to study the influencing mechanism of the digital economy on industrial total factor energy efficiency, and (v) to provide a new perspective for policy makers. The rest of this paper is arranged as follows. "Literature review" presents the literature review. "Construction of the theoretical model" introduces the empirical model and data. "Analysis of empirical results" shows the results and discussion. "Conclusions and Policy Implications" provides the conclusion and policy implications.

Literature review

The origin of total factor energy efficiency

Due to the resource depletion and ecological environment damage caused by the use of fossil energy, studies focusing on energy efficiency have become one of the hotspots in various countries. Among them, the evaluation methods and corresponding indicators are core issues. According to the existing research, the input and output indicators of energy efficiency have transformed from “single input and output” to “multi-input and single output” and “multi-input and multi -(non)expected output.” Regarding the input indicators, the measurement method of energy efficiency was mainly based on the energy intensity indicator at the early stage (a single input and output analysis). However, this method does not take into account the contribution of other factors, such as capital and labor, and the substitution effect among these factors. To fill this gap, the concept of total factor energy efficiency (TFEE) has been introduced to the estimation framework (Hu and Wang 2006). With respect to output indicators, to comprehensively analyse energy efficiency, many studies take not only the desirable outputs into consideration but also the undesirable outputs such as industrial wastewater, soot, and sulfur dioxide emissions (Chen 2019; Xu et al. 2020).

The measurement model for total factor energy efficiency

In addition, the nonparametric data envelopment analysis model (DEA) (Charnes et al. 1978) and parametric stochastic frontier analysis model (SFA) (Aigner et al. 1977) have been widely applied to the assessment of TFEE. The traditional DEA model mainly includes the CCR model and the BCC model (Khairunnisa et al. 2015). The CCR model assumes constant returns to scale, and the BCC model assumes variable returns to scale. The traditional DEA model is a radial model, and there are many derived models on this basis. The main ones are the nonradial slack-based model (SBM) (Zhang et al. 2022a) and the EBM model (Tone and Tsutsui 2010b), which combine radial and nonradial characteristics. Some studies have used the SBM model to estimate the energy efficiency of China’s manufacturing industry. These studies concluded that the regional differences in the energy efficiency of the manufacturing industry vary greatly and that the level is generally low (Li et al. 2019; Wang et al. 2013). However, none of these models considered the role of cross period variables in consecutive periods. The indicators calculated based on this model are only relative values, and there is a problem of incompatibility between periods. Therefore, Fare and Grosskopf first proposed the dynamic DEA model, which set up the cross period variables (Färe and Grosskopf 1997). The model assumes that the input and output factors change in the same proportion. Therefore, Tone and Tsutsui combined the dynamic DEA model with the SBM model to expand into a dynamic SBM model that does not require the same proportional changes in the input and output elements (Tone and Tsutsui 2010a). Compared with the traditional data envelopment method, the advantage of the DSBM model is that the calculated efficiency index is a dynamic index and has cross-period comparability.

The influencing factors on total factor energy efficiency

In addition, the study of the influencing factors of total factor energy efficiency mainly focuses on environmental regulation, technological progress, enterprise scale, FDI, and energy structure. In terms of environmental regulation, some studies conclude that this factor contributes to the improvement of energy efficiency, which verifies the Porter hypothesis (Yang et al. 2021a). Unlike this conclusion, some scholars indicate that when the degree of environmental regulation is relatively low, there is no conducive to the reduction of energy intensity in the manufacturing industry. Meanwhile, when environmental regulation breaks through the critical point, it can significantly promote the reduction of energy intensity (Hou et al. 2020). In addition, the enhancement of public supervision and whistleblowing could stimulate Chinese energy companies to comply with emission regulations (Yang et al. 2022c).

At present, many studies have pointed out that the digital economy can effectively improve production efficiency. However, compared with production efficiency, the study of total factor energy efficiency is more valuable in the construction of an ecological civilization and the realization of carbon emission reduction. Few related studies have mainly concentrated on the dimensions of optimizing the allocation of resources and improving production efficiency and carbon emissions. In terms of the impact of the digital economy on the allocation of resources, from a theoretical perspective, many scholars have found that the digital economy can alleviate the distortion of factor resource allocation caused by information asymmetry, reshape the allocation mechanism, and improve productivity (Goldfarb and Tucker 2019; Hong 2018; Wu and Ren 2022). With respect to the empirical level, some studies have empirically found that the digital economy can dramatically optimize the allocation of factor resources and promote the improvement of productivity at both the enterprise and city levels (Li and Wang 2021). In addition, many studies have pointed out that the digital economy plays a significant role in promoting total factor productivity (Altinoz et al. 2021). However, the concentration of these works varies greatly. Specifically, some studies point out that the digital economy can improve the efficiency of total factor production by upgrading the industrial structure (Zhang and Ma 2022), some indicate that it strengthens the intensity of Rand D investment (Yan and Wu 2021), and others conclude that it promotes investment in human capital (Yang and Jiang 2021). Regarding the impact on carbon emissions, several studies have shown that the development of information and communication technologies (ICTs) has a positive impact on carbon emissions in the long term (Batool et al. 2019; Raheem et al. 2020). The development of ICTs can promote green development by increasing economic productivity and reducing energy intensity (Moyer and Hughes 2012). Moreover, the improvement of ICT infrastructure will also lead to an increase in FDI, which will enhance the development of a sustainable economy (Bhujabal et al. 2021). In contrast, some studies found that the development of ICTs is far from reducing carbon emissions and even has a negative impact on environmental sustainability (Alatas 2021). For example, the development of ICTs has worsened the environmental quality in Southeast Asian countries (Arshad et al. 2020) and has also led to environmental degradation in the Middle East and North Africa (Charfeddine and Kahia 2021). The excessive increase in power consumption related to the rapid development of the communication technology industry may result in a corresponding increase in carbon emissions(Salahuddin and Alam 2015). Meanwhile, some studies also note that the widespread use of the Internet can significantly reduce carbon emissions in the long run (Shobande 2021). Regarding the impact mechanisms, some studies indicate that the digital economy can have a significant negative impact on pollutant emissions by improving innovation efficiency (Miao et al. 2022) and optimizing industrial structure (Deng and Zhang 2022).

The influencing mechanism on total factor energy efficiency

Many studies have confirmed that the development of the digital economy will contribute to technological progress (Zhang et al. 2022a, b), and progress will inevitably affect the total factor energy efficiency.

First, the digital economy has brought a new factor of production—the data elements. This factor is easy to replicate and has nearly zero marginal cost. Meanwhile, it will not be constrained by scarcity and exclusivity. In addition, the penetration of digital technology can endow traditional elements such as labor, capital, and entrepreneurial talent with digitization, intelligence, and networking (Liu and Ru 2022). This will help to improve the productivity of traditional factors.

Second, the digital economy is beneficial for extending the boundary of innovation possibilities. The fundamentals of this kind of economy are rooted in knowledge-intensive industries, such as fifth-generation networks (5G), big data, cloud computing, and artificial intelligence. The integrated development of these industries will contribute to disruptive technological innovation and business model innovation. Furthermore, traditional industries will be forced to take innovative actions to adapt to the changes in the digital era. It has been confirmed that technological progress is an important transmission channel for the digital economy to reduce carbon emissions (Zhong et al. 2022) and to improve green economic efficiency (Li et al. 2021).

Although many studies have identified the influencing mechanism of the digital economy on carbon emission reduction, the transmission channel for the improvement of industrial total factor energy efficiency has not been well examined at the city level. This will be one of the focuses of this study.

