Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Digital economy and synergy effect of pollution reduction and carbon emission reduction: Based on the threshold effect analysis of environmental penalty and pollution intensity

Yang Xiang

sunyang9529@163.com

Chongqing Technology and Business University https://orcid.org/0000-0001-8126-9834

Research Article

Keywords: Digital economy, Synergistic effect of pollution reduction and carbon emission reduction, Environmental penalty intensity, Pollution intensity, Threshold effect, Yangtze River Economic Belt

Posted Date: October 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11547318/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Digital economy and synergy effect of pollution reduction and carbon emission reduction: Based on the threshold effect analysis of environmental penalty and pollution intensity

Abstract: Under the dual circumstances of the “dual carbon” goal promotion and the deep development of the digital economy (DE), clarifying the influence mechanism of the DE on the synergy effect of pollution reduction and carbon emission reduction (SEPRCER) is of great practical significance for promoting the green and high-quality development of the region. This paper is based on the panel data of 108 cities in the Yangtze River Economic Belt (YREB) from 2011 to 2023. It systematically analyzes the evolution characteristics of the DE and the SEPRCER, and empirically examines the influencing mechanism between the two. The results show: (1) The level of the DE in the YREB shows an overall upward trend, while the level of the SEPRCER shows a slight downward trend. Both form a distribution pattern with the Yangtze River Delta (YRD) as the core and multiple growth poles coexisting in space; (2) The influence of the DE on the SEPRCER presents a significant "U" shape relationship, and this conclusion still holds after robustness and endogeneity tests; (3) The relationship between the two shows heterogeneity characteristics. The “U” shape feature is more prominent in the lower reaches of the Yangtze River (LRYR), urban agglomerations, non-resource-based cities, and regions with high economic levels; (4) Both the environmental protection penalty intensity (EPPI) and the pollution intensity (PI) exhibit a significant single-threshold. As the EPPI crosses the threshold value, the turning point of the “U” shape curve for the DE and the SEPRCER will be reached earlier, while the opposite is true for the PI; (5) From the two threshold variables interaction grouping perspective, in the combination of high EPPI and low PI, the “U” shaped inflection points for the DE and the SEPRCER is the earliest. The research conclusions provide theoretical basis for improving the SEPRCER in the YREB.

Key words: Digital economy; Synergistic effect of pollution reduction and carbon emission reduction; Environmental penalty intensity; Pollution intensity; Threshold effect; Yangtze River Economic Belt

1. Introduction

Currently, the problems of global climate change and environmental pollution are becoming increasingly severe. As the largest developing country and carbon emitter in the world, China is facing unprecedented environmental challenges. According to estimates, China's carbon emissions will reach 12.6 billion tons in 2024 (IEA, 2025), accounting for one-third of the global total. Such unrestrained and purely economic social and economic activities will lead to environmental external diseconomies, thereby triggering environmental issues (Hou et al., 2024). To address the severe situation of environmental challenges and achieve sustainable development, the Chinese

government has proposed the “carbon dioxide emissions should strive to peak by 2030 and aim to achieve carbon neutrality by 2060” as a major strategic decision. This significant decision puts forward new requirements for China's economic and social development (Zhang et al., 2025). At the same time, the “Fifteen-Five-Year Plan Outline” of the Chinese government further mentions “synergistically promoting carbon reduction, pollution reduction, green development, and growth” (Xu & Kong, 2025; You et al., 2026). Among them, carbon emissions and air pollutants have the characteristics of the same origin, source, and process (IPCC, 2001), such as fossil energy will not only emit carbon dioxide during combustion and processing and utilization, but also emit air pollutants such as particulate matter, sulfur dioxide, and nitrogen oxides (Dong et al., 2022). Therefore, relying on this characteristic between the two, achieving simultaneous reduction of air pollutants during the process of controlling greenhouse gas emissions, or taking into account the greenhouse gas emission reduction benefits when carrying out regional air pollutant governance, that is, forming the SEPRCER (Meng et al., 2025), has become an efficient environmental governance measure to help China achieve a comprehensive green transformation of economic and social development and build a beautiful China.

In recent years, the DE has developed rapidly and has gradually become the main economic form after the agricultural economy and the industrial economy (Wang, 2024). In 2024, the added value of China's core DE industries accounted for 10.5% of the GDP (National Bureau of Statistics of China, 2025). At the same time, the DE, with its advantages such as low energy consumption, high efficiency, environmental friendliness, and digital technologies (Liu et al., 2025), has enabled the green transformation and upgrading of traditional industries through digital technology empowerment (Liu et al., 2023), as well as optimizing the energy structure and improving environmental governance efficiency (Huang & Lin, 2024; Ren et al., 2023), and thus demonstrates great potential in the field of pollution reduction and carbon emission reduction (PRCER) (Fang, 2025). Meanwhile, the YREB as an important economic growth pole and one of the major strategic regions in China, is also a key area for implementing digital development and promoting coordinated governance of the PRCER (Jin & Li, 2023; Liu et al., 2024). Therefore, it is urgent to clarify how DE can provide support for SEPRCER in cities of the YREB, as this is of great practical significance for promoting the green and low-carbon development of YREB.

The remaining parts of this article are as follows: The second part elaborates on the theoretical mechanisms and research hypotheses. The third part introduces the research methods, indicator system, regions and data sources. The fourth part conducts an empirical analysis of the impact mechanism of the DE on the SEPRCER in the YREB, and discusses the results. The fifth part summarizes the research conclusions of this article and explores corresponding policy recommendations.

2. Literature Review

In recent years, the issue of how to achieve coordinated governance of the PRCER has become a hot topic of concern in the academic community. Studies have shown that the emissions of environmental pollutants and carbon dioxide share significant characteristics of being of the same origin, same source, and same process. This inherent correlation serves as the theoretical basis for the SEPRCER and has been widely recognized by the academic community (Dong et al., 2022). Existing literature mostly focuses on the measurement and evaluation, evolution characteristics, and influencing factors of the SEPRCER. In terms of the measurement and evolution characteristics of

the SEPRCER, Liu et al. (2024) and Li et al. (2023) calculated the level of the SEPRCER based on the data of air pollution intensity and carbon emission intensity, and found that the level of the SEPRCER showed an increasing trend at the city level; Gao et al. (2025) and Liu et al. (2023) included carbon emissions and $PM_{2.5}$ concentration as non-desired outputs in the model using the Data Envelopment Analysis (DEA) method, and found that the level of the SEPRCER showed an upward trend at the provincial level, and the eastern region remained in the leading position; Nie & Lee (2023) and Tang et al. (2022) measured the level of the SEPRCER using the coupling coordination degree (CCD) model. The former found that the distribution pattern of the level of the SEPRCER in China's provincial space was "high in the east and low in the west, and high in the south and low in the north", with significant spatial positive correlation characteristics, while the latter found that the level of the SEPRCER showed a downward trend in the economic zone of the Yellow River Middle Reach; Bai & Qi (2026) first calculated the pollution reduction efficiency (PRE) and the carbon emissions reduction efficiency (CERE) of using the super-efficiency Undesirable-SBM model, and then calculated the level of the SEPRCER using the CCD model. In terms of the influencing factors of the SEPRCER, Wang et al. (2024) found that the energy consumption structure, energy utilization efficiency, per capita GDP, and the proportion of environmental protection investment were important factors affecting the SEPRCER; Yang et al. (2025) believed that improving energy efficiency and promoting green technologies were crucial for enhancing the SEPRCER, while the impact of industrial structure adjustment on the SEPRCER was limited; Chen et al. (2023) found that industrial structure, technological innovation, energy structure, human capital, and economic foundation had significant impacts on the SEPRCER.

With the rapid iteration of digital technology, the DE has accelerated its rise and deeply empowered all aspects of production, consumption, distribution and governance to improve efficiency and quality. It has become a new type of productive force driving high-quality development, and has provided an important opportunity and strong support for the advancement of the SEPRCER (Dong et al., 2022). At present, the existing literature has conducted systematic research on the DE and SEPRCER. The relevant conclusions can be generally summarized into three aspects: First, it focuses on the discussion of the direct relationship between the two. Most studies believe that the DE has a significant positive promoting effect on the SEPRCER (Guo & Wang, 2023; Wang et al., 2025); at the same time, some literature further reveals that the relationship between the two is not a simple linear one, but presents "U" shape (Bai & Qi, 2026; Sun et al., 2025), inverted "U" shape (Tan & Yan, 2025), etc., providing more abundant empirical evidence for understanding the dynamic correlation between the two. Second, in terms of the influencing mechanism, existing studies have analyzed the specific paths through which the DE enables the SEPRCER from multiple perspectives, and found that the DE can act on the SEPRCER through intermediary channels such as promoting energy structure transformation, industrial structure upgrading, technological innovation progress, resource allocation efficiency improvement, strengthening public environmental supervision, releasing entrepreneurial vitality, and economic agglomeration (Chen & Liu, 2025; Feng et al., 2026; Liang et al., 2024; Zhao & Zeng, 2025; Zheng et al., 2026); at the same time, external factors such as digital literacy of talents, development level of digital finance, market structure characteristics, and government behavior will have a significant moderating effect on the relationship between the DE and the SEPRCER, constituting important constraints on the relationship between the two (Yin et al., 2023; Yue & Han, 2025). Third, in terms of spatial effects, existing studies have noticed the important role of geographical spatial factors, confirming that the

impact of the DE on the SEPRCER has a significant spatial spillover effect (Liang et al., 2024); at the same time, affected by regional differences, transmission paths, etc., this spatial spillover effect shows heterogeneity characteristics, both positive spillover (Zhai et al., 2024) and negative spillover (Gao, 2025), and some studies have also found that it presents a "U" shape non-linear spatial evolution pattern (Bai & Qi, 2026).

By reviewing the existing literature, it can be seen that the current academic community has achieved rich research results regarding the impact of the DE on the SEPRCER. However, there is still room for further expansion: On one hand, most existing studies focus on the mediating effect, moderating effect, and spatial spillover effect between the two, while the discussion on the mechanism of the threshold effect is relatively insufficient; on the other hand, the existing analyses mostly use national cities as samples, and there is a lack of detailed examinations at the specific regional level. In view of this, this paper takes 108 cities in the YREB from 2011 to 2023 as the research sample, systematically examines the threshold effect of the EPPI and the PI in the process of the impact of the DE on the SEPRCER, aiming to provide scientific basis and decision-making references for formulating differentiated regional green and low-carbon policies and promoting the collaborative governance of the PRCER based on the DE.

