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The impact of digital infrastructure on energy-environmental efficiency: empirical evidence from China

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Frontier studies have focused on the environmental performance of traditional infrastructure, but have generally neglected the effects and mechanisms of digital infrastructure on energy-environmental efficiency. This study attempts to use fixed effect models and mediating effect model based on panel data from 30 provinces in China from 2010 to 2017 to assess the impact of digital infrastructure on energy environmental efficiency and identify its mechanism. The non-radial directional distance function is used to measure energy environmental efficiency. The empirical results show that digital infrastructure promotes energy-environmental efficiency, which remains robust after a series of tests. Technological progress and energy industry advancement are the pathways through which digital infrastructure affects energy-environmental efficiency. Furthermore, we find that the positive effect of digital infrastructure on energy and environmental efficiency is significant in the east and where factor mismatch is high. Therefore, policymakers should develop digital technology and enact various environmental policies to effectively increase the construction of digital infrastructure, promote investment in technology research and development, accelerate the energy technology progress, and improve energy efficiency.

KEYWORDS

digital infrastructure, energy-environmental efficiency, technological progress, energy industry advancement, factor mismatch

1 Introduction

With rapid economic growth, the country's energy demand has been rapidly increasing, leading to excessive reliance on coal and other fossil fuels. This has had a significant impact on the environment, leading to pollution, greenhouse gas emissions, and other negative consequences. Energy environmental efficiency is a core issue that is currently receiving attention from both governments and society. In the context of global climate change and resource scarcity, it has become increasingly important to use energy as efficiently as possible, while also reducing negative impacts on the environment. In conclusion, the growing interest in energy environmental efficiency research as a way to overcome the resource curse represents a significant shift in scholarly focus and recognition of the importance of sustainable development and environmental protection in the modern economy.

With the development of digital technology, the rapid growth of the digital economy supported by digital infrastructure construction provides potential for improving environmental efficiency and achieving sustainable development. The Chinese government has put forward a plan to strengthen digital infrastructure construction in recent years, aiming to promote the development of digital economy and improve people's livelihood. Digital infrastructure construction is an important strategic plan of the Chinese government, which includes many aspects such as telecommunications, the Internet, big data, cloud computing, and artificial intelligence. Digital infrastructure is a new infrastructure system based on information network and combined with the new generation of information technology, with new technical and economic characteristics (Greenpeace, 2021). Owing to its outstanding advantage in accelerating the digitalization process of social economy, and realizing the innovation of intelligent manufacturing and business operation mode (Wen et al., 2022), digital infrastructure has become a new driving force for sustainable economic growth.

However, the application of digital infrastructure has resulted in increased energy consumption and climate change (Tang and Yang, 2023). Some literature has conducted relevant research on the economic effects of digital infrastructure. Previous literature provides diverse evidence between digital infrastructure and environmental performance. One view suggests that information and communication technology (ICT) or specific types of digital infrastructure reduce carbon dioxide emissions and energy consumption (Fuchs et al., 2020; Dong et al., 2022). While another view suggests the opposite conclusion, which is that digital infrastructure has a positive impact on energy consumption and total carbon emissions (Zhou et al., 2019; Hao et al., 2022; Tang and Yang, 2023). Therefore, there is no consensus on the relationship between digital infrastructure and energy consumption. Furthermore, previous literature has paid little attention to the energy-environmental efficiency of digital infrastructure. Given the complexity and interconnectedness of the relationships between digital infrastructure and energy environment efficiency, further research is needed to develop a comprehensive understanding of these interactions. In addition, the mechanism by which digital infrastructure affects energy environment efficiency is poorly understood and represents a significant research gap. In conclusion, there is a significant gap in knowledge regarding the impact of digital infrastructure on energy environment efficiency that needs to be addressed through further research.

Indeed, the impact of digital infrastructure on energy-environmental efficiency is a key topic of concern. Therefore, we must quantitatively identify the different impacts and mechanisms of digital infrastructure on energy and environmental efficiency from multiple perspectives. We selected the panel data of 31 provinces in China from 2010 to 2017, and used multiple regression models to investigate the effect, mechanism and heterogeneity of digital infrastructure on energy and environmental efficiency. It is worth mentioning that this study discusses the mechanism of the impact of digital infrastructure on energy and environmental efficiency based on technological progress and energy industry advancement.

The main contributions of this study are as follows. First, relevant studies have mainly examined the impact of the digital finance on energy-environmental efficiency, but ignoring the impact of digital infrastructure development on energy and environmental efficiency. Although some studies have explored the relationship between digital infrastructure and carbon dioxide emissions, the impact of digital infrastructure on energy and environmental efficiency has not yet been captured. Our study demonstrates the impact of digital infrastructure on energy and environmental efficiency from both theoretical and empirical perspectives, indicating that our study proposes a new approach to achieving sustainable energy development. Second, previous studies on the mechanisms of environmental effects of telecommunications infrastructure or a specific type of digital infrastructure have mainly focused on government regulation or resident behavior, etc. However, they ignored the structural and technological progress effects of digital infrastructure on energy and environmental efficiency. Third, this study creatively discusses the regional heterogeneity and asymmetry of the impact of digital infrastructure on energy-environmental efficiency due to the differences in digital infrastructure and energy structure in different regions. More specific and practical policies can lay a solid policy support for the current improvement of energy-environmental efficiency.