Contributions of this study

The contributions of this study may include the following aspects. First, existing studies on industrial total factor energy efficiency are mainly focused on the national and provincial levels. In this study, we conduct the analysis at the city level. It is more meaningful to study the changing trend of total factor energy efficiency and its impact mechanism at the city level. Second, not only the desired output but also the undesirable output was considered when applying the Super-Dynamic-SBM model. The efficiency value calculated based on the model is more accurate. Third, the traditional production efficiency evaluation does not take into account the ecological and environmental problems caused by pollution emissions, so it is impossible to comprehensively and reasonably evaluate the quality of economic development. Correspondingly, it is difficult to put forward scientific guidance and suggestions for industrial development. The total factor energy efficiency fully takes the impact of environmental pollution caused by economic development into consideration, which is consistent with the concept of low-carbon development (Hailu and Veeman 2000; Li et al. 2015). Finally, we attempt to explore the transmission channel of the impact of the digital economy on total factor energy efficiency.

Construction of the theoretical model

Super-Dynamic-SBM model with undesirable output

The traditional DEA model is a radial, angular model. The radial measurement method does not take into account the problem of redundant improvement, and the choice of angle makes the efficiency value vary from different input–output angles. In addition, the indicators calculated based on this model are only relative values, and there is a problem of incompatibility between periods. To eliminate these problems, this study adopts the Super-Dynamic-SBM model to estimate industrial energy efficiency.

Suppose there are n decision-making units (DMUs), and each DMU has m inputs and T terms ($t=1, 2, \ldots, T$). Specifically, the formula for the Dynamic-SBM model with VRS and nonangle is as follows:

$$\rho_o^* = min \frac{\frac{1}{T}\sum_{t=1}^{T} w^t \, [1 - \frac{1}{m}(\sum_{i=1}^{m} \frac{w_i^- s_{it}^-}{x_{iot}})]}{\frac{1}{T}\sum_{t=1}^{T} w^t \left[1 + \frac{1}{s + ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{it}^+}{y_{iot}} + \sum_{i=1}^{ngood} \frac{s_{it}^{good}}{z_{it}^{good}}\right)\right]} \tag{1}$$

$$\sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^t = \sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^{t+1} \; (\forall i; t = 1, \ldots, T-1)$$

$$x_{iot} = \sum_{j=1}^{n} x_{ijt} \lambda_j^t + s_{it}^- (i = 1, \ldots m; t = 1, \ldots T)$$

$$y_{iot} = \sum_{j=1}^{n} y_{ijt} \lambda_j^t - s_{it}^+ (i = 1, \ldots s; t = 1, \ldots T)$$

$$z_{iot}^{good} = \sum_{j=1}^{n} z_{ijt}^{good} \lambda_j^t - s_{it}^{good} (i = 1, \ldots, ngood; t = 1, \ldots T)$$

$$\sum_{j=1}^{n} \lambda_j^t = 1 (t = 1, \ldots, T)$$

$$\lambda_j^t \geq 0, s_{it}^- \geq 0, s_{it}^+ \geq 0, s_{it}^{good} \geq 0$$

The most efficient solution is as follows:

$$\rho_{ot} = min \frac{1 - \frac{1}{m}\left(\sum_{i=1}^{m} \frac{w_i^- s_{it}^-}{x_{iot}}\right)}{1 + \frac{1}{s + ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{it}^+}{y_{iot}} + \sum_{i=1}^{ngood} \frac{s_{it}^{good}}{z_{it}^{good}}\right)} (t = 1, \ldots, T)$$

where s_{it}^-, s_{it}^+, s_{it}^{good} are input excess, output shortfall, and link shortfall.

Tobit model

To further study the influential factors on the total factor energy efficiency of the industrial sector in the Yangtze River Delta urban agglomeration, we take the estimated energy efficiency as the dependent variable and factors such as the digital economy as the independent variable. The factors are analysed by using a Tobit model. The model was proposed by the Nobel Laureate (Tobin 1958) and is characterized by the fact that it can be used for regression analysis with limited dependent variables. Since the efficiency value calculated by the DEA model is not less than 0, it is a restricted dependent variable. Therefore, referring to Wang and Su (2020), Yuan et al. (2009), this study adopts the Tobit model. The model is as follows:

$$\begin{aligned} TFEE_{it} &= \alpha_0 + \alpha_1 DIGE_{it} + \alpha_2 DIGE^2{}_{it} \\ &+ \sum_{i \geq 1} \beta_i Controls_{it} + u_t + \lambda_i + \varepsilon_{it} \end{aligned} \tag{2}$$

where $TFEE$ is the total factor energy efficiency, $DIGE$ is the core explanatory variable, $Controls$ is the control variable,ε_{it} is the random error term, α_0 is the constant term, α_i is the coefficient vector of the digital economy, and β_i is the coefficient vector of the control variable. u_t is the time fixed effect, and λ_i is the individual fixed effect.

Threshold model

Considering the differences in the economic development level and technology level of the Yangtze River Delta urban agglomeration, there may be a nonlinear relationship between the total factor energy efficiency and its influential factors. That is, there is a threshold effect. Total factor energy efficiency will show different characteristics when the core explanatory variables cross a certain threshold value. Therefore, this paper refers to the threshold model proposed by Hansen (1999) to conduct an in-depth study on the relationship between total factor energy efficiency and the level of digital economy development. The threshold regression model is as follows:

$$\begin{aligned} TFEE_{it} &= \sigma_0 + \lambda_1 DIGE_{it} I\left(DIGE \leq \gamma_1\right) \\ &+ \lambda_2 DIGE_{it} I(DIGE > \gamma_1) \\ &+ \sum_{i \geq 1} \delta_i Controls_{it} + u_t + \lambda_i + \varepsilon_{it} \end{aligned} \tag{3}$$

where $TFEE$ is the total factor energy efficiency, $DIGE$ stands for the core explanatory variable, and $DIGE$ represents the threshold variable. λ_1 denotes the influential factor of $DIGE \leq \gamma_1$ on total factor energy efficiency, and λ_2 indicates the influential factor of $DIGE > \gamma_1$ on total factor energy efficiency. I represents a characteristic function. After obtaining the estimated values of each parameter, three tests need to be performed: (1) threshold effect test, (2) threshold significance test, and (3) coefficient significance test.

At the same time, the constructed threshold model belongs to the first-order equation using the core explanatory variable $DIGE$. If the threshold effect exists, the core explanatory variable $DIGE$ shows different influential relationships after a certain threshold value. It will also confirm the "U" or inverted "U"-type characteristics that may exist in the Tobit model analysis.

Accordingly, we propose the following verifiable hypothesis:

H1: There is a nonlinear relationship between the digital economy and total factor energy efficiency. The development level of the digital economy is lower, and the effect on the improvement of total factor energy efficiency is larger. In addition, with the development of the digital economy, its marginal contribution to total factor energy efficiency gradually declines.

Examination of the influencing mechanism

To empirically examine the improvement effect of the digital economy on technological progress, we take technological progress as the dependent variable and factors such as the digital economy as the independent variable. The model is as follows:

$$TECH_{it} = \theta_0 + \theta_1 DIGE_{it} + \sum_{i\geq 1} \rho_i Controls_{it} + u_t + \lambda_i + \varepsilon_{it} \tag{4}$$

where $TECH$ is technological progress, $DIGE$ is the digital economy, $Controls$ are the other control variables, ε_{it} is the random error term, α_0 is the constant term, θ_i is the coefficient vector of the digital economy, and ρ_i is the coefficient vector of the control variable. u_t is the time fixed effect, and λ_i is the individual fixed effect.

Accordingly, we propose the following verifiable hypothesis:

H2: The development of the digital economy will promote technological progress. Technological progress may be an important transmission channel for the impact of the digital economy on total factor energy efficiency.