3. Theoretical Analysis

3.1. The direct impact of the DE on the SEPRCER

The logic of the impact of the DE on the SEPRCER evolves dynamically with the stage of development. Its mechanism is closely related to the depth of technology application, the attributes of infrastructure, and the compatibility of the governance system. In the early stage of development, the high energy consumption attribute of digital infrastructure construction led to the consumption of a large amount of fossil energy for the production and operation of facilities such as data centers and signal base stations. At this time, the potential for PRCER of the DE had not been released (Tan & Yan, 2025); meanwhile, due to the early stage of industrial digitalization, the introduction and adaptation of equipment will lead to an energy rebound effect. In the short term, the improvement in production efficiency is difficult to offset the additional energy consumption (Guo & Wang, 2023), thereby causing a phased constraint on the SEPRCER by the DE (Gao, 2025). As the DE continues to develop, digital technology and green technology are deeply integrated (Li et al., 2023), digital infrastructure gradually transforms towards greenness (Bai & Qi, 2026), and the proportion of clean energy substitution gradually increases, and resource utilization efficiency is improved through intelligent manufacturing and flexible production (Jiang et al., 2013); at the same time, industrial internet platforms connect the channels for collaborative emission reduction in the industrial chain (Chen et al., 2020), promoting the acceleration of green technology innovation iterations (Zeng et al., 2026), achieving simultaneous PRCER from the source; moreover, the DE builds a "government-enterprise-society" multi-party governance pattern through precise government regulation, strengthened enterprise responsibility, and public participation supervision (Fang, 2023; Wang & Li, 2022; Yang et al., 2023; Zhao et al., 2020), significantly enhancing the collaborative regulatory capacity. In addition, the DE further strengthens the positive driving effect on the SEPRCER through improvements in energy utilization efficiency, optimization of energy consumption structure, expansion of environmental investment scale, and progress in green technology (Gu et al., 2021; Tang et al., 2022).

Based on this, the following research hypothesis H1 is proposed: The impact of the DE on the SEPRCER follows a “U” shaped curve.

3.2. The threshold effect of EPPI

According to the Porter Hypothesis, reasonable environmental regulations can force enterprises to carry out green technological innovation. The EPPI as the core tool of environmental regulations, changes the ratio of the environmental compliance costs and the green transformation benefits of enterprises, enabling them to offset the compliance costs through "innovation compensation" (Porter & van der Linde, 1995). This promotes enterprises to deeply integrate digital technology with the goals of the PRCER, achieving a transformation of digital technology from an “efficiency tool” to a “green tool”, and ultimately strengthening the SEPRCER (Guo, 2019). However, under low EPPI, the environmental violation costs are lower than the green transformation investment costs. Therefore, enterprises tend to apply digital technologies to enhance production efficiency and increase economic benefits, which hinders the release of environmental improvement effects and delays the entry of the DE into the stage where it positively promotes the SEPRCER (Chen, 2025).

Based on this, the following research hypothesis H2 is proposed: The impact of the DE on the SEPRCER has a threshold effect related to the EPPI.

3.3. The threshold effect of PI

Generally speaking, in the areas where pollution-intensive industries are concentrated, the “high-carbon lock-in” effect is particularly prominent (Lu et al., 2025). Their development is highly dependent on energy-intensive and pollution-intensive industries such as steel, chemicals, and non-ferrous metal smelting. The digital technology application in these regions requires a huge investment to digitally transform and intelligently upgrade traditional high-pollution production lines and end-of-pipe treatment equipment. During the transformation process, problems such as production stagnation and cost escalation may occur (Li et al., 2025). At the same time, fluctuations in energy prices, stringent environmental protection policies and carbon reduction targets will increase the cost pressure for enterprises to transform, and squeeze the funds for their digital transformation. This will reduce the profit margins of enterprises (Liu & Fang, 2025), resulting in the enabling effect of the DE being offset by the transformation costs. Consequently, the DE will be delayed in entering the stage where it positively promotes the SEPRCER (Zhai et al., 2024). It may even experience temporary efficiency losses due to the short-term pain of transformation (Tan & Yan, 2025). However, when the PI of the region is low and the industrial structure is dominated by low-energy consumption manufacturing and light-asset service industries, the introduction of digital technology does not need to bear the high costs of production process reconfiguration and equipment renewal, thus embedding digital technology in the entire production and regional governance chain at a lower cost. At this time, the DE can enter the stage of positive driving on the SEPRCER earlier (Sun et al., 2024).

Based on this, the following research hypothesis H3 is proposed: The impact of the DE on the SEPRCER exhibits a threshold effect related to PI.

4. Methodology and Data

4.1 Methodology

4.1.1 Super-efficiency undesirable-SBM model

The super-efficiency Undesirable-SBM model is an extended model of the data envelopment analysis research method. This model not only can solve the slack variable problem of input-output, but also incorporates non-desirable outputs into the model to evaluate the relative effectiveness of decision-making units (Tone & Tsutsui, 2011). This paper uses the super-efficiency Undesirable-SBM model of Dearun software to calculate the PRE and the CERE of cities. The model formula is as follows (Liu et al., 2025):

$$\begin{aligned} &min\rho = \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1-\frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{rk}}; \\ &s.t.\sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \le x_{ik}; \\ &\sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \le y_{rk}; \\ &\begin{cases} \lambda, s^-, s^+ \ge 0, \\ i = 1,2,\cdots m, \\ r = 1,2,\cdots p, \\ j = 1,2,\cdots n\left(j \neq k\right). \end{cases} \end{aligned} \tag{1}$$

Among them, ρ represents the PRE or the CERE calculated by the model. When $\rho \geq 1$ and $s^+ = s^- = 0$, it indicates that the PRE or the CERE has reached a strong effective state; when $\rho = 1$ and $s^+ \neq 0$ or $s^- \neq 0$, it indicates that the PRE or the CERE has reached a weak effective state; when $\rho < 1$, it indicates that the PRE or the CERE is in an ineffective state.

4.1.2 The CCD model

The CCD model can reflect the collaborative "effects" and overall "efficiency" between two or more systems (Cheng et al., 2026). Therefore, in this paper, the CCD model is used to calculate the CCD between the PRE or the CERE, in order to characterize the level of the SEPRCER. The calculation formula is as follows (Zhang et al., 2025):

$$\begin{aligned} &T = \alpha U_1 + \beta U_2; \\ &C = \frac{2\sqrt{U_1 \times U}}{U_1 + U_2}; \\ &D = \sqrt{C \times T}. \end{aligned} \tag{2}$$

Among them, T represents the linear summation of the PRE and the CERE; U_1 and U_2 respectively represent the PRE and the CERE; α and β respectively represent the contribution rates of the PRE and the CERE to the coordinated development of the two; since both have the characteristic of "sharing the same origin", $\alpha = \beta = 0.5$ (Xiang et al., 2025); C represents the coupling degree (CD) of the PRE and the CERE; D represents the CCD of the PRE and the CERE, that is, the level of the SEPRCER, and the larger the value, the higher the level of the SEPRCER.

4.1.3 Entropy-weighted TOPSIS method

The entropy-weight TOPSIS method is an improved comprehensive evaluation approach that optimizes the traditional TOPSIS model by incorporating the entropy weight method. This method calculates the distances between each evaluation unit and the positive and negative ideal solutions to complete multi-dimensional evaluation ranking and select the optimal solution. It can effectively avoid the interference caused by subjective weighting and reduce the human deviation in the process of setting indicator weights, ensuring the objectivity and scientificity of the evaluation results (Shi et al., 2025). Therefore, this paper adopts the entropy-weight TOPSIS method to measure the level of DE. The calculation formula is as follows (Wang & Wang, 2025):

Firstly, the original data is standardized to eliminate the influence that different indicators have on the weighting of evaluation due to differences in units, scales, and magnitudes:

$$X_{ijt} = \frac{x_{ijt} - min(x_{ijt})}{max(x_{ijt}) - min(x_{ijt})} \tag{3}$$

Among them, X_{ijt} and x_{ijt} represent the standardized data and the original data of the j indicator of the i city in the t year; $max(x_{ijt})$ and $min(x_{ijt})$ represent the maximum and minimum values of the j indicator respectively.

Secondly, the comprehensive level of each indicator is calculated using the entropy weight method:

$$\begin{aligned} P_{ijt} &= \frac{X_{ijt}}{\sum_i^n \sum_t^m X_{ijt}}; \\ E_j &= -\frac{\sum_i^n \sum_t^m (P_{ijt} \times lnP_{ijt})}{ln(n \times m)}; \\ W_j &= \frac{1 - E_j}{\sum_j^r (1 - E_j)}; \\ I_{ijt} &= X_{ijt} \times W_j. \end{aligned} \tag{4}$$

Among them, n, m, and r represent the number of cities, the research period, and the number of indicators respectively; P_{ijt} represents the standardized data of the j indicator of the i city in the t year as a proportion of the total weight of the j indicator; E_j represents the entropy value of the j indicator; W_j represents the weight of the j indicator; I_{ijt} represents the comprehensive level of the j indicator of the i city in the t year calculated through the entropy weight method.

Finally, the final level of the DE is calculated using the TOPSIS method:

$$
\begin{aligned}
&s_j^+ = max(I_{ijt}), j \in j^+;\\
&s_j^- = max(I_{ijt}), j \in j^-;\\
&sep_{it}^+ = \sqrt{\sum_j^r (s_j^+ - I_{ijt})^2};\\
&sep_{it}^- = \sqrt{\sum_j^r (s_j^- - I_{ijt})^2};\\
&DE_{it} = \frac{sep_{it}^-}{sep_{it}^+ + sep_{it}^-}.
\end{aligned}
\tag{5}
$$

Among them, s_j^+ and s_j^- respectively represent the positive ideal solution and the negative ideal solution of the j indicator; sep_{it}^+ and sep_{it}^- respectively represent the Euclidean distance calculated from the positive ideal solution and the negative ideal solution for the i city in the t year; DE_{it} represents the level of the DE of the i city in the t year.

4.2. Variable selection

4.2.1. Dependent variable: SEPRCER

This paper adopts the measurement method of Bai & Qi (2026) to calculate the level of the SEPRCER. Specifically, the super-efficiency Undesirable-SBM model is first used to separately calculate the PRE and the CERE, and then the CCD model is utilized to calculate the level of the SEPRCER. The specific indicator composition is shown in Table 1:

Table 1. Indicators for measuring PRE and CERE

Measurement type	Indicator type	Variable	Unit
PRE	Input	Number of employees	Ten thousand people
		Fixed capital stock	Ten thousand yuan
		Total energy consumption	Ten thousand tons of standard coal
	Expected output	Actual regional GDP	Ten thousand yuan
	Undesirable output	$PM_{2.5}$ emissions	μg/m^3
CERE	Input	Same as above	Same as above
	Expected output	Same as above	Same as above
	Undesirable output	CO_2 emissions	Ten thousand tons

4.2.2. Independent variable: DE

Drawing on the research of Zhao et al. (2020) and Wang & Dong (2025), the DE evaluation index system was constructed from three dimensions: digital transactions (DTR), digital infrastructure (DIN), and informatization development (IDE) (Table 2), and the entropy-weight TOPSIS method was used to measure the level of the DE (Wu et al., 2025).