The remaining parts of the study is as follows: Section 2 describes the literature review. Section 3 presents the theoretical analysis. Section 4 describes the empirical methods and data. Section 5 analyzes the empirical results. Section 6 presents the research conclusions and policy suggestion.

2 Literature review

2.1 Effect of digital infrastructure

The new digital infrastructure is a fundamental project to promote the continuous diffusion of emerging digital technologies such as big data, Internet of Things, artificial intelligence, blockchain, etc. The impact of the digital infrastructure is multidimensional. The literature examines the economic, energy and environmental impacts of certain types of digital infrastructure and information and communication technologies (Chen et al., 2021; Liu et al., 2021). Research on the impact of digital infrastructure on the economy focuses on the contribution of digital infrastructure to economic development. Wu and Yu. (2022) conducted empirical analysis and found that the digital economy has made an important contribution to China's economic growth and productivity improvement. Chen et al. (2022) pointed out that artificial intelligence has a significant positive impact on the upgrading of equipment manufacturing industry, and technological innovation plays an intermediary role in the process of artificial intelligence to enhance the upgrading ability of equipment manufacturing. Li et al. (2023) used the data of listed companies to confirm that AI application has significantly improved the corporate innovation efficiency, and this effect is heterogeneous.

The impact of digital infrastructure on energy consumption and pollution emissions has also been partially studied. On the one hand, digital infrastructure is energy-intensive to some extent. Hintemann (2020) highlighted that the rapid growth of the digital economy has driven a significant increase in energy consumption of data transmission, storage, computing, application and device connectivity. Lange et al. (2020) analyzed the potential impact of digitalization on energy consumption and found that the digital industry (ICT industry) increased energy demand. Usman et al. (2021) analyze the relationship between information and communication technology and energy use in South Asian countries, and propose that the development of information and communication technology industry can achieve rapid economic growth in South Asia, but strengthen energy consumption. On the other hand, digital infrastructure has a positive impact on improving energy efficiency. Ishida. (2015) found that the investment in the information and communication technology industry is conducive to moderate reduction of energy use. Zhao et al. (2022) confirmed that the development of information and communication technology in emerging Asian economies can play a positive role in improving energy efficiency. Xue et al. (2022) discussed the impact of the digital economy on energy consumption, and proposed that the digital economy is conducive to optimizing the energy consumption structure.

2.2 Energy-environmental efficiency and determinate factor

Energy-environmental efficiency is considered as a comprehensive indicator to evaluate the relationship between economic costs and environmental costs, wherein high energy-environment indicates that the minimum use of natural resources and environmental degradation will produce the maximum economic output (Mickwitz et al., 2006). Regarding the driving force of energy-environmental efficiency, many studies focus on socio-economic factors affecting energy-environmental efficiency, including economic development (Guan and Xu, 2016; Zhang et al., 2016; Moutinho et al., 2017), technological progress (Ai et al., 2015; Cao et al., 2021; Zhu et al., 2021), industrial policy (Zhang et al., 2020), and urbanization (Chen et al., 2020). For example, Wu and Lin. (2022) demonstrated the U-shaped relationship between environmental regulation and energy-environmental efficiency in China using the Tobit model and DEA model. Cao et al. (2021) revealed that digital finance has promoted the improvement of China's energy and environmental performance, and technological innovation is the intermediary mechanism for digital finance to affect the energy environment. Zhang et al. (2020) emphasized that the non-radial distance function is used to estimate the energy and environmental efficiency, and tax incentives have a positive impact on the energy and environmental efficiency of mining enterprises.

Some literature focuses on the impact of technology and green innovation. Ali et al. (2022) investigated the relationship between FDI, green innovation, and carbon dioxide emissions and found that green innovation plays a positive role in reducing emissions. Wen et al. (2021) concluded that green innovation has a positive impact on improving environmental quality. Hu et al. (2021) proposed that energy use and trade openness increase carbon dioxide emissions and damage the environment. Ali et al. (2023) have proposed to develop green innovation markets, encourage foreign companies with green technology, and strengthen the connection between FDI and green technology innovation in China. Sattar. (2022) emphasized the role of climate financing and technology transfer in the framework of climate action needs. Zhang and Dilanchiev. (2022) analyzed the factors that affect the efficiency of natural resource utilization, including urbanization, industrial structure, etc.

In addition, some studies have explored the issue of renewable energy and provided clues for this study. Abbas et al. (2022) emphasized the importance of innovation and renewable energy development related to the environment, as well as market regulation, in reducing emissions and achieving green and sustainable development. Hussain et al. (2021) focused on governance as a factor hindering the growth of renewable energy. Sun et al. (2023) proposed that green financing and renewable energy are negatively correlated with carbon dioxide emissions in the short term. Batool et al. (2022) emphasized the importance of exploring renewable energy for energy poor areas.

