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Has digital development achieved a synergistic effect of reducing energy intensity and improving carbon emission performance? evidence from China

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The rapid growth of the Chinese economy has significantly escalated energy consumption and carbon emissions. The imperative to achieve synergies in energy conservation and carbon reduction has never been more pressing. Digital development presents promising avenues for addressing these challenges, making it crucial to investigate its impact on energy intensity (EI) and carbon emission performance (CEP). This study integrates the super efficiency epsilon-based measure (SE-EBM), mediation effect, and threshold effect models to assess the influence of digital development on EI and CEP using data from 267 cities across China from 2011 to 2019. Our findings demonstrate a notable 23.1% reduction in EI and an 18.5% improvement in CEP attributable to digital development. Moreover, our analysis underscores the pivotal role of technological innovation as a transformative conduit. Importantly, we identify significant threshold effects linked to economic development stages. This study not only enriches our understanding of pathways to energy conservation and carbon reduction but also provides compelling evidence supporting policies aimed at fostering and accelerating digital development initiatives.

KEYWORDS

digital development, super efficiency epsilon-based measure model, energy intensity, carbon emission performance, mediation effect model, carbon neutrality

1 Introduction

The rapid expansion of digitalization has profoundly impacted China's production and daily life. According to Pan et al. (2022), the development of the digital economy contributes to promoting the transition towards green production and lifestyles. From 2012 to 2022, China achieved an annual energy consumption growth rate of 6.2%, leading to a cumulative 26.4% decrease in energy intensity (EI), equivalent to a reduction of approximately 1.41 billion tons of standard coal and nearly three billion tons of carbon emissions (CAC, 2022). The integration of the digital economy with traditional industries has enhanced resource utilization efficiency, promoting low-carbon production and sustainability (Ghobakhloo, 2020; Ding et al., 2022). Therefore, digital development significantly contributes to achieving green and low-carbon objectives.

Numerous studies have investigated the energy and environmental impacts of the digital economy (Haseeb et al., 2019; Lange et al., 2020; Zhang et al., 2022; Ma et al., 2022; Guo et al., 2023). However, our study identifies two potential gaps compared to existing research: Firstly, previous studies predominantly focus on energy consumption impacts, neglecting EI. For example, these studies examine digital development's influence on energy consumption (Salahuddin and Alam, 2016; Lange et al., 2020; Ren et al., 2021; Zheng and Wang, 2021), energy transition (Shahbaz et al., 2022), energy security (Lee et al., 2022; Li et al., 2024), and energy sustainability (Wang et al., 2022b). Secondly, existing research predominantly assesses carbon emissions and environmental pollution impacts, neglecting carbon emission performance (CEP). For example, studies explore digital development's effects on carbon emissions (Paschou et al., 2020; Ahmed and Le, 2021; Xu et al., 2021; Zhang et al., 2022; Dong et al., 2022; Dwivedi et al., 2022), environmental quality (Raza and Tang, 2022; Xu et al., 2022), and air pollution (Wu et al., 2023). Moreover, there is limited research focusing on developing countries, particularly China, which faces significant challenges related to carbon emissions and energy consumption (Jiang and Raza, 2023). Therefore, our study aims to fill these gaps in the existing literature, contributing to carbon neutrality goals and promoting digital development in developing countries.

This study offers several significant contributions to the literature. Firstly, while previous studies separately examine energy and carbon emissions (Husaini and Lean, 2022; Khan et al., 2022), our study provides a comprehensive assessment under a unified framework. Secondly, while many studies traditionally use energy consumption and carbon emissions as indicators (Salahuddin et al., 2016; Lange et al., 2020), we introduce metrics for EI and CEP, essential for understanding energy efficiency and emission reduction efforts. Thirdly, whereas existing research often relies on simple linear models (He et al., 2021; Zhang and Liu, 2022), we employ advanced linear models alongside mediation and threshold effect models. These models enable a comprehensive evaluation of the indirect and threshold effects of digital development on EI and CEP. By integrating theoretical insights with empirical analysis, our study provides a nuanced understanding of how digital development influences energy conservation and emission reduction strategies.

This study integrated the super efficiency epsilon-based measure (SE-EBM), mediation effect, and threshold effect models to assess the impact of digital development on EI and CEP using data from 267 cities in China from 2011 to 2019. CEP was calculated using the SE-EBM model, evaluating the linear, nonlinear, and threshold effects of digital development on EI and CEP using fixed effects, mediation effects, and threshold effects models. Furthermore, four robustness analysis methods were employed to test the stability of empirical results.

The logical structure of this study is as follows: Section 2 reviews the literature, Section 3 describes the methodology and data sources, Section 4 presents empirical results, and Section 5 provides conclusions and policy implications.

2 Literature review

2.1 Impact of digital development on energy consumption

Many existing studies have examined the impact of digital development on energy consumption reduction (Schulte et al., 2016; Cao et al., 2021). Cao et al. (2021) used digital finance as an indicator and found significant energy consumption reductions associated with digital development. Scholars have also highlighted digital development's role in enhancing energy sustainability (Wang et al., 2022b; Husaini and Lean, 2022) and promoting the adoption of new energy sources (Li et al., 2021; Hong Nham et al., 2023) or clean energy (Wang et al., 2023). Shahbaz et al. (2022) reported a notable increase in renewable energy usage by 0.021% due to digital development, contributing to green and sustainable development (Chen, 2022).

However, some researchers argue that the growth of the internet has led to increased energy consumption (Ren et al., 2021). Despite this, most studies emphasize the positive impact of digital development on reducing energy consumption and improving sustainability. EI serves as a crucial metric for assessing green and high-quality development, although digital development may adversely affect EI. Unfortunately, research specifically investigating the role of digital development in EI remains limited.

2.2 Impact of digital development on carbon emissions

Numerous studies have demonstrated the positive effect of digital development on reducing carbon emissions (Wang et al., 2022a; Li and Wang, 2022). Wang et al. (2022a) reported that a 1% increase in digital development correlates with a 0.886% decrease in carbon emissions. Digital development has been shown to facilitate significant reductions in carbon emissions through optimized energy mixes aimed at achieving carbon neutrality (Guo et al., 2022). Additionally, studies indicate that digital development plays a critical role in promoting low-carbon sustainable development, particularly in economically advanced eastern regions (Zhang et al., 2022; Lee and Wang, 2022). Some scholars have underscored the role of digital finance in advancing environmental sustainability (Ozturk and Ullah, 2022).

Conversely, others argue that digital development exacerbates carbon emissions, particularly in China (Zhou et al., 2019; Zhang et al., 2022; Li et al., 2018). Zhou et al. (2022) suggested that digital development has contributed to a 6% increase in China's total carbon emissions. Despite these findings, most scholars maintain that digital development ultimately benefits carbon emissions reduction. Existing research has predominantly focused on assessing CEP and its impacts on carbon emissions, overlooking research from the perspective of CEP. CEP is crucial for understanding the relationship between carbon emissions and economic growth, thereby serving as a pivotal indicator for green

