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How digital technology affects regional energy intensity from the perspective of energy economy: a case study of the Yangtze River economic belt

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This study aims to explore the impact of digital technology innovation on energy efficiency and energy intensity, and further provide new insights for addressing emerging challenges in energy economics. Focusing on the panel data of 11 provinces and cities in the Yangtze River Economic Belt from 2010 to 2020, this study thoroughly investigates the process by which the digital economy influences regional energy intensity through the mechanism of technological spillovers, utilizing the fixed-effect model, the mediated-effect model, and the spatial Durbin model. The systematic empirical analysis clearly demonstrates that the vigorous development of the digital economy significantly reduces regional energy intensity, and this effect remains stable after tests for endogeneity and robustness. Further analysis reveals that green technology innovation is a crucial pathway through which the digital economy reduces regional energy intensity. Additionally, the digital economy positively and indirectly lowers the energy intensity of neighboring provinces through technological spillovers. However, it is noteworthy that the rapid growth of the digital economy since 2017 has also triggered the so-called "energy rebound effect," which has led to an increase in energy consumption in neighboring regions to some extent. Therefore, to achieve a sustainable reduction in regional energy intensity and promote coordinated regional development, it is essential to continuously strengthen the development of a digital economy centered on digital technology to fully realize its technological spillover effects. These findings not only provide a scientific basis for the formulation of regional energy policies but also offer valuable insights for China in promoting green development and achieving the goals of carbon peaking and carbon neutrality.

KEYWORDS

digital economy1, energy intensity2, green technology innovation3, spatial spillover effect4, Yangtze River economic Belt5

1 Introduction

Global climate issues have become a serious concern for countries around the world, and energy intensity has a direct impact on the trajectory of climate change. According to the Carbon Dioxide Emissions 2023 report released by the International Energy Agency (IEA), carbon dioxide emissions from global energy consumption will reach a record high in 2023. General Secretary Xi Jinping, on behalf of China and the Chinese people, has clearly stated to the world the strategic goal of "carbon capping and carbon neutrality". To realize these meaningful goals, it is necessary to make innovative breakthroughs in theoretical concepts and technical methods. The 14th Five-Year Plan clearly proposes that by 2025, energy consumption per unit of GDP will be 13.5% lower than in 2020, and makes the digital economy a key factor in achieving carbon neutrality. Chinese government reports also emphasize the importance of accelerating the development of the digital economy and promoting green and low-carbon production technologies. With the rapid development and application of technologies such as artificial intelligence, big data, the Internet of Things, and cloud computing, the digital economy has become a core pillar of the global economy and an important driving force for the evolution of the global industrial structure to a higher level (Liu and Shi, 2024). These technological innovations have not only greatly enriched the connotation of the digital economy, but also laid a solid foundation for its vigorous development worldwide. According to the China Digital Economy Development Report (2023) issued by the China Academy of Information and Communications Technology, the scale of China's digital economy climbed to 50.2 trillion yuan in 2022, with a year-on-year growth of 10.3%, surpassing the nominal growth rate of GDP for 11 consecutive years, and has become an emerging mode and a powerful driving force to promote China's sustainable green economic growth. The digital economy has not only opened up a new development path for the Chinese economy, but also played a pivotal role in shaping new productivity and promoting industrial upgrading, becoming an important strategic fulcrum for China's economic development. In the process of green growth, the new digital economic growth model has both direct and indirect impacts on energy consumption. The direct impact includes the increase in energy consumption due to the investment, construction, operation, maintenance and production of supporting facilities in the development of the digital economy. Indirect im-pacts include the ability of the digital economy to reduce energy intensity by eliminating redundancies in production and improving the efficiency of energy use, transmission, and management (Lange et al., 2020). How the digital economy contributes to energy consumption requires data analysis to elucidate the underlying mechanisms.

As the core engine of China's high level of economic development, the Yangtze River Economic Belt has been positioned as an innovation-driven zone for the development of the digital economy, a green demonstration zone for ecological protection and restoration, and a coordinated development zone for the promotion of regional cooperation through innovative institutional mechanisms. The Yangtze River Economic Belt consists of 11 provinces and municipalities directly under the central government, and by 2021, the digital economy of nine provinces and municipalities directly under the central government, namely, Jiangsu, Zhejiang, Shanghai, Hubei, Sichuan, Hunan, Anhui, Chongqing and Jiangxi, will total more than one trillion yuan. Zhejiang, Shanghai, Hubei, Sichuan, Hunan, Anhui, Chongqing and Jiangxi, as the key regions of digital economy development and high intensity of energy consumption, provide a typical and reference case.

Existing research on the relationship between the digital economy and energy intensity is largely limited to examining whether there is a positive effect, identifying influencing factors, and assessing the impact. However, it does not extensively explore the mechanisms and efficiency of the positive impact of the digital economy on energy intensity. This study focuses on the following key issues: Can the digital economy effectively curb the growth of energy intensity? And how does the digital economy affect energy intensity? Are there spatial spillovers? This study attempts to address these key issues by employing fixed effects, mediation effects, and spatial effects models, thereby bridging existing research gaps. It aims to contribute to the cultivation of new productivity and the reduction of regional energy intensity in China.

2 Literature review

With the rapid progress and continuous innovation of digital technology, the digital economy has become the "core driving force" of national economic growth (Singhal et al., 2018; Chen et al., 2019). With digital technology as the core driving force, the digital economy is creating a new operating paradigm, promoting the formation of new industries, while injecting new vitality into traditional industries, and leading the digital transformation of the world economy. Since the concept of digital economy was put forward (Tapscott, 1996), it has passed through many important development stages from information economy to Internet economy to new economy with the continuous progress of science and technology and the constant change of social needs (Brent and Steven, 1999; Turcan and Juho, 2014; Zhang et al., 2020). Under different historical backgrounds and time environments, the connotation and expansion of the digital economy have their own focus and expansion, showing rich diversity and dynamics, and has not yet formed a unified definition of the standard. Chen et al. provide a more comprehensive interpretation: the digital economy is a new economic model and industry that is diversified and characterized by the use of digital information as the cornerstone resource, the use of the Internet platform as the main medium for in-formation transmission, and the use of digital technological innovation as the key driving force, as well as the development of new economic models and industries. It is a comprehensive economic activity that manifests itself in diversified new economic models and business forms (Chen et al., 2022). This definition not only covers the core elements and characteristics of the digital economy, but also reveals its far-reaching impact on economic development and social progress.