Table 2. Evaluation index system of DE

Primary indicator	Secondary indicators	Measurement method	Unit	Attribute	Weight
DTR	Digital inclusive finance	Urban Digital Inclusive Finance Index	Unitless	Positive	0.0642
DIN	Internet penetration rate	The number of Internet users per hundred people	per hundred people	Positive	0.1027
	The number of mobile	The number of mobile phone users	per hundred	Positive	0.0976

	internet users	per hundred people	people		
IDE	The number of personnel in the information industry	The proportion of computer service and software professionals	%	Positive	0.5626
	Output of the information technology industry	Per capita total telecommunications volume	Yuan	Positive	0.1729

4.2.3. Mechanism variables

(1) EPPI: It is represented by the ratio of the total amount of fines and confiscations by environmental protection bureau of each city in a corresponding year to the total number of penalties (Dai & Zhang, 2023); (2) PI: Following the calculation method of Tian et al. (2018), the PI indices of each industry are summed up and then logarithmically processed to measure the PI at the city level.

4.2.4. Control variables

(1) Population density (POP): Represented by the ratio of the permanent resident population of the city at the end of the year to the built-up area (Rao et al., 2026); (2) Per capita income level (PCIL): Represented by the logarithm of the regional GDP per capita (Chen & Zhang, 2025); (3) The level of opening up to the outside world (OPEN): Represented by the proportion of actual utilized foreign direct investment to the regional GDP (Li et al., 2025); (4) Urbanization level (URL): Represented by the proportion of urban population to the permanent resident population at the end of the year (Huang & Dou, 2024); (5) Environmental governance investment (EGI): Represented by the proportion of environmental pollution control investment to the regional GDP (Zhang & Huang, 2023); (6) Greening level (GRE): Represented by the green coverage rate of the built-up area of the city (Bie et al., 2023); (7) Infrastructure level (INF): Represented by the average road area per capita in the city (Lin et al., 2025).

4.3. Model setting

4.3.1. Basic regression model

To examine the direct impact of the DE on the SEPRCER, a two-way fixed-effects regression model was constructed:

$$SEPRCER_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 DE_{it}^2 + \alpha Control_{it} + \mu_t + \lambda_i + \varepsilon_{it} \tag{6}$$

Among them, *Control* represents the control variable, α represents the regression coefficient, λ_i represents the city fixed effect, μ_t represents the year fixed effect, ε_{it} represents the random error term, and the meanings of the other symbols are the same as those in the previous text.

4.3.2. Threshold effect model

To test the threshold effect of the moderating variable, the threshold regression model proposed by Hansen (1999) was adopted for verification:

$$\begin{aligned} SEPRCER_{it} = {} & \beta_0 + \beta_1 DE_{it} I\left(M_{it} \le \gamma\right) + \beta_2 DE_{it}^2 I\left(M_{it} > \gamma\right) \\ & + \beta Control_{it} + \mu_t + \lambda_i + \varepsilon_{it} \end{aligned} \tag{7}$$

Among them, β represents the regression coefficient, γ is the threshold value, I (•) is the indicator

function, M_{it} is the moderating variable, and the remaining symbols have the same meanings as those mentioned earlier.

4.4. Data sources

Given the availability of data, this paper selects 108 cities in the YREB as the research objects. The research period is from 2011 to 2023. The original data of relevant indicators come from the EPS database, the CSMAR database, the Ali Research Institute, the China Research Data Service Platform, the National Qinghai-Xizang Plateau Science Data Center, and the China Socio-Economic Big Data Research Platform, respectively. Therefore, the sources of the relevant charts and data mentioned later will no longer be separately indicated. At the same time, for some missing data in certain regions in certain years, they have been supplemented using the linear interpolation method. In addition, the descriptive statistics and collinearity test results of each variable are shown in Table 3. It can be seen that the VIF values of all variables are less than 10, indicating that there is no serious multicollinearity problem (Liu & Tan, 2025).

Table 3. Descriptive statistics and collinearity test results

Category	Variable	Sample	Mean	Std.	Min	Median	Max	VIF
Dependent variable	*SEPRCER*	1404	0.2650	0.0476	0.1765	0.2544	0.5558	—
Independent variable	*DE*	1404	0.1002	0.0770	0.0084	0.0862	0.7934	1.5334
Mechanism variables	*EPPI*	1404	4.5088	9.1511	0.0000	0.0000	112.8175	1.0833
	PI	1404	9.3027	1.0380	3.1355	9.1934	12.0138	7.8369
Control variables	*POP*	1404	6.0123	0.6427	4.0087	6.0584	7.7780	3.3609
	PCIL	1404	10.7971	0.7411	1.7777	10.7472	12.6552	4.6185
	OPEN	1404	0.0204	0.0187	0.0000	0.0155	0.1416	1.1707
	URL	1404	0.3419	0.1823	0.0750	0.2976	1.0000	2.0190
	EGI	1404	1.0000	1.3517	0.0078	0.6418	23.4386	1.1767
	GRE	1404	95.3771	11.6448	11.0000	100.0000	100.0000	1.3036
	INF	1404	20.0446	7.8302	0.0000	19.5062	55.5753	1.4245

5. Results and Discussion

5.1. Analysis of evolutionary trends

5.1.1. The evolutionary trends of SEPRCER

To explore the evolution characteristics of the level of the SEPRCER among cities in the YREB, this paper takes 2011 as the base period and selects three-time sections of 2011, 2017, and 2023 at 6-year intervals to draw their spatial distribution map (Fig. 1). It can be seen that the level of the SEPRCER in the YREB showed a slight downward trend from 2011 to 2023, with the regional average dropping from 0.29 to 0.25; the spatial layout gradually formed a distribution pattern centered on the YRD and with multiple growth poles coexisting. Specifically, in 2011, the cities with the highest SEPRCER were Suzhou, Shanghai, and Wuxi; the average level in the LRYR ranked first, then comes the middle reaches of the Yangtze River (MRYR) and the upper reaches of the Yangtze River (URYR). In 2017, the top three cities became Shanghai, Changsha, and Hangzhou; the level of the SEPRCER in the LRYR declined, while it was relatively stable with the MRYR and the URYR. The average values of the three regions remained above 0.25. In 2023, the top three cities were Shanghai, Wuxi, and Changsha; the level of the SEPRCER in the LRYR returned to an

upward trend, while the MRYR and the URYR still showed a downward trend, further widening the development gap with the LRYR.

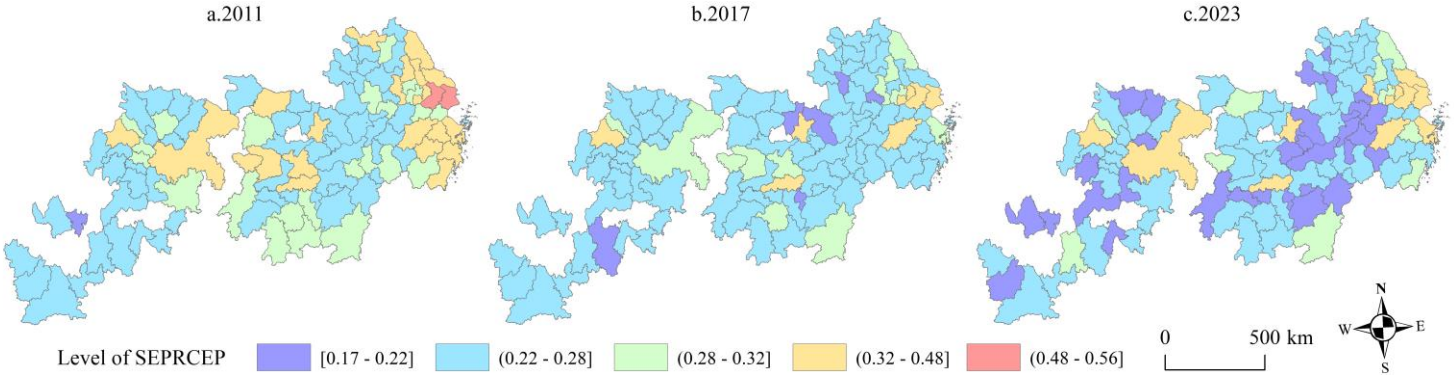


Fig. 1 Spatiotemporal evolution map of level of SEPRCER in the YREB

5.1.2. The evolutionary trends of DE

Furthermore, in order to explore the evolution characteristics of the level of the DE among cities in the YREB, following the aforementioned classification method, three-time sections of 2011, 2017, and 2023 were selected to draw their spatial distribution map (Fig. 2). It is not difficult to observe that from 2011 to 2023, the level of the DE of the YREB showed an overall upward trend, with the regional average increasing from 0.06 to 0.11; the spatial layout gradually formed a distribution pattern centered on the YRD and with multiple growth poles coexisting. Specifically, in 2011, the top three cities in terms of the level of the DE were Hangzhou, Shanghai, and Nanjing; the central area of the YRD initially became a core developed region, with its average level of the DE reaching 0.09, which was higher than 83.33% of the cities in the study area. In 2017, the top three cities changed to Shanghai, Hangzhou, and Chengdu; the average level of the DE of the URYR and the LRYR exceeded 0.11, while the MRYR was at a relatively lagging level, with an average of 0.09. In 2023, the top three cities were Huaihua, Shanghai, and Hangzhou; the MRYR achieved rapid development, and the gap in DE development between it and the URYR and LRYR gradually narrowed.