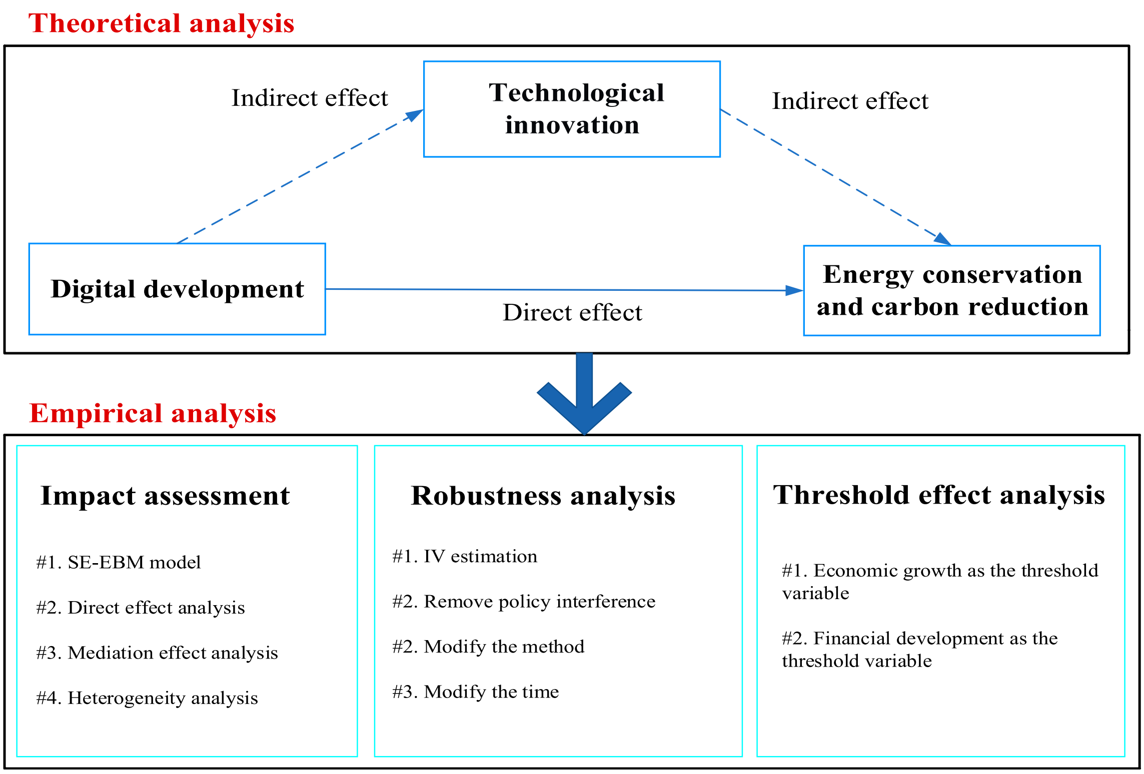

FIGURE 1
Research framework.

TABLE 1 Variable definitions.

Variable	Abbreviation	Definition
Energy intensity	LnEI	Proportion of energy consumption in GDP (log)
Carbon emission performance	LnCEP	Quantified through the SE-EBM model (log)
Digital development	LnDD	Calculations were performed using PCA (log)
Population density	LnPOPD	The ratio of urban population to the urban area (log)
Industrialization	LnIND	Secondary industry's share in city GDP (log)
Service industry	LnSER	The ratio of the tertiary industry to the city's total GDP (log)
Financial development	LnFD	Measured using the urban deposit-loan balance to GDP metric (log)
Energy structure	LnES	Proportion of electricity consumption in total energy use

development. Based on existing research, we propose that digital development presents new opportunities for enhancing CEP, although research specifically evaluating this remains scarce.

2.3 Energy-saving and emission reduction effects of digital development

Achieving synergies in energy conservation and carbon reduction is crucial for sustainable development, aligning with China's goals of peak carbon emissions by 2030 and carbon neutrality by 2060 (SCPRC, 2021; Chen et al., 2018). The Chinese government emphasizes coordinated efforts in energy conservation and carbon reduction through initiatives like the "Notice on the Action Plan for Peak Carbon Emissions by 2030". These efforts aim to increase the share of non-fossil energy consumption to approximately 20% by 2025, reduce energy consumption per unit of GDP by 13.5% from 2020 levels, and lower carbon dioxide emissions per unit of GDP by 18% from 2020 levels.

Existing literature, as reviewed in Section 2.1, Section 2.2, predominantly focuses on separate analyses of energy consumption and carbon emissions, overlooking synergistic effects within a unified framework. Moreover, existing studies often neglect EI and CEP, which are closely tied to economic growth.

TABLE 2 Brief analysis of variables.

Variable	Obs	Mean	Std.Dev	Min	Max
LnEI	2,403	−1.796	0.651	−3.448	2.131
LnCEP	2,403	−0.676	0.413	−3.153	0.425
LnDD	2,403	8.641	0.943	5.801	12.803
LnPOPD	2,403	6.473	0.934	2.263	9.564
LnIND	2,403	3.828	0.272	2.551	4.492
LnSER	2,403	3.808	0.264	2.317	4.425
LnFD	2,403	1.072	0.434	−0.581	3.413
LnES	2,403	−0.230	0.211	−1.429	−0.002

To address these gaps, our study evaluates the synergistic effects of digital development on EI and CEP under a unified framework. Based on the literature review, we hypothesize that digital development synergistically reduces EI and enhances CEP. Our hypotheses are as follows.

Hypothesis 1. Digital development has a significant synergistic effect on reducing EI and enhancing CEP.

2.4 Mechanism analysis

While existing research confirms the positive role of digital development in reducing energy consumption and carbon emissions (Chen et al., 2016; Wurlod and Noailly, 2018; Ajayi and Reiner, 2020; Chakraborty and Mazzanti, 2020), it often lacks theoretical explanations for underlying mechanisms. Digital development facilitates technological innovation and drives investments in technology (Vavilina et al., 2020; Zhou et al., 2020). For instance, Zhou et al. (2020) found that digital development promotes technological innovation, demonstrating robust empirical results using patent counts as indicators.

Technological innovation and scientific inputs are critical pathways through which digital development influences EI and CEP. Scholars have shown that digital development drives technological innovation (Apostolov and Coco, 2021; Li et al., 2017; Radicic and Petkovic, 2023) and that technological innovation positively impacts EI and CEP (Ma et al., 2021; Wahab, 2021; Wang and Liu, 2022). Thus, technological innovation serves as an intermediary variable in the relationship between digital development, EI, and CEP.

China's economic growth has been accompanied by regional disparities in energy and environmental outcomes (Zhang et al., 2022; Shahbaz et al., 2022). Financial development plays a crucial role in achieving carbon neutrality and promoting new energy development. Regional disparities, economic growth, and financial development heterogeneity may influence the impact of digital development on EI and CEP. Figure 1 illustrates our research framework.

Hypothesis 2. Digital development reduces EI and improves CEP through technological innovation.

Hypothesis 3. The impact of digital development on EI and CEP varies across different regions in China.

Hypothesis 4. The relationship between digital development and EI and CEP exhibits threshold effects related to economic growth and financial development.

