A STUDY ON THE IMPACT OF DIGITAL TECHNOLOGY INNOVATION ON ENERGY INTENSITY IN CHINA—BASED ON NONLINEAR AND CAPITAL MISMATCH PERSPECTIVES

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Abstract. Low-carbon economy is the key to sustainable development of all countries in the world. Accelerating technological innovation and improving fossil energy output per unit is an important approach to promote low-carbon development. Taking China's 278 prefecture-level cities as a sample, this study examines the impact of digital technology on energy intensity from the perspective of local effects and spatial spillovers, and analyses the bidirectional moderating effect of capital misallocation. The results of the local effects tests show that digital technology has an inverted U-shaped impact on local energy intensity, i.e. it first increases and then decreases. There are significant heterogeneity, especially in resource-based cities, where digital technology does not have an inverted U-shaped impact on energy intensity. For the local effect results, in the first half of the inverted U-shape, capital misallocation generates an increasing moderating effect. In the second half of the inverted U-shape, capital misallocation generates a weakening moderating effect. Spatial spillover tests show that digital technology has a U-shaped impact on energy intensity in the surrounding area, i.e. it first decreases and then increases. For the spatial spillover effect results, in the first half of the U-shape, capital misallocation generates a weakening moderating effect. In the second half of the U-shape, capital misallocation generates a strengthening moderating effect.
Keywords: *inverted U-shaped relationship, U-shaped relationship, capital misallocation, moderating effect, spatial spillover effect*

Introduction

As the world's most populous country and second largest economy, China's development status will have a significant impact on countries around the world. Since the reform and opening up, China's total energy consumption has grown rapidly, making it the world's largest energy producer and consumer, and the energy problem has become more and more prominent. At the same time, energy is directly related to carbon reduction and environmental issues. To address this, China has proposed to implement a "dual control" policy on energy consumption, both in terms of total volume and intensity, and has set a target to reduce energy consumption per unit of GDP by 13.5% by 2025 compared to 2020. Energy intensity is influenced by various factors, including industrialization, green financial reform, energy price reform and urbanization (Liu et al., 2022; Zhao et al., 2024; Zamani et al., 2024; Wong, 2024). In the context of the information revolution, digital technological innovations and applications represented by 5G, cloud computing, and the Internet of Things undoubtedly provide new opportunities for improving energy efficiency. Although digital technology innovation and application can promote low-carbon development by

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substituting energy elements and optimizing management and production processes, they still rely on the support of energy sources such as electricity and require large-scale energy infrastructure construction to ensure the development and operation of digital technologies (Gong and Wan, 2024). Relevant studies show that the global information and communication technology (ICT) industry's total energy demand for physical operations increased from 658 terawatt-hours in 2007 to 909 terawatt-hours in 2012, and ICT's share of global electricity consumption increased from 3.9% to 4.6% (Van Heddeghem et al., 2014). This suggests that the impact of digital technology on energy intensity may not always be linear. Therefore, clarifying the relationship between digital technology and regional energy intensity, and to analyze the influence mechanism and effect size in order to improve energy efficiency and reduce carbon emissions.

Capital mismatch problems are prevalent globally (Gopinath et al., 2017). In China, where a floating interest rate regime was officially introduced in November 2014, the relatively short history of interest rate liberalization has led to capital mismatch issues due to significant administrative intervention by local government departments in financial sector lending decisions (Li et al., 2022). Capital mismatch is a major cause of total factor productivity losses (Restuccia and Rogerson, 2017). From a macroeconomic perspective, capital mismatch across firms and industries leads to overall total factor productivity losses. From a micro-firm perspective, on the one hand, capital mismatches affect firm entry and exit, financing constraints, and R&D investment decisions, which significantly affect overall total factor productivity. On the other hand, capital mismatches allow firms to increase their profit margins through cost advantages in capital rather than improving their competitiveness through R&D innovation, thus creating a "crowding out" effect on firm innovation. Does capital mismatch affect the relationship between digital technology innovation and energy intensity? What is its impact? These questions need to be explored in depth, both theoretically and practically.

China is the largest developing country and the largest economy in the world, so it is crucial to study China's environmental and economic issues. The conclusions drawn from this study can provide valuable insights for other countries to improve energy utilization, environmental quality and promote sustainable development from the perspective of digital technology and capital mismatch. Conducting this research is obviously significant in two important ways. First, theoretically, it advances research progress on digital technology, capital mismatch and energy use from a new perspective. While individual studies on digital technology, capital mismatch and energy intensity are common, there has been no research that integrates all three. Second, practically, it provides policy implications for improving energy efficiency and promoting low-carbon development, which facilitates the coordinated development of digital technology innovation, capital market development, and environmental protection. Compared to existing research, this paper makes three main marginal contributions: First, it constructs a new research perspective. There is currently no literature that integrates digital technology, capital mismatch and energy intensity into the same research framework, and this paper fills this gap. Second, it examines the impact of digital technology on energy intensity from both local effects and spatial spillovers, further enriching the relevant research content. Third, it uses capital mismatch as a moderating variable to test its effect. The relationship between digital technology and energy intensity has broadened the research frontiers of the three and provided a new start for energy use and environmental protection.

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Literature review

Research on the impact of digital economy and digital technology on energy utilization

Based on the development of information and communication technologies, the digital economy and digital technology have advanced rapidly, and their impact on socio-economic fields is gradually becoming apparent. Among them, the impacts on energy intensity and energy efficiency have attracted considerable attention from many scholars. To address this, this article reviews the literature from two aspects. First, the impact of the development of the digital economy on energy intensity and energy efficiency. Overall, the development of the digital economy can significantly reduce energy intensity (Huang et al., 2023). It also alleviates market distortions in factor markets, promotes technological progress and facilitates manufacturing upgrading, among other ways to reduce energy intensity (Zeng et al., 2023; Yue and Zhang, 2023). In addition, the digital economy can positively and indirectly reduce energy intensity in surrounding areas through technological spillovers (Gao et al., 2024). However, the impact of digital economy development on energy intensity is not linear, but may have an inverted U-shaped relationship (Zhao and Guo, 2023). In terms of energy efficiency, the digital economy can significantly improve total factor energy efficiency, with industrial agglomeration, technological progress and environmental regulation being key transmission channels (Liu and Li, 2023; Zhao and Wang, 2024).

Second, the impact of digital technology on energy intensity and efficiency. Innovation in digital technology will play a crucial role in the transformation of sustainable energy development (Van Summeren et al., 2021). From a regional perspective, the level of informatization can have a significant negative impact on regional energy intensity, with a pronounced spatial spillover effect on energy intensity (Wang et al., 2021). Innovation and application of digital technologies can significantly reduce energy consumption and improve energy efficiency (Wang et al., 2022). The main mechanisms include increased foreign direct investment, industrial structure upgrading and technological innovation, which also have a positive impact on energy efficiency in surrounding areas (Wu et al., 2023). However, the impact of digital technology innovation on total green factor energy efficiency depends on the level of economic development. In particular, when GDP per capita exceeds 24,000 yuan, the marginal improvement effect becomes apparent (Xu et al., 2024). However, research at the firm level has reached opposite conclusions. On the one hand, the application of information and communication technology can intensify market competition and promote the substitution of energy for labor and capital, thereby increasing the energy intensity of enterprises (Wen et al., 2024). On the other hand, digital technology innovation in enterprises can enhance energy efficiency by strengthening environmental responsibility and improving the quality of internal control. Intellectual property protection, information infrastructure and digital industry agglomeration can also promote the positive impact of digital technology innovation on energy efficiency (Lu and Li, 2024).