2.3 Digital infrastructure and energy-environmental efficiency

Driven by the digital economy, the relationship between digitalization and energy efficiency has become a hot topic of research (Hao et al., 2022). There are few literatures that directly empirically investigate digital infrastructure and energy-environmental efficiency. Currently, the literature pays more attention to the impact of information and communication technology (ICT) on energy consumption, and forms two different views. One view is that the ecological effect of information and communication technology can be summarized into three stages: directly generating "electronic waste", improving energy efficiency and forming "rebound effect" (Hilty et al., 2006). Another view is that the energy effect of ICT can be explained by income and substitution effects (Takase and Murota, 2004). The literatures closely related to the research topic of this study mainly include: Fan et al. (2022) proposed that the new digital infrastructure is conducive to promoting the transformation of energy structure, and this positive effect is achieved through green total factor productivity and green finance. Tang and Yang. (2023) discussed the relationship between digital infrastructure and carbon dioxide emissions, and found that digital infrastructure significantly increased the total carbon emissions, *per capita* carbon emissions and carbon intensity of Chinese cities, while digital infrastructure inhibits urban carbon emission reduction and energy conservation by inducing *per capita* energy consumption, total energy input, marginal diminishing factor productivity gains and increasing energy intensity.

2.4 Literature gaps

In summary, the above literature review provides valuable clues for exploring the relationship between digital infrastructure and energy-environmental efficiency. However, there is still room for exploration of the impact of digital infrastructure on energy and environmental efficiency. Firstly, in terms of research framework, previous research has mainly focused on reducing or increasing carbon emissions through the development of digital infrastructure or information and communication technology, and currently no unified results have been obtained. Secondly, in terms of mechanism

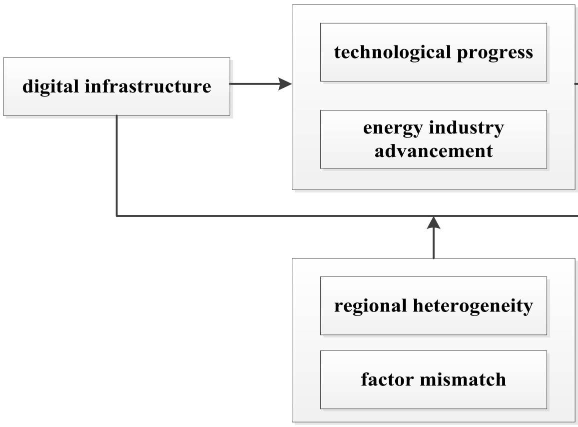

FIGURE 1
Research framework of digital infrastructure affecting energy-environmental efficiency.

research, empirical testing of the impact of digital infrastructure on energy and environmental efficiency from the perspectives of technological and structural effects is still relatively scarce. Thirdly, in terms of research methods, the use of non-radial directional distance function provides a more comprehensive and accurate assessment of energy-environmental efficiency. Finally, the above analysis also emphasizes the necessity of further research to address knowledge gaps and identify the most effective strategies for improving energy and environmental efficiency through digital infrastructure construction.

3 Theoretical analysis

3.1 Direct effect of digital infrastructure on energy-environmental efficiency

Digital infrastructure, owing to its advantages in the promotion and application of digital technology, not only optimizes the government's environmental management policies, but also contributes to the improvement of production processes, factor allocation and energy efficiency of enterprises (Lin and Zhou, 2021; Liu et al., 2022; Wei and Ullah, 2022). Digital infrastructure promotes the wide application of digital technology in enterprise research and development, design, manufacturing, market operation and management, optimizes energy utilization technology and production process, improves energy utilization efficiency and reduces energy consumption. Energy enterprises relying on advanced digital technologies, deepen the application of industrial Internet, big data, cloud computing, cloud storage, artificial intelligence and other digital technologies to build new forms of smart energy, and promote the realization of digital operation and management in all aspects of the enterprise, which is conducive to reducing energy consumption in the process of conversion and transportation, achieving effective energy allocation and promoting the realization of energy efficiency improvement. The construction of digital infrastructure can effectively configure and monitor the transaction, production, transportation and other processes of energy and other production factors through technologies such as big data, cloud computing and artificial intelligence, and build an energy network through the interconnection system to distribute energy to the most needed enterprises to prevent overcapacity and environmental pollution. Digital infrastructure also realizes automation of energy production and improves energy efficiency through intelligent mechanical equipment. In addition, blockchain technology provides enterprises with open and transparent energy information, which is conducive to obtaining more detailed and accurate information about energy prices, production and quality. At the same time, Internet of Things technology provides convenience for enterprises to transport energy products and raw materials, reduce internal transaction costs and transportation costs related to energy, and improve energy efficiency.

Therefore, we present the first hypothesis.

H1. Digital infrastructure has a positive impact on energy-environmental efficiency.

3.2 Indirect effect of digital infrastructure on energy-environmental efficiency

3.2.1 Progressive effect

Digital infrastructure affects technological progress through resource allocation and information support. On the one hand, digital infrastructure accelerates the development of industrial intelligence, drives the growth of high-tech industries, attracts scientific and technological talents, and provides intelligence for technological innovation through knowledge spillover effect. On the other hand, the use of digital technologies provides an efficient and intelligent information platform for innovation activities and promotes the linked innovation spillover of information between different production sectors. The enhancement of intelligence is conducive to optimizing the division of labor and layout of production, and inducing technological innovation in the fields of comprehensive energy utilization, urban traffic management, pollutant reduction and management through the intelligence of infrastructure in the fields of energy, transportation, etc. Technological innovation plays an important role in energy and energy-related fields, especially in improving energy efficiency and environmental performance (Yan et al., 2020; Baloch et al., 2022).

Thus, we present the second hypothesis.

