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The impact of digital economy development on carbon emission efficiency: an empirical analysis based on spatial Durbin model and mediating effect

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Abstract

Against the backdrop of intensified global climate change, countries are facing enormous pressure to reduce emissions while pursuing high-quality economic development. The digital economy is considered to have the potential to reduce carbon emissions. However, existing research mostly focuses on the impact of the digital economy on economic growth and industrial structure, with relatively insufficient research on its environmental impact, especially in terms of carbon emission efficiency. Therefore, based on panel data from 259 prefecture level and above cities in China from 2015 to 2022, this study innovatively constructed a comprehensive evaluation framework using spatial econometric models. Firstly, by constructing a spatial weight matrix, the spatial dependencies between cities could be obtained. Secondly, utilizing the spatial Durbin model ensured that the model could capture the impact of interactions between cities. In addition, to investigate the potential impact mechanism of the digital economy on carbon emission efficiency, this study used the mediation effect test method to systematically analyze the indirect impact of the digital economy promoting technological advancement and optimizing industrial structure on carbon emission efficiency. The results indicated that the digital economy substantially raised carbon emission efficiency, with a 0.017% increase in carbon emission efficiency for every 1% increase. The optimization of industrial structure is the core intermediary path for the digital economy to improve carbon emission efficiency, with a mediating effect of up to 0.490. In contrast, the direct mediating effect of green technology innovation is very weak (0.002) and not statistically significant. This difference suggests that the digital economy may mainly drive carbon efficiency improvement at the current stage by reshaping the macro industrial structure rather than directly stimulating green technology innovation at the enterprise level. In addition, the spatial spillover effect was significant, with a 1% rise in carbon emission efficiency in neighboring cities and a 0.065% increase in target cities. From 2015 to 2022, Moran's I value rose from 0.055 to 0.152, spatial clustering strengthened, Geary's C value decreased from 0.932 to 0.811, and spatial heterogeneity weakened. The study revealed the mechanism by which technological innovation and industrial structure optimization enhanced carbon emission efficiency, providing a new perspective for the regional coordinated development of the digital economy from the perspective of spatial spillover effects.

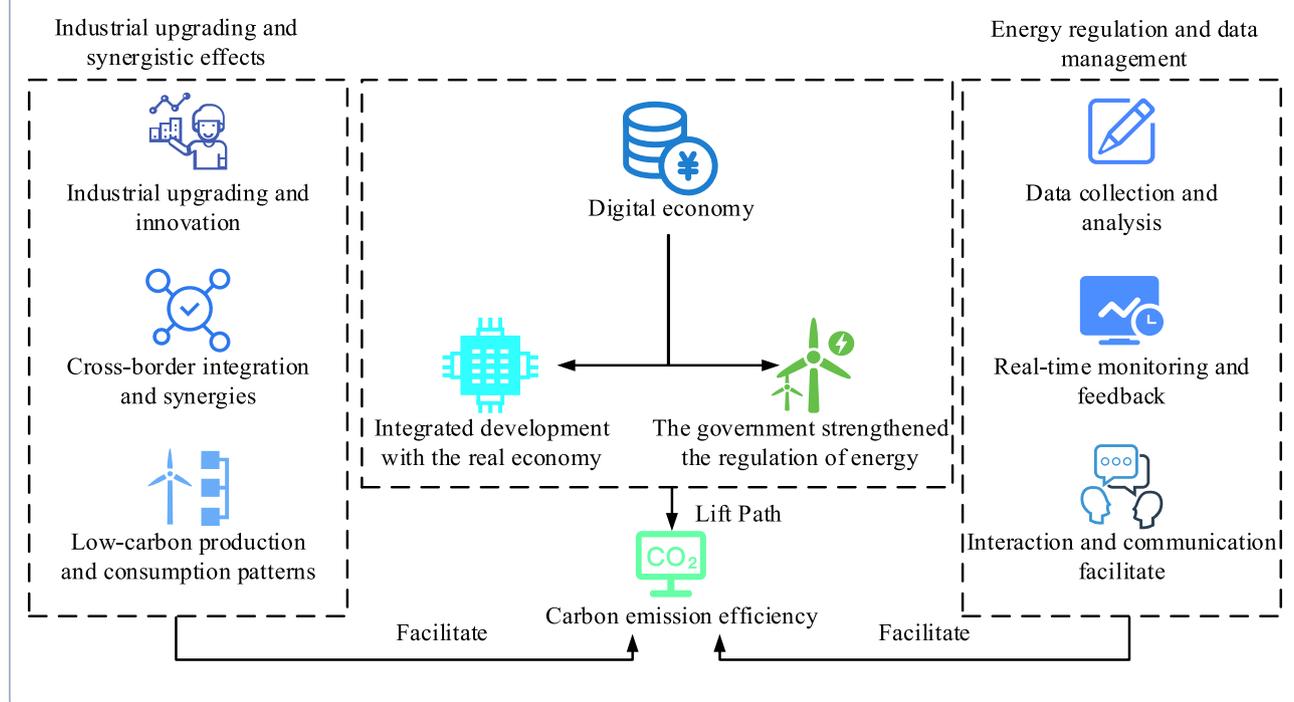
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Highlights