Variable selection and data sources

Selection of input–output indicators

We select three indicators for the input factor: energy, labor, and capital. The added value of industry is selected as the desirable output. A comprehensive pollution index is considered an undesirable output. The carry-over variable is a variable in which the variable of a current period will affect the production of the next period (Lu et al. 2021).

Referring to Bai et al. (2014) and Li and Bai (2016) and due to the data availability, this study chooses the scientific and educational investment of each city as the carry-over factors in the DSBM model. On the one hand, the investment in scientific research has a direct and long-term impact on the improvement of industrial total factor energy efficiency. On the other hand, the investment of education also has a direct and long-term impact on the cultivation of talent elements and technological progress. There is no doubt that the investment of scientific research and education is important for improving the industrial total factor energy efficiency. Moreover, the promotion effect of scientific research and educational investment on total factor energy efficiency is a long-term process, which is unlikely to make a great difference in the short-term. Accordingly, it is appropriate to take scientific research and educational investment as carry-over variables.

The explanations of other related input and output indicators are as follows: (1) Energy: We use the comprehensive energy consumption of the three major industrial categories of the extraction industry, power, and water supply industry and manufacturing industry as the energy indicator. These three major industrial categories include a total of 39 subindustries, and their physical consumption is converted into standard coal equivalent according to the conversion coefficient. (2) Labor: Industrial labor indicators are obtained from the total employment of the three major industrial sectors in each city. (3) Capital: We use the total industrial fixed assets of each city and take 2010 as the base year. Then, we use the fixed asset price index to deflate the corresponding data. (4) Industrial added value: We use the above-scale industrial added value of each city as the output index and take 2010 as the base year. Then, we use the industrial product price index to deflate the corresponding data. There is a comprehensive indicator of undesirable output. It is a pollution index that is calculated based on three pollutants, as follows: (1) the discharge quantity of industrial wastewater, (2) emissions of industrial sulfur dioxide, and (3) industrial soot (dust) emissions. These data are obtained from the China city statistical yearbooks see Table 1.

Influential factor selection for the Tobit model

The existing studies mainly focus on the allocation of resources and production efficiency. Few studies examine the impact of the digital economy on industry energy efficiency. This study intends to fill this gap by introducing the digital economy into the evaluation of industrial total factor energy efficiency. Compared with previous studies, we construct a more comprehensive indicator for the digital economy. This study intends to measure the development level of the digital economy from four levels: the level of digital infrastructure construction, the development level of the digital industry, the level of digital innovation, and digital inclusive finance. Specifically, the four dimensions include ten key metrics. At the level of digital infrastructure construction, we will measure it from the number of Internet users per 100 people, the number of mobile phone users per 100 people and the per capita telecom service level. We measure the development level of the digital industry from the number of e-commerce parks in the city and the per capita postal service

Table 1 Descriptive statistics of the Indexes

Year	Statistics	Capital	Labor	Energy	Industrial added value	Industrial wastewater	Industrial sulfur dioxide	Industrial fumes
2010	Mean	125,000.000	24.102	1200.911	109,000.000	14,161.371	5.951	1.648
	Max	828,000.000	146.821	5732.441	694,000.000	80,468.000	49.641	4.631
	Min	5555.221	1.321	18.000	10,031.000	1485.000	0.241	0.211
	S.D	161,000.000	29.303	1279.712	134,000.000	16,870.171	8.073	1.177
2015	Mean	180,000.000	32.9551	1375.083	157,000.000	11,478.191	4.549	3.678
	Max	839,000.000	212.531	5897.691	789,000.000	60,506.000	15.000	11.141
	Min	11,958.711	1.821	22.081	16,488.000	737.000	0.301	0.311
	S.D	176,000.000	45.035	1333.948	164,000.000	12,216.981	3.124	2.703
2019	Mean	161,000.000	26.391	1365.442	201,000.000	8163.868	1.145	1.409
	Max	748,000.000	183.541	5668.051	967,000.000	36,586.000	5.041	5.721
	Min	10,614.621	1.861	26.661	19,107.000	528.000	0.141	0.081
	S.D	165,000.000	36.036	1314.755	208,000.000	8798.227	0.881	1.234

Capital and industrial added value are expressed in units of million RMB Yuan. Energy and labor are in units of ten-thousand tce (tonnes of standard coal equivalent) and ten-thousand persons. The units of industrial wastewater, sulfur dioxide, and fumes are all of ten-thousand tons

Table 2 Evaluation indicators for measuring the level of development of the *DIGE*

Indicator	Category criteria	Specific description of indicators
Digital economy	Level of digital infrastructure construction	The number of Internet users per 100 people
		The number of mobile phone users per 100 people
		The per capita telecom service level
	Development level of the digital industry	The number of e-commerce parks in city
		The per capita postal service level
	Level of digital innovation	Patents related to the digital economy
		The proportion of computer service and software employees
	Digital inclusive finance	Coverage breadth of digital inclusive finance
		Usage depth of digital inclusive finance
		Digitization level of digital inclusive finance

level. At the level of digital innovation, we will measure it from patents related to the digital economy and the proportion of computer service and software employees. In digital inclusive finance, we will measure it from the coverage breadth of digital inclusive finance, the usage depth of digital inclusive finance, and the digitization level of digital inclusive finance see Table 2.

Regarding the measurement method of the comprehensive development level of the digital economy (DIGE), this paper uses the entropy weight TOPSIS method and the coefficient of variation method for measurement. In addition, the coefficient of variation method will be used for robustness testing.

To protect the ecological environment and sustainable development, the government will adopt environmental regulations to intervene in the energy use of enterprises. Some studies believe that the impact of environmental regulations on total factor energy efficiency may have a “Porter hypothesis” effect (Zhang et al. 2014). On the one hand, environmental regulation will lead to an increase in the production costs of enterprises, which may lead to a decline in productivity. On the other hand, some studies have pointed out that environmental regulations will promote technological innovation in enterprises, which will help enterprises to have more advanced production technology and pollution treatment equipment. This offsets the increase in costs and promotes the improvement of energy efficiency (Geng and Cui 2020). Therefore, it is necessary to choose environmental regulation as a control variable. It is necessary to confirm the effects of environmental regulations on total factor energy efficiency. The construction of environmental regulatory indicators is as follows:

$$ER_{it} = \frac{1}{3}\sum\nolimits_{l=1}^{3} ER_{itl} = \frac{1}{3}\sum\nolimits_{l=1}^{3} \frac{E_{itl}}{\widehat{E_{itl}}} = \frac{1}{3}\sum\nolimits_{l=1}^{3} \frac{\left(e_{itl}/Y_{it}\right)}{\frac{1}{n}\sum\nolimits_{i=1}^{n}\left(e_{itl}/Y_{it}\right)}, 1 = 1,2,3 \quad (5)$$

where e_{itl} indicates the l pollutant emissions of the secondary industry of city i in period t. Y_{it} indicates the outputs of the secondary industry of city i in period t. ER_{it} is environmental regulation. A larger value of ER_{it} indicates stronger environmental regulations.

Many studies have shown that the upgrading of industrial structure is an important driver of China's energy intensity decline (Chen and Xu 2019; Fisher-Vanden et al. 2006). However, some studies have pointed out that technological innovation in the process of industrial structure upgrading can indeed promote the improvement of energy efficiency. At the same time, the crowding effect and free-riding effect produced in the process of industrial structure upgrading will reduce energy efficiency (Zhao and Lin 2019). Therefore, it is necessary to further determine the impact of industrial structure upgrading on total factor energy efficiency. This study also uses it as an important control variable. The specific construction method is as follows:

$$TS_{it} = \sum_{m=1}^{3} y_{itm} lp_{itm} = \sum_{m=1}^{3} \left(Y_{itm}/Y_{it}\right)\left(Y_{itm}/L_{itm}\right), \mathrm{m} = 1, 2, 3 \tag{6}$$

where y_{itm} indicates the weight of industry m in period t of city i. lp_{itm} denotes the labor productivity of industry m in period t of city i. A larger TS_{it} indicates a higher level of industrial structure in the region during period t.