The development of digital economy has greatly promoted the creation of new and diversified business forms and modes in primary, secondary and tertiary industries, which not only promotes the optimization and upgrading of industrial structure, but also further accelerates the profound transformation and comprehensive improvement of the way of life and production mode in modern society. At present, the discussion on the impact of digital economy on energy intensity presents various views, although a unified consensus has not yet been formed, but most researchers tend to believe that the digital economy has a positive inhibitory effect on energy intensity through in-depth analysis and practical observation. Li Ming's study delves into the important role of the digital economy in promoting the global low-carbon transition and helping more cities become green cities. He clearly points out that with the rapid development and wide application of digital economy related technologies, these technologies can greatly stimulate the vitality of technological innovation within industries, promote the green transformation and upgrading of traditional industries, and thus significantly reduce energy intensity, providing solid support and strong impetus for the low-carbon sustainable development of Chinese cities (Li and Yusuf, 2023). This attention stems from the central position of the digital economy in the modern economic system and its potential role in improving the efficiency of resource use and promoting green development. To gain a deeper understanding of this relationship, recent studies have generally adopted quantitative analysis methods to analyze in detail the actual impact of the digital economy on energy consumption by con-structing rigorous mathematical models and statistical techniques. For example, in a study on the factors influencing carbon emissions in the Yangtze River Economic Belt, researchers used a spatial panel econometric model, which showed that economic growth has the potential to improve carbon emission efficiency, which is more important relative to other factors (Cai et al., 2022; Liu and Hao, 2022; Li et al., 2024). In addition, Li's research reveals a non-linear relationship between digital economic growth and carbon emissions, a relationship that is centrally driven by the unique network effects of the digital economy (Li et al., 2021). Through its extensive information connectivity and efficient resource allocation capabilities, the digital economy promotes economic growth while potentially increasing carbon emissions. However, with the further development of the digital economy, its network effect gradually appears, which promotes technological innovation and efficiency improvement, and then re-duces carbon emissions per unit of output. Cai, A. et al. used a spatial panel econometric model based on the STIRPAT equation to analyze panel data from 30 provinces in China. They found that the spatial spillover effect of inter-provincial carbon dioxide emissions is significant. The green technological progress in surrounding provinces has a negative impact on carbon emissions in the province (Cai et al., 2021).

In addition, the spatial impact of the digital economy has become a focus of aca-demic attention. The cross-border sharing and interconnectivity characteristics of the digital economy can overcome the inherent limitations of geographic distance and in-crease the breadth and depth of connections between cities (Fan et al., 2023). Digital elements, as critical factors of production in the digital economy, are non-competitive, have near-zero marginal costs, and are shareable. Using the spatial Durbin model and the spatial DID model, Xu et al. found that the development of the digital economy significantly reduces carbon emissions in both the region and the surrounding areas. However, due to changes in geographical boundaries, the spatial spillover effects of carbon reduction from the digital economy vary significantly across different economic circles (Xu et al., 2022). The strong spatial connectivity and deep integration of the digital economy provide new opportunities for regionally coordinated development and help advance the carbon reduction process. The cross-regional role of the digital economy can also help build a cooperative model for carbon reduction and achieve sustainable development (Liu and Chen, 2023; Mohsin et al., 2024).

Although early academic research has provided a theoretical foundation for stud-ying the influence of the growth of the digital economy on regional energy intensity, existing studies have limitations. Firstly, the majority of research concentrates on the correlation between the digital economy and carbon emissions, with fewer investigations delving into its connection with energy intensity. Secondly, most studies adopt national, provincial, or city-level viewpoints, with limited attention given to mesoscopic perspective from the regional coordinated development strategy. Thirdly, there is a scarcity of studies analyzing the intensity of energy consumption through the lenses of technological and spatial effects. Instead, most research relies on conventional econometric models to examine what digital economy play a role in the energy costs.

There are the prospective innovations and significance of this research. First, the study integrates the mechanisms through one another by which the digital economy and green technological innovation shape energy intensity, and investigates the spatial spillover effects of the digital economy on energy intensity, paying special attention to spatial and temporal variations. Second, this study shifts from a macro to a micro perspective by selecting a representative region for analysis. This approach aims to pro-vide a clearer examination of the relationship between the digital economy and energy intensity in the context of regional coordinated development. Third, the empirical analysis conducted in this study can provide theoretical support and policy insights for China to achieve a low-carbon and green world environment and human welfare.

3 Theoretical analysis and research hypotheses

3.1 The direct and indirect effects of the digital economy

According to existing research, the digital economy's influence through both direct and indirect pathways. Firstly, the digital economy can directly play an important role. National policies that support digital economy industries also facilitate coordinated development across industries, strengthen inter-industry linkages, and improve energy use efficiency (Zuo et al., 2020; Dzwigol et al., 2024). Wu and Gao by exploring the relationship between the digital economy and low-carbon industries, used energy intensity as a substitute variable and conducted robustness tests, finding that the digital economy negatively impacts energy intensity (Wu and Gao, 2020). Zhang and Wei argue that information and communication technology (ICT) complements other pro-duction factors, driving technological progress in enterprises (Zhang and Wei, 2019).

However, many scholars believe that technological innovation in the age of digital economy is the key factor in reducing energy intensity. Data resources that inherently possess green attributes exhibit the characteristics of "Metcalfe's Law", where marginal benefits far exceed marginal costs in terms of environmental performance (Zhang et al., 2024). Research based on technology diffusion theory finds that innovation caused by technology diffusion can promote the optimal allocation of resource elements, improve production efficiency, and innovate organizational models, exhibiting the "Davidow effect" that forces the elimination of obsolete manufacturing capacity and promotes transformation and upgrading (Wang et al., 2021a; Hanelt et al., 2020). Some scholars also argue that the development of the digital economy can cause the expansion of economic scale, which increases the demand and consumption of resources (Li et al., 2010). Overall, the impact of the digital economy on the intensity of energy consumption changes during its development stages. This means that the knowledge spillover effect from the advancement of digital technology plays a vital role in improving pro-duction and power efficiency and reducing energy consumption (Wang and Yu, 2024).

Based on these mechanisms, this study puts forward the following hypotheses.

H1. The digital economy has a suppressive effect on energy intensity.

H2. The digital economy reduces energy intensity via technological progress.

3.2 Digital Economy's spillover effects

Geographically, the distribution characteristics of regions determine a certain degree of interconnection, with closer ties in neighboring regions. As Bai and Chen found in their research, the development of digital technology is not constrained by space and can broadly and quickly impact the economic and cultural development of surrounding areas through the free dissemination of information (Bai and Chen, 2022). According to Raúl Prebisch's "center-periphery" theory, regions form a unified dynamic system where advanced regions spread advanced technologies and experiences to other regions. Digital media facilitate the increase in diffusion speed and expansion of diffusion scope, enhancing the spillover effect. In their research on the impact and mechanism of the development of the digital economy on environmental pollution in Chinese cities, Deng and Zhang found that the digital economy can affect environmental pollution in surrounding regions through spatial spillover effects (Deng and Zhang, 2022). From the perspective of the dynamic diffusion or spillover effects of the digital economy, this technology spillover effect first occurs within the information technology production sector (Cecconelli et al., 2012), then spreads to the information technology usage sector, improving energy efficiency in enterprises and even across the entire industry. For regions with high total energy consumption, technology diffusion can bring significant "demonstration effects" on energy. From a regional development perspective, this can significantly reduce energy intensity.

Therefore, the study proposes hypothesis H3.

H3. The digital economy can decrease the energy intensity of neighboring regions via technology spillover.

4 Model methodology and variable explanation

4.1 Model methodology

To examine hypothesis H1, we formulate the econometric model below to investigate the influence of the digital economy:

$$\ln \mathrm{EI}_{it} = \gamma_0 + \gamma_1 \ln \mathrm{Dige}_{it} + \gamma_c \mathrm{Control}_{it} + \beta_i + \mu_t + \varepsilon_{it} \quad (1)$$

In Equation 1, i is the province and t indicates the year; *EI* means the energy intensity; *Dige* stands for the level of integrated development of the digital economy; *Control* represents the control variables that influence the energy intensity; γ_0, γ_1,and γ_c are the coefficients to be estimated, with γ_1 representing the direct effect of the digital economy on energy intensity, and γ_c representing the direct impact of control variables on energy intensity; β_i represents the province fixed effects, which control for province-specific characteristics; μ means the year fixed effects; ε is the random error term.