Three conclusions can be drawn from the above literature review. First, the existing literature on the impact of digital economy development on energy intensity and energy efficiency is abundant, but there is very little direct research on how digital technology innovation affects energy intensity, and such studies are mainly conducted at the firm level, with a lack of research at the regional level. Second, there is a significant

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difference in measurement between the development of the digital economy and digital technology innovation; the level of development of the digital economy is often measured by an indicator system, while digital technology is generally measured by a single indicator. Third, no literature integrates digital technology innovation, capital misallocation and energy intensity in the same analytical framework.

Study on the impact of factor mismatch on energy utilization

Currently, there is relatively little literature on the impact of resource or factor misallocation on energy intensity and energy efficiency, and such analyses are mainly conducted from an efficiency perspective. Resource misallocation is also referred to as factor price distortion. First, from an overall perspective, factor market distortions reduce the relative efficiency of energy allocation. Compared with labor prices, capital prices are relatively higher, while energy prices are relatively lower, leading to increasingly inefficient energy allocation (Ouyang et al., 2018). Therefore, existing studies consistently conclude that factor price distortion increases energy efficiency losses and significantly hinders energy efficiency improvement (He et al., 2021). Moreover, it mainly hinders energy efficiency improvements through factors such as distorting factor allocation and inhibiting technological progress (Zhang and Huang, 2017). However, there are different conclusions on whether labor price distortion or capital price distortion has a greater negative impact (Li, 2016; Yang, 2016). Second, from the perspective of secondary industry and manufacturing, the relative price distortion of production factors is an important factor hindering the improvement of overall factor energy efficiency in China’s secondary industry (Tan et al., 2019). In regions with lower factor market distortion, the overall factor energy efficiency of manufacturing is higher. Factor market distortion mainly hinders the overall factor energy efficiency improvement of manufacturing by affecting technological efficiency and economies of scale (Sun et al., 2024). Third, from the perspective of industrial structure adjustment, green total factor energy efficiency is simultaneously negatively affected by labor mismatch and capital mismatch. However, capital mismatch has a significant negative spatial spillover effect, while labor mismatch has no spatial spillover effect (Hao et al., 2020).

Existing research has confirmed that factor mismatch significantly hinders the improvement of energy efficiency, with capital mismatch being a key factor among them. According to the existing literature, on the one hand, capital mismatch primarily has a linear effect on energy efficiency, but no literature has addressed energy intensity. On the other hand, the inclusion of capital mismatch as a moderating variable in the relationship between digital technology innovation and regional energy intensity provides a very useful addition to the existing literature.

Theoretical analysis and research hypothesis

The inverted U-shaped impact of digital technology on energy intensity

The direct impact of digital technology innovation on energy intensity can be explored from the perspective of mitigating information asymmetry. On the one hand, overinvestment by firms leads to an overabundance of homogenized products in the market supply, which reduces the efficiency of resource allocation, which in turn increases energy intensity (Gu et al., 2019). Digital technology innovation, as a

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combined use of digital technology, greatly improves information transparency by improving data processing capabilities and converting data into standardized and structured binary data for controlled storage, processing and transmission. The improvement of information transparency means that enterprises can fully understand the production and operation situation based on transparent information, and then supervise the production and operation decisions of enterprises, reducing the possibility of inefficient production and excessive investment (Du et al., 2019). Therefore, by improving information transparency through digital technology innovation, enterprises can reduce ineffective output, reduce the possibility of excessive investment, and then reduce energy intensity. On the other hand, digital technology innovation can effectively accelerate the flow of information across organizational boundaries, improve the efficiency of information use, optimize the allocation of resource elements in all segments of the enterprise, and eliminate the redundancy of resource elements in the production process, which in turn can improve energy efficiency (Peng and Tao, 2022). At the same time, digital technology innovation can create synergies with other energy-saving measures, such as smart manufacturing, smart grids and smart buildings. Through real-time monitoring and control of digital technology innovation, it provides technical support and intelligent management means for energy-saving measures, promotes sustainable energy use, and then realizes the improvement of carbon emission efficiency.

However, the impact of digital technology innovation on energy intensity is not always linear. First, the development of digital technology innovation requires large investments in energy-intensive digital infrastructure. Morley et al. (2018) show that digital infrastructure consumes an increasing share of electricity and will consume more energy as digitalization progresses. Therefore, the initial development of digital technology innovation will stimulate high energy consumption and increase energy intensity. And as the level of digital technology innovation continues to improve, the initial investment in digital infrastructure will gradually have a positive effect, the level of digital industrialization and industrial digitization will continue to increase, and energy intensity will be reduced through refined management of energy and production processes, intelligent decision-making, optimization of resource allocation, and promotion of clean energy development. Therefore, the first hypothesis is proposed.

H1: The effect of digital technology innovation on energy intensity is an inverted U-shaped curve, first increasing and then decreasing.

The moderating effect of capital mismatch

The theory of factor mismatch posits that market mechanism failures are widespread in the operation of a market economy, and that the pursuit of short-term profit maximization by firms and other market agents can lead to the deviation of marginal returns to factors from their actual user prices (Hsieh et al., 2009), thereby distorting factor prices. In a distorted factor market system, the allocation of factors of production such as capital does not reach an optimal level, leading to misallocation and mismatch of capital. The flow, aggregation and allocation of innovation factors such as R&D personnel and capital require market participation, so the level of factor resource allocation directly affects the efficiency of innovation resource utilization (Dai and Liu, 2016). As an important factor resource, capital has a direct impact on technological innovation activities. China's capital factor market reform is relatively

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backward, with a relatively short period of interest rate liberalization, and the indirect financing model dominated by financial credit is still prevalent. Factors such as rising risk premiums, excessively high markup rates, and ownership discrimination raise the actual cost of capital use for firms, thereby increasing the opportunity cost of technological innovation (Hu and Li, 2019). Moreover, when capital price signals are distorted, the market struggles to optimize the allocation of innovative capital based on price signals, which is detrimental to improving technological innovation efficiency.

Capital mismatch thus plays an important moderating role in the inverted U-shaped impact of digital technologies on energy intensity. In the first half of the inverted U-shape (the period of rising energy intensity), capital mismatch amplifies the negative effects of technology adoption through a dual path. On the one hand, the continued misallocation of financial resources to inefficient sectors crowds out the R&D investment needed for digital technology innovation, forcing firms to adopt sub-optimal technological solutions and prolonging energy waste during the technology break-in period. On the other hand, capital mismatch leads to distortions in factor markets, creating structural frictions in the integration process between digital technologies and traditional energy systems, reducing the synergistic efficiency of data elements and traditional energy elements, and increasing marginal energy consumption per unit of output. In the second half of the inverted U-shape (period of declining energy intensity), the inhibiting effect of capital mismatch is more significant. At this time, the energy-saving potential of digital technologies needs to be applied on a large scale to be fully released, but capital allocation distortions hinder technology diffusion. For one, the financial market lags behind in identifying application scenarios for digital technologies, leading to financing constraints for cleantech firms and difficulties in realizing economies of scale. Second, capital mismatch maintains the cost advantage of the traditional energy industry, forming the “bad money driving out good money” effect and slowing down the technological substitution process of energy-consuming enterprises. Third, the resource mismatch caused by the mismatch exacerbates the uneven development of the digital technology ecosystem, and the lack of investment in key supporting technologies creates a technological bottleneck, which weakens the overall effect of energy efficiency improvement. Thus, the second hypothesis of this paper is proposed.

H2: There is a bidirectional moderating effect of capital misallocation on the inverted U-shaped relationship between digital technology and energy intensity.