With regard to the degree of openness, some studies have pointed out that FDI can bring advanced production technology and enhance the host country's independent innovation capability, which will promote the improvement of total factor energy efficiency (Wang 2017; Zhang and Fu 2022). However, some studies have noted that foreign direct investment (FDI) brings mainly low-end industries to China, which may exacerbate China's environmental pollution (Yang and Tian 2017). Therefore, the degree of openness is also an important control variable, and its impact on total factor energy efficiency also needs to be controlled. This paper uses the level of FDI per capita as an indicator of the degree of openness (OPEN). At the same time, to eliminate the effects of dimensions and heteroscedasticity, logarithmic treatment is performed.

Technological innovation means higher output, lower energy consumption, and pollutant emissions. Some studies show that technological advances are the main reason for the decline in energy intensity in China (Ma and Stern 2008). At the same time, technological innovation can be combined with intelligence, which is more conducive to reducing energy consumption (Graetz and Michaels 2018). Therefore, this paper considers technological progress (*TECH*) as an important mechanism variable. Technological progress will be measured by the number of patents per 10,000 people.

The market economy may fail, and enterprises will not consciously carry out pollutant emission reduction and technological innovation. Therefore, proper government regulation of enterprises may promote technology research and energy efficiency improvements (Li et al. 2022a). The degree of government intervention (GOVE) is also a control variable that can not be ignored. In this study, the proportion of government fiscal expenditure in gross domestic product (GDP) is used as an indicator of the degree of government intervention. These data are also collected from China city statistical yearbooks.

Analysis of empirical results

Total factor energy efficiency analysis

Based on the methodology presented above, we obtain the term efficiency and overall efficiency of industrial total factor energy efficiency in the Yangtze River Delta from 2011 to 2019. The overall efficiency during the period is the weighted average of the term efficiencies. The results of the overall efficiency are shown in Table 3. The spatial distributions of 41 cities' overall efficiency are shown in Fig. 1.

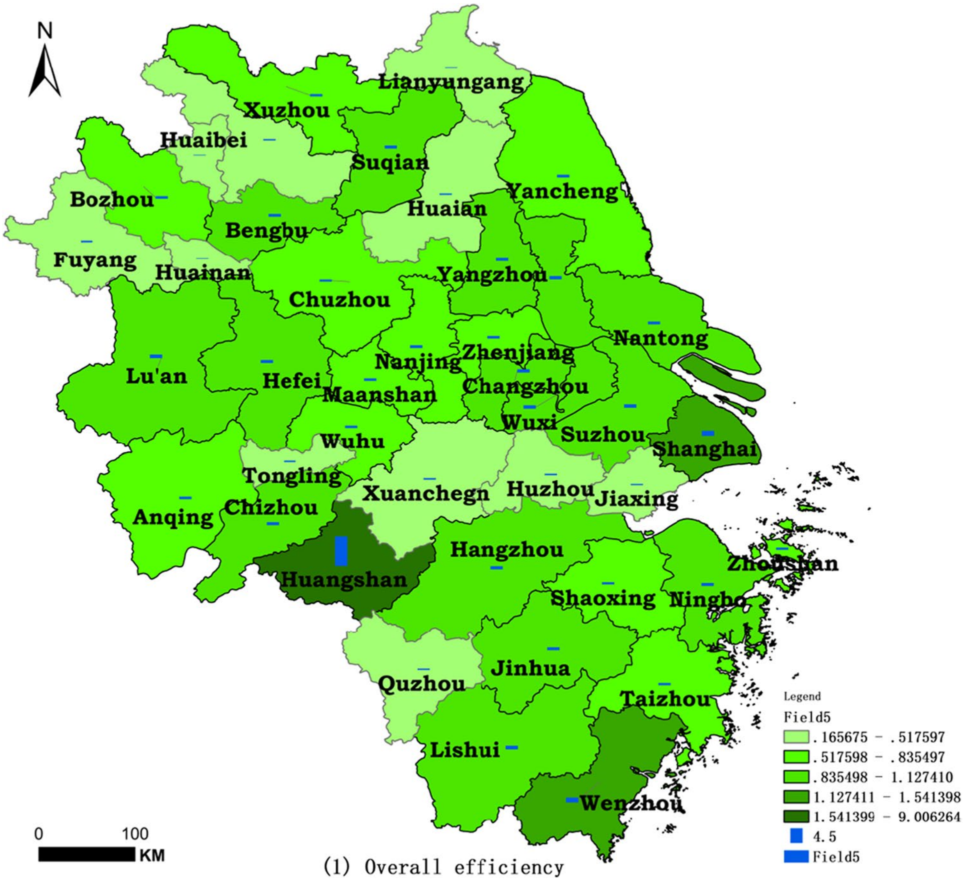
From the provincial perspective, the overall efficiency of the industrial total factor energy efficiency of the entire Yangtze River Delta urban agglomeration is 0.772 (excluding Huangshan). The overall total factor energy efficiency in Shanghai is 1.541. The corresponding indicators of Jiangsu, Zhejiang, and Anhui are 0.839, 0.786, and 0.652, respectively. From the city perspective, according to China City Level, Chinese cities are divided into first-tier cities, second-tier cities, and small cities. In the first-tier cities, the highest industrial total factor energy efficiency is Shanghai (1.541). Shanghai is also the city with the highest total factor energy efficiency in the Yangtze River Delta region (excluding Huangshan). The total factor energy efficiency of several other first-tier cities is Nanjing (0.825), Hangzhou (0.963), Hefei (0.919), Suzhou (1.049), and Ningbo (0.894). As we can see, the total factor energy efficiency of first-tier cities is above average. The specific reasons may lie in the following aspects.

Shanghai is the largest city in China. Shanghai is also the financial center of China. On the one hand, Shanghai's tertiary industry is more developed than the secondary industry. The energy consumption of the tertiary industry is lower. Shanghai has a large number of high-tech industrial parks, such as Zhangjiang Science and Technology Park. In addition, Shanghai has the most developed new energy industries in the region, such as the famous Tesla Gigafactory. It should also be noted that Shanghai has the richest educational resources in the region and the attractiveness of

Table 3 Overall efficiency of TFEE in the region

City-level	Regions	Overall efficiency	City-level	Regions	Overall efficiency
First-tier cities	Shanghai	1.541	Second-tier cities	Wuxi	1.063
	Nanjing	0.825		Changzhou	1.026
	Hangzhou	0.964		Nantong	0.871
	Hefei	0.919		Xuzhou	0.696
	Suzhou	1.049		Jiaxing	0.358
	Ningbo	0.894		Jinhua	0.925
				Shaoxing	0.636
				Wenzhou	1.489
Small cities	Taizhou	0.702	Small cities	Chuzhou	0.657
	Lianyungang	0.446		Chizhou	0.912
	Huaian	0.451		Fuyang	0.518
	Yancheng	0.835		Lu'an	1.127
	Yangzhou	0.898		Bengbu	0.866
	Zhenjiang	0.791		Huainan	0.166
	Taizhou	1.014		Tongling	0.462
	Suqian	0.955		Maanshan	0.783
	Huzhou	0.473		Huaibei	0.199
	Zhoushan	0.674		Wuhu	0.725
	Lishui	1.122		Anqing	0.775
	Quzhou	0.409		Bozhou	0.771
	Xuancheng	0.504		Huangshan	9.006
	Suzhou	0.399			

Fig.1 Spatial distribution of TFEE in the region



(1) Overall efficiency

foreign investment. These all contribute to the improvement of energy efficiency.

