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A study on the carbon emission reduction pathways of China's digital economy from multiple perspectives

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As the share of the digital economy's output continues to rise each year, the emergence of new industries such as e-commerce, mobile payments, and cloud computing has opened new avenues for carbon emission reduction (*CER*). Based on panel data from 30 provinces in China, this article systematically analyzes the CER pathways of China's digital economy (*DE*) from the perspectives of direct effects, indirect effects, threshold effects, and heterogeneity analysis. The main conclusions are as follows: (1) China's *DE* has a significant *CER* effect. (2) The *DE* can indirectly reduce regional carbon emissions (*CE*) by industrial structures and technological innovation, with the mediating effect of technological innovation being more significant than that of industrial structure. (3) Urbanization has threshold effects on the *CER* effect of China's *DE*. Under the influence of urbanization, there is an inverted U-shaped relationship between *DE* and *CE*. (4) Heterogeneity analysis finds that, compared to other types of provinces, the *CER* effect of *DE* is stronger in non-resource-based and economically developed provinces. (5) We propose five tailored recommendations for *CER*: fostering the synergistic development of the *DE* and industrial structure, strengthening the role of technological innovation, advancing urbanization and carbon reduction in a differentiated manner, formulating distinct policies for resource-based and non-resource-based provinces, and enhancing the construction of digital infrastructure in less-developed regions. This article not only establishes a more comprehensive connection between the *DE* and *CER*, but also reveals the differences in the role of technological innovation, industrial structure optimization, urbanization and other factors in the carbon reduction effect of the *DE* through the comparison of different paths and mechanisms.

KEYWORDS

digital economy (DE), carbon emission reduction (CER), impact pathways, mediation effects, threshold effects

1 Introduction

With the increasingly severe global climate change situation, carbon emission reduction (*CER*) has become a focal point of international concern. As the share of the digital economy's output continues to rise each year, the emergence of new industries such as e-commerce, mobile payments, and cloud computing has opened new avenues for *CER*. At its core, the digital economy (*DE*) leverages data, information technology, and digital tools to optimize resource allocation, enhance productivity, and foster innovation. This helps to reduce carbon dioxide emissions across both production and daily life (Abbas et al., 2022). Furthermore, the *Climate Action Roadmap* highlights that the application of digital technology could potentially cut global *CE* by around 15% (Mustajoki et al., 2024). Consequently, the *CER* effect of *DE* has become a prominent topic of interest within academic circles. As the world's largest carbon emitter, China plays a pivotal role in global climate governance, with its success in carbon reduction exerting significant influence on the international stage (Afshan et al., 2023). The rapid development of its *DE* offers abundant practical insights into low-carbon transformation. Meanwhile, the stark disparities in economic development, resource endowment, and industrial structure across China's regions provide an ideal context for examining the relationship between the *DE* and carbon reduction. Additionally, China's accelerated urbanization presents both challenges in energy consumption and opportunities for integrating the *DE* with green development. Guided by its goals of peaking *CE* by 2030 and achieving carbon neutrality by 2060, China's low-carbon policies not only support research into digital economy-driven carbon reduction pathways but also offer valuable lessons and policy references for other nations (Liu et al., 2023).

Existing research indicates that the *DE* can significantly influence regional *CE* through multiple pathways. For instance, the widespread adoption of digital technologies such as cloud computing, facial recognition, and artificial intelligence has reduced resource waste, thereby improving the efficiency of industrial production and urban management (Liu et al., 2020). The proliferation of online services has also decreased the consumption of transportation energy (Imran et al., 2023). Moreover, the *DE* drives industrial restructuring and technological upgrading (Chang et al., 2023). While numerous scholars have explored the *CER* effects of *DE*, few have integrated these factors into a comprehensive analytical framework. There remains a need for systematic research on the multiple pathways and conditions through which the *DE* affects regional *CE*. Additionally, studies on the regional disparities and nonlinear characteristics of the *DE*'s *CER* effects are still relatively scarce. To address the aforementioned research gaps, this study conducts a systematic analysis of the synergistic pathways through which the *DE*, industrial restructuring, technological innovation, and urbanization impact China's *CE*. First, the study employs a System Generalized Method of Moments (*SYS-GMM*) model to test the direct effects of the *DE* on regional *CE*. Second, a mediation model is constructed to analyze the indirect effects of the *DE* on *CE* through industrial structure and technological innovation. The study then introduces urbanization as a threshold variable to explore the nonlinear relationship of the *DE*'s *CER* effects across different stages of urbanization. Finally, the heterogeneity of the *CER* effect of *DE* was examined from the perspectives of resource endowment and economic level.

This study provides a comprehensive framework for academics and policymakers, uncovering the multifaceted pathways through which the *DE* fosters regional carbon reduction. Against the backdrop of a major nation like China, the findings hold extensive practical applications and policy implications. The novelty of this research is reflected in several key aspects: first, it adopts a systematic analytical approach to holistically examine the impacts of the *DE*, industrial structure optimization, technological innovation, and urbanization levels on regional *CE*, distinguishing it from prior studies that focused solely on direct or indirect effects. Second, the study introduces urbanization levels as a threshold variable to analyze the nonlinear carbon reduction effects of the *DE* across different stages of urbanization, addressing a gap in the literature. Third, it explores the regional heterogeneity of the *DE* from the perspectives of resource endowment and economic development, revealing variations in its emission-reduction effects. Finally, by employing the *SYS-GMM* model to analyze direct impacts and a mediation effect model to investigate indirect mechanisms, the study provides a detailed and multidimensional perspective, enhancing both the depth and breadth of the research.

2 Literature review

As environmental issues stemming from climate change grow increasingly severe, scholars have conducted extensive research on *CER*. Numerous scholars have explored the effects of factors such as energy endowment, economic openness, technological progress, industrial upgrading, and *FDI* on regional *CE* (Shaari et al., 2021; Hu et al., 2021; Wen et al., 2021; Wu et al., 2021; Rauf et al., 2023). *DE*, as a new economic growth point, has been validated at both macro and micro levels for its impact on regional *CE*. The rise of the *DE* has introduced new pathways for regional *CER*. Existing research findings primarily examine the *CER* the *DE* from the following three perspectives (Sadiq and Ali, 2024).