3 Method and data

3.1 Method

The methodological approach in this study was carefully chosen to ensure robust analysis. We selected the fixed effects model to assess how digital development impacts EI and CEP, focusing on

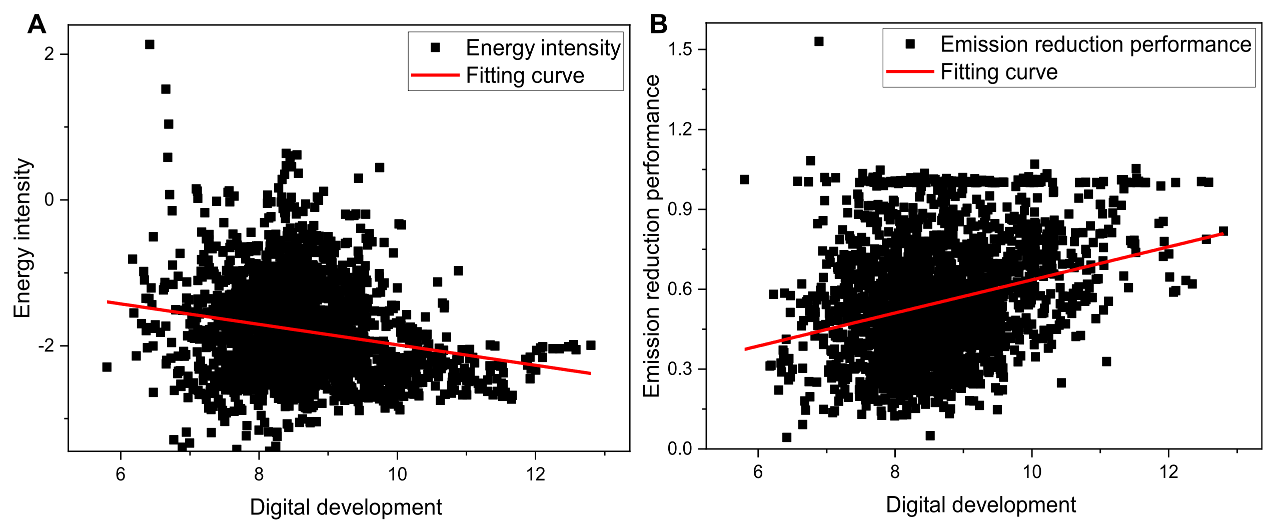

FIGURE 2
Scatter correlation between digital development, energy intensity, and carbon emission performance.

TABLE 3 Baseline regression results.

	Dependent variable: LnEI			Dependent variable: LnCEP		
	(1)	(2)	(3)	(4)	(5)	(6)
LnDD	−0.165***	−0.169***	−0.231***	0.123***	0.136***	0.185***
	(0.026)	(0.021)	(0.016)	(0.011)	(0.007)	(0.007)
LnPOPD		−0.002	−0.024*		−0.034*	−0.025**
		(0.020)	(0.013)		(0.016)	(0.009)
LnIND		−0.103	0.485***		−0.050	−0.435***
		(0.072)	(0.103)		(0.034)	(0.075)
LnSER			0.174*			0.044
			(0.081)			(0.075)
LnFD			0.578***			−0.523***
			(0.044)			(0.024)
LnEL			0.041			−0.022
			(0.140)			(0.039)
CONS	−0.532**	−0.082	−2.889***	−1.737***	−1.436***	−0.063
	(0.218)	(0.565)	(0.726)	(0.090)	(0.177)	(0.554)
FE	YES	YES	YES	YES	YES	YES
N	2,403	2,403	2,403	2,403	2,403	2,403
R^2	0.240	0.242	0.344	0.079	0.085	0.280

Note that standard errors are in parentheses; FE, refers to the fixed effects for both time and city.
[a]$p < 0.1$.
[b]$p < 0.05$, and.
[c]$p < 0.01$.

TABLE 4 Estimation results of the mediating effect.

Variables	Dependent variable: LnEI				Dependent variable: LnCEP			
	LnSI	LnEI	LnTI	LnEI	LnSI	LnCEP	LnTI	LnCEP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnDD	1.260***	−0.104***	0.055***	−0.231***	1.260***	0.104***	0.055***	0.181***
	(0.025)	(0.019)	(0.006)	(0.015)	(0.025)	(0.008)	(0.006)	(0.007)
LnSI		−0.100***				0.064***		
		(0.024)				(0.005)		
LnTI				−0.002*				0.088***
				(0.026)				(0.017)
CONTROL	YES	YES	YES	YES	YES	YES	YES	YES
CONS	−16.305***	−4.527***	−2.464**	−2.863***	−16.305***	1.165***	−2.464**	0.141
	(1.140)	(0.425)	(0.748)	(0.734)	(1.140)	(0.396)	(0.748)	(0.395)
FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2,403	2,403	2,398	2,398	2,403	2,403	2,398	2,398
R^2	0.568	0.376	0.102	0.345	0.568	0.403	0.102	0.288

The standard errors are in parentheses; CONTROL, refers to the controlling variables; FE, refers to the fixed effects for both time and city.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

TABLE 5 Regression results of regional and urban heterogeneity.

	Dependent variable: LnEI			Dependent variable: LnCEP		
	Eastern	Central	Western	Eastern	Central	Western
LnDD	−0.253***	−0.227***	−0.196***	0.008	0.117***	0.051
	(0.020)	(0.010)	(0.027)	(0.030)	(0.028)	(0.034)
CONTROL	YES	YES	YES	YES	YES	YES
CONS	−2.281***	−0.108	−6.375***	−0.089	−1.028	−1.178
	(0.461)	(0.738)	(1.574)	(1.132)	(0.836)	(1.237)
FE	YES	YES	YES	YES	YES	YES
N	1,008	900	495	1,008	900	495
R^2	0.370	0.358	0.353	0.090	0.178	0.150

Note that standard errors are in parentheses; CONTROL, refers to control variables; FE, refers to the fixed effects for both time and city.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

TABLE 6 Regression results of urban heterogeneity.

	Dependent variable: LnEI		Dependent variable: LnCEP	
	TCZ	Non-TCZ	TCZ	Non-TCZ
LnDD	−0.300***	−0.088***	0.210***	0.110***
	(0.015)	(0.015)	(0.014)	(0.007)
CONTROL	YES	YES	YES	YES
CONS	−2.877***	0.031	−3.226***	−2.349**
	(0.543)	(0.548)	(0.743)	(0.770)
FE	YES	YES	YES	YES
N	1,188	1,215	2079	324
R^2	0.417	0.442	0.350	0.396

Note that standard errors are in parentheses; CONTROL, refers to control variables; FE, refers to the fixed effects for both time and city.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

linear effect analysis while controlling for potential individual effects. Subsequently, we employed the panel threshold model to explore nonlinear effects, investigating the thresholds of digital development on EI and CEP. Additionally, we used the mediation effect model to examine the mechanisms through which digital development influences EI and CEP, facilitating path analysis. Hence, our methodology not only adheres to the logical framework of the study but also ensures the applicability and comprehensiveness of the methods.

3.1.1 Baseline model

In our baseline model, digital development serves as the independent variable, while EI and CEP are the dependent variables. This model aims to elucidate how digital development enhances EI and CEP. Referring to the model of Chen et al. (2018), we set the following model:

$$y_{it} = \alpha_0 + b_1 DD_{it} + \sum_{g=1}^{5} f_g x_{git} + \gamma_i + \rho_t + \varepsilon_{it}$$

where y_{it} represents the values of EI and CEP for city i at time t, DD denotes the digital development variable, and b_1 is the coefficient of interest. We anticipated a positive value for b_1, indicating that digital development positively influenced the improvement of both EI and CEP. f represents the parameter for other variables, and x is the control variable. α_0 and ε_{it} correspond to the intercept and error terms, respectively. ρ_t and γ_i captured the time and city fixed effects, respectively.

3.1.2 Panel threshold model

The impact of digital development on EI and CEP is influenced by various factors, leading to a nonlinear relationship between them. To explore this, we propose employing a threshold model to investigate how digital development affects EI and CEP under

TABLE 7 Estimation results of the instrumental variables.