This study also examines whether green technological innovation acts as a mediation variable for the effect of the digital economy on energy intensity, thereby testing hypothesis H2. The specific model for this analysis is as follows:

$$\boldsymbol{\ln EI_{it} = \alpha_0 + \alpha_1 lnDige_{it} + \alpha_c Control_{it} + \beta_i + \mu_t} + \varepsilon_{it} \quad (2)$$

$$\boldsymbol{lnGTI_{it} = \gamma_0 + \gamma_1 lnDige_{it} + \gamma_c Control_{it} + \beta_i} + \mu_t + \varepsilon_{it} \quad (3)$$

In Equations 2, 3, GTI denotes the green technology innovation; α_0 and γ_0 are selected to be constant terms. In addition to these, α_1, α_c, γ_1, γ_c are selected to be coefficients to be estimated.

Subsequently, in order to test hypothesis H3, this paper uses a spatial Durbin model for testing, which is shown in the following equation.

$$\boldsymbol{\ln EI_{it} = \gamma_0 + \rho W \ln EI_{it} + \varphi_a WGTI_{it} + \gamma_1 GTI_{it} + \varphi_b WControl_{it} + \gamma_c Control_{it} + \beta_i + \mu_t} + \varepsilon_{it} \quad (4)$$

In Equation 4, ρ and W represent the spatial autoregressive coefficient and spatial weight matrix, respectively. φ_a and φ_b represent the spatial interaction term elasticity coefficients of the explanatory and control variables, respectively. This spatial Durbin model takes into account the spatial dependence and spatial spillover effects of energy intensity across provinces by introducing a spatial lag term.

4.2 Variable explanation

4.2.1 Core explanatory variable: digital economy

As an emerging sector, the academic research community has not reached a consensus on how to measure the digital economy. Nevertheless, there is a substantial body of digital economy research at the Chinese provincial level. This study summarizes existing

TABLE 1 Metrics for assessing the digital economy level.

Core metric	Secondary metrics	Weight
Industrial Digitalization	Employment in information services	0.070
	Total postal business	0.181
	Total express business	0.198
	Total telecom business	0.124
Digital Industrialization	Total distance of fiber optic cable	0.067
	Total number of domain names	0.084
	Total number of web pages	0.143
	Number of mobile phone users at year-end	0.043
	Mobile phone user penetration rate	0.296
	Number of broadband internet access users	0.061

research experiences and draws on the methods of Wang M. et al. (2021) and Yue and Zhang, 2023; Wang J. et al., 2021; Yue and Zhang, 2023). Industrial digitalization and digital industrialization are two ways of understanding the digital economy. Ten secondary indicators are selected: employment, mail turnover, express turnover, telecommunications turnover, total distance of fiber optic cable, total number of domain names, total number of web pages, mobile phone users at the end of the year, mobile phone penetration rate, and broadband Internet subscribers. These indicators form the rating level of the digital economy at the provincial (municipal) stage in the Yangtze River Economic Belt, as shown in Table 1.

Based on the above metrics, the initial data is standardized, and the entropy technique is utilized for dimensionality reduction to form the comprehensive level of digital economy development index Dige, which serves as the major explanatory variable in this paper. The logarithm of this indicator is then taken for further analysis.

4.2.2 Dependent variable: Energy intensity

As provided below, energy intensity in this paper is defined as the ratio of energy consumption to emissions.

$$\textbf{\textit{Energy Intensity}}\,(\textbf{\textit{EI}}) = \frac{\textbf{\textit{Total Energy Consumption}}\,(\textbf{\textit{10kt of standard coal}})}{\textbf{\textit{Gross Regional Product}}\,(\textbf{\textit{ten thousand yuan}})}$$

4.2.3 Mediating variable: green technological innovation

This study selects green technological innovation (GTI) as the mediating variable. Green technological innovation refers to the concept of green sustainable development, the pursuit of commercial value brought by technological innovation, while paying attention to the social value of environmental protection and resource utilization. In the study of the impact of digital economy on energy consumption intensity, green technological innovation, as a mediating variable, mainly plays a bridging and transferring role. Specifically, the digital economy provides a strong technical support and power source for green technological innovation by promoting the development and application of advanced technologies such as information technology, big data and artificial intelligence. These advanced technologies can promote the optimization and upgrading of all aspects of energy production, transmission and consumption, thereby reducing the intensity of energy consumption. Most scholars currently use the number of patents granted as a measure of green technological innovation. Therefore, following the approach of Deng and Bai (Deng ang Zhang, 2022; Bai and Jiang, 2011), this study uses the logarithm of the number of green invention patents granted per 10,000 people as the measure of green technological innovation.

4.2.4 Control variables

What's more, this study selects five control variables to account for factors influencing changes in the intensity of energy. The following are the specific definitions of each variable:

The Direct Investment of Foreign (*lnFDI*): Represented by the logarithm of the ratio between the real cost of investment from foreign and the GDP for each province (municipality) annually. Foreign direct investment (FDI) contributes to reducing energy intensity and improving energy use efficiency through technology transfer, industrial upgrading and efficiency improvement. However, if FDI focuses mainly on energy-intensive industries or industries with lower environmental standards, it may lead to increased energy consumption and higher energy intensity. Therefore, the impact of FDI on energy intensity is a complex and multidimensional topic, and its effects may vary depending on factors such as region, industry, technology level and policy environment.

The Trade Level of Foreign (*lnFTL*): Represented by the logarithm of the ratio of the total import and export trade amount to GDP for each province (municipality) in a given year. The development of foreign trade will change the structure of domestic energy demand. On the one hand, export-oriented industries may increase the demand for energy, especially energy-intensive industries; on the other hand, with the deepening of international trade, there may be greater domestic introduction of cleaner energy technologies and products, thus optimizing the structure of energy consumption and reducing dependence on fossil energy.

The Structure of Industrial (*IS*): Represented by the ratio of the added value of the tertiary industry to GDP for each province (municipality) in a given year. With the upgrading and transformation of the industrial structure, the amount and type of energy demanded by different industries will change. Generally speaking, primary industries have a relatively low demand for energy, while high-energy-consuming industries such as heavy industries have a higher demand for energy. Therefore, when the proportion of heavy industry in the industrial structure increases, energy intensity tends to rise; while when the proportion of low-energy-consuming industries, such as services and high-tech industries, increases, energy intensity decreases.

The Expenditure of Scientific (*SE*): Represented by the ratio of scientific expenditure to GDP for each province (municipality) in a given year. Science expenditure helps to promote scientific and technological innovation and technological progress, promotes the optimization and upgrading of the industrial structure, facilitates the transformation of the economy from high-energy-consuming and high-polluting traditional industries to low-energy-consuming and

TABLE 2 Descriptive statistics of variables.

Variable	Observation	Mean	S.D.	Minimum	Maximum
lnEI	121	−9.837	0.355	−10.460	−8.617
lnDIGE	121	−2.163	0.915	−4.090	−0.130
lnFDI	121	−3.696	0.701	−6.329	−2.585
lnFTL	121	−1.610	0.959	−3.563	0.501
IS	121	0.094	0.124	−0.014	0.509
SE	121	0.005	0.003	0.002	0.013
lnHPV	121	11.04	1.096	7.194	12.53
lnGTI	121	7.718	1.116	4.977	10.45

low-polluting high-tech industries, and reduces the waste of resources, thereby lowering the overall energy consumption.