Firstly, extensive research has been conducted on the direct impact of the *DE* on regional *CE*. Theoretical research reveals that the direct impact of the *DE* on *CE* lies in a dual dynamic: the enhancement of energy efficiency and resource utilization, coupled with the growth in energy demand. Through the widespread adoption and application of information technology, the *DE* significantly reduces energy waste in traditional production and daily life. Innovations such as the industrial internet, smart manufacturing, online office platforms, and e-commerce effectively lower *CE*. However, the development of the *DE* has also led to energy-intensive activities, such as data center operations, high-performance computing equipment manufacturing, and logistics distribution, contributing to increased *CE*. This results in a coexistence of both positive and negative direct impacts (Haita et al., 2022). Empirical research highlights both linear and nonlinear effects. Linear studies indicate that *DE* can significantly reduce *CE*. For instance, research by Karaki et al. indicates that the *DE* directly lowers *CE* in high-energy-consuming industries by driving digital transformation and enhancing production efficiency (Karaki et al., 2023). However, scholars like Salahuddin et al. hold a contrasting view, arguing that the rapid expansion of *DE* has led to a sharp increase in electricity consumption and the construction of new infrastructure, thereby raising regional *CE* (Salahuddin and Alam, 2015). Additionally, some scholars have found that the *CER* effect of *DE* is non-linear. As the *DE* progresses, its *CER* effects may exhibit threshold effects or an inverted "U"-shaped curve (Li and Wang, 2022). This relationship is similar to the Environmental Kuznets Curve, which posits that environmental degradation accompanies early stages of economic growth, but environmental quality improves with higher economic levels (Hassan et al., 2020).

Secondly, the indirect effects of the *DE* on *CE* has garnered widespread attention from scholars. Theoretical research suggests that the *DE* drives the growth of the tertiary sector, particularly low-energy, high-value-added industries, thereby reducing the overall carbon intensity of industrial activities. Digital technologies facilitate green innovation and its diffusion, promote the transition of energy structures toward cleaner alternatives, and provide new momentum for emission reductions. The digital platform economy optimizes resource allocation, minimizes production redundancies, and supports the widespread adoption of low-carbon production and consumption models. However, theoretical studies also highlight challenges, such as the rebound effect in consumption and the imbalance in technological diffusion, which influence the indirect effects of the *DE* on *CE*. While improving production efficiency, the *DE* may stimulate expanded consumption demand—manifested in activities like online shopping and instant delivery—that leads to increased *CE*. Moreover, regional disparities in the adoption of digital technologies may exacerbate short-term imbalances in *CE* across regions (Dinda, 2004). Empirical studies reveal that the *DE* indirectly influences *CE* through multiple pathways, including industrial structure upgrading, technological innovation, and green finance. Numerous studies indicate that digital technologies have facilitated the transformation of traditional industries into low-carbon and high-value-added industries. Cheng et al. note that the *DE* indirectly reduces *CE* in developed regions by promoting the intelligent and green transformation of manufacturing (Cheng et al., 2023). Furthermore, the *DE* enhances energy utilization efficiency by promoting technological innovation and upgrading. Adebayo's research highlights that the *DE* has also fostered construction of smart transportation systems, which reduce transportation *CE* (Adebayo et al., 2024). In addition, digital technologies have spurred innovation in green financial instruments, such as carbon trading platforms and the digital issuance and management of green bonds (Zhang and Qian, 2023). The widespread application of these tools has facilitated financing for low-carbon projects, consequently leading to reductions in *CE*.

Thirdly, as research has deepened, scholars have discovered that the *CER* effects of the *DE* are influenced by a multitude of elements, including economy, policy, industry, and technology. Studies indicate that in regions with higher levels of economy, the *CER* effects of the *DE* are more pronounced. For example, Wang et al. found that in the economically advanced coastal areas of eastern China, the development of the *DE*, supported by superior digital infrastructure and higher technological capabilities, leads to significant reductions in *CE* (Wang and Zhong, 2023). The formulation of policies also plays a key role in shaping the *CER* effects of the *DE*. Yang et al. discovered that under varying intensities of environmental policies, the *CER* effects of the *DE* exhibit considerable differences. In the presence of market incentive and public participation environmental policies, the *CER* effects of the *DE* become more significant (Yang and Liang, 2023). Furthermore, industrial structure is a key player influencing the *CER* effects of the *DE*. Lyu et al. found that industrial upgrading enhances the *CER* of DE (Lyu et al., 2023).

To sum up, scholars have analyzed the *CER* effects of *DE* from multiple perspectives. While these studies provide valuable insights into the relationship between the *DE* and *CE*, there remain several deficiencies regarding the pathways, influencing factors, and heterogeneity of their effects. (1) The analysis of pathways through which the *DE* influences *CER* tends to be overly one-dimensional, often focusing on either direct or indirect effects without adopting a comprehensive perspective. Some studies incorporate an analysis of influencing factors, such as marketization level, technological capability, or policy environment, when discussing direct or indirect effects; however, the scope and depth of these analyses remain insufficiently broad. (2) Regarding the influencing factors of the *DE* on *CER*, existing literature predominantly focuses on aspects such as economic level, relevant policies, market demand, and technological intensity. While these elements are indeed essential in forming the *CER* effects of the *DE*, the overemphasis on them results in a relatively narrow research perspective, particularly lacking in-depth exploration of urbanization—a critical area of development. (3) The current literature's analysis of the heterogeneity in the *CER* effects of the *DE* often centers around geographical differences, which leads to noticeable limitations in certain respects. Conditions such as varying economic development levels, policy environments, and natural resource endowments can significantly influence the *CER* effects of the *DE*.

Therefore, this study systematically analyzes the *CER* pathways of the *DE* from the perspectives of direct effects, indirect effects, threshold effects, and heterogeneity analysis. Additionally, it introduces urbanization level as a threshold variable to examine the nonlinear characteristics of the *DE*'s *CER* effects at different stages of urbanization. The study further explores the heterogeneity of the *DE*'s influence on regional *CE* based on resource endowments and economic development levels. This comprehensive approach aims to enhance the understanding of the *CER* effects of the *DE* in varied contexts, providing theoretical insights and empirical support for policymakers.

3 Theoretical analysis and research hypotheses

Building on the aforementioned summary of existing research, this study establishes a theoretical analysis framework encompassing four dimensions: direct effects, indirect effects, threshold effects, and heterogeneity analysis, as illustrated in Figure 1. This framework will facilitate an in-depth exploration of the *CER* effects of the *DE* in China and, based on this analysis, will propose research hypotheses.