H2. Digital infrastructure affects the technical progress, which in turn affects energy-environmental efficiency.

3.2.2 Structure effect

Energy and environmental efficiency is used to measure the input-output efficiency of desired and undesired outputs under certain input conditions, which can better portray the balanced development of regional economic growth and environmental governance. To this end, energy and environmental efficiency is to ensure economic output under the premise of minimizing inputs and non-desired outputs. The digital infrastructure is formed by the evolution, integration and iteration of the new generation of information technology such as 5G network, Internet of Things, industrial Internet, artificial intelligence, data center, etc. The digital infrastructure system formed is the concrete representation of network, computing power, new technology and other elements, which can fully penetrate into the industrial chain. Specifically, this study explains the impact of digital infrastructure on the energy industry advancement from three processes: R&D design, manufacturing and market matching. First, digital infrastructure has strong technical attributes, and the integrated application of 5G networks, artificial intelligence, industrial Internet and other general technologies can optimize R&D mode, reduce R&D risks and costs, improve innovation efficiency, and promote energy industry advancement. Second, digital infrastructure facilitates the flow of energy elements, accelerates the flow of energy industry elements to the high-end of the value chain, and promotes the transformation of the energy industry. Third, digital infrastructure reduces energy market demand matching costs, expands matching range, and increases matching speed. The upgrading of industrial structure has improved energy efficiency and reduced resource waste (Wei and Shen, 2007; Zheng et al., 2023).

Thus, we present the third hypothesis.

H3. Digital infrastructure affects the energy industry advancement, which in turn affects energy-environmental efficiency.

As a result, our study explain the energy-environmental efficiency from the perspective of digital infrastructure. We further explain the influencing mechanism of digital infrastructure on energy-environmental efficiency, and tests the heterogeneity. Figure 1 depicts the research framework.

4 Empirical methodology, data and variables

4.1 Empirical method

Referring to Tang and Yang (2023), we constructed the following benchmark regression model to capture the effect of digital infrastructure on energy-environmental efficiency.

$$\begin{aligned} EEP_{i,t} &= \lambda_0 + \lambda_1 Diginf_{i,t} + \lambda_2 GDP_{i,t} + \lambda_3 Indus_{i,t} + \lambda_4 Fiscal_{i,t} \\ &\quad + \lambda_5 Fdi_{i,t} + \lambda_6 Trinf_{i,t} + u_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{1}$$

The indices i denotes province and t denotes year; $Diginf_{i,t}$ is a comprehensive digital infrastructure index. $EEP_{i,t}$ is a comprehensive energy-environmental efficiency index. The core estimation coefficient λ_1 reflects the overall effect of digital infrastructure on energy-environmental efficiency. u_i reflects a province fixed effect, δ_t reflects time trends, and ε_{it} is a random error. We also control for other relevant socioeconomic drivers, including economic development, industrial structure, fiscal expenditure, FDI and transportation infrastructure.

Our research further constructs economic models to investigate the mechanisms by which digital infrastructure affects energy-environmental efficiency. Referring to the Sun et al. (2023), the mechanism confirmation model is as follows:

$$\begin{aligned} Mech_{i,t} &= \theta_0 + \theta_1 Diginf_{i,t} + \theta_2 GDP_{i,t} + \theta_3 Indus_{i,t} + \theta_4 Fiscal_{i,t} \\ &\quad + \theta_5 Fdi_{i,t} + \theta_6 Trinf_{i,t} + u_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} EEP_{i,t} &= \omega_0 + \omega_1 Diginf_{i,t} + \omega_2 Mech_{i,t} + \omega_3 GDP_{i,t} + \omega_4 Indus_{i,t} \\ &\quad + \omega_5 Fiscal_{i,t} + \omega_6 Fdi_{i,t} + \omega_7 Trinf_{i,t} + u_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where $Mech_{i,t}$ is a vector of mechanism variables. Other variables are consistent with the basic model.

4.2 Variable definition

4.2.1 Estimation of digital infrastructure

We quantified the digital infrastructure (*Diginf*) index for each province in four dimensions (as shown in Table 1): number of domain names, Internet broadband access ports, cell phone exchange capacity and length of long-distance optical cable line. Specifically, the number of domain names is measured by the ratio of the number of domain names to the population; the Internet broadband access ports are measured by the ratio of the Internet broadband access ports to the population; and the cell phone exchange capacity is measured by the ratio of the cell phone exchange capacity to the population. In this study, principal component analysis is used to standardize and downscale the indicators to finally obtain the digital infrastructure construction index.

4.2.2 Estimation of energy-environmental efficiency

This study uses the non-radial distance function to measure energy-environmental efficiency. The input elements are capital K, labor L and energy E; The desired output is Gross Domestic Product Y; The unexpected output is the discharge of various wastes in the production process, mainly including sulfur dioxide S, smoke D and waste water W. Thus, the production function is specified as:

$$\begin{aligned} P(K,L,E) &= \{(Y,S,D,W):\ (K,L,E,Y,S,D,W) \in T\} \\ &= \left\{ \begin{array}{c} (K,L,E,Y,S,D,W):\ \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}K_{it} \le K, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}L_{it} \le L \\ \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}E_{it} \le E, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}Y_{it} \ge Y, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}S_{it} = S, \\ \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}D_{it} = D, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}W_{it} = W, z_{it} \ge 0 \end{array} \right\} \end{aligned} \tag{4}$$

TABLE 1 Comprehensive measurement system of digital infrastructure.