Highway Passenger Volume ($lnHPV$): Represented by the logarithm of the total passenger volume for each province (municipality) in a given year. In general, the development of the transportation sector is the main driver of increased energy consumption and carbon emissions. Increased road passenger traffic means more vehicles on the road, which will result in more fuel consumption, which usually leads to a rise in energy consumption, which in turn leads to a rise in energy intensity, i.e., an increase in the amount of energy consumed per unit of economic activity or output.

TABLE 3 Multicollinearity test results.

Variable	VIF	1/VIF
lnDIGE	2.33	0.43
lnFDI	2.18	0.46
lnFTL	2.30	0.43
lnHPV	3.07	0.33
IS	1.95	0.51
SE	4.55	0.22
Mean VIF	2.73	

4.3 Data sources and statistical analysis

The data utilized to research and data analysis come from the "China Statistical Yearbook" and the CNRDS database. This study selected data spanning 2010–2020 from 11 provinces (municipalities) within the Yangtze River Economic Belt, creating a panel dataset consisting of 121 observations over 11 years for these provinces. To enhance data stability and minimize fluctuations, the dependent variable and certain control variables underwent logarithmic transformation.

Descriptive statistics for the variables in this study are outlined in Table 2. The highest recorded value of $lnEI$ is −8.617, while the lowest is −10.46, with a standard deviation of 0.355. For lnDIGE, the maximum value is −0.130, the minimum value is −4.090, and the standard deviation is 0.915. These statistics reveal considerable variations in the development of the digital economy among the provinces and municipalities of the target region of research.

4.4 Data processing and model selection

4.4.1 Multicollinearity test

Multicollinearity occurs when there are high or exact linear correlations among the explanatory variables in a linear regression model, potentially skewing the estimates or complicating accurate estimation. Conducting a multicollinearity test helps assess the correlation levels among the independent variables, allowing for necessary adjustments to the model or more informed interpretation of the regression outcomes, thus improving the model's explanatory capacity.

In this research, the Variance Inflation Factor (VIF) is the primary method used to assess multicollinearity. The VIF quantifies the extent of multicollinearity for each independent variable. A VIF value below 10 suggests a low correlation among the independent variables, indicating minimal negative impact on the accuracy of the regression model. As the outcome of Table 3, it presents the results of the multicollinearity test, showing that all variables have VIF values below 10. This confirms that there is no significant multicollinearity among the independent variables in the analysis.

4.4.2 Model selection

In selecting the baseline regression model, this study initially tested for individual fixed effects, yielding a P-value of 0.000, which is significant at the 1% level, indicating the presence of individual fixed effects. Next, time fixed effects were tested, also resulting in a P-value of 0.000 from the F-test, confirming the existence of time fixed effects. These findings suggest that the fixed effects model is preferable to the mixed effects model. Lastly, the Hausman test produced a P-value of 0.001, passing the 1% significance threshold, indicating that the fixed effects model is more appropriate than the random effects model. Consequently, this study opted for the two-way fixed effects model for the regression analysis, incorporating both two type fixed effects.

TABLE 4 Benchmark regression results.

Variables	(1)	(2)	(3)	(4)
lnDIGE	−0.363*** (-15.58)	−0.418*** (-16.50)	−0.084* (-1.78)	−0.126** (-2.00)
lnFDI	−0.163*** (-5.21)	−0.104*** (-3.97)	−0.090*** (-3.26)	−0.068*** (-2.76)
lnFTL	0.104*** (3.70)	0.131*** (3.09)	−0.066* (-1.79)	0.099** (2.14)
lnHPV	0.114*** (4.53)	0.021 (0.70)	0.007 (0.24)	−0.017 (-0.49)
IS	0.548** (2.54)	−0.857** (-2.03)	0.716*** (3.76)	−0.684* (-1.68)
SE	29.439*** (2.58)	20.917** (2.11)	14.45 (1.47)	17.907** (2.06)
Effects of Time Fixed	NO	NO	YES	YES
Effects of Province Fixed	NO	YES	NO	YES
Constant term	−12.5219*** (-32.37)	−11.172*** (-31.65)	−10.309*** (-21.55)	−9.686*** (-19.22)
R^2	0.876	0.911	0.911	0.942
Observations	121	121	121	121

Note: *, **, *** indicate significance at the 10%, 5%, and 1% probability levels, respectively. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

5 Regression analysis of the impact of the digital economy on energy intensity

5.1 Baseline regression analysis

This paper establishes a examine based on model (1), to determine the connection between objectives of our study. Table 3 presents the baseline regression consequence of this study. So as to ascertain the connection between objectives of our study, the author has conducted a test based on model (1), and Table 3 presents the examine consequence of this study. In Table 4, column (1) demonstrates that the regression coefficients of the digital economy on the intensity of energy are negative when the regression analysis is putting into effect without fixing the province and time. This result passes the highest level of significance test. Concurrently, adjusted for both time and provincial factors, the findings of the study reveal that the core explanatory variable powerfully reduces energy intensity at the 10% significance level. Finally, the study, in part (4), applies a model of two-way fixed-effects with fixed time and provinces simultaneously. This analysis indicates that the coefficient of the core explanatory variable shows a negative value at the 0.01 significance level. This implies that for every 10% growth of the core explanatory variable in the target area of research, the intensity of energy consumption will be reduced by 1.26%. This result provides compelling evidence of the significant function of the digital economy in reducing energy consumption, which is supported by the earlier studies (Guo et al., 2023; Huang et al., 2023; Zeng et al., 2023). The profound interpenetration of the core explanatory variable with the real economy has compelled traditional industries in the Yangtze River Economic Belt to undergo digitalization, networking, and intelligent innovation. In this process, new models relying on the digital economy have emerged, which have significantly reduced energy consumption in the production and consumption chain. This is due to their ability to efficiently disseminate and share information. The efficiency of the process of energy industry, from production to consumption, has been markedly enhanced, thereby demonstrating the remarkable efficacy of using digital technology in promoting low carbonization of production. Therefore, hypothesis H1 is validated.

5.2 Endogeneity test

There is a powerful correlation between the objectives of our study. Firstly, energy, as a fundamental input to digital infrastructure, is a vital resource for its advancement (Huang et al., 2023). Changes in regional energy consumption are directly related to the mode and efficiency of economic operation, which in turn have a profound influence on the development and progress of the digital economy (Xue et al., 2022). Concurrently, the digital economy exerts a direct or indirect influence on partial energy costs (Schulte et al., 2016; Guo et al., 2022) Given the potential bidirectional causality between the objectives of our study, it is imperative to conduct endogeneity testing to ensure the research findings possessing the accuracy and reliability.

In this paper, we refer to the research methods of the earlier researches (Yue and Zhang, 2023; Huang et al., 2019; Tao et al., 2022), and select the historical postal and each partial telecommunications data as an instrumental variable to measure the level of development of the core explanatory variable. This choice is based on two main reasons: First, historical postal and telecommunication data are closely linked to the evolution of the

TABLE 5 Endogeneity test results.