For Nanjing, Nanjing has a complete high-end industrial chain. It has formed an emerging industrial cluster represented by new energy vehicles, smart grids and the high-end equipment manufacturing industry. At the same time, similar to Shanghai, Nanjing also has rich educational resources in the Yangtze River Delta region. This is the foundation of economic development and technological innovation.

For Hangzhou, Hangzhou is a famous Internet city in China. Its own digital industry is developed, and the degree of industry digitalization is high. Hangzhou has Alibaba, China's largest e-commerce platform. Equivalent to the traditional industrial sector, the energy consumption of the digital industry itself is lower. In addition, Hangzhou's digital finance development level is also in a leading position. Hangzhou has Alipay, China's largest mobile payment platform, which will also contribute to the improvement of total factor energy efficiency in the industrial sector.

For Hefei, Hefei's industrial structure upgrade is also at the forefront of the country. Hefei is a famous photovoltaic capital and an important photovoltaic manufacturing base in China. In addition, Hefei's new energy automobile industry is also very developed. Hefei has China's largest new energy automobile companies, BYD and NIO. As we can see, Hefei has seized the opportunity for new energy to achieve industrial transformation and upgrading.

For Suzhou, Suzhou's openness level to foreign direct investment is very high. There are thousands of multinational companies in Suzhou's industrial park, such as the famous Siemens Group in Germany, Samsung in South Korea, and Fujitsu in Japan. There is no doubt that these large numbers of multinational enterprises have brought advanced technology and management experience to Suzhou. This will contribute to Suzhou's economic development and energy efficiency improvement. Similar to Suzhou's, Ningbo's openness level to foreign direct investment is relatively high. However, the difference is that Ningbo's private economy is very developed. Private enterprises have given Ningbo a stronger ability to innovate.

For second-tier cities, the overall efficiency of the total factor energy efficiency of second-tier cities is 0.863. The second-tier cities are all in Jiangsu Province and Zhejiang Province. We find that the overall total factor energy efficiency of second-tier cities is also above average. For these cities, first of all, their own industrial structure is higher than that of small cities. Second, these cities can receive nearby industrial transfers from first-tier cities and international industry shifts. These factors make second-tier cities have higher technology and energy efficiency than smaller cities.

For small cities, the overall efficiency of the total factor energy efficiency of small cities is 0.677 (excluding Huangshan). The small cities are mainly concentrated in Anhui Province. As we can see, the overall efficiency of small cities is below average. On the whole, on the one hand, the economic development level of Anhui Province is lower than that of Jiangsu Province, Zhejiang Province and Shanghai. On the other hand, the industrial structure of these cities is also lower. From the perspective of specific cities, Huainan (0.166) and Huaibei (0.199) are important energy bases in the Yangtze River Delta region. They are the largest coal-supplying cities in the region. Tongling (0.462) is an important raw material copper supply base in the Yangtze River Delta region. These can be a phenomenon called the "resource curse." However, it should be pointed out that the highest overall efficiency is Huangshan (9.006) of Anhui Province in the Yangtze River Delta region. On the one hand, the reason for this is that Huangshan does not have much heavy industry as a small city. Huangshan is a world-famous tourist city. Economic development is mainly based on tourism, not industry. Finally, it should be noted that Huangshan is located in the upper reaches of the Qiantang River. To protect the development of downstream cities, the industrial development of Huangshan has also been restricted.

According to the distribution of these cities, we find that the cities located in Jiangsu Province, Zhejiang Province, and Shanghai show relatively higher improvements, while the cities belonging to Anhui Province show relatively weaker performance. R and D investment, industrial structure, and openness levels in developed regions usually perform better than those in backwards regions, which may lead to this result (Ren et al. 2016).

Analysis of the influencing factors

Drawing on existing research, this section uses the Tobit model for regression analysis. The total factor energy efficiency (TFEE) calculated above is taken as the dependent variable, and the five influential factors of digital economy (DIGE), environmental regulation (ER), the upgrading of industrial structure (TS), the degree of foreign investment development (OPEN), and the degree of government intervention (GOVE) are used as explanatory variables. To further investigate whether there is a nonlinear relationship between the digital economy and total factor energy efficiency, we added its quadratic term for analysis. The specific results are shown in Table 4.

As shown in Table 4, models (1) and (2) are analysed based on Tobit. Models (3) and (4) are regression analyses based on ordinary OLS. To further investigate whether there is a nonlinear relationship between the digital economy and total factor energy efficiency, we added its quadratic term for analysis in models (2) and (4). Comparing models (1) and (3), models (2) and (4) show that the regression coefficients of the influencing factors of models (1) and (3) are consistent, whether using the

Table 4 Analysis of the influence mechanism of TFEE based on the Tobit model

Independent variable	Tobit (1)	Tobit (2)	OLS (3)	OLS (4)
DIGE	1.262** (0.667)	9.793*** (1.788)	1.262* (0.722)	9.793*** (1.937)
DIGE^2		−9.342*** (1.826)		−9.342*** (1.979)
ER	2.721*** (0.285)	2.993*** (0.281)	2.721*** (0.309)	2.993*** (0.304)
TS	1.249*** (0.395)	1.027*** (0.388)	1.249*** (0.432)	1.027** (0.421)
OPEN	0.152** (0.077)	0.163** (0.074)	0.152* (0.083)	0.163** (0.081)
GOVE	1.353 (1.256)	1.553 (1.214)	1.353 (1.359)	1.553 (1.317)
_cons	−2.261*** (0.742)	−3.8762*** (0.783)	−1.321** (0.594)	−2.001** (0.592)
City	*Control*	*Control*	*Control*	*Control*
Year	*Control*	*Control*	*Control*	*Control*
Prob > chi^2	0.000	0.000	0.000	0.000
N	369	369	369	369

Standard errors in parentheses

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$

Tobit model or OLS regression. The regression coefficients of the influencing factors of models (2) and (4) are also consistent. However, the significance levels of models (2) and (4) decreased compared to those of models (1) and (3). This is because the efficiency value calculated by the DEA model is not less than 0; it is a restricted dependent variable. Therefore, the regression results of the Tobit model are more accurate than those of OLS regression. Robustness standard errors at the city level are used in model (5). In the next analysis, this study will mainly analyse the regression results of model (5). Finally, models (1), (2), (3), (4), and (5) control the effects of both the individual and the time see Table 5.

Table 5 Analysis of the influencing factors of TFEE based on the OLS model

Model (5) TFEE	Coefficient	Robust Std. err	*t* value	*p* value
DIGE	3.076*	1.749	1.76	0.086
DIGE^2	−3.174*	1.772	−1.79	0.080
ER	1.421***	0.350	4.06	0.000
TS	0.751***	0.169	4.45	0.000
OPEN	0.064	0.046	1.40	0.169
GOVE	0.125	0.592	0.22	0.830
_cons	−0.314	0.504	−0.62	0.537
City	*Control*			
Year	*Control*			

$F(14,40) = 1.76$, Prob $> F = 0.0812$

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

In Models (1) and (2) based on Tobit analysis, the core explanatory variable *DIGE* is significant at least at the 5% significance level. Other control variables are also significant. In Model (5) based on the OLS analysis, the core explanatory variable *DIGE* is also significant at least at the significance level of 10%. This shows that the digital economy does have a positive role in promoting the improvement of total factor energy efficiency after controlling for a series of influencing factors in the Yangtze River Delta urban agglomeration. For control variables, environmental regulations *ER* and upgrading of industrial structure *TS* remain significant at 1%. However, the level of foreign investment development *OPEN* and the government intervention *GOVE* decreased relatively much compared to model (2).