Variables	Dependent variable: LnEI		Dependent variable: LnCEP	
	First stage regression	Second stage regression	First stage regression	Second stage regression
IV1: L.Y				
L.Y	0.932***		0.932***	
	(0.009)		(0.009)	
LnDD		−0.239***		0.200***
		(0.018)		(0.011)
CONTROL	YES	YES	YES	YES
CONS	YES	YES	YES	YES
Endogeneity tests		5.703**		14.047***
Partial R-sq		0.868		0.868
Kleibergen–Paap rk LM		84.362***		84.362***
Kleibergen–Paap rk Wald F		99.571		99.571
FE	YES	YES	YES	YES
N	2,136	2,136	2,136	2,136
R^2	0.915	0.205	0.915	0.277
IV2:Telephone × Internet				
Telephone × Internet	0.207***		0.207***	
	(0.011)		(0.011)	
LnDD		−0.223***		0.217***
		(0.023)		(0.015)
CONTROL	YES	YES	YES	YES
CONS	YES	YES	YES	YES
Endogeneity tests		5.603**		6.585**
Partial R-sq		0.768		0.768
Kleibergen–Paap rk LM		5.007**		5.007**
Kleibergen–Paap rk Wald F		13.921		13.921
FE	YES	YES	YES	YES
N	2,403	2,403	2,403	2,403
R^2	0.552	0.192	0.552	0.277

Note that standard errors are in parentheses; CONTROL, refers to control variables; FE, refers to the fixed effects for both time and city.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

different conditions. Given significant regional disparities in economic growth and financial development (Zhang et al., 2022; Shahbaz et al., 2022), these variables are considered potential thresholds that may reveal distinct effects on EI and CEP.

By incorporating these threshold variables, we aim to capture the nonlinear dynamics of the relationship and precisely identify the thresholds at which digital economic development impacts EI and CEP (Zhou and Li, 2022). Referring to the model of Zhou and Li (2022), We include the identified threshold variables to elucidate the nonlinear effects of digital development on EI and CEP:

$$
\begin{aligned}
y_{it} &= \alpha_i + b_1 DD_{it} I(c < h_1) + b_2 DD_{it} I(h_1 \le c < h_2) \\
&\quad + b_3 DD_{it} I(h_2 \le c < h_3) + b_4 DD_{it} I(c \ge h_3) + \sum_{g=1}^{5} f_g X_{git} + \gamma_i \\
&\quad + \rho_t + \varepsilon_{it}
\end{aligned}
$$

TABLE 8 Excluding the impact of other policies.

Variables	Remove SC policy		Remove CET policy	
	LnEI	LnCEP	LnEI	LnCEP
LnDD	−0.233***	0.184***	−0.245***	0.198***
	(0.018)	(0.008)	(0.010)	(0.007)
CONTROL	YES	YES	YES	YES
CONS	−3.259***	0.708	−3.226***	0.504
	(0.604)	(0.387)	(0.743)	(0.450)
FE	YES	YES	YES	YES
N	2,106	2,106	2079	2079
R^2	0.340	0.363	0.350	0.369

Note that standard errors are in parentheses; CONTROL, refers to control variables.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

TABLE 9 Regression results of the GMM estimation.

Variables	Dependent variable: LnEI	Dependent variable: LnCEP
	(1)	(2)
L.EI	0.753***	
	(0.024)	
L.CEP		0.450***
		(0.040)
LnDD	−0.068***	0.097***
	(0.014)	(0.014)
CONTROL	YES	YES
FE	YES	YES
N	2,403	2,403
Wald	45,589.25***	6089.65***
AR (1)	0.000	0.000
AR (2)	0.475	0.102
Sargan test	764.89	792.25
Hansen test	157.10	173.01

Note that standard errors are in parentheses, CONTROL, refers to the control variable, and FE, refers to the fixed effects for both time and city.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

where c and h stand for the threshold variable and value, respectively. The study considered economic growth and financial development as threshold variables, with an indicative function (I) applied. A value of one was assigned when correct; otherwise, a value of 0 was assigned. The remaining parameters are identical to Model (1).

3.1.3 Mediation effect model

In this section, we design the channels through which technological investment and innovation impact innovation by constructing a mechanistic analytical model to ensure the accuracy and comprehensiveness of the model (Lee et al., 2022). Referring to the model of Lee et al. (2022), we set the following model:

$$y_{it} = a_0 + a_1 DD_{it} + \sum\nolimits_{g=1}^{5} f_g x_{git} + \gamma_i + \rho_t + \varepsilon_{it}$$

$$m_{it} = d_0 + d_1 DD_{it} + \sum\nolimits_{g=1}^{5} f_g x_{git} + \gamma_i + \rho_t + \varepsilon_{it}$$

$$y_{it} = e_0 + e_1 DD_{it} + e_2 m_{it} + \sum\nolimits_{g=1}^{5} f_g x_{git} + \gamma_i + \rho_t + \varepsilon_{it}$$

where m denotes the intermediate variable encompassing two forms: scientific input (SI) and technological innovation (TI). The coefficient e_2 is crucial, and if significant, it indicates a substantial mediating effect of m. Our study anticipated both positive and negative outcomes for e_2. The parameter f is to be estimated, while a_0, d_0, e_0, and ε_{it} represent the intercepts and error terms, respectively. The remaining parameters are identical to Model (1).

3.2 Variables

3.2.1 Dependent variable

(i) EI. The EI variable serves as a crucial strategy for achieving carbon neutrality and fostering sustainable economic development. Numerous scholars have investigated the influence of EI on carbon emissions (Shahbaz et al., 2015; Huang et al., 2020). A commonly employed indicator for energy conservation was the EI, which assesses the proportion of energy consumption to GDP. As a pivotal metric for shaping energy policies, EI plays a significant role in advancing green development (Bashir et al., 2021). In this study, we applied the proportional method to compute the share of energy to GDP, which serves as an indicator of EI based on existing research (Zhou et al., 2022).

(ii) CEP. The CEP is a crucial metric for evaluating the efficacy of green development. In this study, the SE-EBM model, as referenced in prior works (Tone and Tsutsui, 2010; Akbari et al., 2020; Jalo et al., 2021; Zhou and Li, 2024), was employed to compute the CEP index. The detailed calculation process of the SE-EBM model is provided in Appendix A.

The model's input indicators encompassed labor, capital, and energy consumption, while its output indicators encompassed economic development and environmental pollution. Labour was quantified using the urban working population, and capital was measured by summing current and fixed capital at year-end. Energy consumption included liquefied petroleum gas, natural gas, electricity, and heating and was converted to standard coal values based on prior research (Ru et al., 2015) (unit: 10,000 tons of standard coal). The GDP measures economic output (unit: 100 million yuan), while sulfur dioxide emissions assess environmental outcomes

TABLE 10 Regression results after narrowing the study period and excluding key cities.

Variable	Dependent variable: LnEI			Dependent variable: LnCEP		
	2012–2019	2013–2018	2014–2017	2012–2019	2013–2018	2014–2017
	(1)	(2)	(3)	(4)	(5)	(6)
LnDD	−0.233***	−0.232***	−0.235***	0.184***	0.181***	0.195***
	(0.017)	(0.019)	(0.026)	(0.008)	(0.010)	(0.007)
CONTROL	YES	YES	YES	YES	YES	YES
CONS	−2.366**	−3.110**	0.001	0.442	0.980**	0.001
	(0.752)	(0.804)	(0.001)	(0.402)	(0.265)	(0.001)
FE	YES	YES	YES	YES	YES	YES
N	2,136	1,602	1,068	2,136	1,602	1,068
R^2	0.359	0.358	0.350	0.377	0.371	0.396

Note that standard errors are in parentheses; CONTROL, refers to the control variable.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

(unit: 10,000 tons) (Bi et al., 2014; Shan et al., 2020; Zhou and Li, 2020; Zhou et al., 2023).