Variable	First phase	Second phase
	lnDIGE	*lnEI*
IV	0.512*** (6.20)	
lnDIGE		−0.361*** (-2.92)
Control Variables	YES	YES
Effects of Time Fixed	YES	YES
Effects of Province Fixed	YES	YES
Constant term	−9.552 *** (-10.15)	−11.24*** (-17.81)
adj-R^2	0.989	0.965
Observations	121	121
Kleibergen-Paap rk LM statistic		24.221*** [0.000]
Cragg-Donald Wald F statistic		43.773
Kleibergen-Paap Wald rk F statistic		38.459 {16.38}

Note: ***, **, and * denote severally significance at the 0.01, 0.05, and 0.1 levels. The number in parentheses is selected to be z-values. The number in square brackets is selected to be *p*-values. Moreover, the number in curly braces is selected to be essential numbers at the 10% level of test.

digital economy. The modern digital economy can be regarded as a natural continuation of the development of postal and telecommunication business in history. Therefore, the total historical postal and telecommunication business can be used as a historical indicator to reflect the initial state and the level of provincial development in terms of digital communication infrastructure. Secondly, as a historical indicator, the total historical postal and telecommunication business is unlikely to be directly affected by the influence of the digital economy on energy intensity in the Yangtze River Economic Belt during the study period. Furthermore, it has a low correlation with other factors that may affect the intensity of energy, thus fulfilling the situation of exogeneity.

Considering the data's accessibility and convenience, the total volume of postal and telegraphic business of target province in 1996 was selected as an instrumental variable in this paper. However, this data is cross-sectional, therefore model regression analysis cannot be performed directly on it. To address this limitation, we employ the approach of Nunn and Qian (Nunn and Qian, 2014) and introduce a time-varying variable, namely, the number of Internet broadband subscribers in each year. This variable is multiplied by the total amount of postal and telecommunications business in each province in 1996 to construct an interaction term. So as to mitigate the influence of data fluctuations on the findings, this interaction term was logged, and it served as the last instrumental variable (IV). Next, the validity of this instrumental variable was tested using the two-stage least squares (2SLS) approach. The results of the test are detailed in Table 5. The results of the test show that the Kleibergen-Paap Wald rk F statistic of 38.46 significantly exceeds the critical value of 16.38 at the 10% significance level for the Stock-Yogo weak identification test. In addition, the Wald F statistic for the Cragg-Donald weak instrumental variable test is 43.773, which is much larger than the Stock-Yogo weak identification test has a critical value of 16.38 at the 10% significance level, thus also supporting the conclusion that there is no weak instrumental variable problem. This figure conclusively confirms that the instrumental variable used in this study is robust, thereby enhancing the credibility of the model's analysis and the dependability of its findings. The two-stage regression analysis concerning the digital economy and energy intensity demonstrates a distinct negative coefficient for the digital economy, which is statistically significant at the 1% level. This further supports the substantial impact of the digital economy in diminishing energy intensity, consistent with prior regression results. Moreover, this analysis underscores the transformative potential of digital technologies in promoting energy efficiency across various sectors, aligning with global sustainability goals.

5.3 Robustness test

5.3.1 Lagged dependent variable

To more accurately capture the potential time lag in how inputs from the digital economy influence energy consumption, we have employed lagged explanatory variables. The results, as detailed in columns (1) and (2) of Table 6, display the regression outcomes for variables lagged by one and two periods, respectively. These findings reveal that the impact of the digital economy on energy intensity remains negative and statistically significant at the 10% level, which reinforces the robustness of our earlier results. This analysis of lagged variables indicates that the effects are not merely immediate but persist over the long term. As the digital economy progresses,

TABLE 6 Robustness test results.

	(1)	(2)	(3)	(4)
	Lagged One-Period explanatory variables	Lagged two-period explanatory variables	Added Population Control	shrinkage treatment
lnDIGE	−0.128* (-1.89)	−0.163** (-2.19)	−0.117 * (-1.87)	−0.129** (-2.07)
Constant term	−10.043*** (-18.72)	−10.096*** (-18.04)	−15.584*** (-3.95)	−9.631*** (-19.94)
Control Variables	YES	YES	YES	YES
Effects of Time Fixed	YES	YES	YES	YES
Effects of Province Fixed	YES	YES	YES	YES
Observations	121	121	121	121
adj-R^2	0.935	0.927	0.943	0.942

Note: *, **, *** indicate significance severally at the 10%, 5%, and 1% probability levels. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

digital technologies are not only transforming energy consumption but also reshaping the supply and demand dynamics of energy, leading to a profound and enduring influence on energy utilization patterns. This ongoing transformation suggests a sustainable shift towards more efficient energy use facilitated by digital advancements (Xue et al., 2022).

5.3.2 Adding control variables

To account for the possibility of omitted variables influencing energy intensity, this study adds population size as a control variable for further robustness testing. If the province possesses higher population density, it may have higher levels of energy costs, and conversely, lower levels (Deng et al., 2022). To reduce data volatility, the demographic variable is measured by the logarithm of the year-end resident population of each province. Table 6 column (3) provide further evidence for the influence after adding population size as a control variable, indicating that the effect remains significantly negative.

5.3.3 Two-Way Shrinkage treatment of variables

In response to the possible occurrence of extreme values among the control variables, this study adopts the method proposed by Chen et al. by implementing a 1% Two-Way Shrinkage treatment to these variables (Chen et al., 2020). This approach aims to reduce the impact of outliers on the analysis results. As indicated in column (4) of Table 6, the influence of the digital economy on energy intensity continues to be negative and achieves statistical significance at the 5% level. This outcome aligns with several previously discussed findings within this research, demonstrating consistency in the negative correlation between the digital economy and energy intensity across different analytical approaches.

5.4 Mechanism analysis

Drawing from the comprehensive analysis and tests conducted, the hypothesis that "the digital economy suppresses energy intensity" has been substantiated. Nonetheless, further investigation is required to understand the specific mechanisms underlying this effect. To this end, this study employs the mediation effect test method outlined by Wen and Ye (2014), incorporating modifications recommended by Ting Jiang (2022). The primary aim of this mediation effect test is to explore whether the digital economy facilitates green technological innovation. The digital economy, with its powerful data processing and analysis capabilities, provides strong technical support for the research and development of green technologies. Through the application of technologies such as big data, cloud computing and artificial intelligence, enterprises are able to identify market demand more accurately, optimize the research and development process and accelerate the innovation process of green technologies. Green technology innovation effectively reduces energy consumption through the introduction of new energy utilization methods and production modes. While the innovation of green technology promotes intelligent manufacturing, circular economy and other modes, enterprises are able to realize the recycling and efficient use of energy in the production process, thus significantly reducing the intensity of energy consumption. Therefore, the digital economy has introduced new energy utilization methods and production modes through green technology innovation, effectively reducing energy consumption.

Detailed results of the mediation effect test are presented in Table 7. To ensure the robustness of the regression outcomes, this paper adopts a strategy of multiple transformations of fixed effects to analyze the influence of the digital economy on green technological innovation. The findings indicate that, irrespective of adjustments for provincial or temporal factors, the digital economy exerts a significant positive impact on green technological innovation, validated at the 1% significance level. These results underscore the crucial role of the burgeoning digital economy as a catalyst for green technological innovation.

In accordance with the preceding hypothesis, H1, which was validated to show that the digital economy significantly reduces energy intensity, our analysis extends to propose a second hypothesis. We hypothesize that there exists a transmission

TABLE 7 Mediation effect test results.