In addition, environmental regulation has contributed to the improvement of total factor energy efficiency. Local governments strengthening environmental constraints may lead to industrial sectors increasing technological innovation, improving production technology, innovating management, and continuously optimizing resource allocation to achieve greener production methods. These actions can help to reduce energy inputs, improve TFEE, and compensate for the increase in internal costs brought by environmental constraints through "innovation compensation"(Liu et al. 2020).

The results of the positive coefficient of TS indicate that industrial structure upgrading will lead to high efficiency of energy, labor, and capital input and improve the total factor energy efficiency. The reason is that, on the one hand, the upgrading of the industrial structure will increase the productivity of all industries. On the other hand, the upgrading of the industrial structure will also increase the proportion of tertiary industry and reduce the proportion of secondary industry. The industrial sector is an energy- and capital-intensive industry. In the later stage of industrialization, the continuous repetition of low-end industrial investment will lead to extensive consumption of energy and capital. Therefore, the government needs to continuously adjust the industrial structure and promote industrial upgrading. Moreover, we can not ignore the critical role of the integrated development of manufacturing and service industries in industrialization. The lag in the serviceability of the manufacturing industry will also hinder the improvement of enterprise competitiveness and industrial transformation and upgrading (Zhang et al. 2021, 2018).

With respect to the positive impact of foreign investment, the advanced technical level and management experience brought by foreign investors may promote the improvement of energy efficiency. This result also validates the research of Zhao et al. (2022), who point out that FDI can improve energy efficiency and reduce carbon emissions.

Business behavior is often short-sighted. They often invest large amounts of energy and other factors to obtain more benefits in the short term. These companies neglect long-term development, resulting in wasted energy, massive pollution, and inefficient energy use. At the same time, some large enterprises may form oligopolies to obtain huge monopoly profits, which will inhibit the innovation of private enterprises and downstream enterprises (Guo and Liu 2019; He 2017) and hinder the technological progress and industrial upgrading of the whole industry. Therefore, it is necessary for the government to intervene at the macro level. The government should formulate the development plan of the industry and guide the orderly development of each enterprise and the entire industry. Government intervention at the macro level is similar to a beacon on the sea, which is crucial to the improvement in total factor energy efficiency.

To further speculate whether there is a nonlinear correlation between the digital economy and total factor energy efficiency, a quadratic term of the digital economy is introduced in models (2), (4), and (5). The results imply that both the monomial and quadratic terms passed the significance test at the 10% level, and the coefficients of the quadratic terms are negative. This also validates H1. There is an inverted U-shaped relationship between the digital economy and total factor energy efficiency. The impact path of the digital economy on promoting industrial total factor energy efficiency may come from the following:

First, the digital economy improves total factor energy efficiency through digital industrialization and industrial digitalization (Kohli and Melville 2019; Zhou et al. 2021). In addition, the development of the digital economy will also contribute to the optimization of the industrial structure (Yang et al. 2021b). Industrial digitalization is the main development trend of the digital economy in the future (Bukht and Heeks 2017). The integration of the digital economy and the manufacturing industry will be helpful to reshape the production process of traditional industries and realize energy real-time measures and carbon emission prediction (Zhang and Ji 2019).

Second, the digital economy reduces the cost of access to knowledge and learning. With the remarkable development of information technology, it makes access to knowledge and information easier, multichannel, and low-cost. Under this circumstance, both the enterprises and individuals will obtain improvements.

Third, the digital economy also stimulates the digitization of traditional finance. Digital finance can promote energy efficiency by improving the level of regional innovation and entrepreneurship(Zhang and Li 2022), corporate revenue, and financial efficiency channels (Chen and Jiang 2021).

There is inverted “U-shaped” relationship between the digital economy and total factor energy efficiency. This result implies that with the development of the digital economy, its marginal contribution to energy efficiency has gradually weakened. This result is also consistent with the findings presented by Fan and Xu (2021), Miao et al. (2022). They point out that with the development of the digital economy, the green economy and carbon emissions have an inverted “U-shaped” relationship. They also note that the energy rebound effect may lead to this situation. Accordingly, great attention should be given to the energy consumption of the development of the digital economy in the future. At present, the total scale of China’s digital economy ranks second in the world. The amount of data generated from digital terminals each year is exponential. As a critical energy consumer and pollutant emitter, the energy demand of data centers will inevitably increase with the growth of the digital industry.

Han (2022) pointed out that the electricity consumed by the national data center in 2020 is equivalent to approximately 1.7% of the national total. The digital element has been integrated into the terminal of social production and economic life. The energy consumption of terminal electronic products tends to increase dramatically. In addition, the production of electronic products involves the mining of rare metals and the recycling of waste. The large-scale mining of rare metals will also lead to an increase in energy consumption and corresponding pollution.

Threshold effect analysis

The impact of the development of the digital economy on total factor energy efficiency may have certain threshold characteristics. If the development of the digital economy is less than a certain “threshold,” the promotion effect on total factor energy efficiency is stronger. If the level of development of the digital economy exceeds the “threshold,”

Table 6 Threshold effect test

Threshold variables	Threshold number	Threshold value	*f* value	*p* value	Critical value		
					10%	5%	1%
DIGE	Single	0.444	20.44	0.079	18.7691	24.7691	39.3865

its impact on improving efficiency will weaken. Accordingly, this study applies the threshold model for further analysis(Hansen 1999). The digital economy is taken as the core explanatory variable and as the threshold variable. Based on model (6), we will examine whether there is a threshold effect.

The threshold test regression results are shown in Table 6. To further illustrate the significant existence of threshold values, the threshold confidence interval for model (6) is given intuitively in the form of a likelihood function plot. As shown in Table 6, the digital economy threshold variable passes the single threshold test with a threshold value of 0.444. This indicates that the level of digital economy development has different effects on efficiency around the value of 0.444. The LR test result of Fig. 2 implies that the point estimate of the threshold value is within the 95% confidence interval. The length of the confidence interval is small, which indicates that the threshold value is statistically close to the true value. Therefore, the null hypothesis claims that the threshold value is equal to the actual value and can not be rejected, and the recognition effect of the threshold value is good.

Table 7 shows the threshold model regression results based on OLS regression analysis. Specifically, taking the development level of the digital economy as the threshold variable, when the development level of the digital economy is lower than the critical value of 0.444, the coefficient is as high as 4.113. Meanwhile, this result is significant. When the level of digital economy development exceeds the threshold value of 0.444, the coefficient drops significantly to 2.451. This result indicates that the promotion

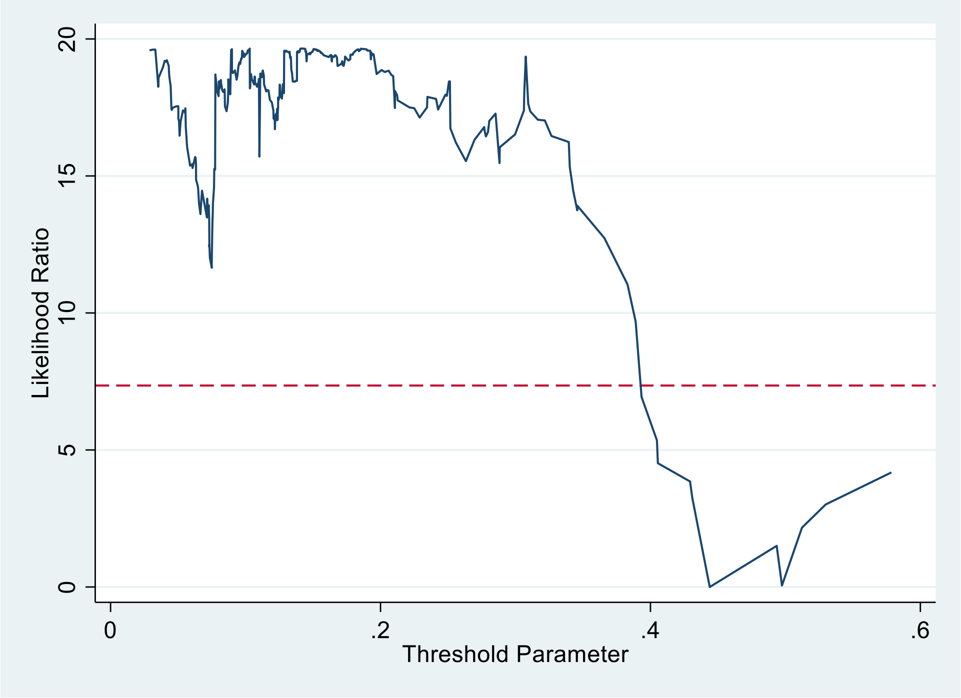
Table 7 Threshold model regression results