Methods and data

Model setting

Baseline regression model

To test the inverted U-shaped impact of digital technology innovation on urban energy intensity and to estimate the “technological threshold” of urban energy intensity decline. This paper builds on the methodology of Atta et al. (2025) to construct a panel econometric model of the impact of digital technology innovation on urban energy intensity. The model is a two-way fixed-benefit model, as shown in *Equation 1*.

$$EI_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 DT_{it}^2 + \beta_3 X_{it} + u_i + \varepsilon_t + v_{it} \quad \text{(Eq.1)}$$

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In *Equation 1*, *EI* is the energy intensity of the city. *DT* represents the level of digital technology innovation. β_1 represents the coefficient of influence of *DT* on *EI*. β_2 represents the coefficient of influence of DT^2 on *EI*. *i* represents the city. *t* represents the year. *X* represents a set of control variables. u_i and ε_t represent the fixed effects of individual and annual factors in a city, respectively, to control for the influence of unobservable urban and macroeconomic factors on energy intensity. v_{it} is the random error term. Meanwhile, in order to test the impact of digital technological innovation on energy intensity in a multi-method way, this paper also uses the hybrid OLS model for estimation. However, the analysis is mainly based on the results of the two-way fixed effects model.

Regulating effect model

To test the moderating effect of capital mismatch on the relationship between digital technology innovation and energy intensity. This article refers to the method of Haans et al. (2016) and builds a moderating effect model *Equation 2* by adding the interaction term between capital mismatch and the core explanatory variables *DT* and DT^2 based on *Equation 1*.

$$EI_{it} = \gamma_0 + \gamma_1 DT_{it} + \gamma_2 DT_{it}^2 + \gamma_3 DT_{it} \times CM_{it} + \gamma_4 DT^2{}_{it} \times CM_{it} + \gamma_5 X_{it} + u_i + \varepsilon_t + v_{it} \quad \text{(Eq.2)}$$

In *Equation 2*, γ_1 represents the coefficient of influence of digital technology innovation on urban energy intensity under the influence of regulatory variables. $DT_{it} \times CM_{it}$ and $DT^2{}_{it} \times CM_{it}$ represent the product of digital technology innovation and urban energy intensity. γ_3, γ_4 represent the coefficient of the regulatory effect of the regulatory variable. The meaning and estimation method of the other parameters are the same as in *Equation 1*.

Variable selection

Dependent variable

Energy Intensity (*EI*). Energy intensity is the main indicator that reflects the level of energy consumption and energy conservation, and is used to study changes in economic structure and energy efficiency. This paper adopts energy consumption per unit of GDP, which is the ratio of total annual energy consumption to actual GDP, to measure energy intensity (Tao et al., 2024). Total energy consumption mainly includes four main energy sources: coal, oil, electricity and natural gas. Data on coal, electricity and LPG supply and use were obtained from the 2007-2022 China Urban Statistical Yearbook, and total energy consumption was calculated by converting energy using the Energy Conversion Standard Coal Reference Coefficient. This paper follows the approach of Lin et al. (2023), which uses urban electricity, gas, and LPG data to convert energy consumption, and then combines it with GDP to calculate the energy intensity value. The specific calculation formula is given in *Equation 3*.

$$EI = \ln[(ele \times a + cg \times b + lpg \times c) / GDP] \quad \text{(Eq.3)}$$

In *Equation 3*, *ele*, *cg* and *lpg* represent electricity consumption, total gas supply and total LPG supply respectively. The *a*, *b* and *c* represent the share of coal-fired electricity

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generation, the conversion coefficient of coal gas to standard coal and the conversion coefficient of LPG to standard coal respectively. The reference coefficients for the energy equivalent of standard coal are taken from the 2022 China Energy Statistics Yearbook. The coal to electricity generation ratio is 1.229 (kg standard coal/kWh), the gas to standard coal factor is 6 (kg standard coal/kg) and the LPG to standard coal factor is 1.7143 (kg standard coal/kg). The higher the *EI* value, the more energy is consumed per unit of *GDP*, i.e. the higher the energy intensity value. The lower the *EI*, the lower the energy intensity.

Core explanatory variables

Digital Technology (*DT*). This article refers to existing literature methods and uses the number of regional digital economy patent applications as an indicator to measure the level of digital technology innovation in that region (Jia et al., 2024). For the definition of digital economy patents, this article relies on the statistical methods used by Tao et al. (2023): it refers to the "International Patent Classification and National Economic Industry Classification Reference Table (2018)" published by the China National Intellectual Property Administration and the "Digital Economy and Its Core Industries Statistical Classification (2021)" published by the National Bureau of Statistics. First, all patents are categorized into their respective national economic industry classifications based on the main classification numbers. They are then matched to the designated digital economy industries to determine whether they are digital economy patents. Finally, the number of digital economy patent applications and grants in prefecture-level cities is statistically analyzed. This article chooses to use the number of patent applications rather than the number of grants as an indicator of the level of innovation because the patent granting process typically takes 1-2 years and involves examination and payment of annual fees, which introduces more uncertainty and instability. Therefore, the number of patent applications may be a more timely and reliable reflection of the innovation capacity of a company or region.

Regulating variables

Capital Misallocation (*CM*). In a perfectly competitive market economy, economic agents allocate resources according to price signals. However, when factor markets are distorted, price signals are weakened, leading to deviations between actual and expected returns to factors of production such as capital, and preventing the optimal allocation of resources by market mechanisms. Therefore, the distortion of resource factors can also measure the degree of resource misallocation. Based on the study by Lan (2024), the process and formula for calculating the degree of resource mismatch is as follows.

$$KM = \frac{1}{\gamma_{K_i}} - 1$$

The γ_{K_i} represents the absolute distortion coefficient of capital prices in city i, which can be replaced by the relative distortion coefficient $\hat{\gamma}_{K_i}$ in the actual calculations.

$$\hat{\gamma}_{K_i} = (\frac{K_i}{K})/(\frac{s_i \beta_{K_i}}{\beta_K}) \quad \text{(Eq.4)}$$

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In *Equation 4*, s_i is the share of city *i* output in the economy's total output, and $\beta_K = \sum_i^N s_i \beta_K$ is the value of the capital contribution under output weighting. The $s_i \beta_{K_i} / \beta_K$ measures the share of capital used by city i in the total capital of the whole economy when capital is effectively allocated. The K_i/K represents the actual proportion of capital used in city *i*. If $\hat{\gamma}_{K_i}$ is greater than 1, it indicates that the actual allocation level of capital factors in city *i* is higher than the theoretical effective allocation level relative to the whole economy, indicating excessive capital allocation. Conversely, it indicates an under-allocation of capital in city *i*.

When solving *Equation 4*, it is necessary to estimate the capital factor output elasticity β_{K_i} of each region. This article follows the approach of the relevant literature and uses the Solow residual method for the calculation, assuming that the production function is a C-D function with constant returns to scale.

$$Y_{it} = AK_{it}^{\beta_{K_i}} L_{it}^{1-\beta_{K_i}} \quad \text{(Eq.5)}$$

Further transform into:

$$\ln(Y_{it} / L_{it}) = \ln A + \beta_{K_i} \ln(K_{it} / L_{it}) + \delta_t + \mu_i + \varepsilon_{it} \quad \text{(Eq.6)}$$

In *Equation 6*, the output aggregate Y_{it} is expressed in terms of the real GDP of city *i* in year *t*. The output aggregate Y_{it} is calculated by deflating the nominal GDP of city *i* with the GDP deflator for each year. It is calculated from the nominal GDP of each year according to the GDP deflator, with 2006 as the base period. Capital input K_{it} denotes the capital stock of city *i* in year *t*. It is calculated using the perpetual inventory method, with a depreciation rate of 9.6%. On this basis, *Equation 6* is regressed using a panel model with variable coefficients to estimate the capital output elasticity of each city using panel data for 2006-2021. Substituting the calculated β_{K_i} back into *Equations 4* and *3*, the capital mismatch index (*CM*) of each city can be calculated.