3.1 Direct effects

The *DE* directly promotes regional *CER* through various pathways, primarily manifesting in two aspects. Firstly, centered on data and information technology, the *DE* exhibits characteristics of low-cost diffusion and increasing returns to scale. It is widely applied in urban energy management, transportation management, and industrial production optimization, thereby enhancing resource utilization efficiency and reducing *CE*. Secondly, the technological innovations empowered by the *DE* transform people's work and lifestyles. The prevalence of online work, education, healthcare, and

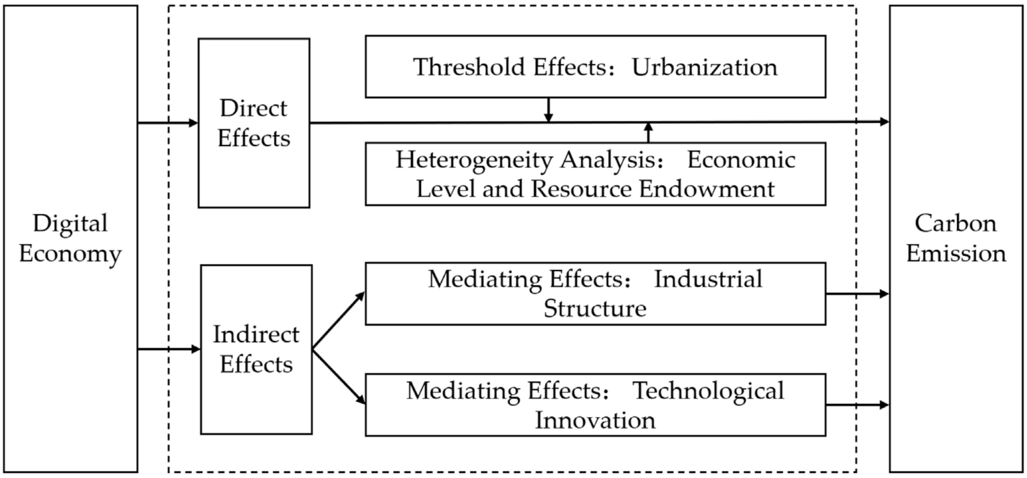

FIGURE 1
Theoretical analysis framework for *CER* effects in the *DE*.

shopping has diminished energy consumption associated with daily commuting and commercial activities, significantly lowering regional *CE* (Chen L. et al., 2023). Consequently, this study proposes the hypothesis H1: The *DE* contributes to the reduction of regional *CE*.

3.2 Indirect effects

3.2.1 Industrial structure effects

The *DE* promotes regional industrial structure optimization through the following pathways, thereby reducing *CE* (Liu et al., 2022): (1) Advancing Industrial Digitalization: It facilitates the integration of the Internet, big data, and artificial intelligence into traditional industries, enhancing production efficiency. (2) Fostering Low-Carbon Emerging Industries: The *DE* has given rise to new industries, such as information technology and e-commerce, which are inherently low in *CE*. (3) Optimizing the Service Sector: The integration of digital technologies with the service industry has popularized online services and remote work, leading to reduced energy consumption in transportation and office spaces. (4) Enhancing Industrial Cluster Effects: The *DE* promotes the formation of industrial clusters, improving collaborative efficiency and reducing redundant infrastructure and logistics transport.

These optimizations collectively drive the digitalization of regional industries, foster low-carbon emerging sectors, refine the service industry, and strengthen industrial cluster effects, effectively reducing *CE*. Therefore, this study proposes the hypothesis H2: The *DE* indirectly facilitates regional *CER* by optimizing the industrial structure.

3.2.2 Technological innovation effects

The *DE* accelerates regional technological innovation, thereby contributing to *CER*s through the following mechanisms (Wang et al., 2023). (1) Resource Aggregation: The *DE* fosters the concentration of innovative resources such as talent, capital, and technology, creating an efficient innovation ecosystem that enhances collaboration and technology sharing among enterprises. (2) Increased R&D Investment: The *DE* attracts greater investment in technological research and development from both enterprises and governments, facilitating the generation and application of new technologies. (3) Optimized Innovation Environment: The proliferation of digital technologies provides technical support for innovation, lowering the barriers to entry and expediting the commercialization of innovative outcomes. (4) Emergence of New Industries: The rise of emerging industries not only serves as a crucial domain for technological innovation but also drives the overall improvement of regional technological standards.

These technological advancements collectively enhance energy and resource utilization efficiency, promote the application of clean energy, and transform production and consumption patterns, resulting in a significant reduction in urban *CE*. Therefore, this study proposes the hypothesis H3: The *DE* indirectly reduces regional *CE* by promoting technological innovation.

3.3 Threshold effects

The effects of the *DE* on urban *CER* exhibit significant variation across different stages of urbanization, potentially demonstrating nonlinear characteristics that reflect a threshold effect (Jiang et al., 2022). In the early stage of urbanization, due to underdeveloped infrastructure and lagging industrial structures, *DE* technologies (such as the Internet of Things, big data, and intelligent management systems) are challenging to implement effectively. As a result, the *CER* impact is limited, and there might even be increased energy consumption and *CE* due to the construction of digital infrastructure and rising consumption demand. For instance, the growth of e-commerce can lead to higher demand for high-carbon logistics. In the intermediate stage of urbanization, as infrastructure gradually improves, the *DE* plays a more prominent role in optimizing industrial structures and enhancing resource utilization efficiency. Particularly in the development of emerging

TABLE 1 Explanation of regression model variables.

Variable		Variable definition	Unit	Symbol
Interpreted Variable	Carbon Emissions	Carbon Dioxide Emissions	Hundred Million Tons	*CE*
Core Explanatory Variable	Digital Economy Intensity	Evaluation Indicators for the Level of Digital Economy Development	—	*DEI*
Control Variables	Economic Level	Regional Population/GDP	Ten Thousand Yuan Per Capita	*EL*
	Population Size	Regional Population/Area	Persons Per Square Kilometer	*PS*
	Openness Level	Foreign Direct Investment/GDP	%	*OL*
	Environmental Regulations	Industrial Pollution Control Investment/Industrial Added Value	%	*ER*
Mediation Variable	Industrial Structure	Tertiary Industry Output/Secondary Industry Output	—	*IS*
	Technological Innovation	Authorized Patent Applications/GDP	Items Per Hundred Million Yuan	*TI*
Threshold Variable	Urbanization Construction	Urban Population/Total Population	%	*UC*

industries and smart city initiatives, the application of low-carbon technologies is accelerated, leading to a noticeable reduction in *CE*. However, due to insufficient infrastructure and management levels, the *CER* potential is not yet fully realized. Upon reaching the advanced stage of urbanization, urban infrastructure becomes highly modernized, and the *DE* permeates all aspects of urban life. Digital technologies are fully integrated into energy management, traffic coordination, industrial production, and urban planning, significantly enhancing resource utilization efficiency and minimizing *CE*, thereby maximizing the *CER* effect.

In summary, this study proposes the hypothesis H4: The impact of the *DE* on *CE* exhibits a nonlinear threshold effect that varies with the level of urbanization.

3.4 Heterogeneity analysis

Analyzing the heterogeneity of the *DE*'s impact on regional *CE* through the dimensions of resource endowment and economic development levels provides a more comprehensive understanding of its *CER* effects and potential across different contexts. Such a multidimensional analysis helps in formulating targeted policy measures to optimize the trajectory of digital economic development, thereby achieving sustainable development goals at the regional level.

3.4.1 Resource endowment heterogeneity analysis

Resource-based regions typically face higher *CE*, but the *DE* can drive innovation in green extraction technologies, leading to more efficient resource development. In contrast, non-resource-based regions can leverage the data economy to enhance resource utilization efficiency and optimize industrial structures, potentially achieving *CER* more rapidly (Xu and Cai, 2024). Therefore, this study proposes hypothesis H5: Resource endowment moderates the *CER* effect of the *DE*. Compared to resource-based regions, the *CER* impact of the *DE* is more pronounced in non-resource-based areas.