Model (6) TFEE	Coefficient	Robust Std. err	*t* value	*p* value
DIGE_0	4.113***	1.021	4.001	0.000
DIGE_1	2.451***	0.772	3.171	0.002
ER	2.952**	0.308	9.57	0.000
TS	1.063**	0.425	2.5	0.013
OPEN	0.173**	0.082	2.12	0.035
GOVE	1.471	1.331	1.11	0.269
_cons	− 1.702***	0.589	− 2.89	0.004
City	*Control*	*Control*	*Control*	*Control*
Year	*Control*	*Control*	*Control*	*Control*

$F(14,314) = 8.80$, $\text{Prob} > F = 0.0000$

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Fig.2 Likelihood function test



effect of digital economy development on energy efficiency declines when the digital economy reaches a high level.

The explanations about these results can be addressed as follows. On the one hand, the digital infrastructure and human capital are relatively insufficient in underdeveloped regions. The development of the digital economy may lead to the phenomenon of "siphoning," and various resources are concentrated in large cities, which distorts the efficiency improvement in developing regions, thus resulting in the "Matthew effect." In the process of the rapid development of the digital economy, the industrial sector in underdeveloped regions can quickly obtain technology and management experience from advanced regions. It is helpful to achieve leapfrog development of management and realize the "technology leap" of late-developing economies (Li and Zhao 2018). On the other hand, with the diffusion and popularization of digital technology, it is necessary to carry out independent innovation to improve efficiency. Technological innovation often encounters bottlenecks at this time, and the improvement of efficiency slows down. Therefore, if the development of the digital economy reaches a certain level, its promotion effect on total factor energy efficiency will weaken.

The result of threshold regression is based on the analysis of the Monomial term in model (6). The coefficient of the term decreases significantly after exceeding the threshold value. This further verifies that there is indeed an inverted U-shaped relationship between the digital economy and the total factor energy efficiency in model (5).

Analysis of the influencing mechanism

To analyse the impact mechanism of the digital economy on total factor energy efficiency in depth, we use a two-step method to verify the transmission channel. The specific empirical results are shown in Table 8. According to Table 8, we confirmed that the development of the digital economy will promote technological progress. It is at the 1% significance level. This result is consistent with Zhang et al. (2022a, 2022b).

To alleviate the problem of endogeneity and obtain more robust results, we further verify whether there is a promotion effect of the digital economy on technological progress through the instrumental variable method. We select two instrumental variables to obtain more precise results. Specifically, the number of Internet users of the country in the previous year was multiplied by the number of post offices in each city in 1984 as an instrumental variable. Meanwhile, the lag two-phase of the core explanatory variable was used as a second instrumental variable. The specific empirical results are presented in Table 9.

As shown in Table 9, the digital economy still plays an important role in promoting technological progress. It is also at the 1% significance level. In addition, the weak instrumental variable test result (F value = 49.981) is greater than 10, indicating that there is no problem with the weak instrumental variable. Overidentifying test results (p value = 0.113) indicated that we should accept the null hypothesis that all instrumental variables are exogenous.

The development of the digital economy emphasizes the application of new technologies and the transformation of new industries, and its development facilitates the traditional economy's transformation to digitization and intelligentization. More specifically, the development of the digital economy has increased the number of invention patents per capita, which is the direct manifestation of technological progress.

Regarding the impact of technological progress, it has been widely confirmed that it is important in the improvement of industrial total factor energy efficiency (Du et al. 2022; Li et al. 2022a, b). The promotion effect may raise from several respects.

First, technological progress promotes the expansion of production frontiers. Digital technologies such as 5G, cloud computing, and big data can accurately match supply and demand and optimize the allocation of traditional factors. This will enable the output to approach the production frontier as much as possible under the condition that the input of energy, capital, labor, and other factors remains unchanged to improve the total factor energy efficiency.

Second, technological progress contributes to the scale economy and scope economy. In the digital era, related

Table 8 Analysis of the influencing mechanism of total factor energy efficiency

Model (7) TECH	Coefficient	Robust Std. err	T	$p > t$
DIGE	10.137***	2.505	4.05	0.000
Control variables	*Control*			
City	*Control*			
Year	*Control*			

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9 Analysis of the influencing mechanism of total factor energy efficiency

Model (8) TECH	Coefficient	Robust Std. err	T	$p > t$
DIGE(IV)	15.281***	2.509	6.09	0.000
Control variables	*Control*			
City	*Control*			
Year	*Control*			

Weak instrumental variable test: F value = 49.981

Overidentifying test: $p = 0.1125$

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

technologies reduce the average cost of production and operation, resulting in economies of scale. In addition, the combination of rich data resources and corresponding intelligent technology can make the product/service types of enterprises more diversified and promote enterprises to improve the scope economy.

Moreover, technological progress significantly reduces transaction costs. There are kinds of transaction costs, the most important of which are communication costs and information matching costs. On the one hand, the rapid progress of information technology has made communication between managers and producers in different countries and regions more convenient and efficient. On the other hand, information technology can break through temporal and spatial limitations to effectively match information on market supply and demand. These impacts will reduce market transaction costs and thus improve total factor energy efficiency.

Finally, technological progress will directly improve the energy utilization efficiency in the production process and increase the adoption of clean energy. These all identified the promotion effect of progress on industrial total factor energy efficiency.

In sum, it is safe to conclude that the digital economy and technological progress can be mutually reinforcing. As a result, industrial total factor energy efficiency benefits from this progress in many ways.

Endogeneity analysis

Endogeneity is an inevitable problem in economic research. On the one hand, there may be a reverse causal relationship between the development level of the urban digital economy and total factor energy efficiency. On the other hand, there are many factors that affect the total factor energy efficiency. It is impossible to control all the influencing factors. This study attempts to alleviate endogenous problems by adopting the instrumental variable method.

Referring to Zhao et al. (2020), the historical data of post offices of each city in 1984 were used as an instrumental variable for the comprehensive index of digital economy development. On the one hand, the development of traditional information technology in China is undertaken by China Post. Therefore, the areas with a large number of post offices in history are also very likely to be areas with a high level of digital economic development. In this sense, the selection of the number of post offices as an instrumental variable for the development level of the regional digital economy satisfies the relevance requirement. On the other hand, as a traditional communication facility, the impact of the post office on the industrial total factor energy efficiency gradually weakens. Therefore, the selection of the number of historical post offices as an instrumental variable satisfies the exclusivity requirement. Notably, the original data of the selected instrumental variables are in the form of a cross section and can not be directly used for the quantitative analysis of the panel data. Referring to Nunn and Qian (2014), a time-varying variable is introduced to construct the instrumental variable of the panel data (Nunn and Qian 2014).