Control variables

In addition to the core explanatory variable of digital technology affecting energy intensity, energy intensity is inevitably affected by other economic factors. If these factors are not included in the model estimation, it may lead to biases in the empirical results. Therefore, these factors need to be included in the model to control for them in the empirical analysis. Based on existing research, this paper selects five indicators as control variables. The level of economic development (*pgdp*), measured by the GDP per capita of prefecture-level cities, which is taken logarithmically in the econometric analysis. Urbanization (*urb*), measured by the share of urban population in the total population of prefecture-level cities. Population size (*pop*), measured by the total population at the end of each year in prefecture-level cities and taken logarithmically in econometric analysis. Industrial structure (*indu*), measured by the ratio of the output value of tertiary industry to that of secondary industry. Fiscal autonomy (*fis*), measured by the ratio of local government autonomous fiscal revenues to autonomous fiscal expenditures.

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Data sources

Based on data availability, this paper adopts sample data from 278 prefecture-level cities in China from 2006 to 2021 for empirical analysis, and the sample does not include Tibet, Hong Kong, Macau and Taiwan regions. The data on digital technology innovation patents are obtained from the official website of Dawei Data (https://pat.daweisoft.com/home). Other data sources include "China Urban Statistical Yearbook", "China Urban Construction Statistical Yearbook", "China Statistical Yearbook", statistical yearbooks and bulletins of various prefecture-level cities, and socio-economic big data platforms. After excluding samples with excessive missing data, this paper uses linear interpolation to fill in some missing values, resulting in a final sample of 4448 observations from 278 prefecture-level cities. At the same time, in order to reduce dimensional differences and mitigate the impact of heteroscedasticity, the variables of digital technology patents, per capita GDP, and population size were logarithmized. For indicators measured in monetary terms, this paper uses 2006 as the base year for data deflation in order to eliminate the impact of price factors. Descriptive statistics for each variable are presented in *Table 1*.

Analysis of time trend changes

Examining changes in digital technology innovation and energy intensity over time. As shown in *Figure 1,* China's digital technology patents show a rapid growth trend. In 2006, the total number of digital technology patents in 278 prefecture-level cities was 38,600, with an average of 139 patents per prefecture-level city. By 2021, the total number of digital technology patents in 278 prefecture-level cities will be 836,500, with an average of 3009 patents per prefecture-level city. The number of digital technology patents has increased by almost 22 times. Energy intensity, on the other hand, shows a fluctuating trend. The overall energy intensity shows a decreasing state in the period 2006-2015, while it shows an increasing state in the period 2016-2021. This changing trend is closely related to the economic development situation. Since 2016, China has faced the impact of major events such as the US-China trade and the global public health crisis, and economic growth has been weak, leading to an increase in energy intensity.

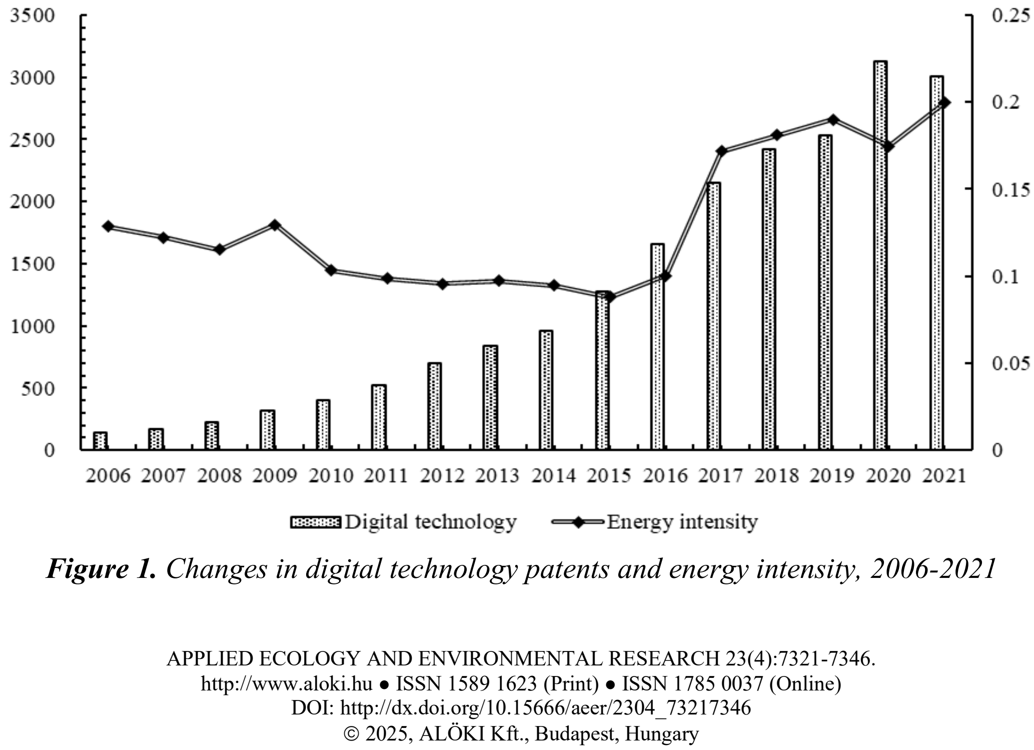

Figure 1. *Changes in digital technology patents and energy intensity, 2006-2021*

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Table 1. *Descriptive statistics*

Variable name	Sample capacity	Mean	Median	Least value	Crest value	Standard deviation
Energy Intensity (*EI*)	4448	1.3065	0.9649	0.0769	61.7683	1.7819
Digital Technology (*DT*)	4448	5.0536	5.0752	0	11.6707	2.1162
Capital misallocation (*KM*)	4448	0.5311	0.3545	0.0001	47.5710	1.2014
The level of economic development (*pgdp*)	4448	10.2977	10.2602	7.9255	12.7425	0.7482
Urbanization (*urb*)	4448	0.5222	0.5064	0.1151	1	0.1631
Population size (*pop*)	4448	5.8547	5.9137	2.8685	7.3499	0.6760
Industrial structure (*indu*)	4448	0.4012	0.3933	0.0858	0.8049	0.0978
Fiscal autonomy (*fis*)	4448	0.4571	0.4229	0.0543	1.1665	0.2231

Empirical test results

Baseline regression results

To improve the reliability of the benchmark regression test results, this paper uses mixed OLS models and fixed effects models for regression estimation, divided into five scenarios as shown in *Table 2*. Columns (1) and (2) are the estimation results of the mixed OLS model. Columns (3) to (5) are the estimation results of the fixed effects model. Columns (1) and (3) are the results without control variables. Column (4) is the estimation result of the fixed effects model without time effects. Column (5) is the bidirectional fixed effects estimation result, controlling for both time and individual effects simultaneously. In all five scenarios, the estimated coefficient of *DT* is significantly positive at the 1% level, indicating that digital technology innovation significantly improves energy intensity. The estimation coefficient of DT^2 is significantly negative at the 1% level, indicating that digital technology innovation significantly reduces energy intensity. Therefore, under five scenarios, digital technology innovation can have a significant inverted U-shaped impact on energy intensity. Hypothesis H1 is confirmed.

For the control variables, this can be seen in column (5). Economic development significantly reduces energy intensity, and as the level of economic development increases, so does the level of technology, which improves the efficiency of energy use and thus reduces energy intensity. The acceleration of urbanization and the expansion of urban population lead to population and economic agglomeration, causing a sharp increase in energy consumption, which in turn increases energy intensity. At the same time, the growth of the tertiary sector requires a certain amount of energy consumption as its foundation, such as the development of the digital economy, which requires substantial electricity input. Therefore, over a period of time, the development of the tertiary sector can potentially increase energy intensity. Finally, as the main function of the government is to provide public services, with the improvement of economic development and the level of social governance, fiscal resources will be mainly directed to the public sector and the direct impact on economic activities will gradually weaken, thus reducing the influence on energy intensity.