- Deeply analyzed the potential mechanism of digital economy affecting carbon emission efficiency through mediation effect testing;
- Moran's I and Geary's C were utilized to test spatial correlation and analyze the spatial spillover effects of the digital economy;
- Digital economy can directly promote the improvement of carbon emission efficiency through two core paths: incremental control and stock reduction.

Keywords Digital technology, Innovation, Carbon reduction pathway, Spatial spillover effect, Spatial Durbin model

Graphical Abstract



1 Introduction

Against the backdrop of intensified global climate change, frequent extreme weather and ecological degradation have become common challenges faced by all mankind, and promoting green and low-carbon transformation is urgent (Lin et al. 2023). As the main source of carbon emissions (CE), the improvement of CE efficiency in cities is of crucial significance for achieving global climate governance goals (Wang and Li 2023). In this context, the booming development of the digital economy (DE) centered on information technology has not only reshaped traditional production and consumption patterns, but is also considered to have significant potential in promoting carbon emissions reduction (Oh 2023; Rong 2022). However, existing research has focused more on the impact

of the DE on economic growth and industrial structure, while neglecting its environmental effects and not fully considering spatial factors, resulting in incomplete and inaccurate evaluations of the relationship between the DE and CE efficiency (Tan et al. 2024a). Therefore, based on the theories of environmental economics and spatial analysis, this study constructs an integrated analysis framework that integrates direct effects, mediating pathways, and spatial spillovers to systematically analyze the multidimensional mechanism of DE on CE efficiency. This study not only expands the analytical dimensions of DE environmental effects in theory, but also achieves collaborative innovation in spatial econometrics and mechanism testing methods. The research aims to provide new empirical evidence for understanding the green effects of

DE, and to provide scientific references for regional collaborative emission reduction and digital green development policies.

2 Literature review

DE is a new economic form that uses data resources as key elements and modern information networks as carriers to promote economic efficiency improvement and structural optimization through digital transformation. Currently, many researchers around the world have conducted extensive discussions on the application of DE. Xu et al. (2024) used the Generalized Method of Moments (GMM) to explore the impact of DE and changes in quality of life on CEs. They used provincial data from China from 2006 to 2018 and combined key component examination to compute relevant indices. The results showed that a non-linear, inverted U-shaped correlation existed between the DE and living standard on CEs. The advancement of the DE improved the quality of life while reducing its impact on CEs. Wang et al. (2022) studied 248 prefecture level cities, exploring the spatial spillover effects (SSEs) of DE advancement on CEs reduction. They used Moran's I Index (Moran's I) testing and Spatial Durbin Model (SDM). The outcomes showed that the CEs of industrial cities in Northeast and Central China were higher than those in the eastern coastal areas. The development of DE significantly reduced CEs and had spatial effects, indicating a close relationship between cities. Based on six urban agglomerations in China from 2011 to 2019, Yan et al. (2023) found that the DE significantly reduced CE intensity, which was enhanced through indirect effects such as green technology innovation (GTI), and the effect became more pronounced as the degree of marketization increased. In addition, the impact varies by region and quantile, and the overall effect of urban agglomerations was better than other cities, providing new references for the development of DE and carbon reduction policies. Chen et al. (2022) analyzed the relationship between DE, industrial structure, and CEs using mediation effects and spatial panel models based on data from 30 provinces. The research showed that the DE directly reduced CEs and indirectly suppressed them by optimizing industrial structure, but there was a certain degree of inhibition on structural optimization. Yan et al. (2023) used fixed, mediating, and moderating effect models to explore the impact and mechanism of DE on CE intensity in order to promote the construction of urban agglomerations. The results indicate that the development of urban agglomerations can significantly reduce CE intensity, and the higher the degree of marketization of urban agglomerations, the more significant the impact of DE on reducing CE