	(1) *ln GTI*	(2) *ln GTI*	(3) *ln GTI*	(4) *ln GTI*
lnDIGE	0.398*** (3.49)	0.937*** (15.33)	0.600*** (5.31)	0.334*** (2.81)
Constant term	7.735*** (22.11)	10.163*** (11.94)	6.637*** (6.88)	5.829*** (6.15)
Control Variables	NO	YES	YES	YES
Effects of Province Fixed Effects	YES	YES	NO	YES
Effects of Time Fixed	YES	NO	YES	YES
Observations	121	121	121	121
adj-R^2	0.963	0.928	0.967	0.971

Note: *, **, *** indicate significance severally at the 0.1, 0.05, and 0.01 probability levels. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

TABLE 8 Global Moran's I of green technological innovation.

Year	W1		W2		W3	
	Moran's I	p	Moran's I	p	Moran's I	p
2010	0.017	0.103	0.174	0.064*	0.308	0.041**
2011	0.025	0.078*	0.165	0.071*	0.338	0.027**
2012	0.027	0.072*	0.177	0.058*	0.357	0.020**
2013	0.014	0.108	0.134	0.110	0.301	0.042**
2014	0.024	0.079*	0.144	0.095*	0.331	0.028**
2015	0.022	0.082*	0.156	0.078*	0.334	0.026**
2016	0.029	0.063*	0.146	0.087*	0.351	0.019**
2017	0.031	0.059*	0.148	0.086*	0.348	0.020**
2018	0.038	0.046**	0.137	0.097*	0.361	0.017**
2019	0.053	0.026**	0.143	0.087*	0.399	0.009***
2020	0.052	0.027**	0.142	0.089*	0.400	0.009***

Note: *, **, *** indicate significance severally at the 0.1, 0.05, and 0.01 probability levels. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

mechanism linking the digital economy, green technological innovation, and energy intensity reduction. Supporting this hypothesis, recent research by scholars like Luo et al. (2022) and Sun and Zhou, 2022 suggests that the digital economy can lower energy intensity through avenues of technological progress and innovation. This indicates that advancements in technology, driven by digital economic activities, may serve as key mediators in enhancing energy efficiency and thus, contributing to a decrease in energy intensity (Luo et al., 2022; Sun and Zhou, 2022).

Given the supportive evidence, it is indeed reasonable to propose Hypothesis H2. This conclusion not only substantiates the findings of our study but also introduces a new perspective on managing future energy strategies and fostering green technological innovations. By understanding and harnessing the interplay between the digital economy and technological advancements, policymakers and businesses can develop more effective approaches to reduce energy intensity and promote sustainable energy use. This insight opens avenues for further research and practical applications in the realm of energy efficiency and digital transformation.

6 Spatial analysis of the impact of the digital economy on energy intensity

6.1 Spatial correlation test

Before analyzing spatial effects, this study rigorously tests the spatial relevance of green technological innovation. To ensure the robustness of these test results, we utilize three distinct spatial weighting matrices: the inverse distance weighting matrix (W1), the economic distance weighting matrix (W2), and the neighboring distance weighting matrix (W3). Subsequently, the global Moran's index for green technological innovation is calculated.

The results, as shown in Table 8, reveal that the Moran's index for green technological innovation is statistically significant at the

10% level in most years, across all weighting matrices employed. This evidence strongly suggests that green technological innovation, driven by the digital economy, has a significant positive spatial dependence. Therefore, in assessing the impact of the digital economy on energy intensity, it is crucial to fully account for the technology spillover effect. This comprehensive approach ensures that the broader implications of technological advancements are considered in the analysis of how the digital economy influences energy intensity.

6.2 Spatial effect analysis

To determine the most suitable spatial model for analyzing spatial effects, this study adopts methodologies inspired by Elhorst (Elhorst, 2014). The selection process began with the Lagrange Multiplier (LM) test. The results indicated that the Robust Lagrange multiplier statistic for the spatial error model (SEM) was 4.033, which passed the significance threshold at the 5% level. Similarly, the Robust Lagrange multiplier statistic for the spatial lag model (SAR) was 3.795, achieving significance at the 10% level, thereby validating the selection of both SEM and SAR models. Following the LM test, the Likelihood Ratio (LR) test was conducted. The results from both the LR-SEM and LR-SAR demonstrated significance at the 1% level, indicating a strong statistical justification for their use. These findings suggested that the spatial Durbin model (SDM), which integrates elements of both SAR and SEM, could not be simplified into either the spatial lag model or the spatial error model alone; hence, the combined SDM was chosen as the optimal model for this analysis. Furthermore, the model selection process incorporated the Hausman test to differentiate between the fixed effects and random effects models. The results clearly favored the fixed effects model over the random effects model, which was particularly relevant given the significant variations observed both temporally and individually among the study variables. Ultimately, the spatial Durbin model was selected as the analytical tool, providing a comprehensive framework for evaluating the spatial dependencies and effects in the context of green technological innovation influenced by the digital economy.

Tables 9–11 present the outcomes from the spatial model analysis utilizing different spatial weight matrices. These findings reveal that the Log-likelihood values for the spatial Durbin model (SDM) are consistently higher than those for the spatial error model (SEM) and the spatial autoregressive model (SAR) across all matrices, suggesting a superior fit of the SDM for this analysis. Particularly, the Log-likelihood value is highest with the W1 spatial weight matrix, prompting a detailed examination of the results presented in Table 9. The analysis in Table 9 shows that the spatial autoregressive coefficient for green technological innovation is significantly negative at the 1% level. This result implies that within the provinces of the Yangtze River Economic Belt, green technological innovation spurred by the digital economy exhibits a significant negative spatial dependence. Specifically, advancements in technology in one province tend to decrease energy intensity in neighboring provinces (Li et al., 2024). This diffusion effect is indicative of how digital technology enables surrounding areas to benefit from technology spillovers, thereby enhancing energy efficiency and reducing energy intensity. The significant negative spatial lag term for green technological innovation further suggests that technological advancements in neighboring regions can substantially diminish energy consumption. This underscores the critical role of technology spillover effects. Hence, fostering the comprehensive development of the digital economy is crucial for optimizing resource allocation and realizing the environmental benefits it facilitates, especially in terms of reduced energy consumption and enhanced efficiency across the Yangtze River Economic Belt (Gao and He, 2024).

In order to thoroughly assess the impact of core explanatory variables within the spatial model, merely examining the regression coefficients is insufficient, as these do not provide a clear indication of the marginal impacts. Instead, the spatial effects are explored by decomposing them into direct, indirect, and total effects. This decomposition is conducted using the partial differentiation method as proposed by LeSage and Pace, 2009. Table 9's decomposition of spatial effects into direct and indirect components provides key insights into the role of the digital economy in influencing energy intensity. The direct effect of green technological innovation, promoted by the digital economy, on regional energy intensity is negative. Although this effect is not statistically significant, it suggests a potential for digital technology to reduce energy consumption. The lack of significant impact might be attributed to the current stage of digital technology application within the energy sector not yet achieving a critical level of influence on energy efficiency. Additionally, the influence of digital technology on energy intensity may exhibit a delayed response, not immediately observable within the short-term data analysis. This scenario underscores the need to further develop the digital economy. Enhancing its value creation capacity can lead to more rapid innovation and development in traditional industries, driven by digital technologies. Such advancements could eventually lead to significant reductions in regional energy consumption and promote green development. Moreover, the indirect effect of green technological innovation is significantly negative (−0.719) at the 1% level, indicating a substantial negative spillover effect on the energy intensity of neighboring provinces. This finding highlights the importance of technological spillovers facilitated by the digital economy, which effectively reduce energy intensity in adjacent regions. This aligns with existing research, confirming that the spread of green technological innovations can have beneficial regional impacts beyond their origin points, enhancing overall energy efficiency across broader geographic areas. Such insights are crucial for policymakers aiming to leverage digital technology for sustainable development and regional energy planning (Chen et al., 2023). The negative and significant total effect of digital technology on energy intensity, as demonstrated at the 1% level, underscores its profound impact across both spatial and temporal dimensions. This effect is largely driven by the utilization and sharing of frontier digital technologies such as big data, cloud computing, and the Internet of Things. These technologies are pivotal in enhancing regional energy efficiency by facilitating improvements on both the supply and demand sides of energy use. On the supply side, digital technologies integrate into production processes, optimizing energy use and reducing waste. This not only increases energy efficiency but also contributes to the sustainability of production activities by minimizing the environmental footprint. On the demand side, these technologies empower consumers to respond more dynamically to

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TABLE 9 Results of spatial modeling analysis under the inverse distance weight matrix.