3.4.2 Economic level heterogeneity analysis

Economically developed regions possess superior technology and infrastructure, which allows the *DE* to have a more significant positive impact on *CER*. In contrast, less developed regions may face the risk of increased *CE* during the initial stages of digital economic development. However, as economic conditions improve and infrastructure is enhanced, the potential for *CER* gradually emerges (Zheng and Fen, 2023). Therefore, this study proposes hypothesis H6: Economic development level moderates the *CER* effect of the *DE*, with more pronounced effects observed in economically developed regions.

4 Research design

4.1 Variable selection

As shown in Table 1, the variables in this study include the interpreted variable, core explanatory variable, control variables, mediating variables, and threshold variable. Drawing from the *Four-Aspects Framework* of the *DE* proposed in the *China Digital Economy Development Report (2020)* by the China Academy of Information and Communications Technology (CAICT), we constructed an evaluation index system for assessing the level of the *DE*, as illustrated in Table 2 (Su et al., 2022). This evaluation index system was used to assess regional *DE* levels, and the results served as the core explanatory variables.

4.2 Model construction

To comprehensively analyze the impact of the *DE* on regional *CE*, this study employs three main econometric models: the *SYS-GMM* model, the mediation model, and the threshold model.

The *SYS-GMM* model is well-suited for dynamic panel data analysis, effectively addressing endogeneity issues caused by lagged dependent variables while controlling for heteroscedasticity and

TABLE 2 Evaluation index system for *DE*.

Level 1	Level 2	Level 3	Unit
Digital Economy	Digital industry	Number of Employees in the Digital Industry	Ten Thousand People
		Per capita total telecommunications services	Ten Thousand Yuan Per Person
		Number of Listed Companies in the Electronics and Information Manufacturing Industry	Enterprises
		Number of Listed Companies Related to the Internet	Enterprises
	Industry Digitalization	Agricultural Digitalization Index	—
		Industrial Digitalization Index	—
		Service Industry Digitalization Index	—
	Digital Governance	Government Website Development Index	—
		Number of Smart City Pilot Projects	Units
	Data Valorization	Number of Data Trading Institutions	Units
		Number of Data Open Platforms	Units

serial correlation. Given the significant temporal dependence of carbon emission intensity and the potential reverse impact of *CE* on *DE* development, the *SYS-GMM* approach enhances estimation efficiency and ensures the robustness of the model results by constructing instrumental variables for both the differenced and level equations (Fatima et al., 2022). Therefore, study uses the *SYS-GMM* model to conduct in-depth analysis of the direct impact of the *DE* on China's *CE*. The *SYS-GMM* model constructed is shown in Equation 1 below. In Equation 1, i and t denote cities and years, respectively; *CE* represents regional *CE*, while *DEI* serves as the level of regional *DE*. *EL*, *PS*, *OL*, and ER correspond to the variables economic level, population size, degree of openness, and intensity of environmental regulations, respectively. u_i and v_t correspond to city-specific fixed effects and time fixed effects, while ε_{it} denotes the random error term.

$$lnCE_{it} = \alpha_0 + \alpha_1 lnCE_{it-1} + \alpha_2 \ln DEI_{it} + \alpha_3 lnEL_{it} + \alpha_4 lnPS_{it} + \alpha_5 lnOL_{it} + \alpha_6 lnER_{it} + v_t + u_i + \varepsilon_{it} \quad (1)$$

To validate hypotheses H2 and H3, which propose that the *DE* indirectly influences regional *CE* by optimizing industrial structure and promoting technological innovation, we construct mediation models based on Equation 1, as shown in Equations 2, 3. The mediation model decomposes the total effect into direct and indirect effects, unveiling the pathways through which *DE* development influences carbon emission intensity. By incorporating industrial structure optimization and technological innovation as mediating variables, the model delineates the mechanisms through which the *DE* impacts *CE* via multiple indirect channels (Amara et al., 2023). In this context, *M* represents the mediating variables, which include industrial structure and technological innovation. The remaining variables are consistent with those in Equation 1.

$$lnM_{it} = \beta_0 + \beta_1 lnDEI_{it} + \beta_2 \ln EL_{it} + \beta_3 \ln PS_{it} + \beta_4 lnOL_{it} + \beta_5 lnER_{it} + v_t + u_i + \varepsilon_{it} \quad (2)$$

TABLE 3 Variable description statistical results.

Variable	Mean	Std. Dev.	Minimum	Maximum
CE	3.622	2.283	0.379	10.441
DEI	0.174	0.111	0.023	0.635
EL	4.035	3.215	0.271	20.028
PS	0.298	1.326	0.076	0.597
OL	0.340	0.282	0.0141	1.429
ER	0.402	0.362	0.017	2.851
IS	0.948	0.409	0.561	5.136
TI	1.104	5.545	0.041	11.508
UC	0.583	0.189	0.349	0.896

$$\ln CE_{it} = \gamma_0 + \gamma_1 \ln CI_{it-1} + \gamma_2 lnM_{it} + \gamma_3 \ln DEI_{it} + \gamma_4 lnEL_{it} + \gamma_5 \ln PS_{it} + \gamma_6 lnOL_{it} + \gamma_7 lnER_{it} + v_t + u_i + \varepsilon_{it} \quad (3)$$

Furthermore, to validate hypothesis H4, we construct a threshold model, as illustrated in Equation 4. The threshold model effectively identifies potential nonlinear relationships and phase-specific characteristics between variables, making it well-suited to uncover the complex dynamics between *DE* development and carbon emission intensity (Ostadzad, 2022). At different stages of *DE* development, its impact on *CE* may transition from promotion to suppression. By employing segmented analysis to capture this threshold effect, the model provides targeted and stratified policy recommendations. Here, *UC* and η respectively represent the level of regional urbanization and the threshold value. The remaining variables are consistent with those in Equation 1.

TABLE 4 Regression result of Equation 1.