3.2.2 Independent variables

The independent variable in this study was digital development, constituting a comprehensive index derived from various elements. According to previous studies (Bukht and Heeks, 2017; Li and Wang, 2022; Yi et al., 2022; Zhu and Chen, 2022; Wu et al., 2023), digital development encompasses five key dimensions: (1) telecom business revenue (measured in ten thousand yuan), (2) computer employment (measured by the number of people employed), (3) internet broadband households (measured in ten thousand households), (4) mobile phone users (measured in 10,000 persons), and (5) the inclusive finance index (measured without units).

To simplify and consolidate these dimensions into a single index, the principal component analysis (PCA) method was employed—a widely adopted approach for constructing composite indicators (Interlenghi et al., 2017; Pan et al., 2022). Consequently, the study employed the PCA method to construct the digital development index.

3.2.3 Control variables

To mitigate the potential interference of extraneous factors on EI and CEP, we controlled for five relevant variables in this study: (1) population density, which was measured as the ratio of total urban registered population to urban area at year-end (Danish et al., 2020); (2) industrialization, which was measured by the proportion of the GDP of the secondary industry to the total GDP in each year (Li et al., 2022); (3) service industry development, which was calculated as the proportion of tertiary industry added value in GDP (Li et al., 2022); (4) financial development, which was measured as the ratio of urban deposit and loan balance to the urban total GDP (Qu et al., 2020); and (5) energy structure, which was measured as the ratio of electricity consumption to the total energy consumption (Zhou and Li, 2022). We present the definitions and sources of the variables used in Table 1.

3.3 Data sources

This study employed panel data encompassing 267 Chinese cities from 2011 to 2019. The data sources included the China Urban Statistical Yearbook (CUS, 2021), National Bureau of Statistics (NBS, 2021), China Energy Administration (CEA, 2021), and China Environmental Statistical Yearbook (CES, 2021). The control and dependent variables originated from CUS and NBS, while the independent variable was derived from CUS. The environmental pollution data were sourced from the CES. Table 2 summarizes the statistical analysis of the key variables. The dataset encompassed 267 cities over 9 years, totaling 2,403 observations.

Figure 2 depicts the scatter correlation between digital development, EI, and CEP. The results show a negative correlation between digital development and EI and a positive correlation with CEP. This implies that digital development has the potential to reduce EI and improve CEP. To enhance the empirical analysis results, these variables underwent a logarithmic transformation.

4 Results and discussion

4.1 Impact assessment analysis

4.1.1 Direct effect analysis

To address potential serial correlation and heteroscedasticity, we utilized a robust standard error estimation equation clustered by city and a benchmark regression model.

TABLE 11 Estimated results of the panel threshold model.

	Dependent variable: LnEI	Dependent variable: LnCEP
	(1)	(2)
LnDD (h < 5.253)	−0.119***	
	(0.031)	
LnDD (5.253 ≤ h < 5.376)	−0.073**	
	(0.029)	
LnDD (5.376 ≤ h < 5.456)	−0.054*	
	(0.028)	
LnDD (h ≥ 5.456)	−0.027	
	(0.028)	
LnDD (h < 6.489)		0.000
		(0.017)
LnDD (6.489 ≤ h < 6.533)		0.021
		(0.017)
LnDD (6.533 ≤ h < 7.286)		0.044***
		(0.017)
LnDD (h ≥ 7.286)		0.065***
		(0.017)
CONTROL	Yes	Yes
CONS	Yes	Yes
FE	Yes	Yes
N	2,403	2,403
R^2	0.367	0.202

The standard errors are in parentheses, and CONTROL, refers to the control variable.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

Table 3 summarizes the results of the direct effect analysis. Columns (1) to (3) show the impact of digital development on EI, while columns (4) to (6) detail its influence on CEP. The LnDD regression coefficients in columns (1) to (3) were all negative, statistically significant at the 1% level, and amounted to −0.165, −0.169, and −0.231, respectively. This indicated a significant reduction in EI of 0.231 units due to digital development, aligning with previous studies (Husaini and Lean, 2022; Shahbaz et al., 2022), which found a 2.1% increase in renewable energy attributed to digital advancements.

Columns (4) to (6) reveal positive LnDD regression coefficients of 0.123, 0.136, and 0.185, respectively, which are statistically significant at the 1% level. This suggested that digital development could enhance CEP.

The control variables also yielded significant results. The positive and statistically significant coefficients of LnIND and LnFD suggested that industrialization and finance fostered EI. However, our findings did not support the role of population density in CEP improvement, contrary to the conclusions of other scholars (Morikawa, 2012). Additionally, population density, industrialization, and financial development negatively impacted CEP, consistent with existing research (Morikawa, 2012). Therefore, Hypothesis 1 was confirmed.

4.1.2 Mediation effect analysis

In this section, we employed an intermediary effect model, incorporating scientific input and technological innovation as mediating variables. Our study yielded substantial and noteworthy results, which are briefly summarized in Table 4.

When the dependent variable is EI, we find a statistically significant positive correlation between EI and technological input, with a coefficient value of 1.260, indicating that digital development significantly enhances SI. The second column shows regression coefficients of −0.104 and −0.100 for digital development and technological input, respectively, both of which are significant, indicating that digital development and SI significantly reduce EI, with SI exerting a significant mediating effect. In columns three and four, TI is also positively influenced by digital development, with scholars revealing the mediating effect of TI on EI (Voigt et al., 2014; Wurlod and Noailly, 2018).

When the dependent variable is CEP, our findings regarding the impact of digital development align with the results for EI. Specifically, columns (5) through (8) reveal a significant positive impact on CEP, with SI and TI also showing significant positive effects, confirming the mediating role of CEP (He et al., 2021; Zhang and Liu, 2022). These findings suggest that digital development, through increased scientific input and technological innovation, can significantly reduce EI and enhance CEP. Thus, this conclusion validates Hypothesis 2 that digital development influences EI and CEP through SI and TI.

4.1.3 Heterogeneity analysis

Table 5 shows that the regression coefficients of LnDD across regions were all significantly negatively correlated with EI at the 1% level, with coefficient values of −0.253, −0.227, and −0.196, respectively. This implies that digital development significantly reduces EI in all regions, with the strongest impact observed in the eastern region and the weakest in the western region. When the dependent variable was CEP, the coefficient of LnDD was significantly positively correlated only with the central region, with a coefficient value of 0.117, while the eastern and western regions showed positive effects but were not significant. This indicated that digital development significantly increased CEP only in the central region. This result was consistent with previous research (Guang et al., 2019). These findings suggest significant heterogeneity effects of digital development on EI and CEP. The reason for the above phenomenon may lie in the differences in efficiency improvement between regional development and pollution emissions. Variations in resource endowment and technological levels across different cities contribute to the heterogeneity of digital development. Despite the advanced technology and economic strength in the eastern region, it still faces significant challenges in terms of energy conservation and emission reduction. With its lower