	SAR	SEM	SDM
ρ (rho)	0.146 (1.02)		−0.818*** (-3.40)
Λ		0.267 (1.49)	
lnGTI	−0.066 (-0.53)	−0.052 (-0.44)	−0.174** (-1.98)
W × *lnGTI*			−1.285*** (-2.71)
Log-likelihood	163.5	163.9	208.6
Direct effect	−0.062 (-0.48)		−0.085 (-1.12)
Indirect effect	−0.223 (-0.46)		−0.719*** (-2.68)
Total effect	−0.085 (-0.51)		−0.805*** (-2.64)
Control Variables	YES	YES	YES
Fixed effect	YES	YES	YES
Observations	121	121	121
R^2	0.211	0.095	0.857
Variance	0.004*** (4.28)	0.004*** (4.52)	0.002*** (6.46)

Note: *, **, *** indicate significance severally at the 0.1, 0.05, and 0.01 probability levels. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

TABLE 10 Results of spatial modeling analysis under the economic distance weight matrix.

	SAR	SEM	SDM
ρ (rho)	−0.772*** (-4.39)		−0.723*** (-4.70)
Λ		−1.050*** (-8.44)	
lnGTI	0.114 (-1.05)	−0.148*** (-1.75)	−0.133* (-1.89)
W × *lnGTI*			−0.335** (-2.41)
Log-likelihood	173.8	182.0	203.1
Direct effect	−0.124 (-0.99)		−0.096 (-1.10)
Indirect effect	0.059 (0.95)		−0.180 (-1.50)
Total effect	−0.064 (-0.98)		−0.276** (-2.52)
Control Variables	YES	YES	YES
Fixed effect	YES	YES	YES
Observations	121	121	121
R^2	0.359	0.481	0.774
Variance	0.003*** (3.38)	0.002*** (3.53)	0.002*** (5.04)

Note: *, **, *** indicate significance severally at the 0.1, 0.05, and 0.01 probability levels. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

TABLE 11 Results of spatial model analysis under the neighbor distance weight matrix.

	SAR	SEM	SDM
ρ (rho)	0.305** (2.46)		−0.039 (-0.27)
Λ		0.138*** (2.61)	
lnGTI	−0.041 (-0.36)	−0.026 (-0.25)	−0.091* (-1.85)
$W \times lnGTI$			−0.202 (-1.38)
Log-likelihood	167.3	170.7	208.3
Direct effect	−0.039 (-0.31)		−0.086 (-1.52)
Indirect effect	−0.022 (-0.32)		−0.197 (-1.44)
Total effect	−0.061 (-0.33)		−0.283** (-2.48)
Control Variables	YES	YES	YES
Fixed effect	YES	YES	YES
Observations	121	121	121
R^2	0.084	0.234	0.098
Variance	0.004*** (4.59)	0.003*** (4.76)	0.002*** (4.64)

Note: *, **, *** indicate significance severally at the 0.1, 0.05, and 0.01 probability levels. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

fluctuations in energy demand. Smart energy management systems, for instance, can adjust consumption based on real-time data, preventing unnecessary energy use and contributing to overall energy conservation. The broad and impactful suppression of energy intensity by digital technologies indicates their crucial role in shaping a more energy-efficient future. This aligns with global efforts towards achieving sustainable development goals, particularly in reducing energy consumption and mitigating environmental impact. Policymakers and industry leaders should, therefore, prioritize the integration of these technologies into regional and national energy strategies to harness their full potential in driving down energy intensity and fostering sustainable economic growth.

6.3 Spatiotemporal heterogeneity analysis

The significant role of the digital economy in shaping energy consumption patterns is highlighted by its evolution and emphasis in policy frameworks. The formal acknowledgment of the “digital economy” in China’s Government Work Report in 2017, and its consistent highlight in subsequent years through 2022, have marked critical milestones that catalyzed the rapid growth and dynamic development of the digital economy. This policy-driven acceleration has been instrumental in fostering the integration of digital technologies across various sectors. In response to this pivotal shift, a detailed analysis was conducted to understand the dynamic characteristics of the digital economy with a particular focus on the period before and after 2016, which serves as a temporal boundary for assessing changes in impacts. The empirical results presented in Table 12 from this analysis indicate that between 2010 and 2016, green technological innovation driven by the digital economy had a statistically significant indirect effect on reducing energy intensity, recorded at −0.844 at the 1% significance level. This effect signifies that provinces in the Yangtze River Economic Belt have benefited from technological spillovers prompted by the digital economy’s growth. The diffusion of digital technologies, such as automation and intelligent systems, has been pivotal. These technologies have been extensively adopted and have substantially improved production efficiency by optimizing operational workflows and reducing waste, thereby decreasing energy consumption per unit of output. This transformation has not only led to direct reductions in energy usage but also contributed to broader regional impacts through spillover effects, where technological advancements in one province have beneficial implications for neighboring provinces. Such findings underscore the transformative potential of the digital economy in promoting sustainable development by enhancing energy efficiency and reducing the environmental impacts of industrial activities. These insights are crucial for policymakers and industry stakeholders aiming to leverage digital innovations for economic growth and sustainability in the Yangtze River Economic Belt and beyond.

However, the observed shift in the impact of the digital economy on energy intensity from 2017 to 2020 presents a compelling case of the “energy rebound effect. “The empirical results indicating an indirect effect of 0.287, significant at the 5% level, suggest that instead of reducing energy intensity, the green technological

TABLE 12 Empirical analysis results of spatiotemporal heterogeneity.

	2010–2016	2017–2020
ρ (rho)	−0.961*** (-4.73)	−1.940*** (-9.56)
$lnGTI$	−0.196** (-2.08)	0.098* (1.79)
$W \times lnGTI$	−1.640*** (-3.69)	0.740** (2.26)
Direct effect	−0.071 (-0.97)	0.004 (0.07)
Indirect effect	−0.844*** (-4.48)	0.287** (1.99)
Total effect	−0.915*** (-3.92)	0.291** (2.20)
Control Variables	YES	YES
Fixed effect	YES	YES
Observations	121	121
R^2	0.879	0.649
Variance	0.001*** (5.61)	0.000*** (3.07)

Note: *, **, *** indicate significance severally at the 0.1, 0.05, and 0.01 probability levels. The numbers in parentheses indicate t-statistics; the same convention applies to the subsequent tables.