Robustness test

U-shaped relationship test

First, the benchmark regression results show that the first-order coefficients of the core explanatory variable, digital technology, are significantly positive and the second-

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order coefficients are significantly negative, in line with theoretical expectations. This suggests that the impact of digital technology innovation on energy intensity follows an inverted U-shape. To better illustrate the inverted U-shaped relationship between the two, this article uses a scatterplot as shown in *Figure 2*. Due to the quadratic coefficient of -0.0340 in digital technology, the slope of the curve is relatively small, but overall it shows an inverted U-shaped characteristic.

Table 2. *Baseline regression results*

Variable	(1)	(2)	(3)	(4)	(5)
DT	0.1494*** (0.03802)	0.2726*** (0.0365)	0.3868*** (0.0593)	0.3917*** (0.0600)	0.4490*** (0.0612)
DT^2	-0.0141*** (0.0031)	-0.0234*** (0.0039)	-0.0355*** (0.0051)	-0.0248*** (0.0053)	-0.0340*** (0.0056)
pgdp		-0.1569** (0.0757)		-1.0660*** (0.1600)	-2.6655*** (0.4322)
urb		2.4265*** (0.3704)		2.5937*** (0.4614)	2.2234*** (0.4076)
pop		-0.8137*** (0.0872)		02384 (0.2948)	0.8342*** (0.3102)
indu		1.2641*** (0.3941)		5.0021*** (0.6025)	1.5707** (0.7637)
fis		-0.3898** (0.1754)		-0.6136* (0.3208)	0.4327 (0.4185)
Constant	0.9734*** (0.1153)	5.4144*** (0.9626)	0.0303 (0.1539)	5.7225*** (1.5835)	17.4378*** (3.4588)
Time effect	No	No	Yes	No	Yes
Urban effects	No	No	Yes	Yes	Yes
Sample capacity	4448	4448	4448	4448	4448
R^2	0.0024	0.1554	0.5377	0.5233	0.5460

(1) *, ** and *** denote significance levels of 10%, 5% and 1% respectively. The standard error is given in brackets. (2) "Yes" and "No" indicate whether the model controls for the relevant variables

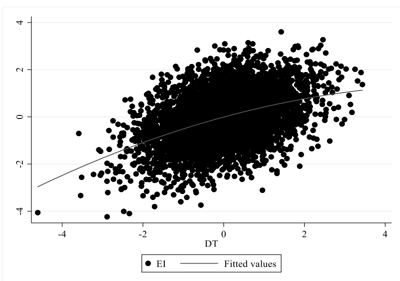

Figure 2. *Inverted U-shaped relationship between digital technologies and energy intensity*

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Secondly, Haans et al. (2016) pointed out that the significant DT^2 coefficient alone does not fully confirm the existence of an inverted U-shaped relationship, therefore it is necessary to test for an inverted U-shaped relationship. This paper tests the relationship between digital technology innovation, capital mismatch and energy intensity, and the results are shown in *Table 3*. The results show that the level range of digital technology innovation is (0.0000, 11.6707), with a turning point at 5.4415. The slope of the left interval is 0.3868, which is significant at the 1% level. The slope of the right interval is -0.4428, which is also significant at the 1% level. This result indicates that there is an inverted U-shaped relationship between digital technology innovation and energy intensity.

Table 3. *Inverted U-shaped relationship test results*

Variable	Interval	Slope	T-value	P > | t |
Lower bound	0	0.3868	6.5174	0
Upper bound	11.6707	-0.4428	-5.9213	0

S-type relationship test

To rule out the possibility of an S-shaped relationship between digital technology innovation and energy intensity, this paper constructs DT^3 and enters it into the regression model, the test results are shown in column (1) of *Table 4*. The regression coefficient of DT^3 is not significant, that is, there is no S-shaped relationship. Meanwhile, both the regression coefficients of DT and DT^2 have undergone some changes. This test result confirms that the conclusions of this study are robust.

Quantile regression tests

The above measurement analysis is based on the average value perspective, without specifically examining the differences in the impact of digital technology development in regions with different energy intensities. In order to address this, the quantile regression model is also used in this paper. This method estimates the conditional quantiles of the dependent variable using the explanatory variables and provides more robust estimation results compared to OLS models. In this paper, 25%, 50% and 75% are selected as quantiles for the regression. The regression results are presented in columns (2) to (4) of *Table 4*. The test results for the three quantiles are broadly consistent with the benchmark regression results.

Staged inspection

In order to improve the development level of urban broadband and vigorously promote the informatization process, China's "Broadband China" strategy and implementation plan, released in August 2013, clearly outlined key tasks such as actively conducting regional pilot demonstrations, accelerating broadband network optimization and upgrading, and promoting the improvement of the broadband network industry chain. In 2014, China initiated the establishment of Broadband China Demonstration Cities. For this purpose, this article divides the observation period into 2006-2013 and 2014-2021. The test results are shown in columns (5) and (6) of *Table 4*. In the 2006-2013 period, the estimated coefficient of DT was positive but insignificant.

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The estimated coefficient of DT^2 is significantly negative. In the 2014-2021 period, the estimated coefficient of DT is significantly positive, while the estimated coefficient of DT^2 is significantly negative. The results of the subsequent stages are generally similar to the results of the baseline regression.

Endogeneity test

Delaying the core explanatory variable by one period and then performing a two-way fixed effects regression estimation can avoid the impact of current energy intensity on digital technology innovation, thereby overcoming the endogeneity problem caused by reverse causality. The process is divided into two steps: first, digital technology is lagged by one period, and then these data are included in the model for regression estimation. From the regression results in column (7) of *Table 4,* it can be seen that after delaying digital technology by one period, the estimated coefficients of digital technology on energy intensity are 0.4559 and -0.0354, respectively, and both are significant at the 1% level. This result is basically consistent with the benchmark regression results in terms of coefficient values and significance.

Table 4. *Robustness test*

Variable	**(1) S-shaped relationship**	**(2) 25%**	**(3) 50%**	**(4) 75%**	**(5) 2006-2013**	**(6) 2014-2021**	**(7) Lag one period**
DT	0.3985*** (0.1097)	0.1447*** (0.0062)	0.1532*** (0.0076)	0.1451*** (0.0082)	0.0966 (0.0655)	0.4754** (0.2134)	0.4559*** (0.0676)
DT^2	-0.0227 (0.0227)	-0.0091*** (0.0005)	-0.0094*** (0.0007)	-0.0085*** (0.0008)	-0.0217*** (0.0077)	-0.0232* (0.0126)	-0.0354*** (0.0062)
DT^3	-0.0009 (0.0014)						
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.2381*** (3.4274)	6.3515*** (0.3403)	6.9255***(0.5 581)	9.2117*** (0.4881)	4.5831 (4.4170)	5.0698 (4.6464)	19.1215*** (3.8502)
Time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample capacity	4448	4448	4448	4448	2224	2224	4170
R^2	0.5461	0.5418	0.5796	0.6549	0.5335	0.5343	0.5640

(1) *, ** and *** denote significance levels of 10%, 5% and 1% respectively. The standard error is given in brackets. (2) “Yes” indicates that the model controls for the relevant variables

Heterogeneity analysis

Whether it is a resource-based city

Resource-based cities rely on the extraction and processing of resources such as minerals and forests. With the extensive exploitation and depletion of advantageous resources, most resource-based cities face crises such as insufficient production factors, monolithic industrial structures and sluggish economic growth. Compared with non-resource-based cities, resource-based cities are dominated by the energy industry, with a high proportion of energy-intensive and highly polluting projects, and weaker concentrations of production factors such as technology, talent and networks. Therefore, dividing the sample into resource-based and non-resource-based cities better reflects the heterogeneous impact of digital technology on energy intensity under different

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economic models and industrial structures. According to the National Sustainable Development Plan for Resource-Based Cities issued by China in 2013, the sample cities are divided into two groups: resource-based cities and non-resource-based cities. This document defines resource-based cities as those whose leading industry is the extraction and processing of natural resources such as minerals and forests in the region. In this paper's sample, there are 112 resource-based cities, accounting for 43.9%, and 166 non-resource-based cities. The test results are presented in columns (1) and (2) of *Table 5*. In resource-based cities, the estimated coefficient of DT^2 is insignificant, i.e. digital technology cannot reduce energy intensity. In non-resource-based cities, on the other hand, the estimated coefficient of DT^2 is significantly negative, indicating that digital technology innovation can reduce energy intensity.