Indicators	unit	Meaning of indicators	Indicator attributes
the number of domain names	10,000 units/10,000 people	domain name resource allocation	+
Internet broadband access ports	million/10,000 people	Internet hardware	+
cell phone exchange capacity	million/10,000 people	Mobile communication hardware	+
length of long-distance optical cable line	10,000 km	Fiber optic infrastructure construction	+

Based on the principle of output expansion while minimizing pollutant emissions, the non-radial directional distance function is defined as follows:

$$\vec{D}(K,L,E,Y,S,D,W;g) = \sup\{w^T\beta\colon\ ((K,L,E,Y,S,D,W) + g\cdot \mathrm{diag}(\beta)) \in P\} \quad (5)$$

where w^T is the weight vector, β is a slack vector that can be scaled up or down for each input-output variable, g denotes the directional vector of input and output changes, $\mathrm{diag}(\beta)$ denotes the diagonalization of the β vector.

Energy-environmental efficiency examines the maximum proportion of energy inputs, the maximum proportion of curtailment of undesired outputs, and the maximum proportion of expansion of desired outputs, with constant capital and labor inputs. Therefore, the weights of capital and labor variables are set to 0, and the weights of other variables are still assigned according to the principle that inputs, consensual and non-consensual outputs are equally important, i.e., the weight vector in the energy and environmental efficiency index model is set as:

$$w^T = \left(0,0,\frac{1}{3},\frac{1}{3},\frac{1}{9},\frac{1}{9},\frac{1}{9}\right) \quad (6)$$

The direction vector is set as:

$$g = (0,0,-E,Y,-S,-D,-W) \quad (7)$$

The linear programming problem is as follows:

$$\begin{gathered}\vec{D}(K,L,E,Y,S,D,W) = \max\left\{\frac{1}{3}\beta_E + \frac{1}{3}\beta_Y + \frac{1}{9}\beta_S + \frac{1}{9}\beta_D + \frac{1}{9}\beta_W\right\}\\ \text{s.t.} \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}K_{it} \le K, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}L_{it} \le L,\\ \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}E_{it} \le E - \beta_E g_E, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}Y_{it} \ge Y + \beta_Y g_Y,\\ \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}S_{it} = S - \beta_S g_S, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}D_{it} = D - \beta_D g_D, \sum_{t=1}^{T}\sum_{i=1}^{N} z_{it}W_{it}\\ = W - \beta_W g_W,\\ z_{it} \ge 0, i = 1,2,\ldots,N, t = 1,2,\ldots,T \text{且} \beta_E,\beta_Y,\beta_S,\beta_D,\beta_W \ge 0\end{gathered} \quad (8)$$

The optimal solution of the relaxation variable is

$$\beta_{it}^{*} = \left(\beta_{it,K}^{*},\beta_{it,L}^{*},\beta_{it,E}^{*},\beta_{it,Y}^{*},\beta_{it,S}^{*},\beta_{it,D}^{*},\beta_{it,w}^{*}\right)^T \quad (9)$$

The energy-environmental efficiency (EEP) model is as follows:

TABLE 2 Statistical descriptions of main variables.

Variable	Obs	Mean	Std Dev	Min	Max
EEP	240	0.3911	0.2241	0.0890	1.0000
Diginf	240	−0.095	0.5815	−0.9800	2.1600
GDP	240	10.6930	0.4477	9.4818	11.7675
Indus	240	0.4423	0.0940	0.2861	0.8055
Fiscal	240	0.2417	0.1014	0.1058	0.6268
Fdi	240	2.1393	3.1992	0.0165	24.4070
Trinf	240	0.9668	0.5422	0.0892	2.5234

$$EEP_{it} = \frac{1}{6}\left(\begin{gathered}\frac{Y_{it}/E_{it}}{(Y_{it}+\beta_{Y,it}^{*}Y_{it})/(E_{it}-\beta_{E,it}^{*}E_{it})} + \frac{Y_{it}/S_{it}}{(Y_{it}+\beta_{Y,it}^{*}Y_{it})/(S_{it}-\beta_{S,it}^{*}S_{it})}\\ + \frac{Y_{it}/D_{it}}{(Y_{it}+\beta_{Y,it}^{*}Y_{it})/(D_{it}-\beta_{D,it}^{*}D_{it})} + \frac{Y_{it}/W_{it}}{(Y_{it}+\beta_{Y,it}^{*}Y_{it})/(W_{it}-\beta_{W,it}^{*}W_{it})}\end{gathered}\right) \quad (10)$$

4.2.3 Control variables

1) economic development: GDP *per capita* is used to control the economic development of each region; 2) industrial structure: the ratio of non-agricultural value added to GDP is used to measure the industrial structure; 3) fiscal expenditure: the ratio of fiscal expenditure to GDP is used to measure fiscal expenditure; 4) FDI: the ratio of foreign direct investment to population is used to measure the FDI; and 5) transportation infrastructure: the weight is given according to the freight density, that is $wRail + Road$, Where Road is the mileage of highway, Rail is the mileage of railway, and w is the ratio of railway freight density to highway freight density.