As shown in Table 10, the *F* value of 31.226 of the weak instrumental variable test result is greater than 10, indicating that there is no problem with the weak instrumental variable. Overidentifying test results indicated that the *p* value was 0.261. We should accept the null hypothesis that all instrumental variables are exogenous. Table 11 reports the regression results of the two-stage least squares method. As shown in Table 11, the coefficient of the impact of the digital economy on total factor energy efficiency is 7.385, which is still significant at the 1% level. This result is basically consistent with the regression result of model (1). In summary, after considering the endogenous problem, the development of the digital economy does have a role in promoting the total factor energy efficiency of the industrial sector.

Robustness tests

(1) In 2013 and 2014, China launched pilot projects to build a water ecological civilization city. The project

Table 11 Instrumental variables of 2SLS regression

Model (9) TFEE	Coefficient	Robust Std. err	*t* value	*p* value
DIGE	7.385***	2.165	3.41	0.001
ER	3.183***	0.739	4.31	0.000
TS	1.673***	0.521	3.21	0.001
OPEN	0.291***	0.102	2.85	0.004
GOVE	1.917	1.341	1.43	0.153
_cons	−7.511***	2.289	−3.28	0.001
City	Control			
Year	Control			

R-squared: 0.884, Prob > chi^2: 0.000, number of obs: 369

Table 10 Weak instrumental variable and overidentifying test

Weak instrumental variable test	Variable	*R*-sq	Adjusted *R*-sq	Partial *R*-sq	Robust *F* (1.314)	Prob > *F*
	DIGE	0.9723	0.9661	0.3565	31.2264	0.0000
Overidentifying test	Score $\text{chi}^2(1) = 1.26579$, $p = 0.2606$					

is aimed at protecting the ecological environment. Since the launch of the project, a total investment of 750 billion yuan has been completed. The policy of the national water ecological civilization city may affect the explanatory variables, explained variables, and other variables of the article at the same time, causing bias in the empirical regression results of the article. Therefore, to ensure the robustness of this study, the method of difference-in-differences will be used in the following analysis to control for the influence of policy effects. The specific model is as follows:

$$TFEE_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_2 DIGE_{it} + \sum \beta_i X_{it} + u_t + \lambda_i + \varepsilon_{it} \tag{7}$$

where DID_{it} is the national water ecological civilization city dummy variable. The coefficient, α_1, is the effect of the policy on the total factor energy efficiency of the industry. The coefficient, α_2, is the effect of the digital economy on total factor energy efficiency after controlling for the impact of the policy. u_t is the time fixed effect, λ_i is the individual fixed effect, and ε_{it} is the random error term. The specific regression results are shown in Table 12.

As shown by model (10), the influence coefficient of "national water ecological civilization city" on total factor energy efficiency was positive. However, the significance level was low, at only 0.25. This suggests that the effect of the policy is not obvious. After controlling for the effect of the policy, the role of the digital economy in promoting industrial total factor energy efficiency is still significant. In addition, other explanatory variables remain significant overall. Therefore, the policy has a limited impact on the explanatory variables in this article and does not cause deviations in the results of empirical regression.

(2) To further test whether there is an endogenous problem of mutual causation, the lagging terms of the core explanatory variable ($DIGE_{t-1}$) are brought into the regression analysis by drawing on the treatment method of endogenous problems (Guo and Luo 2016). The logic is that the improvement of total factor energy efficiency in the t-period has almost no impact on the level of digital economy development in the $(t-1)$ period. Therefore, if the level of digital economy development in period $(t-1)$ still has the same influencing relationship on the *TFEE* of period t as in the previous analysis, it can be shown that the results are still stable when endogenous problems are considered. As shown in model (11), the core conclusions of this article are still verified.

(3) Transform the core explanatory variables. The level of digital economy development used in the previous study was calculated based on the entropy weight TOPSIS method. Now, we reconduct the robustness test with the level of digital economy development based on the coefficient of variation method. We name it DIGE2. Moreover, we change the composition of the indicator of digital economy development. We change the proportion of computer service and software employees to the total employment of computer service and software in each city. We change the number of Internet users per 100 people to the total number of Internet users of each city. We change the number of mobile phone users

Table 12 Robustness test results

Independent variable	Model (10) TFEE	Model (11) TFEE	Model (12) TFEE	Model (13) TFEE	Model (14) τ = 0. 5
DID	0.107				
DIGE	1.326**				0.432***
L.DIGE		4.861**			
DIGE2			9.248***		
DIGE2^2			−6.891***		
DIGE3				11.098***	
DIGE3^2				−9.529***	
ER	2.691***	5.468***	2.904***	3.049***	1.639***
TS	1.261***	2.459*	1.082***	1.204***	0.949***
OPEN	0.162**	0.525**	0.345*	0.163**	−0.152
GOVE	1.254	6.243*	1.794	1.857	1.194***
_cons	−2.296***	−9.767***	−3.733***	−4.445***	−0.063
City	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control

Number of obs = 369

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

per 100 people to the total number of mobile phone users in each city. We change the per capita telecom service level to the total telecom revenue of each city. We change the per capita postal service level to the total postal revenue of each city. We name it DIGE3. Models (12) and (13) show that there is still an inverted U-shaped relationship between the digital economy and total factor energy efficiency. The core conclusions of this paper are still verified.

(4) In quantile regression, to further test the robustness, the quantile regression model is used to test the robustness of the threshold model in the preceding article. Model (14) presents the results of the impact of digital economy DIGE on total factor energy efficiency TFEE under the 50% and quantiles. It shows that there are indeed different marginal effects of the digital economy on total factor energy efficiency at different stages of development. In summary, the conclusions drawn above have good robustness.

Conclusions and policy implications

Based on the panel data of the industrial sector in the Yangtze River Delta urban agglomeration from 2011 to 2019, this paper applies the Super-Dynamic-SBM model and the TOBIT, threshold, and DID models to examine the promotion effect of the digital economy on industrial energy efficiency. The main conclusions are as follows.

First, the industrial energy efficiency of cities in the Yangtze River Delta generally showed an upwards trend. The efficiency improvement during the study period was significant, but the efficiency changes in different cities varied greatly. The differences in ecological protection, industrial structure, and degree of openness lead to this result.

Second, the development of the digital economy plays a significant role in improving the total factor energy efficiency. Moreover, the impact of the digital economy on total factor energy efficiency has a single threshold effect. Meanwhile, its impact on the improvement of total factor energy efficiency exhibits a marginal decreasing trend. In other words, the influence of the digital economy on industrial total factor energy efficiency shows an inverted "U" law.

Third, the development of the digital economy can contribute to technological progress. Technological progress will also improve the total factor energy efficiency level of industry. Technological progress is an important transmission channel of the digital economy on total factor energy efficiency. Based on the conclusions, this study proposes corresponding policy implications. First, we must pay more attention to industrial energy efficiency in underdeveloped regions, such as Anhui. Technical progress and the strengthening of digital infrastructure should be priorities. In developed regions, such as Shanghai, Jiangsu, and Zhejiang, we should focus on the energy consumption and environmental impact raised by digital industries and industrial digitalization, for example, accelerating the project of the "East Data and West Computing." The transmission cost of data is much lower than the transmission cost of energy. In addition, the government also needs to promote the coordination and linkage of the east and the west and realize the clean energy consumption of the data center in western China. Ultimately, the coordinated development of technological progress and the digital economy should be emphasized by the government in each city.

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Data availability The data in this manuscript mainly come from China city statistical yearbooks, and the relevant details are presented in the manuscript.

Declarations

Ethics approval and consent to participant Not applicable.

Consent for publication Not applicable.

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