Whether it is a low-carbon pilot city

To promote and implement the concept of low-carbon development, China launched low-carbon city pilot projects in July 2010, expanded the pilot scope in November 2012 and January 2017, and finally formed three batches of low-carbon pilot cities. The pilot cities are required to actively reflect the requirements of green and low-carbon development in urban planning, industrial systems, lifestyles and consumption patterns. Digital technology, as an emerging technology, brings advantages such as cross-temporal information dissemination, data creation and reduced transaction costs, which help to promote the transformation of production and lifestyles into green, low-carbon, energy-efficient and efficient models, thereby influencing low-carbon development. For this reason, this paper divides the sample into low-carbon pilot cities and non-low-carbon pilot cities, and conducts heterogeneity tests accordingly. There are 119 pilot cities (42.8%) and 159 non-pilot cities. The test results are shown in columns (3) and (4) of *Table 5*. In both low-carbon pilot cities and non-low-carbon pilot cities, digital technology has an inverted U-shaped impact on energy intensity. However, in low-carbon pilot cities the impact of digital technology on energy intensity is more pronounced.

Whether it is a pilot city for "Broadband China"

Digital infrastructure is the foundation for the development of digital technology and the digital economy. The "Broadband China" strategy is an important initiative launched by China to promote the rapid development of digital infrastructure and take the initiative in the development of the digital economy. This policy aims to create comprehensive conditions for the development of the digital economy through measures such as increasing the number of broadband users, improving broadband penetration rates, enhancing broadband network capabilities and promoting broadband information applications. China successively launched three batches of "Broadband China" demonstration city construction in 120 cities in 2014, 2015 and 2016. Does the Broadband China pilot have a different impact on digital technology and energy intensity? For this purpose, the sample is divided into Broadband China pilot cities and non-pilot cities. There are 104 pilot cities (37.4%) and 174 non-pilot cities. The results are presented in columns (5) and (6) of *Table 5*. In both Broadband China pilot cities and non-pilot cities, digital technology has an inverted U-shaped impact on energy intensity. However, in the Broadband China pilot cities, the impact of digital technology on energy intensity is more pronounced.

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***Table 5.** Test results of heterogeneity and moderating effects*

Variable	(1) Resource-based	(2) Non-resource	(3) Low-carbon pilot projects	(4) Non-low carbon pilot	(5) "Broadband China" pilot project	(6) Non-"Broadband China" pilot	(7) Regulatory effect
DT	0.2934** (0.1049)	0.5919*** (0.0741)	0.4337*** (0.1072)	0.4192*** (0.0749)	0.5751*** (0.0883)	0.3588*** (0.0740)	0.4412*** (0.0606)
DT^2	-0.0185 (0.0126)	-0.0531*** (0.0065)	-0.0381*** (0.0105)	-0.0283*** (0.0059)	-0.0354*** (0.0067)	-0.0320*** (0.0075)	-0.0344*** (0.0055)
$DT \times CM$							0.1335** (0.0619)
$DT^2 \times CM$							-0.0136** (0.0055)
CM							-0.0728*** (0.0197)
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.7085*** (4.7338)	22.1653** (5.6751)	26.0566*** (5.7924)	11.9475*** (3.9030)	23.6531*** (4.4066)	12.4464** (5.1547)	17.1812*** (3.4687)
Time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample capacity	1792	2656	1904	2544	1664	2784	4448
R^2	0.4627	0.6376	0.5216	0.5613	0.6649	0.5006	0.5475

(1) ** and *** represent 5% and 1% levels of significance respectively. The standard error is given in brackets. (2) "Yes" indicates that the model controls for the relevant variables

Test for moderating effect

Before conducting the moderated effects test, in order to avoid the problem of multicollinearity, before generating the interaction term in this paper, the moderating and independent variables are zero-mean treated, and then the zero-mean treated independent variables are multiplied by the moderating variables to form the interaction term. Based on *Equation 2*, the moderating effect of capital mismatch was tested, and the test results are shown in column (7) of *Table 5*. The estimated coefficient of DT is significantly positive, and the estimated coefficient of $DT \times CM$ is also significantly positive. While the estimated coefficients for DT are significantly negative, the estimated coefficients for $DT^2 \times CM$ are also significantly negative. The results indicate that in the early stages of digital technology development, digital technology increases energy intensity while capital mismatch has a positive moderating effect. However, as the level of digital technology innovation improves, digital technology reduces energy intensity while capital mismatch has a negative moderating effect. Therefore, for the inverted U-shaped relationship between digital technology innovation and energy intensity, capital mismatch plays an increasing moderating role in the first half of the inverted U-shape and a decreasing moderating role in the second half. Assuming H2 holds. In summary, the existence of capital mismatch makes it difficult to effectively unleash the reducing effect of digital technology innovation on energy intensity.

Analysis of spatial spillovers

To further explore whether digital technology innovation has spatial spillover effects on urban energy intensity and to test whether there is a moderating effect of capital misallocation on this spatial spillover effect, this paper will examine the spatial

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correlation of key variables and use a geographic adjacency matrix to test the spatial spillover effect. The methodology of the spatial spillover test is mainly based on the study by Zhu et al. (2024).

Spatial correlation test

In order to investigate the spatial spillover effects of digital technology innovation on energy intensity, it is first necessary to test whether there is a spatial correlation between the two. This paper uses a geographical adjacency matrix and Moran's I spatial autocorrelation test to confirm the spatial association and its strength of the variables. The specific calculation formula is given in *Equation 7*.

$$Morans'\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(v_j-\bar{v})(v_i-\bar{\bar{v}})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{Eq.7}$$

In *Equation 7*, w_{ij} is the geographical adjacency matrix, n is the total number of sample cities. The range of Moran's I is between -1 and 1. If the index value is greater than 0, it indicates positive spatial correlation. If it is less than 0, it indicates negative spatial correlation. The results of the global Moran's I index test are presented in *Table 6*. From 2006 to 2021, the global Morans' I index for digital technology and energy intensity was greater than 0 in 278 cities, and it was significant at the 1% level most of the time. This indicates that there is positive spatial autocorrelation in the digital technology and energy intensity of the sample cities. The 278 cities show significant spatial clustering characteristics in both digital technology and energy intensity variables, but the degree of clustering varies over time.