Variable	Coefficient
$lnCE_{it-1}$	0.165**
$lnDEI_{it}$	−0.471***
$lnEL_{it}$	0.172***
$lnPS_{it}$	0.247
$lnOL_{it}$	−0.073***
$lnER_{it}$	−0.221***
*Cons_*	
Hansen Test	0.252
AR(1) Test	0.001
AR(2) Test	0.421

***p < 0.01, **p < 0.05.

$$lnCE_{it} = \alpha_0 + \alpha_1 \ln CI_{it-1} + \alpha_2 \ln DEI_{it} \cdot \mathrm{I}(\ln\mathrm{UC} \le \eta) + \alpha_3 \ln DEI_{it} \cdot \mathrm{I}(\ln\mathrm{UC} > \eta) + \alpha_4 lnEL_{it} + \alpha_5 lnPS_{it} + \alpha_6 lnOL_{it} + \alpha_7 \ln ER_{it} + v_t + u_i + \varepsilon_{it} \tag{4}$$

4.3 Data description

This study analyzes the relationship between the *DE* and *CE* in China, based on data from 30 provincial-level administrative regions from 2011 to 2023. The data sources include https://data.csmar.com/, https://www.ceads.net.cn/, https://www.stats.gov.cn/sj/ndsj/, and https://www.cei.cn/. For missing values, interpolation methods were employed to fill the gaps. To mitigate the impact of inflation, monetary values were adjusted to 2011 as the base year. The descriptive analysis results of the variables are shown in Table 3.

5 Empirical analysis

5.1 Empirical analysis of direct effects

The regression results of the SYS-GMM model are shown in Table 4. Firstly, the AR (1) test shows a p-value less than 0.05, indicating the presence of first-order autocorrelation, which aligns with our expected results. The AR (2) test, with a p-value greater than 0.1, suggests that there is no issue of second-order autocorrelation, thereby passing the autocorrelation test. The Hansen test yields a p-value greater than 0.1, indicating that there is no problem of over-identification. In summary, the *SYS-GMM* model constructed in this study is valid.

From the perspective of the core explanatory variable, the *lnDEI* coefficient is negative. This indicates that China's *DE* has a suppressive effect on *CE*. Hypothesis H1 has been validated. The underlying reason is that the *DE* not only transcends the spatial and temporal barriers of information dissemination, thereby reducing transaction costs and optimizing the spatial allocation of resources, but it also enhances the capacity for carbon emission management. Moreover, it can promote the transformation of traditional industries towards low-carbon, facilitate the development of clean energy, and drive the low-carbon transformation of cities.

Based on the analysis of the dependent variable, it was found that the estimated coefficient of $\ln CE_{it-1}$ is significantly positive. Indicating that regional *CE* have characteristics of sustainability and inertia. That is, the *CE* of the region this year are affected by last year's *CE*. This persistence can be attributed to the short-term stability of factors such as regional production structure, energy consumption patterns, and technological levels, as well as the lag in policy and market adjustments.

Finally, regarding the control variables, the regression coefficient for *lnEL* is significantly positive, while the coefficients for *lnOL* and *lnER* are significantly negative, and the coefficient for *lnPS* is not significant. First, the results indicate that the expansion of economic activities is accompanied by an increase in *CE*. This is especially true when economic growth relies heavily on energy-intensive industries, aligning with the expectations of this study. Second, foreign investment contributes to *CER* in China, as foreign-enterprises typically bring more advanced green technologies and stricter environmental standards, and they generally favor high-value-added, low-carbon industries. Third, strengthening environmental regulations helps to curb *CE*, as such regulations increase production costs, compelling enterprises to improve production processes and operational practices, thereby facilitating regional low-carbon transitions.

5.2 Empirical analysis of mediating effects

The regression results of the mediation models are shown in Table 5. Columns (1) and (2) in Table 5 are the regression results of the mediating effect of industrial structure. Column (1) reveals that the coefficient of *lnDEI* on the mediating variable *lnIS* is significantly positive, indicating that the *DE* fosters the transformation of China's industrial structure. Column (2) shows that the coefficient of *lnDEI* is −0.318, with an absolute value smaller than the absolute value of the regression coefficient of *lnDEI* (−0.471) in Equation 1. After introducing the mediating variable, the *CER* of the *DE* remains significant, But the coefficient has weakened and the mediating variable has a significant impact. This indicates a partial mediating effect via industrial structure, suggesting that the *CER* effect of the *DE* is not solely dependent on this pathway but can also directly influence the dependent variable through other means. This finding supports hypothesis H2. For instance, in Beijing, the service sector accounted for 84.8% of GDP in 2023, and the share of information technology industries within the service sector has been steadily rising. By promoting the development of the service sector and high-tech industries, Beijing has significantly reduced its dependence on traditional, high-pollution industries, achieving effective control over *CE*.

Columns (3) and (4) are the regression results of the mediating effect of technological innovation. Column (3) indicates that the coefficient of *lnDEI* on *lnTI* is significantly positive, suggesting that the *DE* can promote regional technological innovation. Column (4) shows that the coefficient of *lnDEI* is −0.281, with an absolute value smaller than the regression coefficient of *lnDEI* (−0.471) in

TABLE 5 Regression results of mediation effect.

Variable	Industrial structure mediation effect		Technological innovation mediation effect	
	(1)	(2)	(3)	(4)
	lnIS	*lnCE*	*lnTI*	*lnCE*
$\ln CE_{it-1}$		0.125**		0.172**
$\ln DEI_{it}$	0.481***	−0.312***	0.521***	−0.281***
$\ln EL_{it}$	−0.563**	0.429***	0.362***	0.505***
$lnPS_{it}$	−1.752**	0.229	−0.147**	0.192
$lnOL_{it}$	0.388**	−0.095***	−0.401	−0.054***
$\ln ER_{it}$	0.062	−0.143***	0.021***	−0.162***
$\ln IS_{it}$		−0.432**		
$\ln TI_{it}$				−0.632***
*Cons_*				
Hansen Test		0.337		0.472
AR(1) Test		0.001		0.001
AR(2) Test		0.338		0.652
R^2	0.871		0.831	

***p < 0.01, **p < 0.05.

TABLE 6 Threshold effect test.

Threshold variable	Threshold	Fstat	Prob.
lnUC	Single	41.08	0.003
	Double	31.66	0.265
	Triple	23.18	0.327

TABLE 7 Threshold calculation.

Model	Threshold	Lower	Upper
Single Threshold	−0.146	−0.159	−0.134

TABLE 8 Threshold effect regression results.

Variable	Coefficient
$lnDEI_{it}$ ($lnUC \leq -0.146$)	0.172***
$lnDEI_{it}$ ($lnUC \rangle -0.146$)	−0.371***
Controls	Yes
*Cons_*	0.472***
R-squared	0.806
Prob > F	F = 0.000

***p < 0.01, **p < 0.05.

Equation 1. This indicates that the mediating effect through technological innovation is also a partial mediating effect. *TI* serves as an effective channel for the *DE* to exert its *CER* function, thereby validating hypothesis H3. For example, Alibaba collaborated with Hangzhou Energy Group to develop an intelligent power grid system based on digital technology. This system optimizes electricity dispatching, reducing energy waste, and is expected to lower *CE* by more than 300,000 tons annually.

Moreover, Columns (2) and (4) reveal that the regression coefficient of the mediating variable $lnTI$ is greater than that of $lnIS$. This indicates that compared to the *IS*, *TI* plays a more critical role in *DE*'s *CER*. This can be attributed to the fact that adjustments and upgrades in industrial structure require a prolonged transition period, often involving the reallocation of resources, corporate transformation, and retraining of the workforce. In contrast, the *CER* effects brought about by technological innovation are more direct, widespread, and exhibit significant spillover benefits.