4.3 Data description

The sample data for this study are panel data for 30 provinces and municipalities in China from 2010–2017. The selection of 2010 as the starting year is mainly limited by the availability of data. The data sources for each variable involved in this study are mainly the China Statistical Yearbook, the provincial statistical yearbooks, the statistical database of the Ministry of Commerce and the China Macroeconomic Database. Table 2 reports the summary statistics of key variables that are used in this study.

Table 3 reports the correlation matrix, which is used to examine whether thepredictors were multicollinear or not. According to the results in Table 3, there is no multicollinearity problem.

TABLE 3 Correlation matrix.

	EEP	*Diginf*	*GDP*	*Indus*	*Fiscal*	*Fdi*	*Trinf*
EEP	1.0000	—	—	—	—	—	—
Diginf	0.6305	1.0000	—	—	—	—	—
GDP	0.7345	0.7206	1.0000	—	—	—	—
Indus	0.7079	0.6719	0.6087	1.0000	—	—	—
Fiscal	−0.3866	−0.0843	−0.4130	−0.0160	1.0000	—	—
Fdi	0.6214	0.3159	0.6469	0.5376	−0.2528	1.0000	—
Trinf	0.5539	0.1590	0.5099	0.4155	−0.5635	0.5912	1.0000

5 Empirical analysis

5.1 Benchmark regression analysis

The core of empirical research is to analyze the impact of digital infrastructure on energy-environmental efficiency. The benchmark regression results are shown in columns (1)–(4) of Table 4. The regression coefficient of digital infrastructure is significantly positive at the 1% level, which shows that digital infrastructure plays a significant role in promoting energy-environmental efficiency. Digital infrastructure is widely used to compress time and space restrictions on the flow of factors and resources, so that long-distance spatial connections are no longer restricted, which leads to more adequate regulation of capital flow, logistics and information flow, and regulates and optimizes the allocation of resource factors. The 5G, big data, artificial intelligence, Internet of Things and other new generation of information technology and the integration of the real economy to promote the digital transformation of the energy industry, improve the efficiency of energy and other utilization, reduce pollutant emissions, improve the quality of the ecological environment and energy and environmental efficiency.

The results of the impact of digital infrastructure on energy environmental efficiency have been compared with previous research findings, revealing some significant differences and similarities. First, previous research mainly focused on the relationship between the digital infrastructure and energy structure. Fan et al. (2022) have paid attention to the transformation of energy structure and proposed that digital infrastructure has promoted the transformation of energy structure, and green total factor productivity and green finance have played an important role in this promotion effect. Our study means that digital infrastructure can improve energy-environmental efficiency and achieve sustainable development. In other words, our finding is consistent with Du et al. (2023) that the digital infrastructure construction has effectively carbon emission efficiency. Indeed, there is a study that proposes conclusions with opposite meanings from ours. Tang and Yang. (2023) summarized that digital infrastructure has ultimately promoted total carbon dioxide emissions by increasing *per capita* energy consumption and energy intensity.

5.2 Analysis of mechanism verification

5.2.1 Progressive effect

To test whether digital infrastructure promotes energy-environmental efficiency by affecting the technological progress, we selected the total factor productivity as an index to reflect the technological progress. The empirical results are reported in Table 5. We find that the coefficient of digital infrastructure is positive in column (1), and the estimated coefficient passed, indicating that there is a positive correlation between digital infrastructure and technological progress. That is, the technological progress has improved energy-environmental efficiency, which has been proved. This may be because the digital infrastructure not only

TABLE 4 Regression of digital infrastructure on energy-environmental efficiency.

	(1)	(2)	(3)	(4)
Diginf	0.1844*** (0.018)	0.0755* (0.042)	0.0999*** (0.034)	0.0945** (0.037)
GDP	—	—	−0.0085 (0.042)	−0.0912 (0.121)
Indus	—	—	0.7636** (0.290)	0.2414 (0.284)
Fiscal	—	—	−0.6735* (0.369)	−0.5713 (0.478)
Fdi	—	—	0.0113* (0.006)	0.0125** (0.006)
Trinf	—	—	0.3430** (0.160)	0.3107* (0.161)
constant	0.4087*** (0.002)	0.3455*** (0.033)	−0.0394 (0.444)	1.0329 (1.252)
Time FE	N	Y	N	Y
Province FE	Y	Y	Y	Y
Observations	0.599	0.708	0.693	0.755
R-Squared	240	240	240	240

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level; T-statistics are reported in parentheses.

TABLE 5 Mechanism verification.

	(1)	(2)	(3)	(4)
Diginf	0.0483** (0.024)	0.0614* (0.034)	0.0158* (0.009)	0.0678** (0.032)
technological progress	—	0.6857* (0.367)	—	—
energy industry advancement	—	—	—	1.6897*** (0.372)
GDP	−0.0681 (0.063)	−0.0445 (0.115)	0.0391 (0.025)	−0.1574 (0.122)
Indus	−0.1971 (0.173)	0.3766 (0.276)	−0.8830*** (0.099)	1.7334*** (0.405)
Fiscal	−0.1913 (0.197)	−0.4401 (0.499)	0.0747 (0.080)	−0.6975 (0.427)
Fdi	0.0021 (0.002)	0.0111* (0.006)	0.0010 (0.001)	0.0108 (0.007)
Trinf	0.0783 (0.061)	0.2570* (0.147)	0.0612 (0.046)	0.2072 (0.147)
constant	0.8299 (0.717)	0.4639 (1.237)	0.3092 (0.258)	0.5104 (1.272)
Time FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Observations	0.544	0.781	0.945	0.783
R-Squared	240	240	240	240