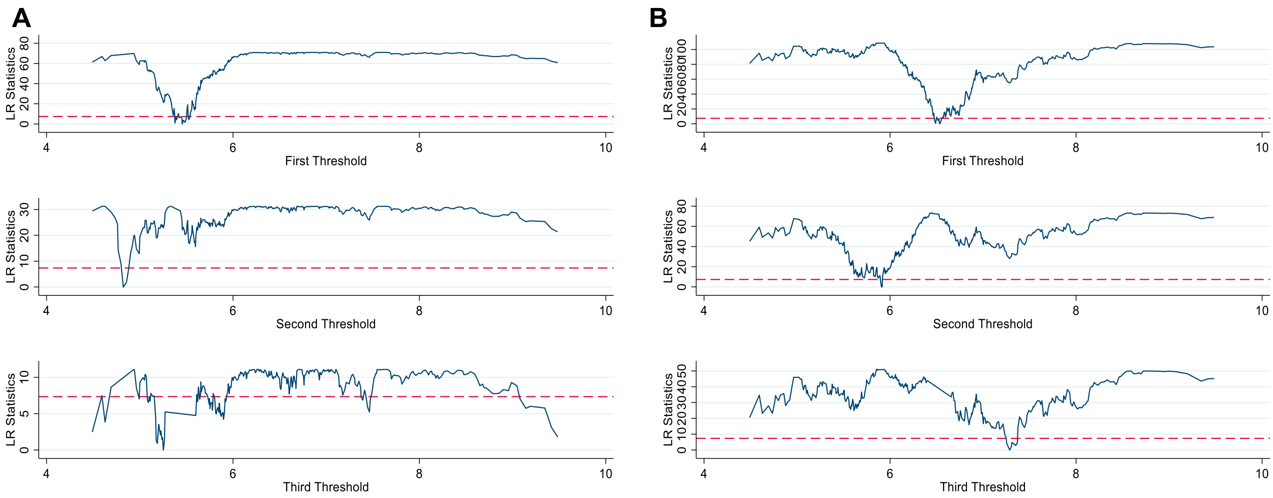

FIGURE 3
Threshold parameter of threshold variables. Note: **(A)** and **(B)** refer to the dependent variables energy intensity and carbon emission performance, respectively; the solid blue line refers to the LR; and the red dotted line indicates the 95% confidence interval.

technological level, the western region exerts less influence on CEP than does the central region. These findings support Hypothesis 3.

The establishment of China's two control zones (TCZ), including acid rain control zones and sulfur dioxide pollution control zones, primarily aims to manage and regulate environmental protection (Zhou et al., 2023). Consequently, these policies create significant heterogeneity in urban energy conservation and emissions reduction efforts. Analyzing the heterogeneous effects of TCZ policies on energy conservation and emissions reduction across different cities is essential for understanding their outcomes in diverse environmental contexts. Therefore, it is imperative for this study to conduct an analysis of TCZ heterogeneity.

Table 6 summarizes the urban heterogeneity results. When EI serves as the dependent variable, cities within TCZ exhibit regression coefficients of DD with absolute values (0.300) greater than those in Non-TCZ areas (0.088), indicating substantial energy-saving benefits of DD within TCZ. Similarly, when CEP is the dependent variable, cities within TCZ (0.210) show regression coefficients of DD greater than those in Non-TCZ areas (0.110), highlighting significant emission reduction benefits of DD within TCZ. These findings underscore the significant heterogeneous effects of digital economic development between TCZ and Non-TCZ areas.

4.2 Robustness analysis

This study employed four methods for robustness analysis. (1) The instrumental variable (IV) method was used to address endogeneity issues. This method introduced exogenous IVs that were correlated with the independent variable but unrelated to the error term, thereby improving the accuracy and reliability of the regression results. (2) The method of excluding other policy interferences aimed to eliminate the interference of other policies, enabling a more accurate assessment of the impact of the factors under consideration on the results and ensuring the reliability and robustness of the research conclusions. (3) The substitution method was utilized to mitigate endpoint issues, enhancing the model's goodness of fit and explanatory power. (4) The method of altering the research period was employed to control for time-related concerns, ensuring the accuracy and robustness of causal relationships.

4.2.1 Instrumental variable approach

To address potential endogeneity issues in examining the reduction in EI and improvement in CEP, this study adopted the widely used IV method in energy and environmental economics (Barrera-Santana et al., 2022; Xue et al., 2022). The lagged terms of EI and CEP were chosen as IV1 due to their correlation with the independent variable. Furthermore, city telecommunications data from 1984 served as IV2 (Nunn and Qian, 2014), reflecting the influence of telecommunication infrastructure on internet technologies, including technology advancement and usage patterns. A time-varying variable was utilized, and a panel instrument variable was formulated using the interaction of internet and telephone counts, designated "Telephone◊Internet." Additionally, we acknowledged the waning influence of traditional telecommunication tools, such as landline telephones, on economic growth as their usage decreased.

The regression coefficients of IV1 and IV2 were positive and substantial in both models, verifying the appropriateness of IV selection, as shown in Table 7. This study addressed endogeneity concerns, and the second-stage regression analysis revealed that the regression coefficient of LnDD was significant at the 1% level. These findings aligned with the direct effects analysis and exceeded the baseline regression results, supporting the view that endogeneity underestimated the impact.

Endogeneity tests confirmed the endogeneity of digital development. The LM statistic significantly rejected the null

TABLE 12 Estimated results of the panel threshold model.

Variables	Dependent variable: LnEI	Dependent variable: LnCEP
	(1)	(2)
lnDD (h < 0.091)	0.080***	
	(0.030)	
lnDD (0.091 ≤ h < 0.574)	0.049*	
	(0.028)	
lnDD (0.574 ≤ h < 1.092)	0.030	
	(0.028)	
lnDD (h ≥ 1.092)	0.021	
	(0.028)	
lnDD (h < 0.166)		0.025
		(0.018)
lnDD (0.166 ≤ h < 0.563)		0.045***
		(0.017)
lnDD (0.563 ≤ h < 1.859)		0.062***
		(0.017)
lnDD (h ≥ 1.859)		0.084***
		(0.018)
CONTROL	YES	YES
CONS	YES	YES
FE	YES	YES
N	2,403	2,403
R^2	0.341	0.141

The standard errors are in parentheses, and CONTROL, refers to the control variable.
[a]$p < 0.1$.
[b]$p < 0.05$.
[c]$p < 0.01$.

hypothesis of insufficient IV identification. Moreover, the Wald F-statistic exceeded the threshold of the Stock-Yogo weak identification test, indicating the adequacy of the IV choice.

When CEP was the dependent variable, the regression coefficient of LnDD was significant at the 1% level, suggesting that digital development improved CEP. After addressing the endogeneity problem, the coefficient of LnDD increased, indicating that endogeneity caused the lower baseline results.

4.2.2 Remove policy interference

During the study period, the Chinese government implemented several policies to promote energy consumption and reduce emissions. However, as these policies could impact EI and CEP, we excluded two policies, namely, the smart city pilot policy (SC) (Mathiesen et al., 2015) and the carbon emissions trading policy (CET) (Chen et al., 2020), to obtain more accurate estimates.

Table 8 presents the estimated results, excluding the impact of these policies. Even after excluding the SC policy, we found that the regression coefficients of LnDD remained significantly above the 1% level, at −0.233 and 0.184, respectively. This suggested that the results of our study were robust even after excluding the SC policy. Furthermore, after excluding the CET policy, the regression coefficients of LnDD were −0.245 and 0.198, which were significant at the 1% level. This indicated that the results remained similar to the benchmark results even after excluding the CET policy. However, the impact of digital development was found to be more significant after excluding the CET policy, suggesting that CET policies did have an effect on the role of digital development in EI and CEP.

4.2.3 Method modification

In this section, we investigated alternative estimation methods to analyse the conclusions. While the ordinary least squares method excelled under classical assumptions, the generalized method of moments (GMM) remained valid even without exact distribution information of random perturbations (Hashmi and Alam, 2019; Zakari et al., 2022). It was also robust to heteroskedasticity and autocorrelation, violating classical assumptions. Many scholars have applied GMM in environmental science and economics (Omri and Afi, 2020; Ozturk and Ullah, 2022). Therefore, we employed this method to assess the robustness of the impact of digital development on EI and CEP.