Table 6. *Moran's I index of global digital technology and energy intensity from 2006 to 2021*

	Digital technique			**Energy intensity**		
	I	***z***	***P-value***	***I***	***z***	***P-value***
2006	0.089	12.824	0.000	0.010	2.219	0.013
2007	0.092	13.267	0.000	0.046	7.185	0.000
2008	0.096	13.853	0.000	0.045	7.277	0.000
2009	0.115	16.475	0.000	0.009	3.456	0.000
2010	0.122	17.499	0.000	0.026	4.285	0.000
2011	0.116	16.549	0.000	0.044	6.854	0.000
2012	0.115	16.407	0.000	0.054	8.312	0.000
2013	0.114	16.316	0.000	0.060	9.657	0.000
2014	0.116	16.638	0.000	0.065	10.573	0.000
2015	0.117	16.673	0.000	0.037	5.796	0.000
2016	0.125	17.869	0.000	0.068	12.905	0.000
2017	0.136	19.395	0.000	0.084	13.407	0.000
2018	0.136	19.399	0.000	0082	12.514	0.000
2019	0.131	18.682	0.000	0.062	9.609	0.000
2020	0.131	18.732	0.000	0.063	10.039	0.000
2021	0.118	16.868	0.000	0.054	8.735	0.000

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To further analyze the spatial correlation between regions, this paper uses the Moran's I scatterplot to characterize the spatial distribution characteristics of digital technology and energy intensity. The local spatial autocorrelation is tested using the Local Moran's I index, whose calculation formula is shown in *Equation 8*.

$$Local\ Morans'\ I = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^{n} W_{ij} (x_j - \bar{x}) \qquad \text{(Eq.8)}$$

In *Equation 8*, the Local Moran's I index represents the degree of association between the observed values of the city and the surrounding cities. By organizing the observations of each city, a scatter plot of the Local Moran's I index can be generated. According to energy intensity, spatial association patterns are categorized into four types: the first type, the High Intensity Zone (HH), where both the observed area and the surrounding areas have a high energy intensity; the second type, the Transitional Zone (LH), where the energy intensity of the observed area is lower than that of the surrounding areas; the third type, the Low Intensity Zone (LL), where both the observed area and the surrounding areas have a low energy intensity; the fourth type, the Radiant Zone (HL), where the energy intensity of the observed area is higher than that of the surrounding areas. *Figure 3* shows the Moran's I scatter plot of energy intensity for 2021, and *Figure 4* shows the Moran's I scatter plot of digital technology innovation level for 2021. The numbers in the two figures represent the sample, i.e. the cities at prefecture level. It can be observed that there is a positive correlation in regional energy intensity, and it shows clustering characteristics. Specifically, energy intensity is mainly clustered in the third type of region, while digital technology innovation is mainly clustered in the first and third type of regions.

Spatial econometric model construction

Due to the spatial heterogeneity and correlation of energy intensity, local energy intensity may be influenced by neighboring cities, leading to certain biases in the estimation results of traditional measurement methods. Therefore, it is necessary to incorporate appropriate spatial econometric models for a comprehensive evaluation. Spatial econometric models mainly include spatial lag models (SLM), spatial error models (SEM) and spatial Durbin models (SDM). SLM primarily examines the spatial diffusion effect of the explained variable. SEM includes interaction terms of the error terms and focuses on revealing the impact of unobserved independent variables on the explained variable. However, SDM is a general form of SLM and SEM that has both spatial autocorrelation and spillover effects, effectively measuring the spatial effects of the observed variable. This paper further selects models using LM tests, LR tests, Wald tests and Hausman tests. According to the test results in *Table 7,* this paper finally decides to use a two-way fixed effects SDM test to examine the spatial spillover effect of digital technology innovation on energy intensity. The specific model is shown in *Equation 9*.

$$EI_{it} = \delta \sum_{j=1}^{n} w_{ij} EI_{it} + \alpha_1 DT_{it} + \alpha_2 DT_{it}^2 + \alpha_3 X_{it} + \theta_1 \sum_{j=1}^{n} w_{ij} DT_{it} + \theta_2 \sum_{j=1}^{n} w_{ij} DT_{it}^2 + \theta_3 \sum_{j=1}^{n} w_{ij} X_{it} + u_i + \varepsilon_i + v_{it} \qquad \text{(Eq.9)}$$

In *Equation 9*, δ is the spatial autoregressive coefficient. The α is the coefficient of the explanatory variables. The θ is the spatial autoregressive coefficient of the exogenous variables. The w is the spatial weight matrix. The other parameters have the same meaning as in *Equation 1*.

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Spatial effect test results

The results of the regression analysis of the spatial panel Durbin model are presented in *Table 8*. Within the region, the estimated coefficients of *DT* and DT^2 are 0.4949 and -0.0444 respectively, which both pass the test at the 1% significance level. This indicates that digital technological innovation has an inverted U-shaped effect on energy intensity in the region, i.e. it is initially a boosting effect and then turns into a dampening effect. However, for the neighboring regions, the estimated coefficients of *DT* and DT^2 are -1.4769 and 0.1529 respectively, which pass the test at the 1% significance level. This indicates that digital technological innovation has a U-shaped effect on energy intensity in neighboring regions, i.e. an initial dampening effect and then a boosting effect.

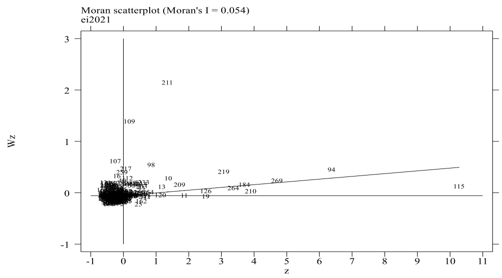

***Figure 3.** Moran's I scatter plot of energy intensity in 2021*

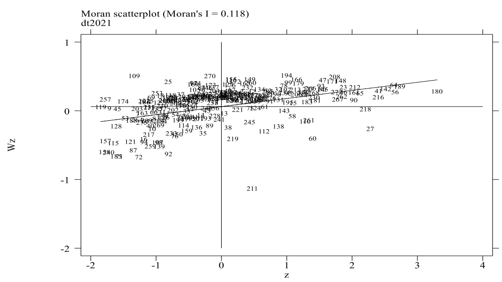

***Figure 4.** Moran's I scatter plot of digital technology innovation level in 2021*

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Table 7. *Diagnostic test results of spatial measurement*

Method of calibration	Test indicators	Statistic	*P-value*
LM checkout (spatial error)	Morans I	10.533	0.000
	LM	104.960	0.000
	RLM	86.007	0.000
LM checkout (spatial lag)	LM	34.318	0.000
	RLM	15.365	0.000
Wald checkout	SDM & SAR	283.720	0.000
	SDM & SEM	280.280	0.000
LR checkout	SDM & SAR	60.750	0.000
	SDM & SEM	63.320	0.000
Hausman test		46.120	0.000

Table 8. *Regression results of spatial Durbin model*

Variable	(1) Main	(2) WX	(3) Direct effect	(4) Indirect effects	(5) Total effect
DT	0.4949*** (0.0514)	-1.4769*** (0.3325)	0.4994*** (0.0529)	-1.3374*** (0.2762)	-0.8379*** (0.2684)
DT^2	-0.0444*** (0.0053)	0.1529*** (0.0267)	-0.0449*** (0.0053)	0.1386*** (0.0235)	0.0937*** (0.0219)
Controlled variable	Yes				
rho	-0.1931*** (0.0583)				
sigma2_e	1.4178*** (0.0301)				
Sample capacity	4448				
R^2	0.0535				

(1) *** represents the 1% significance level. The standard error is given in brackets. (2) “Yes” means that the model controls for the relevant variables

The effects of the spatial Durbin model are decomposed into direct and indirect effects, as shown in *Table 8*. Among them, the direct effect shows that the estimated coefficients of both *DT* and DT^2 are significant at the 1% level in the local region with coefficient values of 0.4994 and -0.0449, confirming the existence of an inverted U-shaped effect on energy intensity in the region. The indirect effect (spillover effect) shows that for neighboring regions, the estimated coefficient of *DT* is negative and significant at the 1% level of significance, indicating that DT can reduce energy intensity in neighboring regions. However, the estimated coefficient of DT^2 is significantly positive, indicating that it will increase the intensity of energy sources in the later period. Therefore, it can be concluded that digital technology innovation has an U-shaped effect on the energy intensity of the surrounding areas. The reason for this phenomenon may be that with the continuous improvement of the city’s digital technology level, the digitalization level of local industries has been improved, accelerating local industrial upgrading and low-carbon development. Meanwhile, industrial upgrading and green development will encourage high-energy-consuming enterprises to relocate to surrounding areas, leading to increased energy consumption in these regions.