5.3 Empirical analysis of threshold effects

The *CER* effect of the *DE* is influenced by various economic factors. Therefore, this study introduces *UC* as a threshold variable to further analyze the *CER* effect of *DE* under different urbanization levels. According to the Hansen test principle, this study used Bootstrap method to repeatedly sample 300 times and conducted urbanization threshold effect test on the sample data. The results are shown in Tables 6, 7. Table 6 shows that *lnUC* only passed the single-threshold test. The single-threshold estimate and its 95% confidence interval are shown in Table 7. The estimated value of

TABLE 9 Heterogeneity analysis based on resource endowment and economic level.

Variable	Resource endowment		Economic level	
	(1)	(2)	(3)	(4)
	Resource-based province	Non-resource-based province	Economically developed province	Economically underdeveloped province
$lnCE_{it-1}$	1.765***	0.985***	0.765***	1.765***
$lnDEI_{it}$	−0.236***	−0.569***	−0.629***	−0.185***
Controls	Yes	Yes	Yes	Yes
Hansen Test	0.257	0.138	0.373	0.207
AR(1) Test	0.000	0.001	0.000	0.002
AR(2) Test	0.267	0.433	0.343	0.129

***p < 0.01, **p < 0.05.

the single threshold for the variable *lnUC* and its 95% confidence interval are displayed in Table 7.

The calculation results of *lnUC* threshold effect are shown in Table 8. The threshold variable *lnUC* passed the significance test, both when it was less than −0.146 and when it was greater than −0.146. When *lnUC* is less than −0.146, the impact coefficient is 0.172, indicating that the *DE* can increase *CE* at this time. At this initial stage of urbanization, due to underdeveloped infrastructure and a lagging industrial structure, *DE* technologies struggle to be effectively applied, leading to limited *CER* outcomes. Additionally, the construction of *DE* and the growth of new electronic consumption demand contribute to increased *CE*. When *lnUC* exceeds −0.146, the impact coefficient is −0.371, showing that the *DE* has a significant inhibiting effect on regional *CE*. As infrastructure gradually improves, the *DE* plays a more pronounced role in optimizing industrial structures and enhancing resource utilization efficiency. Especially in the development of emerging industries and smart city construction, it promotes the application of low-carbon technologies, significantly reducing regional *CE*. For instance, the urbanization rate in Jiangsu Province has reached 72%. Against a backdrop of high urbanization, the integration of the *DE* with urban management has greatly enhanced the efficiency of urban energy use. Real-time monitoring and optimization of urban traffic, energy, and water supply systems through big data and IoT technologies have effectively reduced *CE*. In contrast, regions with lower urbanization levels, such as Gansu and Guizhou, show a more limited effect of the *DE* on *CER*. For example, the urbanization rate in Gansu Province was only 55% in 2023. Due to underdeveloped infrastructure and low *DE* levels, its *CER* effect is weak.

The conclusions above indicate that the relationship between *DE* and *CE*, influenced by regional urbanization levels, exhibits an inverted "U" shape, thereby confirming hypothesis H4. This suggests that the *DE* can only truly unleash its *CER* potential and facilitate regional low-carbon and sustainable development when urbanization levels reach a certain threshold.

5.4 Heterogeneity analysis

5.4.1 Resource endowment heterogeneity analysis

Natural resources are a key factor affecting the *CER* of a region. Thus, this study conducts a heterogeneity analysis of the *CER* effects of the *DE* from the perspective of resource endowments. Based on the *List of Resource-Based Cities in China* and the criteria for identifying resource-based provinces, this paper designates Shanxi, Shaanxi, Guizhou, and Gansu as resource-based provinces, while categorizing the others as non-resource-based provinces. The heterogeneity analysis results based on the perspective of resource endowment are shown in columns (1) and (2) of Table 9. In both columns, the coefficients of *lnDEI* are significantly negative. This indicates that *DE* can effectively reduce *CE* in two types of provinces. Moreover, its impact is more pronounced in non-resource-based provinces, thereby validating hypothesis H5. Currently, the industrial structure of China's resource-based provinces is relatively singular, heavily reliant on fossil fuels, with insufficient development of emerging strategic industries. The difficulty of industrial structure transformation greatly limits the *CER* effect of *DE*. For instance, in Ningxia, the coal and petrochemical industries dominate the provincial economy. Despite recent efforts to promote digital mining and smart grid technologies, the overall reduction effect remains limited.

5.4.2 Economic level heterogeneity analysis

Given that economically developed regions possess well-established infrastructure and human resources, they are better positioned for the rapid advancement of the *DE*. This study further analyzed the *CER* effect of *DE* from the perspective of economic level differences. This study divides 30 provinces in China into economically developed provinces and economically underdeveloped provinces based on their average GDP. The heterogeneity analysis results based on the perspective of economic level are shown in columns (3) and (4) of Table 9. In both columns, the *lnDEI* coefficients are significantly negative, indicating that the *DE* significantly promotes *CER* in both economically developed and underdeveloped provinces.

Furthermore, the *CER* effect of the *DE* is greater in economically developed provinces than in their underdeveloped counterparts, thus validating hypothesis H6. Compared to underdeveloped provinces, economically developed regions enjoy superior digital infrastructure, higher levels of digital technology, and greater capacities for digital trade. Additionally, these developed provinces benefit from significantly higher levels of financial investment and talent support in the realm of the *DE*, resulting in more pronounced *CER* benefits. For instance, Shanghai's "Smart Energy Platform" employs digital technology to achieve efficient energy management, significantly reducing the city's *CE*. In contrast, underdeveloped regions in the western part of China experience lagging *CER* effects due to insufficient *DE* development. For example, in Guizhou Province, the *DE* accounts for only about 10% of GDP, with energy consumption still primarily reliant on coal. Even when efforts are made to promote digital platforms for energy management, the overall effectiveness of carbon emission control remains relatively limited.

6 Discussion

This study systematically analyzes the mechanisms by which the *DE* contributes to *CER* in China. Through examinations of direct and indirect impacts, threshold effects, and heterogeneity analysis, it arrives at multi-layered conclusions. This section will conduct a horizontal and vertical comparative analysis of the research findings in relation to existing studies, exploring the differences between this study and other relevant research and further elucidating the underlying causes of these discrepancies.