Table 9 summarizes the GMM regression results. Our model tests confirmed the validity of all the assumptions, with significant AR (1) and insignificant AR (2), aligning with the nature of GMM. Additionally, the Sargan and Hansen tests met the necessary conditions. The regression coefficients of LnDD were −0.068 and 0.097, both of which are significant at the 1% level. This indicated that digital development significantly reduced EI and enhanced CEP, which is consistent with the results obtained from the direct effect analysis. We were confident in the reliability of our conclusions.

4.2.4 Modifying the time

To address potential biased estimation results arising from different study periods (Vieira et al., 2018), we proposed setting distinct study spans. Specifically, we assessed the periods of 2012–2019, 2013–2018, and 2014–2017 to mitigate temporal interference. Table 10 illustrates that the influence of digital development on EI remained consistent across various study periods, as evidenced by the consistently negative and significant coefficients of LnDD in columns (1)–(3).

In terms of CEP, the regression coefficients of LnDD were consistently positive and significant at the 1% level in columns (4)–(6), indicating a consistent impact across different study periods. However, it was observed that these coefficients increased with the duration of the study period, suggesting that the sample period did indeed influence the effect of digital development.

4.3 Threshold effect analysis

4.3.1 Economic growth as the threshold variable

This study employed a panel threshold model to explore the nonlinear impact of different levels of regional economic growth on

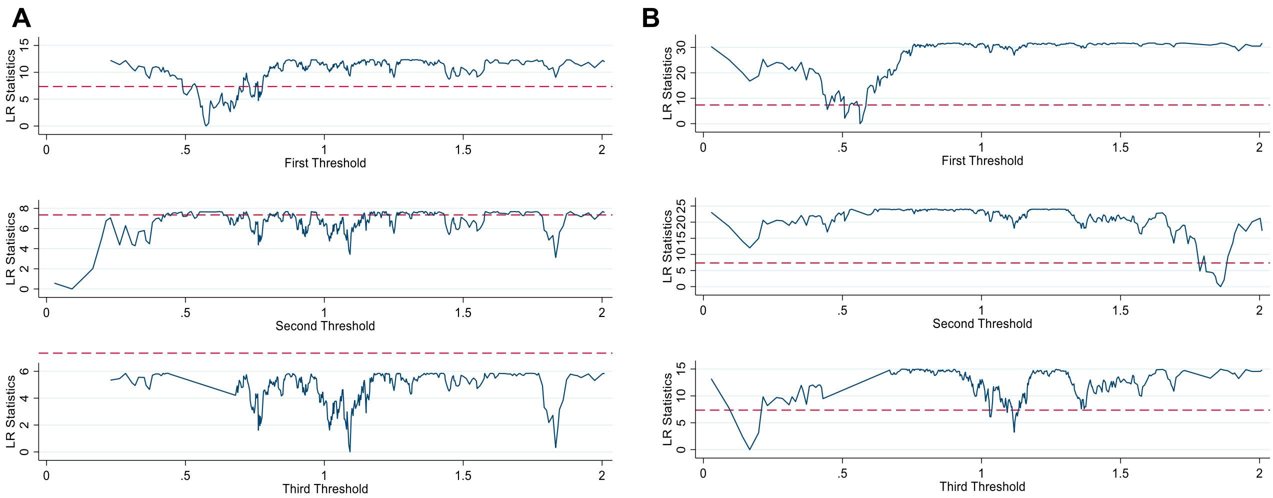

FIGURE 4
Threshold parameter of threshold variables. Note: **(A)** and **(B)** refer to the dependent variables energy intensity and carbon emission performance, respectively; the solid blue line refers to the LR; and the red dotted line indicates the 95% confidence interval).

EI and CEP (Ibrahim &Vo, 2021; Zhou and Li, 2022). As depicted in Table B1, economic growth had a significant impact on EI at the single and double thresholds but not at the triple threshold, indicating a double threshold effect. Similarly, economic growth was deemed insignificant at three thresholds when CEP served as the dependent variable, suggesting a triple threshold effect for the threshold variable.

Table 11 indicates that the impact of digital development on EI and CEP varies across different thresholds of economic growth. When EI is the dependent variable, as the economic growth threshold increases, the regression coefficient of LnDD shows a linear decreasing trend, ranging from −0.119 to −0.027. Additionally, the significance of the coefficients decreases, suggesting that as economic growth accelerates, the effect of digital development on EI gradually weakens, confirming Hypothesis 4. However, when CEP is the dependent variable, the regression coefficient of LnDD exhibits a linear increasing trend, rising with the increase in the threshold but becoming significant only after surpassing the second threshold. This finding implies that the stronger economic growth is, the stronger the effect of digitalization on CEP. As depicted in Figure 3, these findings underscore the importance of incorporating digital development in the pursuit of sustainable development.

In summary, the threshold values derived from the threshold testing in this study possess not only statistical significance but also profound economic implications. They reveal distinct influence pathways and intensities of digital transformation on EI and CEP across various stages of economic growth. These discoveries not only deepen our understanding of the relationship between digital transformation and sustainable development but also offer valuable guidance for policymakers, emphasizing the need to consider the current stage of economic growth and the specific effects of digital transformation when formulating and implementing relevant policies.

4.3.2 Financial development as a threshold variable

Regional financial levels may influence energy use and emission reduction (Habiba et al., 2022; Razzaq et al., 2022), with a focus on the threshold effect of financial development. According to Table B2, financial development was not a significant factor at the single, double, or triple thresholds when EI was the dependent variable. However, when CEP was the dependent variable, financial development was substantial at the single and double thresholds but not at the triple threshold, suggesting a triple threshold effect.

Table 12 reveals that as the threshold of financial development increases, the regression coefficient of LnDD gradually decreases, indicating that with better financial development, the effect of digitalization on EI gradually diminishes. The most significant impact is observed when financial development is below the first threshold. For CEP, the influence of digital development increases with increasing financial development, becoming significant after surpassing the first threshold, indicating the presence of a threshold effect of financial development on CEP. We provide a visual representation of these changes in Figure 4. These findings illustrate the significant threshold effects of financial development on the impact of digitalization on EI and CEP.

Employing financial development as a threshold variable in examining the impact of digital economy on EI and CEP carries significant economic implications and values. It serves to uncover the intrinsic link between the digital economy and financial development, thereby facilitating the green transformation and high-quality development of the economy. This approach sheds light on the diverse pathways and effects of digital economy development on EI and CEP across varying levels of financial development. Regions with advanced financial systems tend to allocate capital more efficiently towards innovative, digital, and low-carbon projects, thereby accelerating the optimization of energy structures and reducing carbon emissions. Additionally, it fosters the green transition of energy structures, diminishes CEP, and mitigates financial and market risks incurred during enterprises' digital transformation journey. Ultimately, this ensures the sustained positive influence of the digital economy on both EI and CEP.

5 Conclusions and implications

5.1 Conclusions

Enhancing energy efficiency and reducing carbon emissions are crucial for achieving China's carbon neutrality goals and sustainable development objectives. This study focuses on Chinese cities and empirically evaluates the synergistic effects of digital development on EI and CEP. The research yielded several significant findings, summarized below:

The findings indicate a substantial 23.1% reduction in EI and an 18.5% increase in CEP attributed to digital development. To strengthen the robustness of our conclusions, we conducted four additional tests, all of which consistently reaffirmed our findings. Furthermore, our study identifies that digital development influences EI and CEP by fostering technological innovation. Notably, we observed a threshold effect on EI and CEP concerning economic and financial development.

5.2 Implications

Drawing from our findings, we propose the following policy recommendations.