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level; T-statistics are reported in parentheses.

has the same public service functions as traditional infrastructure, but also integrates 5G, Internet of Things, big data, artificial intelligence, satellite internet and other new generation technologies, which can not only promote the flow and sharing of technology between enterprises and regions, but also can effectively reduce the cost and time of enterprise research and development and stimulate technological progress. According to the column (2) of Table 5, the regression coefficient of digital infrastructure is significantly negative at the 1% level, and the regression coefficient of technological progress is significantly positive at the 10% level. Therefore, we quantify the contribution of progress effects to energy and environmental efficiency in the context of digital infrastructure development and provide additional insights on how digital infrastructure affects energy-environmental efficiency through technological progress.

5.2.2 Structure effect

We examined the accumulation effect on energy-environmental efficiency by introducing energy industry advancement. In the same way, to test whether digital infrastructure promotes energy-environmental efficiency by affecting the energy industry advancement, we selected the proportion of industrial added value to GDP to measure the energy industry advancement. The empirical results are reported in Table 5. We find that the coefficient of digital infrastructure is significantly positive at the 5% level in column (3). The estimates show that the digital infrastructure contributes positively to the improve the energy industry advancement. Influenced by the high permeability of digital technology, digital infrastructure has spillover effects in the creation of new industrial models, technological innovation and high value-added flow of factors. The positive externalities generated by digital infrastructure will boost the investment demand of enterprises and consumers, strongly promote the integration of energy consumption markets, induce a large amount of investment into the downstream market of energy industry, and drive the development of energy industry structure in the direction of advanced. According to the column (4) of Table 5, the regression coefficient of digital infrastructure is significantly negative at the 1% level, and the regression coefficient of energy industry advancement is significantly positive at the 10% level. That is, the energy industry advancement has improved energy and environmental efficiency, which has been proved.

5.3 Heterogeneity analysis

We observe regional differences in the effect of digital infrastructure on energy-environmental efficiency. The study divides the whole samples into three groups: the eastern region, and the central and western regions according to the China Statistical Yearbook. The results of regional heterogeneity are shown in Table 6. The results show that the effect of digital infrastructure on energy-environmental efficiency is significant in the eastern region, that is, the digital infrastructure improve the improvement of energy-environmental efficiency the eastern region. The promotion effect of digital infrastructure on energy and environmental efficiency is not significant in the central and western regions.

Table 6 reports the test results of the heterogeneity of factor allocation. Among them, the regression coefficient of digital infrastructure in areas with low factor mismatch is not significant, while the regression coefficient of digital infrastructure in areas with high factor mismatch is 0.8, which is significant at the statistical level of 5%. This shows that for regions with low factor allocation efficiency, digital infrastructure construction can accelerate the optimal allocation of factors, while for regions with high factor allocation efficiency, digital infrastructure has a limited role in promoting energy and environmental efficiency. Areas with a high degree of factor

TABLE 6 Heterogeneity analysis result.

	(1)	(2)	(3)	(4)	(5)
	eastern	central region	western region	high factor mismatch	low factor mismatch
Diginf	0.1197** (0.053)	0.0791 (0.082)	0.0182 (0.033)	0.0707** (0.029)	0.0597 (0.052)
Control	Y	Y	Y	Y	Y
constant	−2.2989 (3.418)	−3.7482 (2.365)	1.0696 (1.057)	4.1848** (1.519)	−3.6799** (1.523)
Time FE	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y
Observations	0.763	0.920	0.859	0.899	0.827
R-Squared	88	64	88	96	144

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level; T-statistics are reported in parentheses.

TABLE 7 Analysis results of endogeneity issues.

	(1)	(2)
Diginf	—	0.1405*** (0.036)
L.Diginf	0.0842** (0.041)	—
Control	Y	Y
constant	0.5362 (1.387)	1.0618 (0.9083)
Time FE	Y	Y
Province FE	Y	Y
Observations	0.751	0.953
R-Squared	240	240

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level; T-statistics are reported in parentheses.

mismatch have great room for improvement in the optimal allocation of energy industry factors. The construction of digital infrastructure can accelerate the upgrading of the energy industry to the high end of the value chain, enhance the advanced allocation ability of the flow of energy industry elements, and improve the energy-environmental efficiency.

5.4 Robustness test

5.4.1 Analysis of endogeneity issues

Furthermore, in order to alleviate the possibility of bidirectional causality in regression, this study conducted regression with digital infrastructure lagging behind by one order, and the results are shown in Table 7. As shown in column (1) of Table 7, the digital infrastructure with a lag order has a significant positive effect on energy and environmental efficiency, which also further confirms that the impact of digital infrastructure construction has a lag effect. To further alleviate the estimation bias caused by the endogeneity of variables, this article uses the first-order lag of digital infrastructure as a tool variable for two-stage least squares estimation. The results are shown in column (2) of Table 7, and it can be found that the conclusion has not changed significantly.