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Test results of spatial adjustment effect

The moderating effect of capital mismatch has been verified in the previous section. To further analyze the spatial regulatory effect of capital mismatch, $DT \times CM$ and $DT^2 \times CM$ are introduced into *Equation 9*, respectively, and the results are shown in *Table 9*. After decomposing the spatial effect, the indirect effect of $DT \times CM$ is significantly negative and the indirect effect of $DT^2 \times CM$ is significantly positive. The results show that there is a U-shaped effect of digital technology innovation on energy intensity in the neighborhood. The results suggest that digital technology innovation has a U-shaped effect on the energy intensity of the surrounding area. In the first half of the U-shape, digital technology innovation significantly reduces energy intensity in surrounding areas, while capital misallocation has a weakening moderating effect. In the second half of the U-shape, digital technology innovation significantly increases energy intensity in the surrounding areas, while capital misallocation has an increasing moderating effect. In summary, in terms of spatial spillovers, capital misallocation inhibits the reduction of energy intensity in other regions.

Table 9. *Test results of spatial adjustment effect*

Variable	(1) Main	(2) WX	(3) Direct effects	(4) Indirect effects	(5) Total effect
DT	0.4798*** (0.0522)	-1.0508*** (0.3924)	0.4838*** (0.0536)	-0.9749*** (0.3250)	-0.4911 (0.3241)
DT^2	-0.0421*** (0.0053)	0.1270*** (0.0275)	-0.0427*** (0.0053)	0.1153*** (0.0259)	0.0726*** (0.0245)
$DT \times CM$	0.1416** (0.0590)	-2.7636*** (0.5837)	0.1448** (0.0562)	-2.2849*** (0.5008)	-2.1401*** (0.5026)
$DT^2 \times CM$	-0.0139*** (0.0049)	0.2638*** (0.0577)	-0.0142*** (0.0047)	0.2174*** (0.0484)	0.2032*** (0.0485)
CM	-0.0695*** (0.0218)	0.3094 (0.3350)	-0.0678*** (0.0208)	0.2515 (0.2666)	0.1837 (0.2667)
Controlled variable	Yes				
rho	-0.2041*** (0.0592)				
sigma2_e	1.4058*** (0.0298)				
Sample capacity	4448				
R^2	0.0000				

(1) ** and *** represent the 5% and 1% levels of significance respectively. The standard error is given in brackets. (2) “Yes” indicates that the model controls for the relevant variables

Discussion

Results discussion

Using a sample of 278 prefecture-level cities in China, this paper investigates the non-linear impact of digital technological innovation on energy intensity and also analyses the role of capital mismatch in this impact process. Three results are derived from the previous empirical tests. First, there is an inverted U-shaped impact of digital technological innovation on energy intensity, i.e. it is first enhanced and then

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suppressed. In particular, the estimated coefficient of the primary digital technology is 0.4490 and the estimated coefficient of the quadratic is -0.0340, and both are significant at the 1% level. And after a series of robustness tests, the results still hold. This is consistent with the findings of Liu et al. (2025) that there is a U-shaped relationship between digital technology innovation and urban carbon emission efficiency. As the current economy is in a period of transition and development, China has successively introduced low-carbon and digital development policies. Based on these policies, there is some variability in the impact of digital technology innovation on energy intensity. Second, capital mismatch, a common economic phenomenon, is innovatively introduced into the analysis. According to the econometric model test, it is found that in the inverted U-shaped impact of digital technological innovation on energy intensity, there is a bidirectional moderating effect of capital mismatch. In the first half of the inverted U-shape, capital mismatch plays a reinforcing role, which strengthens the energy intensity improvement effect of digital technology. In the second half of the inverted U-shape, capital mismatch plays a weakening role, both of which weaken the energy intensity reduction effect of digital technology. Third, this paper further analyses the spatial spillover perspective and concludes that the estimated coefficients of primary and secondary digital technology are -1.4769 and 0.1529, respectively, and both are significant at the 1% level. This suggests that there is a U-shaped effect of digital technology innovation on energy intensity in neighboring regions. This is generally consistent with the findings of Liu and Han (2024). However, this result contradicts the direct impact result in the previous section. On the other hand, the spatial spillovers associated with capital mismatch show the same two-way moderating effect. The three results of this paper comprehensively demonstrate the diversified impacts of digital technological innovation on energy intensity, especially by analyzing the moderating effect of capital mismatch. The results of this paper are highly innovative, address the shortcomings of existing studies, and can provide empirical evidence for regional digital technology innovation and low-carbon development.

Research limitations and future research

The limitations of this article are mainly in two aspects. First, the sample size of this article is 278 prefecture-level cities in China, without adopting more representative county-level samples, mainly due to the difficulty in obtaining county-level data. Second, the analysis of the intrinsic mechanism of digital technology affecting energy intensity is not yet comprehensive; this article only conducts a regulatory effect analysis from the perspective of capital misallocation, which may have other influencing mechanisms. These two shortcomings will be further investigated in the future.

Conclusion and policy implications

This paper selects 278 prefecture-level cities in China as the observation sample, with the observation period from 2006 to 2021, and theoretically analyses and empirically tests the impact effect of digital technology innovation on energy intensity, as well as the moderating effect of capital mismatch on this impact effect. Three main research conclusions are reached. First, digital technology innovation has an inverted U-shaped impact on energy intensity, first increasing and then decreasing, and passes several robustness tests. Heterogeneity analysis shows that in resource-based cities, since resources are the main pillar of economic development, the impact of digital

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technology innovation on energy intensity reduction is insignificant and does not show inverted U-shaped characteristics. In non-resource-based cities, however, there is a significant inverted U-shaped characteristic. In low-carbon pilot cities, non-low-carbon pilot cities, Broadband China pilot cities and non-Broadband China pilot cities, digital technology innovation has an inverted U-shaped impact on energy intensity. Second, capital mismatch has a significant moderating effect on the inverted U-shaped relationship between digital technology innovation and energy intensity. In the first half of the inverted U-shape, capital mismatch has a positive moderating effect on the total impact results. In the second half of the inverted U-shape, capital mismatch has a negative moderating effect on total impact. Third, digital technology innovation has a spatial spillover effect on energy intensity and exhibits a significant U-shaped characteristic, meaning that digital technology innovation affects energy intensity in the surrounding areas through spatial spillover effects. In the first half of the U-shape, there is a negative moderating effect of capital mismatch on spatial spillovers. In the second half of the U-shape, there is a positive moderating effect of capital mismatch on spatial spillovers. Capital mismatch is not conducive to reducing energy intensity through digital technology.

Based on the above conclusions, this paper proposes the following policy implications. First, enhance the innovation capability of digital technology. Continue to promote the deep integration of the real economy and the digital economy, with special emphasis on integration with the energy industry and high-energy-consuming industries, provide realistic needs and application scenarios for digital technology innovation, and promote the momentum of digital technology innovation. Second, expand the application areas of digital technology, accelerate the transformation of digital technology achievements, and promote the industrialization of digital technology and the digital transformation of industries. Rely on digital technology, use digital technology to transform productivity, and promote the digital transformation of the energy industry and high-energy-consuming industries and other real economies. Third, improve the efficiency of capital allocation. Further promote the free flow of capital and advance the reform of interest rate marketization, optimize capital allocation, reduce the financing cost for enterprises and other market entities engaged in technological innovation and energy use, and guide more capital to converge in innovative fields. Fourth, promote the balanced regional development of digital technology innovation and enhance the positive externalities of digital technology. Given the negative spatial spillover effects of digital technology on energy use, it is necessary, on the one hand, to promote the balanced regional development of digital technology to mitigate the negative externalities of digital technology on energy intensity. On the other hand, the regional industrial layout should be further optimized, allowing for reasonable regional differences, such as those between resource-based and non-resource-based cities. However, the overall energy intensity reduction effect of digital technology should be continuously improved.

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