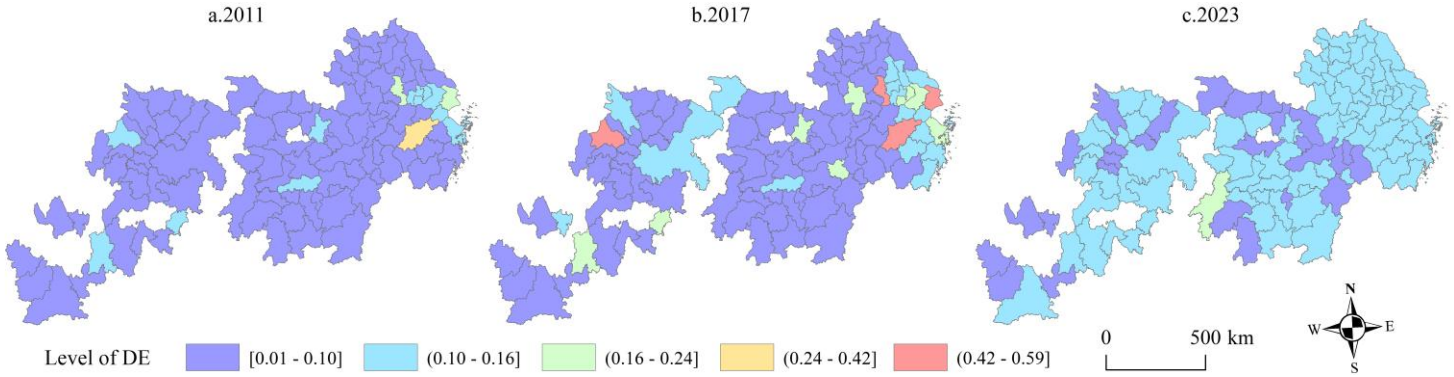


Fig. 2 Spatiotemporal evolution map of level of DE in the YREB

5.2. Benchmark regression analysis

A double fixed-effect model was adopted to examine the impact of the DE on the SEPRCER. The results are shown in Table 4. Among them, the column 1 shows the regression result of the DE on the SEPRCER without considering the control variables. The columns 2 to 8 show the regression results after adding control variables one by one. The results show that regardless of whether the control variables are included or not, the coefficient of the first term of the DE is negative, and the

coefficient of the second term is positive, and it passes the significance test at the 1% level. Therefore, it is confirmed that the impact of the DE on the SEPRCER has a significant "U" shape relationship. Therefore, Hypothesis H1 is established. From the full-variable regression result in the column 8, the coefficients of the first term and the second term of the DE are -0.2815 and 0.2831 respectively. By calculation, the value of the curve's inflection point is 0.497. That is, when the level of the DE crosses the critical value of 0.497, its promoting effect on the SEPRCER begins to appear and gradually strengthens.

Table 4. Results of baseline regression

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DE	-0.3168***	-0.2935***	-0.3032***	-0.3010***	-0.2955***	-0.2847***	-0.2870***	-0.2815***
	(0.0466)	(0.0474)	(0.0477)	(0.0476)	(0.0477)	(0.0470)	(0.0474)	(0.0472)
DE²	0.3216***	0.2961***	0.3080***	0.3049***	0.2984***	0.2859***	0.2892***	0.2831***
	(0.0728)	(0.0726)	(0.0730)	(0.0726)	(0.0725)	(0.0707)	(0.0713)	(0.0708)
POP		0.0417**	0.0395**	0.0395**	0.0390**	0.0374**	0.0378**	0.0363**
		(0.0179)	(0.0176)	(0.0176)	(0.0175)	(0.0174)	(0.0174)	(0.0170)
PCIL			0.0098**	0.0093**	0.0094*	0.0096*	0.0093*	0.0097**
			(0.0046)	(0.0047)	(0.0049)	(0.0050)	(0.0050)	(0.0049)
OPEN				-0.0532	-0.0385	-0.0212	-0.0206	-0.0182
				(0.0791)	(0.0780)	(0.0743)	(0.0745)	(0.0744)
URL					-0.0216**	-0.0226**	-0.0225**	-0.0241**
					(0.0094)	(0.0094)	(0.0094)	(0.0094)
EGI						-0.0012	-0.0012	-0.0012
						(0.0010)	(0.0010)	(0.0009)
GRE							0.0000	0.0000
							(0.0000)	(0.0000)
INF								-0.0002**
								(0.0001)
Cons	0.2916***	0.0390	-0.0533	-0.0461	-0.0382	-0.0305	-0.0327	-0.0243
	(0.0036)	(0.1084)	(0.1112)	(0.1089)	(0.1083)	(0.1076)	(0.1077)	(0.1058)
city	√	√	√	√	√	√	√	√
year	√	√	√	√	√	√	√	√
Obs	1404	1404	1404	1404	1404	1404	1404	1404
adj. R²	0.894	0.895	0.898	0.898	0.898	0.898	0.898	0.899

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. The values in () are the standard errors, and the same applies below.

In terms of control variables, the coefficients of the POP and the PCIL are both positive, and have passed the test at the 5% significance level, indicating that the POP and the PCIL can enhance the SEPRCER. However, this impact is very limited. The coefficients of the URL and the INF are both negative, and have also passed the 5% significance test. This might be due to the fact that during the process of urbanization expansion and infrastructure construction, due to increased resource consumption and pollution emissions, the SEPRCER was inhibited. The coefficients of the OPEN, the EGI and GRE are not significant. This might be because the environmental effect of OPEN in the YREB has not fully manifested, and there are regional differences in the EGI and the GRE,

thereby weakening the influence of these variables on the SEPRCER.

5.3. Endogeneity test analysis

Due to measurement errors, omitted variables, bidirectional causality, etc., endogeneity problems may arise, leading to biases in the empirical results. Therefore, the two-stage least squares method (2SLS) is adopted to further identify the impact of the DE on the SEPRCER. In terms of the selection of instrumental variable (IV), drawing on the ideas of Huang et al. (2019) and Xu et al. (2017), the interaction term and its quadratic term of the number of fixed-line telephone users in 2000 and the national information technology service revenue of the previous year were selected. The reason for choosing this IV is that the number of fixed-line telephones in 2000 is historical data, which is exogenous and closely related to the foundation of DE development. The national information technology service revenue is a macro variable and has no direct correlation with the SEPRCER in a single city. This meets the requirements of the correlation and exogeneity of the IV. The results of the endogeneity test are shown in Table 5. It can be seen that in the test of the identification deficiency of the IV, the LM value is 11.928, which rejects the null hypothesis at the 1% significance level, indicating that there is a significant correlation between the IV and the DE. At the same time, in the weak IV test, the Wald F value is 55.919, which is greater than the critical value of 7.03 in the Stock-Yogo test at the 10% level, indicating that the selected IV are reasonable and effective. Column 3 of Table 4 shows the regression results of the second stage. It can be seen that the coefficient of the DE in the first stage is significantly negative, and the coefficient of the quadratic term is significantly positive, which is consistent with the benchmark regression results. This indicates that after dealing with potential endogeneity problems, the impact of the DE on the SEPRCER still shows a “U” shape curve characteristic, verifying the reliability of the benchmark regression results.

Table 5. Results of endogeneity test

Variable	(1) *DE*	(2) DE^2	(3) *SEPRCER*
IV	-0.0041	0.0020	
	(0.0045)	(0.0036)	
IV^2	-0.0002**	-0.0003***	
	(0.0001)	(0.0001)	
DE			-0.6059***
			(0.1792)
DE^2			0.5996**
			(0.2459)
LM 值		11.928	
		{0.001}	
Wald F 值		55.919	
		[7.03]	
Control	√	√	√
city	√	√	√
year	√	√	√
Obs	1404	1404	1404

Notes: The values in {} are the P-values, and the values in [] are the critical values for the weak IV

test.

5.4. Robustness test analysis

To ensure the reliability of the benchmark regression results, we conducted the following robustness tests and listed the results in Table 6. Firstly, we changed the measurement method of the DE and re-measured its level using the CRITIC entropy weighting method, and then conducted the regression analysis, as shown in the column 1; Secondly, we excluded the sample data of the central directly-administered cities. Since there are significant differences in the data of the central directly-administered cities and prefecture-level cities, this will affect the research results. Therefore, we excluded the sample data of Shanghai and Chongqing, and conducted the regression analysis again, as shown in the column 2; Thirdly, we excluded the data of special years. Since the sample data of 2020, 2021, and 2022 were interfered by the special influence of the Chinese COVID-19 epidemic, we excluded these three years' data and conducted the regression analysis again, as shown in the column 3; Fourthly, we truncated the data. The variables were truncated 1% downward and upward at both ends, and then conducted the regression analysis, and the results are shown in the column 4. From Table 6, it can be seen that under these four testing methods, the coefficient signs and significance of the core explanatory variables are basically consistent with the benchmark regression results, which indicates that the research conclusion has good robustness.

Table 6. Results of robustness test

Variable	(1)	(2)	(3)	(4)
DE	-0.2247***	-0.2882***	-0.2919***	-0.3419***
	(0.0517)	(0.0406)	(0.0570)	(0.0398)
DE^2	0.1422*	0.3143***	0.3145***	0.4068***
	(0.0730)	(0.0593)	(0.0853)	(0.0585)
Cons	-0.0655	-0.0468	-0.0035	-0.3191***
	(0.1077)	(0.1061)	(0.1149)	(0.1060)
Control	√	√	√	√
city	√	√	√	√
year	√	√	√	√
Obs	1404	1378	1080	1404
adj. R^2	0.896	0.892	0.903	0.914

5.5. Heterogeneity test analysis

When studying the impact of the DE on the SEPRCER, the heterogeneity characteristics brought about by differences in regional location, policy systems, resource endowment, and economic development among cities cannot be ignored. Therefore, the heterogeneity test was conducted by grouping according to different dimensions, and the results are shown in Table 7. From the perspective of regional heterogeneity (Columns 1 and 2 represent the LRYR and non-LRYR), the absolute values of the coefficients of the first and second terms of the DE in the LRYR are greater than those in the non-LRYR, and the curve inflection point of the LRYR is 0.473, which is slightly lower than 0.478 of the non-LRYR. This indicates that in the initial stage of DE development in the LRYR, the negative inhibitory effect on the SEPRCER is stronger, and the critical level at which the marginal impact turns from reduction to increase appears earlier; once this inflection point is crossed, the positive promoting effect of the DE on the SEPRCER will be significantly better than

that of the non-LRYR. The reasons for this are that the digital infrastructure in the LRYR is more complete and the digital governance capabilities of the government and enterprises are stronger, so the conversion cost of the digitization is lower, and it can quickly break through the bottleneck in the initial stage of development; after crossing the inflection point, the LRYR, with its scale advantages and industrial chain synergy foundation in energy conservation and environmental protection, high-end manufacturing, etc., can further release a stronger positive promoting effect of the DE.

Table 7. Results of heterogeneity test

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DE	-0.3807***	-0.2907***	-0.3337***	0.1262	-0.1917	-0.3173***	-0.2567***	-0.2429**
	(0.0989)	(0.0605)	(0.0589)	(0.1191)	(0.1607)	(0.0604)	(0.0731)	(0.1136)
DE^2	0.4021***	0.3401***	0.3524***	-0.6101	0.7966	0.3379***	0.2771***	0.2541
	(0.1357)	(0.1189)	(0.0848)	(0.4883)	(0.7171)	(0.0867)	(0.1017)	(0.4337)
Cons	-0.0416	-0.2168*	-0.5117***	0.2246***	0.1298	-1.0676***	-1.5249***	0.1909***
	(0.1209)	(0.1278)	(0.1609)	(0.0454)	(0.0810)	(0.1669)	(0.2660)	(0.0584)
Control	√	√	√	√	√	√	√	√
city	√	√	√	√	√	√	√	√
year	√	√	√	√	√	√	√	√
Obs	533	871	1001	403	507	897	481	923
adj. R^2	0.910	0.892	0.909	0.844	0.819	0.908	0.911	0.837

From the perspective of policy heterogeneity (Columns 3 and 4 represent urban agglomerations and non-urban agglomerations respectively), the DE and SEPRCER in urban agglomerations shows a significant "U" shape curve relationship, with the turning point being 0.474. The development of the DE in non-urban agglomerations is insufficient to have a significant nonlinear impact on the SEPRCER. The difference between the two may stem from the fact that urban agglomerations have more complete digital infrastructure, more concentrated industrial resources, and more advanced digital technologies, thereby laying a solid foundation for empowering the DE; while non-urban agglomerations are constrained by weak economic development foundations and insufficient digital infrastructure support, making it difficult for the empowerment effect of the DE to be effectively released.