The findings of this research indicate that the *DE* has a significant *CER* effect. Existing literature similarly confirms the potential of the *DE* in *CER*. For instance, Li et al. found that digital technologies optimize energy efficiency, thereby reducing *CE* (Li et al., 2022). However, Zhang et al. posited that in certain less developed regions, the catalytic effect of the *DE* may be constrained by inadequate infrastructure (Zhang W. et al., 2022). This observation aligns with our study's conclusion that the *CER* effects of the *DE* are not significant in some areas. This discrepancy suggests that while the *DE* exhibits considerable *CER* effects, its efficacy is influenced by regional development levels. By further differentiating the *CER* effects between developed and underdeveloped regions, this study deepens this conclusion. Developed regions, leveraging advanced digital infrastructure and high levels of technological reserves, can more effectively unlock the carbon reduction potential of the *DE*. In contrast, in underdeveloped regions, inadequate infrastructure and lagging technological capabilities may constrain the carbon reduction effects of the *DE*. Therefore, we recommend tailoring strategies to local conditions to maximize the carbon reduction benefits of the *DE*. This includes enhancing broadband networks and data center construction in underdeveloped regions while fostering technological research and industrial clustering in developed regions (Chang et al., 2024).

The empirical analysis results show that *DE* indirectly reduces China's *CE* by optimizing industrial structure and accelerating technological innovation. And the mediating effect of accelerating technological innovation is greater than that of optimizing industrial structure. This conclusion is consistent with many related literature. Such as, Wang et al. indicate that the *DE* promotes technological advancement and application, thus accelerating the *CER* process (Wang et al., 2022). Similarly, Cheng et al. suggest that the *DE* fosters industrial transformation, contributing to the acceleration of *CER* (Cheng et al., 2023). However, unlike existing research, this study reveals that the mediating effect of technological innovation surpasses that of industrial structure optimization. The investigation indicates that technological innovation, driven by the rapid spread of technology, can yield rapid *CER* effects. In contrast, optimizing the industrial structure typically requires a longer adjustment period. Furthermore, technological innovation possesses cross-industry spillover effects, making its *CER* impact more pronounced. Industrial structure adjustments are constrained by factors such as regional economic structure and resource endowments. This is particularly evident in China's central and western regions, where traditional heavy industries dominate, leading to a lag in the *CER* effects of industrial structure optimization. Thus, while both pathways contribute to reducing *CE*, the immediacy and breadth of technological innovation render it a more critical factor in driving *CER* efforts in the context of the *DE*. Technological innovation, through the widespread application of digital technologies and cross-sectoral spillover effects, can rapidly achieve carbon reductions with more pronounced overall outcomes. In contrast, industrial structure optimization, involving deep adjustments to the economic framework, is constrained by factors such as regional resource endowments and the proportion of traditional heavy industries. This process requires longer adjustment cycles, leading to relatively delayed effects. Therefore, we recommend that governments intensify support for technological innovation, encouraging the application of digital technologies in energy conservation and environmental protection. Simultaneously, regional coordinated development should be promoted by optimizing industrial structures, with a focus on supporting green transitions in central and western regions to reduce reliance on traditional heavy industries (Shi et al., 2023).

This study finds that the relationship between the *DE* and *CE* presents an inverted "U" shape influenced by urbanization factors. With the continuous expansion of regional urban areas, the *CER* effect of the *DE* shifts from promoting regional *CE* to suppressing them. This conclusion is similar to the findings of Musah et al., who noted that in the early stages of urbanization, increased urban construction and energy demand lead to higher *CE* (Musah et al., 2021). However, as urbanization deepens, the gradual improvement of digital infrastructure enhances energy efficiency, resulting in a decline in *CE*. The research conclusion of this study further validates the findings of scholars such as Musah. It underscores the importance of reaching a certain level of urbanization for the *DE* to fully leverage its potential for *CER*. This relationship emphasizes the need for targeted policies that foster digital infrastructure development alongside urbanization to ensure sustainable environmental outcomes. The impact of the *DE* on *CE* exhibits an inverted "U"-shaped pattern, highlighting the phased characteristics of digital economic development during urbanization. Its carbon reduction potential can only be fully realized after reaching a certain level of urbanization. Therefore, we recommend implementing phased, differentiated policies. In the early stages of urbanization, efforts should focus on guiding low-carbon city construction and enhancing the application of clean energy and green building technologies. In the mid-to-late stages, investments in digital infrastructure should be increased to improve energy efficiency and promote the application of digital technologies in energy management, traffic optimization, and other domains (Wu et al., 2023).

This study found that *DE* exhibits *CER* effects on both resource-based and non-resource-based provinces, with a greater effect on non-resource-based provinces. The analysis of economic level heterogeneity indicates that the *CER* effect of the *DE* is significantly higher in economically developed regions compared to less developed ones. The conclusion regarding the heterogeneity of resource endowments is supported by numerous scholars. For instance, research by Chen et al. shows that resource-based provinces rely heavily on traditional energy sources, which limits the development of the *DE* due to the difficulties associated with transforming their industrial structure (Chen S. et al., 2023). In contrast, non-resource-based provinces, characterized by more diversified industrial structures, are more amenable to the adoption of digital technologies, thus exhibiting stronger *CER* effects. In comparison to existing heterogeneity studies related to economic levels, this research further emphasizes that, despite the challenges posed by weaker economic foundations in less developed areas, increasing investment in digital infrastructure can still enhance *CER* effects. This is particularly true when driven by technological innovation, highlighting the potential for digital transformation to promote sustainable development even in economically disadvantaged regions. Resource-based provinces, constrained by their reliance on traditional energy and the challenges of industrial transformation, face limitations in realizing the carbon reduction potential of the *DE*. In contrast, economically developed regions, with robust infrastructure and abundant technological resources, excel in fostering synergy between the *DE* and carbon reduction. Therefore, we recommend that resource-based provinces accelerate industrial transformation, reduce dependence on traditional energy, and promote the deep integration of digital technologies with energy management. For economically underdeveloped regions, we propose increasing fiscal support and targeted investment to prioritize digital infrastructure development. Establishing technological innovation platforms is essential to narrowing regional disparities in the development of the *DE* and its carbon reduction effects (Zhang J. et al., 2022).

In summary, this study not only establishes a more comprehensive connection between the *DE* and *CER* but also compares different pathways and mechanisms involved. It indicates that the *CER* effect of *DE* is constrained by many factors. This further highlights the necessity for differentiated policies tailored to various regions and stages of development, ensuring that *CER* strategies effectively leverage the unique characteristics and challenges of each area.

7 Conclusion, policy implications and limitations

7.1 Conclusion and policy implications

This study systematically analyzes the carbon reduction pathways of China's *DE* from the perspectives of direct impacts, indirect effects, threshold effects, and heterogeneity analysis. The main conclusions are as follows: First, the development of the *DE* can significantly reduce regional *CE*. Second, the *DE* can indirectly lower regional *CE* by optimizing industrial structures and promoting technological innovation, both of which constitute partial mediation effects. Furthermore, technological innovation currently plays a more significant role in the carbon reduction effect of the *DE* compared to industrial structure optimization in China. Third, urbanization levels exhibit a significant threshold effect on the carbon reduction impact of the *DE*, showing an inverted "U-shaped" relationship between the *DE* and *CE*. Fourth, the carbon reduction effects of the *DE* are more pronounced in non-resource-based provinces and economically developed regions. Based on these findings, we propose the following five carbon reduction recommendations.