(1) Enhance Digital Industry Policies: Strengthen policies related to the digital industry to maximize the positive impact of digital development on energy conservation and carbon reduction in China. Encourage businesses to invest in digital technologies, particularly in sectors such as smart manufacturing, IoT, and big data analytics. Promote the adoption of digital energy efficiency monitoring systems for real-time energy usage analysis.
(2) Promote Investment in Digital Technology Innovation: Foster investment in digital technology innovation, especially within the energy sector. Establish dedicated funds to support innovative applications of digital technology, AI, and big data in energy management. Facilitate collaboration between businesses and research institutions to drive research and application of digital technologies in energy efficiency.
(3) Tailor Policies to Regional Differences: Formulate differentiated policy measures based on regional disparities. Promote the application of digital technology in energy-intensive sectors in regions experiencing significant impacts of digital development. Strengthen digital infrastructure in regions with lesser impacts to enhance digitization. Consider economic and financial disparities in policymaking by providing financial incentives for digital technology adoption in less developed areas and guiding advanced energy management system implementation in more developed regions.

However, this study has notable limitations. Alternative methodologies for measuring EI and CEP indicators may exist. Additionally, our analysis focused on two impact mechanisms, potentially overlooking other underlying pathways. Future research should address these limitations by incorporating additional indicators, datasets, and mechanistic pathways to comprehensively understand the complex relationships among digital development, energy, and the environment.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SW: Funding acquisition, Methodology, Resources, Visualization, Writing–original draft. HZ: Formal Analysis, Funding acquisition, Investigation, Supervision, Writing–review and editing. GY: Funding acquisition, Software, Supervision, Writing–original draft. AZ: Conceptualization, Formal Analysis, Funding acquisition, Methodology, Software, Writing–original draft. JL: Writing–review and editing, Formal analysis, Funding acquisition, Resources.

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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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Appendix A Measurement of emission reduction performance

Several approaches have been developed to assess CEP, encompassing both parametric and nonparametric methods. Parametric techniques, such as the proportional method (Shahbaz et al., 2015) and stochastic Frontier analysis (SFA) (Lin and Long, 2015; Du and Lin, 2017), hinge on stringent production function assumptions and single-factor analysis, respectively. Nonparametric methods, notably data envelopment analysis (DEA) (Tone, 2001; Li and Lin, 2017; Sueyoshi et al., 2017; An et al., 2020; Yu and Zhang, 2019; Wu et al., 2021; Zhou A. et al., 2022), have seen widespread use, with a particular emphasis on the Charnes, Cooper, and Rhodes (CCR) model. Nevertheless, these methodologies have limitations, such as unrealistic assumptions for parametric approaches and the dependence on a single distance function for nonparametric methods.

To address these challenges, we adopted the SE-EBM model introduced by Tone and Tsutsui (2010), which incorporates both radial and nonradial distance functions. This approach allowed us to surmount the constraints associated with existing methodologies, providing a more holistic assessment of CEP. The initial model was formulated as the following equation:

$$\gamma^{*} = \min_{\chi,\tau,\varpi^{-}} \rho - \sigma_x \sum\nolimits_{i=1}^{m} \frac{\varphi_i^{-}\varpi_i^{-}}{v_{io}}$$

$$\begin{cases} \rho v_{io} - \sum_{j=1}^{n} \tau_j v_{ij} - \varpi_i^{-} = 0, i = 1, \cdots, m \\ \sum_{j=1}^{n} \tau_j \omega_{rj} \geq \omega_{ro}, r = 1, \cdots, \eta \\ \tau_j \geq 0 \\ \varpi_i^{-} \geq 0 \end{cases}$$

In this equation, γ represents the DEA optimal efficiency value, ρ denotes the efficiency value under radial conditions, and ϖ_i corresponds to the ith input element in the nonradial condition. The symbol φ signifies the weight assigned to the input indicator and must adhere to the constraint $\sum_{i=1}^{m} \varphi_i = 1$, where σ_x indicates the changing trend of radial distances and the vector parameters of nonradial distances. Finally, τ captures the relative weights of the input elements, and (ν_{io}, ω_{ro}) captures the input and output vectors of the oth decision unit. Here, if the value of σ_x was equal to 1, the model was considered a CCR model. If the value of σ_x was one and the value of χ was 0, the model was an SBM, and the EBM needed to calculate these parameters in advance. When $\gamma = 1$, the efficiency is effective. Since the relationship between input and output includes radial and nonradial relationships, we used the extended EBM model. The model settings were as follows:

$$\gamma^{*} = \min \frac{\rho - \sigma_x \sum_{i=1}^{m} \frac{\varphi_i^{-}\varpi_i^{-}}{v_{io}}}{m + \sigma_\omega \sum_{r=1}^{\varpi} \frac{\varphi_r^{+}\varpi_r^{+}}{\omega_{io}} + \sigma_s \sum_{u=1}^{q} \frac{\varphi_u^{s-}\varpi_u^{s-}}{s_{io}}}$$

$$s.t. \begin{cases} \sum_{j=1}^{n} \tau_j v_{ij} + \varpi_i^{-} - \rho v_{io} = 0, i = 1, \cdots, n \\ \sum_{j=1}^{n} \tau_j \omega_{rj} - \varpi_r^{+} - m\nu_{ro} = 0, i = 1, \cdots, \theta \\ \sum_{j=1}^{n} \tau_j s_{tj} + \varpi_t^{f-} - m s_{to} = 0, t = 1, \cdots, q \\ \tau_j \geq 0, \varpi_i^{-} \geq 0, \varpi_r^{+} \geq 0, \varpi_t^{s-} \geq 0 \end{cases}$$

The parameter s_{to} captures the tth undesired output of the oth city, $(\varpi_r^{+}, \varpi_t^{s-})$ represents the slack vectors of the expected and undesired results, and when their values are greater than 0, we need to improve the energy efficiency in technology. φ_r^{+} and φ_t^{-} captured the desired and undesired output indicators on the rth and tth, respectively. According to these findings, when numerous decision-making units exhibit optimal efficiency, distinguishing the best-performing unit becomes challenging. To address this issue, this study improved the original EBM model by introducing a modified version known as the SE-EBM model (Andersen and Petersen, 1993; Zhou and Li, 2021), permitting values greater than 1.

Appendix B

TABLE B1 Threshold effect test results

Threshold	RSS	MSE	Fstat	p-Value	Crit10	Crit5	Crit1
Dependent variable: LnEI							
Single	281.632	0.117	79.740	0.000	27.315	34.416	41.933
Double	277.901	0.116	32.150	0.046	25.822	31.242	52.410
Triple	276.613	0.115	11.140	0.706	29.294	32.961	48.553
Dependent variable: LnCEP							
Single	108.286	0.045	117.310	0.000	23.427	25.552	31.096
Double	105.002	0.043	74.880	0.000	19.239	21.685	28.265
Triple	102.801	0.042	51.270	0.870	102.246	110.234	126.979

TABLE B2 Threshold effect test results

Threshold	RSS	MSE	Fstat	p-Value	Crit10	Crit5	Crit1
Dependent variable: LnEI							
Single	289.572	0.121	11.920	0.430	20.768	25.729	30.024
Double	288.642	0.121	7.710	0.666	15.676	17.866	23.931
Triple	287.936	0.120	5.870	0.850	15.634	17.191	23.584
Dependent variable: LnCEP							
Single	112.423	0.047	24.910	0.003	14.964	17.679	22.416
Double	111.302	0.046	24.110	0.000	14.631	17.150	19.400
Triple	110.608	0.046	15.030	0.626	39.834	46.230	53.863