From the perspective of resource heterogeneity (Columns 5 and 6 represent resource-based cities and non-resource-based cities respectively), the impact of the DE on the SEPRCER in non-resource-based cities shows a significant "U" shape curve feature, with the turning point being 0.471. However, there is no significant nonlinear relationship between the DE and the SEPRCER in resource-based cities. This result may be attributed to the diversified industrial structure and well-established digital infrastructure layout of non-resource-based cities, which have laid a good foundation for enabling the DE to enhance the SEPRCER; while resource-based cities are constrained by a single industrial structure, fixed development paths, and insufficient DE transformation motivation, making it difficult for enabling effect of the DE to be effectively exerted.

In terms of economic development heterogeneity (Columns 7 and 8 represent high-income regions and low-income regions respectively), the DE and SEPRCER in high-income regions (those with a per capita regional GDP above the average) shows a significant "U" shape curve relationship, with the inflection point at 0.463. However, there is no significant nonlinear relationship between the two

in low-income regions. The reasons for this are as follows: High-income regions have abundant capital accumulation, which enables them to continuously increase capital investment in areas such as DE development and environmentally friendly industries, thereby supporting the enabling role of the DE; Low-income regions are constrained by their stage of development, and their economic growth mostly adopts a simplistic model. Moreover, the digital application technology level is low, so they lack the capital and technical conditions to support the enabling role of the DE.

5.6. Threshold effect analysis

According to the theoretical analysis in the previous text, there may be a certain threshold effect between the EPPI and the PI in the relationship between the DE and SEPRCER. Therefore, these two variables are taken as threshold variables for the threshold effect test.

5.6.1. Analysis of the threshold effect of EPPI

Due to the possible significant differences in the EPPI among different cities, during the process of the impact of the DE on the SEPRCER, the relationship between the two may exhibit differentiated influence characteristics depending on the level of the EPPI. Therefore, the threshold effect of the EPPI was tested using the Bootstrap method. Table 8 reports the results of the threshold existence test for the EPPI. It can be seen that there is a significant single threshold effect for the EPPI, and it failed the double threshold test. Specifically, the estimated threshold value of the EPPI is 0.3635. After being tested at a 5% significance level, its 95% confidence interval is [0.0000, 0.7632]. Thus, the hypothesis H2 is confirmed.

Table 8. Results of threshold test of EPPI

Variable	Threshold number	F-statistic	P-value	1%	5%	10%	Threshold value	95% Confidence interval
EPPI	Single	23.81**	0.0110	23.9484	17.8236	15.0851	0.3635	[0.0000, 0.7632]
	Double	4.82	0.6380	41.0622	17.8777	14.0570		

In order to further explore whether the impact of the DE on the SEPRCER shows different characteristics under different levels of the EPPI, a grouped regression was conducted based on the threshold conditions of the EPPI (Table 9). From the regression results, it can be seen that in different EPPI ranges, the first term of the DE is significantly negative, and the coefficient of the second term is significantly positive, and both have passed the 1% significance test. This indicates that regardless of whether the EPPI crosses the threshold critical value, the impact of the DE on the SEPRCER shows a significant “U” shape feature. From the size of the coefficients and the characteristics of the turning points, there is significant heterogeneity between the two groups of intervals: at low EPPI, the coefficient of the second term of the DE is 0.3194, and the “U” shape curve trend is relatively gentle, with the corresponding turning point being 0.4795; at high EPPI, the coefficient of the second term of the DE rises to 0.6829, with a significant increase in the coefficient, and the steepness of the “U” shape curve significantly increases, with the corresponding turning point dropping to 0.2335. This result indicates that a higher EPPI forms a rigid constraint, forcing enterprises to apply more digital technologies to green production and precise pollution control. The complementary effect of institutional constraints and technological empowerment is formed, which significantly amplifies the positive promoting effect of the DE on the SEPRCER, and can effectively shorten the effect cycle. That is, the DE only needs a lower development level to break through the turning point and quickly release the positive promoting effect on the SEPRCER.

Table 9. Results of threshold regression of EPPI

Variable	Threshold condition	*SEPRCER*
DE	*EPPI*<0.3635	-0.3063***
		(0.0485)
DE^2	*EPPI*<0.3635	0.3194***
		(0.0688)
DE	*EPPI*≥0.3635	-0.3189***
		(0.0575)
DE^2	*EPPI*≥0.3635	0.6829***
		(0.1754)
Cons		0.0320
		(0.1693)
Control		√
city		√
year		√
Obs		1404
adj. R^2		0.544

5.6.2. Analysis of the threshold effect of PI

Due to the possible significant differences in the PI among different cities, during the process of the impact of the DE on the SEPRCER, the relationship between the two may exhibit differentiated influence characteristics depending on the level of the PI. Therefore, we conducted a test using the Bootstrap method to examine the threshold effect of the PI. Table 10 reports the results of the threshold existence test for the PI. It can be seen that the estimated threshold value of the PI is 10.7450, which passes the significance test at the 5% level, and the 95% confidence interval is [10.7242, 10.7728]. Thus, the hypothesis H3 is confirmed.

Table 10. Results of threshold test of PI

Variable	Threshold number	F-statistic	P-value	1%	5%	10%	Threshold value	95% Confidence interval
PI	Single	52.43**	0.0130	56.7139	39.6100	33.8216	10.7450	[10.7242, 10.7728]
	Double	25.67	0.1670	96.5299	70.6875	48.4467		

To further explore whether there are differential characteristics in the impact of the DE on the SEPRCER under different PI, a grouped regression analysis was conducted based on the PI threshold. The specific results are shown in Table 11. The regression results indicate that regardless of whether the PI exceeds the threshold value of 10.745, the coefficient of the first term of the DE is significantly negative, and the coefficient of the second term is significantly positive. All of them passed the 1% significance test, meaning that under different PI, the DE and SEPRCER still shows a stable and significant “U” shape non-linear relationship. Considering the size of the coefficients and the curve shape, the two groups show obvious heterogeneity characteristics. In the low PI range, the second coefficient of the DE is 0.3736, and the “U” shape curve trend is steeper, with a stronger nonlinear influence effect; in the high PI range, the second coefficient of the DE drops to 0.3465, and the “U” shape curve becomes smooth, and the turning point rises from 0.4119 to 0.5351. The reasons for this are that in low PI areas, the industrial structure is cleaner, and the burden of pollution

control is smaller, making digital technology more suitable for green adaptation, and it can fully exert the optimization effect of governance; while in high PI areas, due to the lock-in effect of high energy-consuming and high-emission industries, the resistance to industrial transformation is greater, and thus, the DE needs a higher level of development to break through the turning point.

Table 11. Results of threshold regression of PI

Variable	Threshold condition	*SEPRCER*
DE	*PI*<10.7450	-0.3078***
		(0.0522)
DE^2	*PI*<10.7450	0.3736***
		(0.0710)
DE	*PI*≥10.7450	-0.3708***
		(0.0625)
DE^2	*PI*≥10.7450	0.3465***
		(0.0728)
Cons		-0.0043
		(0.1735)
Control		√
city		√
year		√
Obs		1404
adj. R^2		0.560

5.6.3. Further analysis

To further investigate the interaction heterogeneity characteristics of the DE on the SEPRCER under the two threshold constraints of the EPPI and PI, this paper sets up groups based on the critical values of the two threshold variables: samples with EPPI higher than the threshold value are defined as the high EPPI group, and those lower than the threshold value are defined as the low EPPI group; samples with PI higher than the threshold value are defined as the high PI group, and those lower than the threshold value are defined as the low PI group. Based on this, the entire sample is divided into four combination scenarios: high EPPI - low PI, high EPPI - high PI, low EPPI - low PI, and low EPPI - high PI. An interaction grouped heterogeneity regression is conducted accordingly, and the specific results are shown in Table 12. From the grouped regression results, it can be clearly seen that in the regressions of the four combination scenarios, the coefficient of the first term of the DE is significantly negative, and the coefficient of the second term is significantly positive, and all pass the significance tests at the corresponding statistical levels. This indicates that regardless of the combination form of the EPPI and PI, the impact of the DE on the SEPRCER is consistently and stably presented in a “U” shape nonlinear pattern, and this nonlinear characteristic has strong robustness.

Table 12. The partitioned heterogeneity regression results of the two threshold variables interaction based on EPI and PI

Variable	(1)	(2)	(3)	(4)
	High EPPI - Low PI	High EPPI - High PI	Low EPPI - Low PI	Low EPPI - High PI
DE	-0.3369***	-2.3045*	-0.3386***	-0.3540**

	(0.1020)	(1.2272)	(0.0636)	(0.1461)
DE^2	0.8864***	6.9352*	0.3653***	0.3758**
	(0.2690)	(3.7587)	(0.0933)	(0.1714)
Cons	-0.2294	-3.3848*	-0.5885***	-6.5628***
	(0.1984)	(1.7576)	(0.2074)	(1.2767)
Control	√	√	√	√
city	√	√	√	√
year	√	√	√	√
Obs	490	49	785	80
adj. R^2	0.891	0.991	0.913	0.924

From the perspective of coefficient magnitude, the steepness of the curve, and the characteristics of the samples, the four groups of samples exhibit significant heterogeneity differences. Under the high EPPI - low PI group, the coefficient of the second term of the DE reaches 0.8864, which is significantly higher than that of the other groups. The "U" shape curve is the steepest, and the sample observations are sufficient, with a good regression fitting effect. The statistical results are robust and reliable. In the high EPPI - high PI group, although the coefficient of the second term of the DE is as high as 6.9352, the "U" shape non-linear feature is the most intense. However, it only passes the 10% significance test and the sample size is only 49, so the coefficient fluctuation range is large, and the results lack universal applicability. Under the low EPPI, regardless of the PI, the coefficient of the second term of the DE remains between 0.36 and 0.38, which is relatively small and the difference is slight. The "U" shape curve trend is smoother. In terms of the underlying logic, high EPPI can form a strong environmental regulatory constraint, effectively activating the regulatory empowerment and green impetus of the DE. In contrast, regions with high PI have a higher degree of clean industrial structure, less pollution stock management pressure, and are more likely to release the green collaborative governance efficiency of the DE. The combination of the high EPPI - low PI group enables the DE to cross the turning point at a lower level, thereby fully amplifying the promoting effect on the SEPRCER. In addition, regions with high PI are constrained by the path dependence of high energy consumption and high emission industries. Even with strengthened environmental regulations, it is prone to extreme coefficient fluctuations and insufficient sample support. While regions with low EPPI have a weak regulatory constraint, it is difficult to fully drive enterprises to carry out digital green transformation, weakening the later enhancement effect of the DE on the SEPRCER. Ultimately, this is manifested as a flattening of the "U" shape curve and a convergence of the non-linear influence intensity.