5.4.2 Excluding cities directly under the central government

In order to exclude the bias of the estimation results caused by the difference of regional economic development and to enhance the universality of the results of the impact of digital infrastructure on energy and environmental efficiency, and considering that the cities directly under the central government (Beijing, Tianjin, Shanghai and Chongqing) are more economically developed and have advantages in the development of digital economy and the quality of technical personnel, the sample data of cities directly under the central government are excluded from this paper, and the further estimation results are shown in Table 8. The estimation results show that the positive effect of digital infrastructure on energy and environmental efficiency is significant at the 1% level, and the estimation results of this study are well robust, which is consistent with the expectation.

5.4.3 Replacing explained variables

Considering that the core explanatory variables may have measurement bias, this study takes the number of Internet domain names as a replacement variable for digital infrastructure from the perspective of industry digitization. Internet domain names, as a key basic resource of the Internet, reflect the scale of network development and the popularity of the Internet industry in

TABLE 8 Robustness test result.

	(1)	(2)	(3)	(4)
Diginf	0.0976** (0.035)	0.0889** (0.035)	—	—
substitute variables	—	—	0.2535*** (0.066)	0.2412** (0.094)
Control	Y	Y	Y	Y
constant	0.0102 (0.432)	−0.2270 (1.030)	−0.2896 (0.364)	0.9313 (1.239)
Time FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Observations	0.720	0.815	0.691	0.752
R-Squared	208	208	240	240

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level; T-statistics are reported in parentheses.

the digital era. The corresponding regression results are shown in Table 8. The coefficient of the effect of the replaced digital infrastructure variable on energy-environmental efficiency is still significantly positive, which is consistent with the estimated results obtained from the previously used measures.

6 Conclusions and implications

Digital infrastructure has become an important engine to promote the structural transformation of traditional industries and the development of innovative industries. The relationship between digital infrastructure and environmental performance is also of great interest. In the context of China's accelerated layout of digital infrastructure, we quantitatively identify the different impacts and mechanisms of digital infrastructure on energy and environmental efficiency from multiple perspectives. We selected the panel data of 31 provinces in China from 2010 to 2017, and used multiple regression models to investigate the effect, mechanism and heterogeneity of digital infrastructure on energy and environmental efficiency. The findings of the study are as follows: First, the digital infrastructure promotes energy-environmental efficiency, which remains robust after a series of tests. We also found that the impact of digital infrastructure on energy and environmental efficiency has a lag effect. Second, technological progress and energy industry advancement are the pathways through which digital infrastructure affects energy-environmental efficiency. Furthermore, we find that the positive effect of digital infrastructure on energy and environmental efficiency is significant in the east and where factor mismatch is high.

Based on the findings of this study, the following policy implications were obtained.

The promotion effect of digital infrastructure construction on energy and environmental efficiency has been effectively verified. Therefore, it is necessary to comprehensively deploy and accelerate the construction of digital infrastructure, improve energy and environmental efficiency, and promote green development. To this end, first, the government should increase the capital, labor and technology investment in digital infrastructure construction to enhance the scale of regional digital infrastructure construction; Second, we should accelerate the cultivation of artificial intelligence, big data, cloud computing and other digital technologies, deepen the market value of digital technology, and improve the service effect of digital infrastructure construction; Third, we should use digital infrastructure inputs to improve the automation and digitization of production processes and energy use, and effectively improve the efficiency of energy resource use. In addition, we need to accelerate the integrated development and widespread use of digital infrastructure inputs and environmentally friendly technologies to digitally innovate energy management and use, and strengthen digitalization in the energy sector.

Based on the differential characteristics of regional resource endowment and factor allocation of energy industry, the optimal resource allocation mechanism of digital infrastructure construction is given full play. The research results show that digital infrastructure plays a stronger role in the eastern region and the region with low factor allocation efficiency. Therefore, the government should formulate targeted policies and plans for the construction of digital infrastructure, meet the actual needs of regional development, reasonably allocate the production materials for digital infrastructure construction, so as to reduce environmental pollution and improve energy efficiency.

We need to use digital infrastructure inputs to promote energy technology advancement and efficiency improvement. Firstly, the development of high-end energy industry should be accelerated, and the transformation and upgrading of the energy industry structure should be promoted by making full use of digital infrastructure inputs. Secondly, we should make full use of digital infrastructure investment to enhance the technological innovation capacity of the energy industry, and promote the energy industry to speed up the renewal of technical equipment and process optimization and upgrading. Thirdly, we should enhance investment in science and technology innovation, increase the exchange of talents and technical cooperation in digital infrastructure construction, focus on the core digital frontier and disruptive innovation technologies, strengthen the exchange and cooperation of digital talents and technologies between regions, alleviate the imbalance of regional digital infrastructure construction.

There are several aspects worth further exploration in the future of this research. Firstly, more mechanisms can be explored to explain the impact of digital infrastructure on energy and environmental efficiency from different perspectives. Second, this study provides a detailed explanation of the heterogeneity of the impact of digital infrastructure on energy and environmental efficiency under different conditions, and provides corresponding policy insights. In the future, the impact of digital infrastructure on energy and environmental efficiency can be quantified from a more microscopic perspective, providing more specific corporate behavior.

Data availability statement

The original contributions presented in the study are included in the article/supplementary materials, further inquiries can be directed to the corresponding author.

Author contributions

XS: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Methodology, Project administration, Resources, Software, Supervision, Visualization, Writing–original draft, Writing–review and editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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