innovations driven by the digital economy during this period actually increased it in the provinces of the Yangtze River Economic Belt and their neighboring regions. (Meshulam et al., 2023; Lange et al., 2020). The inclusion of the digital economy in the Government Work Report and its subsequent emphasis likely accelerated investment and expansion in digital technologies. While this expansion intended to optimize efficiency and productivity, it also appears to have driven up overall energy demand, illustrating the complex interactions between technological advancement and energy consumption. This phenomenon underscores the necessity for a nuanced approach to digital economy policies. Policymakers must consider not only the direct impacts of digital technology on efficiency but also the broader effects on consumption patterns and energy demand. Integrating strategies to mitigate the rebound effect, could be crucial in achieving the ultimate goal of reducing overall energy intensity. On the one hand, the deep development of the digital economy requires substantial energy consumption for support, leading to increased economic activities and, consequently, increased energy demand and consumption. On the other hand, the development of the digital economy has also fostered new high-energy-consumption industries or consumption patterns. While the digital economy is developing rapidly, the transformation of the energy structure lags behind, causing high-energy-consumption fossil fuels to remain dominant. Therefore, it is important to recognize the energy rebound brought about by the large-scale infrastructure of the digital economy (Lei et al., 2023) and include the rebound effect in the assessment of the digital economy's shared environment (Meshulam et al., 2023). This brings important insights to our research. We should not only focus on the role that the development of digital technology plays in reducing energy use, but also consider the changes in the economy, society, ecology, and other aspects brought about by the innovation and application of green and digital technology. Additionally, we should propose countermeasures to address the rebound effect in energy use and provide differentiated strategies based on different regions.

7 Conclusions and implications

7.1 Conclusions

This paper empirically analyzes the impact of digital economy on regional energy efficiency and energy consumption intensity from the perspectives of energy economy and technology spillovers, based on the panel data of 2010–2020 of the 11 target provinces in our study, and puts forward policy recommendations about how digital technology can cope with energy economy risks, energy rebound effects, as well as improve energy efficiency and reduce energy intensity. The conclusions are as follows: First of all, the digital economy has a significant inhibitory influence on regional energy intensity, and the results still satisfy after the many examinations. Second, the pathway of the digital economy to influence energy intensity is mainly realized through green technological innovation, and the digital economy sharply cut down the intensity of energy by innovating digital technological. Third, using the spatial Durbin model analysis, it is suggested that for the provinces in the Yangtze River Economic Belt, the digital economy effectively suppresses the adjacent regions consumption of energy through technology spillover effects in the initial stages. This is mainly due to the application and optimization of emerging technologies that can enhance energy efficiency. However, over time, the sustainability and stability of this suppressive effect become more complex, especially since 2017 when the green economy and digital economy was officially included in the Government Work Report and received national-level attention and promotion. The accelerated expansion of the digital economy has occasionally deviated from its projected path. Additionally, this rapid growth has precipitated a substantial surge in energy consumption within sectors like data centers, big data processing, and artificial intelligence. As the adoption of digital services and products intensifies, the increasing dependence of both consumers and businesses on these technologies indirectly escalates energy demand. This situation gives rise to the “energy rebound effect,” where energy savings achieved through technological advancements are offset by increased consumption due to the broader application and deeper integration of these technologies, resulting in a net rise in overall energy costs.

7.2 Policy implications

This study also makes the following recommendations and insights:

First and foremost, empower economic development through the digital economy. Although many provinces have digital economies exceeding one trillion yuan, there are still issues of uneven development. Efforts should be made to promote the construction of digital infrastructure, achieve higher quality interconnectivity, and accelerate the construction of new productive forces. This will provide a solid foundation for the digital industry to promote environment be better and address issues of unbalanced and inadequate digital economy development.

Secondly, encourage the integration and innovation of digital and green technologies. As the principal method for digital technological development, continued investment in such innovations is crucial. Simultaneously, it is important to strengthen the connections between developed provinces and their neighboring regions, enhancing the breadth and depth of these relationships. Additionally, it is essential to actively leverage the scale economies of industrial division and the technology spillover effect to achieve coordinated development and avoid the rebound effect on both the energy supply and demand sides. Adequate and stable financial support for digital projects is also necessary to mitigate the impact of economic conditions, stabilize the digital economy market, and fully harness its key role in controlling energy intensity.

Thirdly, in the construction of digital infrastructure such as data centers and communication networks, it is advisable to encourage regions to adopt energy-saving technologies and implement smart energy management systems to optimize energy use and reduce waste. Additionally, strong support should be provided for the development of energy-efficient software to ensure minimal energy consumption during operation.

Fourthly, creating a favorable environment for green digital technology innovation is equally crucial. This involves multiple domains, including policy frameworks, legal regulations, public acceptance, and the dissemination of digital culture. The effectiveness of green technology innovations should be assessed over time and through practical application, with active efforts to promote the application of scientific research outcomes in daily life and production. Additionally, it is important to value and encourage feedback from citizens, who serve as user representatives, based on their experiences and evaluations. Such feedback should serve as critical standards for assessment and improvement, thereby cultivating fertile ground for the multidimensional development of green technological innovation and the digital economy.

Finally, efforts should be focused on promoting unified regional coordinated development. It is crucial to acknowledge the reality of uneven regional development. Therefore, the development of new productive forces should be tailored to local conditions, recognizing the differences in digital economy development across regions. Scientific and reasonable development plans should be formulated, guided by policy, to break down technical and industrial barriers between regions. This will ensure that the digital economy benefits the economic and social development of all regions while maintaining the principle of coordinated regional development.

In addition to these measures, this study suggests that attention should not only be focused on governments and businesses but also on societal actors. It is important to intensify efforts to educate the public about the importance of energy conservation and to widely disseminate the role of the digital economy in reducing energy consumption. Strengthening the development and application of digital technologies from a societal perspective can enhance their beneficial effects on the social environment, as well as their ability to restore and improve the ecological environment.

7.3 Limitations and future prospects

Furthermore, this study has certain limitations. Firstly, the research is confined to provincial units within the Yangtze River Economic Belt and does not include cities or towns, which affects the comprehensiveness and reliability of the data. Future research could expand to include city and town levels to obtain more detailed and specific data, thus providing a more comprehensive understanding of the impact of the digital economy on energy intensity. Secondly, while the Yangtze River Economic Belt serves as a typical demonstration area and the findings of this study are valuable for reference, the unique characteristics of the Yangtze River Economic Belt may limit the applicability of the results to other regions. Therefore, future research should consider including other regions for comparison to assess the generalizability of the findings. Additionally, in the process of selecting and designing spatial econometric models, there may be biases or insufficient consideration of influencing factors such as economic structure, educational level, cultural concepts, and urban-rural differences. Future research could benefit from employing more comprehensive models, such as system dynamics models or deep learning models, to enhance the credibility of the research conclusions. Therefore, future research should aim to broaden the scope of research subjects, carefully consider the selection of influencing factors, establish a more comprehensive indicator system, obtain more detailed data, and use multiple models for verification. This will ensure a thorough understanding of the impact pathways of the digital economy on energy intensity, enhance the credibility and referential value of empirical analysis, and provide valuable development insights for a wider range of regions and industries.

Data availability statement

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

Author contributions

SG: Writing–original draft, Writing–review and editing, Conceptualization, Data curation, Investigation, Methodology. XL: Conceptualization, Methodology, Supervision, Writing–original draft, Writing–review and editing. HD: Data curation, Methodology, Validation, Writing–review and editing. SL: Validation, Visualization, Writing–review and editing. XS: Methodology, Supervision, Validation, Visualization, Writing–review and editing.

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Conflict of interest

The authors declare 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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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2024.1468512/full#supplementary-material

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