5.7. Discussion

5.7.1. Benchmark regression discussion

The benchmark regression results of this study show that the DE has a significant "U" shape curve impact on the SEPRCER in the YREB. That is, in the early stage of development, it shows an inhibitory effect, and after crossing the turning point, it turns into a positive promoting effect. This conclusion is highly consistent with the research results of Zhao et al. (2026), Sun et al. (2025), and Li & Diao (2025), verifying that the DE has a "first inhibition, then promotion" phased pattern on SEPRCER. In the early stage of DE development, the high energy consumption characteristics of digital infrastructure construction, the adaptation costs of industrial digital transformation, and the energy rebound effect jointly lead to short-term constraints on the SEPRCER (Gao, 2025; Guo &

Wang, 2023); as digital technology and green governance are deeply integrated, the acceleration of clean energy structure and the upgrading of environmental supervision intelligence, the green enabling effect of the DE gradually takes the lead, promoting the steady improvement of the level of the SEPRCER (Huang & Lin, 2024; Ren et al., 2023).

However, the academic community has not reached a unified consensus on this issue. Zheng et al. (2026) and Hu (2023) believe that the DE has always shown a linear positive promotion effect on the SEPRCER, and no "U" shape inflection point was found; Qian et al. (2025) emphasized that the DE may continue to have negative impacts due to the energy rebound effect. The main reason for the differences in conclusions lies in the following: previous studies mostly used national samples, ignoring the regional characteristics of the YREB, which are eco-friendly and have stronger regulations; some studies did not incorporate a long-term dynamic perspective, making it difficult to capture the phased changes in short-term costs and long-term benefits. This paper based on data from 108 cities from 2011 to 2023, after undergoing endogenous processing and multiple robustness tests, the "U" shape relationship remained highly significant, indicating that this phased pattern has strong reliability and regional specificity.

5.7.2. Mechanism discussion

The mechanism analysis indicates that both the EPPI and the PI have a significant single-threshold effect. Moreover, by altering the position of the inflection point and the shape of the "U" curve, they exert heterogeneous influences on the "U" relationship between the DE and the SEPRCER.

Firstly, when the EPPI exceeds the threshold limit, it makes the "U" shaped curve for the impact of the DE on the SEPRCER significantly steeper, and the turning point occurs significantly earlier. This conclusion is consistent with the internal logic of the Porter hypothesis (Porter & van der Linde, 1995), and also confirms the research judgments of Yan et al. (2024) and Liao & Xiao (2025) regarding that strict environmental regulations can accelerate green innovation and shorten the technological transformation cycle. Higher EPPI will form a rigid constraint, driving enterprises to apply digital technologies to clean production and pollution control processes more quickly (Liang & Hu, 2025), enabling the DE to cross the bottleneck earlier and achieving more prominent green empowerment effects, which are consistent with the empirical results of this paper.

Secondly, as the PI exceeds the threshold value, it makes the "U" shaped curve for the impact of the DE on the SEPRCER significantly smoother, and the turning point occurs significantly backward. This finding is highly consistent with the conclusions proposed by Lu et al. (2025) regarding the path lock-in of high-pollution industries and those by Zhai et al. (2024) regarding the excessively high costs of digital transformation. Cities with higher PI mostly rely on high-energy-consuming industries and have higher transformation costs, thus making the green transformation through digital technology more difficult, leading to the need for the DE to reach a higher level to achieve a breakthrough from negative to positive. Additionally, Fang & Yu (2024) argue that the more severe the pollution, the greater the potential of the DE for emission reduction and the more obvious the effect. The reason for the difference lies in that such studies focus on theoretical emission reduction potential, while this paper, based on real urban data, discovers that in high-pollution areas, due to industrial inertia, capital constraints, and technical bottlenecks, the DE for emission reduction effect is difficult to truly take effect.

Finally, this paper further incorporates the EPPI and the PI into the two-threshold interaction

framework. It is found that in the high EPPI - low PI group, the “U” shape inflection point for the impact of DE on the SEPRCER is the earliest, enabling the DE to cross this inflection point earlier and exert a positive promoting effect. This conclusion is an important expansion of existing literature, compensating for the shortcomings of the single-threshold perspective, and more clearly revealing the external constraints and applicable conditions of the empowerment of the DE for the SEPRCER.

5.7.3. Deficiency and prospect

This study systematically examined the impact and mechanism of the DE on the SEPRCER. However, this study still has certain limitations: Firstly, this paper examines the impact of the DE from the macro level of cities, but fails to reveal the specific transmission path from the perspective of enterprises' micro production, technological choice, and green investment. The micro mechanism needs to be further explored; Secondly, this paper only examines two threshold variables, namely the EPPI and the PI, and has not included more potential constraint variables. The research framework can still be expanded; Thirdly, the sample in this study only covers 108 cities in the YREB, and the universality of the research conclusions at the national level needs to be further verified.

Given these limitations, future research can be deepened in three aspects: Firstly, conduct multi-level analysis by integrating enterprise micro-data with urban panel data to more clearly reveal the micro-mechanisms of the impact of the DE on SEPRCER; Secondly, incorporate spatial spillover effects into the model to examine the regional linkage impact of DE on the SEPRCER; Thirdly, carry out causal identification around quasi-natural experiments such as digital pilot projects and low-carbon pilot projects to further enhance the reliability of the conclusions and the policy reference value.

6. Conclusions and policy implications

This paper is based on the panel data of 108 cities in the YREB from 2011 to 2023. It employs the super-efficiency undesirable SBM model, the CCD model, the entropy-weight TOPSIS method, the two-way fixed effect model, and the panel threshold model to systematically analyze the evolution characteristics of the DE and the SEPRCER, and to empirically test its impact effect, heterogeneity, and threshold mechanism. The main conclusions are as follows: (1) From 2011 to 2023, the level of the DE in the YREB showed an overall upward trend, while the level of the SEPRCER showed a slight downward trend. Moreover, both have gradually formed a distribution pattern centered on the YRD and coexisting multiple growth poles throughout the YREB; (2) The impact of the DE on the SEPRCER in the YREB presented a significant “U” shape curve relationship, and this conclusion remained valid after robustness tests and endogeneity handling; (3) The relationship between the two has significant heterogeneity characteristics in terms of region, policy, resources, and economy. The “U” shape feature is more prominent in the LRYR, urban agglomerations, non-resource-based cities, and regions with high economic levels; (4) Both the EPPI and the PI have significant single-threshold characteristics. As the EPPI crosses the threshold value, the “U” shape curve for the DE and the SEPRCER becomes steeper, and the turning point appears earlier, while the PI is the opposite; (5) From the two threshold interaction grouping perspective, in the combination scenario of high EPPI and low PI, the “U” shape turning point for the DE and SEPRCER is the earliest and the curve is the steepest.

Based on the above research conclusions and in light of the actual situation of the YREB, the following policy recommendations are drawn:

Firstly, based on the spatial and temporal patterns and heterogeneity characteristics, implement a strategy of classified measures and phased advancement to enable the DE to contribute to SEPRCER. For the LRYR, urban agglomerations, non-resource-based and high-income cities, leveraging their digital foundations and industrial advantages, accelerate the integration of digital technologies with green production, carbon emission monitoring, and intelligent environmental supervision, and promote them to cross the “U” shape turning point as soon as possible, fully releasing the positive promoting effect; for the MRYR and the URYR, resource-based and low-income cities, prioritize the improvement of digital infrastructure shortcomings, steadily promote the digitalization and greening transformation of traditional industries, reduce the pain of transformation and short-term energy consumption shocks, and avoid “one-size-fits-all” approaches. At the same time, establish a cross-regional coordination mechanism to promote the orderly radiation of digital technologies and green governance models from the YRD to the MRYR and the URYR, strive to reverse the downward trend of the SEPRCER, and achieve balanced improvement throughout the region.

Secondly, strengthen the guidance of the two-threshold mechanism and establish an optimal collaborative governance model of "high EPPI and low PI". On one hand, enhance the rigidity of EPPI and the accuracy of law enforcement, and through strict regulations, urge enterprises to accelerate their digital green transformation, so that the “U” shape turning point of the impact of the DE on the SEPRCER appears earlier, the curve becomes steeper, and they enter the positive promotion stage more quickly; on the other hand, strictly control the PI of the region, strictly control the blind expansion of “high-energy-consuming and high-polluting” industries, accelerate the digital clean transformation of high-polluting industries, and weaken the constraints on transformation and the backward shift of the turning point brought by high pollution. On this basis, focus on creating an optimal policy combination of high EPPI and low PI, give priority to building digital green transformation demonstration zones, and maximize the strongest promoting effect of DE on the SEPRCER.