(1) Promote Synergy Between the *DE* and Industrial Structure: Governments should accelerate the digital transformation of traditional industries, particularly in resource-dependent provinces and economically underdeveloped regions (Xu and Cai, 2024). Encourage the application of digital technology in energy intensive industries and accelerate industrial transformation. For instance, Shanxi, a typical resource-dependent province, relies heavily on high-energy-consuming industries like coal. Due to the significant proportion of heavy industry in its industrial structure, the *CER* effects are often less pronounced than in non-resource-based provinces. Therefore, it is recommended that Shanxi accelerate industrial adjustment, especially by increasing investment in new energy and high-tech industries. Additionally, in economically underdeveloped western regions like Guizhou and Gansu, efforts to advance the *DE* should be coupled with the digitalization of the coal industry. Improve the production efficiency of the coal industry through digital technology.

(2) Strengthen the Core Role of Technological Innovation in *CER*: Increase investment in technological integration, especially in the innovative integration of digital technology and energy technology (Zhang et al., 2021). Governments should incentivize companies to develop and adopt low-carbon technologies while providing innovation support for small and medium-sized enterprises (SMEs). This study reveals that the role of technological innovation in the *CER* effect of *DE* is higher than that of industrial structure. Economically developed eastern regions, such as Guangdong, Jiangsu, and Zhejiang, have already made substantial progress in technological innovation. These regions should further leverage their technological advantages to promote the application of cutting-edge technologies like 5G, IoT, and big data across energy, transportation, and manufacturing sectors. Although less developed regions, such as Ningxia and Qinghai, may not have the same economic advantages, they can still benefit by learning from the innovation experiences of the more advanced eastern provinces. Encourage the integration of digital technology and energy technology to improve the efficiency of traditional energy extraction.

(3) Promote Coordinated Development of Urbanization and *CER* with Differentiated Approaches: Regions with varying levels of urbanization should adopt differentiated policies to coordinate urbanization and *CER* efforts. Areas with lower urbanization levels should focus on strengthening

infrastructure development and optimizing energy use, while highly urbanized regions should prioritize improving urban management efficiency, promoting smart city development, and advancing low-carbon initiatives. For western provinces with lower urbanization rates, such as Sichuan and Yunnan, it is essential to avoid excessive reliance on traditional fossil fuels during urbanization. Efforts should be made to adopt clean energy solutions and high-efficiency building technologies. In new urban planning, integrating digital technologies with low-carbon concepts can drive the construction of green and smart cities. For the highly urbanized eastern coastal regions like Shanghai and Beijing, efforts should focus on further enhancing urban management efficiency. Promoting the application of low-carbon technologies such as smart transportation, intelligent buildings, and smart grids will be key to achieving sustainable urban development (Ayres and Williams, 2004).

(4) Differentiated Policy Design for Resource-Based and Non-Resource-Based Provinces: Resource-based provinces should focus on promoting industrial transformation and ecological protection, reducing dependence on traditional energy industries (Chen, 2022). Non-resource-based provinces should continue to leverage the advantages of the *DE* to drive the widespread adoption and innovation of low-carbon technologies. For resource-based provinces like Inner Mongolia and Xinjiang, the government should gradually reduce the proportion of resource industry structure and promote the development of clean energy industries. Additionally, these regions can foster the growth of *DE*-related ecological industries (such as smart agriculture and green tourism) to replace traditional high-pollution sectors. Non-resource-based provinces like Jiangsu and Zhejiang have already been at the forefront of *DE* development and industrial structure optimization. These regions should continue to build on their strengths in *DE* and technological innovation, further expanding the application of low-carbon technologies across various industries.

(5) Enhance Digital Infrastructure Development in Underdeveloped Regions: The government should accelerate the infrastructure construction of central and western provinces, narrow the gap in the *DE*, and thus enhance their *CER* capabilities (Kim, 2006). For underdeveloped areas like Gansu and Guizhou, it is recommended to boost investments in digital infrastructure, promoting the widespread application of big data and 5G networks. This will support the broad development of the *DE* in these regions. For instance, Guizhou has been actively developing its big data industry in recent years, gradually elevating the level of *DE* development and creating favorable conditions for *CER*.

7.2 Limitations and future recommendations

This study reveals the carbon reduction effects of *DE* development and its mechanisms, but certain limitations remain. First, the panel data used in this research has temporal and spatial constraints. Due to data availability issues, the study covers a relatively limited timeframe and does not include all regions. Future research could extend the time series and expand the geographical scope to examine the differential impacts of the *DE* on *CE* across various development stages and regions. Second, this study adopts a macro-level empirical analysis. While it uncovers the overall impact of the *DE* on *CE*, the mechanisms at the micro level require further exploration. For instance, how specific industries leverage digital technologies to reduce *CE* and whether the carbon reduction effects of the *DE* vary across different industrial structures are questions for future investigation. Lastly, this study focuses primarily on the mediating effects of industrial structure optimization and technological innovation in the relationship between the *DE* and *CE*. Future research could incorporate additional potential mechanisms, such as improvements in resource allocation efficiency and heightened public environmental awareness, to comprehensively understand the multifaceted impacts of the *DE* on low-carbon transitions.

Future research should address these limitations, broaden data sources, and deepen the exploration of mechanisms to enhance understanding of the relationship between the *DE* and carbon reduction. First, incorporating non-traditional data sources such as remote sensing data, IoT monitoring data, and internet big data can compensate for the limitations of panel data. These high-frequency data sources can dynamically capture real-time relationships between digital economic activities and carbon emission changes, providing more precise evaluations. Second, integrating industry-specific data will enable an in-depth analysis of the contributions of specific digital technologies (such as artificial intelligence, big data, and cloud computing) to carbon reduction in various sectors. It is essential to investigate how these technologies operate within different industries and their potential in promoting green supply chains, enhancing energy efficiency, and minimizing waste. Third, employing spatial econometric methods can reveal the cross-regional spillover effects of the *DE* on *CE*. For instance, future research could explore whether the development of the *DE* in developed regions indirectly impacts *CE* in surrounding underdeveloped areas through industrial relocation or technology diffusion, and assess the positive and negative aspects of such spillover effects. Finally, examining the synergy between *DE* development and climate policies (such as carbon taxes and carbon trading markets) is crucial. Research could investigate how policy support amplifies the carbon reduction effects of the *DE* while analyzing the potential hindrances of overly aggressive or poorly coordinated policies on digital economic development.

Data availability statement

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

Author contributions

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

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Conflict of interest

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

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The author(s) declare that no Generative AI was used in the creation of this manuscript.

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