References

Bai, T. T., & Qi, Y. (2026). Research on the impact of digital economy on the synergistic reduction of pollution and carbon emissions: an analysis of the mediating role based on green technology innovation. *Science Research Management*, *47*(1), 132-142. https:/doi.org/10.19571/j.cnki.1000-2995.2026.01.013

Bie, A., Yang, S. G., & Shu, Y. X. (2023). Does the e-commerce transformation of cities promote carbon emission reduction? Evidence from a quasi-natural experiment based on national e-commerce demonstration cities. *Industrial Economics Research*, *22*(4), 1-14. https:/doi.org/10.13269/j.cnki.ier.2023.04.003

Chen, E., & Zhang, H. (2025). The relationship between public health expenditure and urban economic resilience. *Frontiers in Public Health*, *13*, 1550528. https:/doi.org/10.3389/fpubh.2025.1550528

Chen, J., Gao, M., Cheng, S., Hou, W., Song, M., Liu, X., Liu, Y., & Shan, Y. (2020). County-level CO2

emissions and sequestration in china during 1997–2017. *Scientific Data*, *7*(1), 391. https:/doi.org/10.1038/s41597-020-00736-3

Chen, S., Tan, Z., Mu, S., Wang, J., Chen, Y., & He, X. (2023). Synergy level of pollution and carbon reduction in the yangtze river economic belt: spatial-temporal evolution characteristics and driving factors. *Sustainable Cities and Society*, *98*, 104859. https:/doi.org/10.1016/j.scs.2023.104859

Chen, Y. (2025). Impact of environmental regulations on industrial green transformation. *On Economic Problems*, *47*(4), 111-119. https:/doi.org/10.16011/j.cnki.jjwt.2025.04.004

Chen, Y., & Liu, J. (2025). Digital economy and carbon emissions: spatial spillover effect and industrial structure mediation effect in china. *Technological and Economic Development of Economy*, *31*(3), 793-818. https:/doi.org/10.3846/tede.2025.22955

Cheng, L., Zhang, Y., Xiang, Y., & Wang, W. (2026). Research on the impact of rural digitization on the synergistic development of rural environment and economic systems: evidence from china. *Environment, Development and Sustainability*, *28*(4), 10487-10524. https:/doi.org/10.1007/s10668-025-07225-w

Dai, Y. A., & Zhang, X. (2023). Spatial spillover of environmental policy and urban energy-directed technological change. *The Journal of World Economy*, *46*(5), 119-151. https:/doi.org/10.19985/j.cnki.cassjwe.2023.05.005

Dong, F., Li, Y., Qin, C., Zhang, X., Chen, Y., Zhao, X., & Wang, C. (2022). Information infrastructure and greenhouse gas emission performance in urban china: a difference-in-differences analysis. *Journal of Environmental Management*, *316*, 115252. https:/doi.org/10.1016/j.jenvman.2022.115252

Dong, Z., Xia, C., Fang, K., & Zhang, W. (2022). Effect of the carbon emissions trading policy on the co-benefits of carbon emissions reduction and air pollution control. *Energy Policy*, *165*, 112998. https:/doi.org/10.1016/j.enpol.2022.112998

Fang, D. L. (2023). Impact of digital economy on energy utilization efficiency of chinese cities from the perspective of technology empowerment and spillover. *Resources Science*, *45*(2), 296-307. https:/doi.org/10.18402/resci.2023.02.05

Fang, J. (2025).Digital empowerment drives the comprehensive green transformation of economic and social development. In *Chinese Social Sciences Today*. Beijing.

Fang, Y., & Yu, X. (2024). The impact of industrial digitalization on reducing air pollution and carbon emission: perspectives from the productivity paradox. *Systems Engineering-Theory & Practice*, *44*(9), 2795-2818. https:/doi.org/10.12011/SETP2023-0832

Feng, Y., Liu, J., & Nie, C. (2026). How does digital economy affect synergy of carbon mitigation and pollution reduction? Evidence from next-generation internet demonstration city construction in china. *Environment, Development and Sustainability*, *28*(2), 4665-4695. https:/doi.org/10.1007/s10668-024-05178-0

Gao, W. L. (2025). The synergistic effects and spatial mechanisms of the digital economy on urban pollution reduction and carbon emission reduction. *East China Economic Management*, *39*(3), 70-82. https:/doi.org/10.19629/j.cnki.34-1014/f.240608011

Gao, Z., Jia, Z., Zhao, Y., & Hao, Y. (2025). Enhancing the synergistic pathways of industrial pollution and carbon reduction (PCR) in china: an energy efficiency perspective. *Energies*, *18*(10), 2413. https:/doi.org/10.3390/en18102413

Gu, G., Wang, Z., & Wu, L. (2021). Carbon emission reductions under global low-carbon technology transfer and its policy mix with r&d improvement. *Energy*, *216*, 119300.

https:/doi.org/10.1016/j.energy.2020.119300

Guo, J. (2019). The effects of environmental regulation on green technology innovation——evidence of the porter effect in china. *Finance & Trade Economics*, *40*(3), 147-160. https:/doi.org/10.3969/j.issn.1002-8102.2019.03.010

Guo, P., & Wang, G. Y. (2023). The synergistic effect of digital economy on pollution and carbon reduction and the influence mechanism:an empirical test based on prefecture-level city data. *Resources Science*, *45*(11), 2117-2129. https:/doi.org/10.18402/resci.2023.11.02

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference. *Journal of Econometrics*, *93*(2), 345-368. https:/doi.org/10.1016/S0304-4076(99)00025-1

Hou, J., Shi, C., Fan, G., & Xu, H. (2024). Research on the impact and intermediary effect of carbon emission trading policy on carbon emission efficiency in china. *Atmospheric Pollution Research*, *15*(4), 102045. https:/doi.org/10.1016/j.apr.2024.102045

Hu, J. (2023). Synergistic effect of pollution reduction and carbon emission mitigation in the digital economy. *Journal of Environmental Management*, *337*, 117755. https:/doi.org/10.1016/j.jenvman.2023.117755

Huang, C., & Lin, B. (2024). Digital economy solutions towards carbon neutrality: the critical role of energy efficiency and energy structure transformation. *Energy*, *306*, 132524. https:/doi.org/10.1016/j.energy.2024.132524

Huang, M., & Dou, X. (2024). How does the development of the digital economy release the consumption potential of residents? *Journal of Shanghai University of Finance and Economics*, *26*(1), 79-93. https:/doi.org/10.16538/j.cnki.jsufe.2024.01.006

Huang, Q. H., Yu, Y. Z., & Zhang, S. L. (2019). Internet development and productivity growth in manufacturing industry: internal mechanism and china experiences. *China Industrial Economics*, *36*(8), 5-23. https:/doi.org/10.19581/j.cnki.ciejournal.2019.08.001

Iea. (2025). *Global energy review 2025*. Retrieved from https://www.iea.org/reports/global-energy-review-2025. Accessed 17 April 2026.

Ipcc. (2001). *TAR climate change 2001: synthesis report*. Retrieved from https://www.ipcc.ch/report/ar3/syr/. Accessed 17 April 2026.

Jiang, P., Chen, Y., Geng, Y., Dong, W., Xue, B., Xu, B., & Li, W. (2013). Analysis of the co-benefits of climate change mitigation and air pollution reduction in china. *Journal of Cleaner Production*, *58*, 130-137. https:/doi.org/10.1016/j.jclepro.2013.07.042

Jin, S., & Li, X. (2023). Impact of the establishment of national key ecological function zones on carbon emission intensity: taking the yangtze river economic belt as the research area. *Economic Geography*, *43*(9), 139-147. https:/doi.org/10.15957/j.cnki.jjdl.2023.09.015

Li, F., & Diao, Z. (2025). The impact of digital infrastructure on the synergistic effects of urban pollution and carbon reduction: empirical evidence from china. *Frontiers in Environmental Science*, *13*, 1453151. https:/doi.org/10.3389/fenvs.2025.1453151

Li, H., Ding, Y., Bie, F., Shahbaz, M., & Erokhin, V. (2025). Digital economy, foreign direct investment, and environmental pollution: empirical evidence from china. *Journal of the Knowledge Economy*, *16*(2), 10421-10451. https:/doi.org/10.1007/s13132-024-02282-4

Li, J. M., Wei, W. Q., Zhang, P., Han, X. L., Yang, Y. X., Xue, Q., & Yu, Y. M. (2023). Promoting effect of digital economy development on the coordination of pollution and carbon reduction at the municipal level. *Economic Geography*, *43*(12), 169-180. https:/doi.org/10.15957/j.cnki.jjdl.2023.12.017

Li, T., Cui, G. G., & Sun, G. Q. (2025). Structural dimensions and scale development of digitalization capabilities in manufacturing interfirm network. *Business and Management Journal*, *47*(9), 190-208. https:/doi.org/10.19616/j.cnki.bmj.2025.09.010

Liang, C., Chen, X., & Di, Q. (2024). Path to pollution and carbon reduction synergy from the perspective of the digital economy: fresh evidence from 292 prefecture-level cities in china. *Environmental Research*, *252*, 119050. https:/doi.org/10.1016/j.envres.2024.119050

Liang, K., & Hu, Y. (2025). Digital economy development, environmental regulation, and green technology innovation in manufacturing. *Sustainability*, *17*(17), 7955. https:/doi.org/10.3390/su17177955

Liao, Z., & Xiao, L. (2025). Government environmental regulation, media attention, and corporate green innovation. *International Review of Economics & Finance*, *97*, 103751. https:/doi.org/10.1016/j.iref.2024.103751

Lin, S., Zuo, L., & Cen, T. (2025). Digital infrastructure and intra-provincial balanced development: evidence from china's provincial panel data. *PLoS One*, *20*(6), e0324132. https:/doi.org/10.1371/journal.pone.0324132

Liu, B., & Fang, X. (2025). Analysis of the impact of digital economy on carbon emissions and its mediation effect. *Frontiers in Environmental Science*, *13*, 1635153. https:/doi.org/10.3389/fenvs.2025.1635153

Liu, F., Kumar, J., Sun, H., & Edziah, B. K. (2025). Harnessing the digital economy for sustainable energy efficiency: an empirical analysis of china's yangtze river delta. *Economics-the Open Access Open-Assessment E-Journal*, *19*(1), 20250136. https:/doi.org/10.1515/econ-2025-0136

Liu, H. J., Guo, K. X., & Qiao, L. C. (2023). Quantitative evaluation of co-benefits of air pollution reduction and carbon emission reduction: based on marginal abatement cost. *Statistical Research*, *40*(4), 19-33. https:/doi.org/10.19343/j.cnki.11-1302/c.2023.04.002

Liu, H. W., & Tan, M. (2025). Research on the influence of artificial intelligence on the new quality productive forces of the NEV industry. *Science Research Management*, *46*(12), 33-44. https:/doi.org/10.19571/j.cnki.1000-2995.2025.12.004

Liu, S., Yang, W., Wen, H., & He, C. (2025). Impact of digital infrastructure on urban green eco-efficiency: an empirical analysis in china. *International Journal of Climate Change Strategies and Management*, *17*(2), 47-69. https:/doi.org/10.1108/IJCCSM-11-2024-0197

Liu, Y. B., Deng, W. F., Li, S. S., Wei, G. E., & Li, R. Z. (2024). The impact of digital industry agglomeration on synergistic pollution reduction and carbon emission reduction: taking the yangtze river economic belt as an example. *Resources Science*, *46*(4), 744-760. https:/doi.org/10.18402/resci.2024.04.07

Liu, Y., Zhao, X., Liu, Y., & Kong, F. (2023). The dynamic impact of digital economy on the green development of traditional manufacturing industry: evidence from china. *Economic Analysis and Policy*, *80*, 143-160. https:/doi.org/10.1016/j.eap.2023.08.005

Lu, S., Luo, S. L., & Zhou, K. (2025). Research on digital-energy coupling coordination and its impact on industrial pollution reduction and carbon emission eeduction. *Research of Environmental Sciences*, *38*(3), 524-538. https:/doi.org/10.13198/j.issn.1001-6929.2024.12.08

Meng, Q., Chen, X., Wang, H., Shen, W., Duan, P., & Liu, X. (2025). Spatiotemporal evolution and driving factors of the synergistic effects of pollution control and carbon reduction in china. *Ecological Indicators*, *170*, 113103. https:/doi.org/10.1016/j.ecolind.2025.113103

National Bureau of Statistics of China. (2025). *Value added of china's core industries of the digital*

economy takes up 10.5% of GDP in 2024. Retrieved from https://www.stats.gov.cn/english/PressRelease/202512/t20251231_1962222.html. Accessed 17 April 2026.

Nie, C., & Lee, C. (2023). Synergy of pollution control and carbon reduction in china: spatial–temporal characteristics, regional differences, and convergence. *Environmental Impact Assessment Review*, *101*, 107110. https:/doi.org/10.1016/j.eiar.2023.107110

Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, *9*(4), 97-118. https:/doi.org/10.1257/jep.9.4.97

Qian, Q., Xian, B., Wang, Y., & Li, X. (2025). The impact of digital economy on carbon emissions: based on the rebound effect. *Energy*, *333*, 137345. https:/doi.org/10.1016/j.energy.2025.137345

Rao, Y., Zhang, K., He, Q., & Wu, C. (2026). From synchronization to divergence: analysis of coupling degree and influencing factors of population density in urban and rural built-up areas of china. *Land*, *15*(2), 263. https:/doi.org/10.3390/land15020263

Ren, S., Hao, Y., & Wu, H. (2023). Digitalization and environment governance: does internet development reduce environmental pollution? *Journal of Environmental Planning and Management*, *66*(7), 1533-1562. https:/doi.org/10.1080/09640568.2022.2033959

Shi, W., Li, F., Jiang, L., & Zhou, J. (2025). Coupling and coordination between the digital economy and carbon emissions in the yangtze river economic belt. *Scientific Reports*, *15*(1), 43330. https:/doi.org/10.1038/s41598-025-27282-5

Sun, P., Nisar, U., Qiao, Z., Ahmad, S., Kathuria, K., Al Bahir, A., & Ahmad, M. (2024). Digital economy, technology, and urban carbon emissions nexus: an investigation using the threshold effects and mediation effects tests. *Frontiers in Environmental Science*, *12*, 1454256. https:/doi.org/10.3389/fenvs.2024.1454256

Sun, S., Zhang, M., Liu, L., & Zhou, D. (2025). Synergistic governance efficiency of industrial pollution and CO2 emissions under the digital economy. *Journal of Environmental Management*, *374*, 124148. https:/doi.org/10.1016/j.jenvman.2025.124148

Tan, F. F., & Yan, X. C. (2025). Synergistic effects of pollution and carbon emission reductions in a digital economy: a case study of the yangtze river delta urban agglomeration. *Environmental Science*, *46*(7), 4175-4185. https:/doi.org/10.13227/j.hjkx.202406127

Tang, X. B., Zhang, Y., Cao, L. Z., Zhang, J. M., & Chen, X. H. (2022). Spatio-temporal characteristics and influencing mechanism of synergistic effect of pollution and carbon emission reduction in china. *Research of Environmental Sciences*, *35*(10), 2252-2263. https:/doi.org/10.13198/j.issn.1001-6929.2022.08.10

Tian, G. H., Miao, C. H., Hu, Z. Q., & Miao, J. M. (2018). Environmental regulation, local protection and the spatial distribution of pollution-intensive industries in china. *Acta Geographica Sinica*, *73*(10), 1954-1969. https:/doi.org/10.11821/dlxb201810010

Tone, K., & Tsutsui, M. (2011). Applying an efficiency measure of desirable and undesirable outputs in DEA to u.s. Electric utilities. *Journal of CENTRUM Cathedra: The Business and Economics Research Journal*, *4*(2), 236-249. https:/doi.org/10.7835/jcc-berj-2011-0061

Wang, L. (2024). Research on the transformation of chinese government regulation in the era of the digital economy. *Journal of Management World*, *40*(3), 110-126. https:/doi.org/10.19744/j.cnki.11-1235/f.2024.0027

Wang, S., Liu, S., & Li, X. (2025). Research on the impact mechanism of the digital economy spatial correlation network on pollution reduction and carbon reduction. *Journal of China University of*

Geosciences Social Sciences Edition, *25*(2), 105-119. https:/doi.org/10.16493/j.cnki.42-1627/c.20250228.003

Wang, W., & Wang, Q. (2025). Does the digital economy boost enterprise labor demand? An empirical analysis of typical listed firms in china. *Economic Analysis and Policy*, *88*, 1112-1130. https:/doi.org/10.1016/j.eap.2025.10.021

Wang, X. Y., & Li, J. Y. (2022). Did the digital economy effectively promote energy conservation and CO2 reduction? *China Population, Resources and Environment*, *32*(11), 83-95. https:/doi.org/10.12062/cpre.20221022

Wang, Y. L., Li, B. X., Zhang, Y. X., Zhao, Y., Miao, C. K., & An, J. Q. (2024). Spatiotemporal characteristics and influencing factors of the synergistic effect of pollution reduction and carbon reduction in china. *Environmental Science*, *45*(9), 4993-5002. https:/doi.org/10.13227/j.hjkx.202308108

Wang, Y. Q., & Dong, H. J. (2025). Impact mechanism and spatial effects of digital economyon urban carbon emission performance. *Geographical Science*, *45*(3), 506-517. https:/doi.org/10.13249/j.cnki.sgs.20230649

Wu, D. D., Ma, R. F., & Feng, X. G. (2025). Spatial effects and mechanism of digital economy enabling tourism industry resilience in china. *Geographical Science*, *45*(12), 2586-2599. https:/doi.org/10.13249/j.cnki.sgs.20240954

Xiang, S., Huang, X., Lin, N., & Yi, Z. (2025). Synergistic reduction of air pollutants and carbon emissions in chengdu-chongqing urban agglomeration, china: spatial-temporal characteristics, regional differences, and dynamic evolution. *Journal of Cleaner Production*, *493*, 144929. https:/doi.org/10.1016/j.jclepro.2025.144929

Xu, H. L., Cheng, L. H., & Sun, T. Y. (2017). The effect of the input servitization of manufacturing on upgrading export domestic value added of enterprises——empirical evidence from chinese micro-enterprise. *China Industrial Economics*, *34*(10), 62-80. https:/doi.org/10.19581/j.cnki.ciejournal.2017.10.005

Xu, Z., & Kong, R. (2025). Comprehensive green transformation of economic and social development during the 15th five-year plan period: era value, realistic challenges, and practical approaches. *Journal of Southwest University Social Science Edition*, *51*(6), 10-21. https:/doi.org/10.13718/j.cnki.xdsk.2025.06.002

Yan, Z., Yu, Y., Du, K., & Zhang, N. (2024). How does environmental regulation promote green technology innovation? Evidence from china's total emission control policy. *Ecological Economics*, *219*, 108137. https:/doi.org/10.1016/j.ecolecon.2024.108137

Yang, G. Q., Wang, H. S., Fang, H. S., & Yue, Z. Y. (2023). Carbon reduction effect of digital economy: theoretical analysis and empirical evidence. *China Industrial Economics*, *40*(3), 80-98. https:/doi.org/10.19581/j.cnki.ciejournal.2023.05.005

Yang, Y., Xu, H., Yang, X., Zhang, Y., & Liu, T. (2025). Exploring synergistic efficiency of air pollution and carbon reduction and its influencing factors: insights from china. *Resources, Conservation and Recycling*, *212*, 107973. https:/doi.org/10.1016/j.resconrec.2024.107973

Yin, B., Kuang, P., & Deng, X. (2023). The effect of synergistic pollution and carbon reduction in the digital economy: quasi-experimental evidence from chinese cities. *Frontiers in Energy Research*, (11), 1267355. https:/doi.org/10.3389/fenrg.2023.1267355

You, J., Li, Y., & Song, Y. (2026). Urban pollution–carbon coordination in china: spatial spillovers and non-equilibrium dynamics. *Urban Climate*, *65*, 102765. https:/doi.org/10.1016/j.uclim.2025.102765

Yue, L., & Han, L. (2025). The digital empowerment promotes synergistic efficiency in regional pollution reduction and carbon emission reduction—analysis of the moderating effects of market structure and government behavior. *Journal of Cleaner Production*, *493*, 144867. https:/doi.org/10.1016/j.jclepro.2025.144867

Zeng, L., Zhou, X., & Li, Q. (2026). Research on the impact of environmental regulations on green patent output in the yangtze river economic belt: the moderating effect based on intellectual property protection. *Science Research Management*, *47*(3), 137-145. https:/doi.org/10.19571/j.cnki.1000-2995.2026.03.014

Zhai, Z., Zhang, T., Yi, M., Guan, Y., & Zhou, Y. (2024). Digital economy and the synergistic governance of pollutants and carbon emissions: facilitation or obstruction? *Environmental Research*, *258*, 119470. https:/doi.org/10.1016/j.envres.2024.119470

Zhang, X., Wei, Y., Wang, T., Shen, J., Zhao, T., & Dong, L. (2025). Spatial correlation network on synergy between carbon reduction and pollution control in key areas for air pollution prevent and control. *Journal of Cleaner Production*, *491*, 144777. https:/doi.org/10.1016/j.jclepro.2025.144777

Zhang, Y. L., Liu, P. C., & Yu, Y. J. (2025). The synergy of voluntary and compliance carbon markets. *China Industrial Economics*, *42*(6), 43-61. https:/doi.org/10.19581/j.cnki.ciejournal.2025.06.002

Zhang, Y., & Huang, H. (2023). The impact of digital economy development on inequity of carbon emissions. *Resources Science*, *45*(6), 1223-1238. https:/doi.org/10.18402/resci.2023.06.10

Zhao, T., Zhang, Z., & Liang, S. K. (2020). Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban china. *Journal of Management World*, *36*(10), 65-76. https:/doi.org/10.19744/j.cnki.11-1235/f.2020.0154

Zhao, X., Pi, Z., & Guo, Z. (2026). How does digital technology innovation drive synergistic reduction of pollution and carbon emissions? The u-shaped effect in china. *International Review of Economics & Finance*, *105*, 104881. https:/doi.org/10.1016/j.iref.2025.104881

Zhao, X., & Zeng, Y. (2025). How does digital economy empowering synergistic governance of pollution and carbon reduction? An empirical study in the yellow river basin of china. *Current Science*, *5*(3), 2254-2268. https:/doi.org/10.52845/CS/2025-5-3-16

Zheng, J., Zhao, S., Tan, Y., & Balsalobre-Lorente, D. (2026). Does the digital economy promote synergy between pollution control and carbon reduction? Evidence from china. *Environment, Development and Sustainability*, *28*(2), 2683-2716. https:/doi.org/10.1007/s10668-024-04964-0