intensity. Wang and Zhong (2023) investigated whether DE could promote macroeconomic growth and green low-carbon economic development in the context of rapid global digital technology development. They used a difference in differences (DID) model to explore how DE can reduce CE intensity. The results indicated that the development of DE is beneficial for reducing the CE intensity of local cities, and there is strong heterogeneity in its impact on CE intensity in different regions and types of cities. These studies collectively reveal the multiple pathways and complexities through which DE affects CE.

In addition to directly exploring the impact of DE, another type of research focuses on the measurement methods, spatial distribution patterns, and broader influencing factors and policy effects of CE itself. For example, Du et al. (2022) analyzed the CE efficiency (CEE) and spatial distribution characteristics of China's building sector grounded on data from 2005 to 2016, and found that the efficiency exhibited a disparity, being higher in the east and lower in the west, with spatial dependence and agglomeration. Markov chain analysis indicated that there was a significant SSE on CEE, with efficient provinces having a positive impact on their surrounding areas and inefficient provinces having a negative impact. Zhang et al. (2022) applied Tobit model to assess the impact of green finance on CEE grounded on data from 27 provinces and cities. The outcomes indicated that China's CEE was generally low, showing a downward trend in the east, middle, and west. Green finance significantly improved CEE, but there were significant regional differences. Zhang and Xu (2022) calculated the CEE of the Yangtze River Delta region from 2005 to 2019 utilizing the calculated directional distance function framework of slack and the Malmquist Luenberger index. The results showed significant inter provincial differences but overall an increase. Through panel Tobit model analysis of influencing factors, it is proposed that regions with high coupling coordination should regulate their per capita electricity usage, optimizing urbanization and industrial structure. Guo and Ma's (2023) research focused on the policy level and studied the influence of China's CEs trading system from 2008 to 2018 on green and balanced development through a multi-period Difference in Differences (DID) model. The outcomes indicated that the Emissions Trading Scheme (ETS) substantially elevated the standard of green balance. These studies have deepened the understanding of the characteristics and driving forces of CE efficiency from different perspectives, providing a basis for formulating differentiated policies.

In summary, although existing studies have preliminarily explored the impact of DE on CE through spatial econometric models and mediation analysis, such as

Wang et al. (2022), Chen et al. (2022), Du et al. (2022), etc. However, the integrated analysis of the mechanism of action is not yet systematic, especially the lack of multi-path parallel testing of technological innovation, industrial structure, and spatial spillover effects. In addition, existing research still has significant shortcomings in indicator construction, mechanism identification, and regional heterogeneity analysis. Therefore, this study aims to fill the research gap by constructing SDM, introducing multidimensional mediation mechanisms, and expanding city level panel data, in order to provide new empirical evidence and policy implications for understanding the multi-path and cross regional impacts of the digital economy on carbon emission efficiency.

3 Impact of DE development based on spatial metrology on CEs

To explore the impact mechanism of DE on CE efficiency, this study innovatively integrates panel data from 259 prefecture level and above cities in China from 2015 to 2022, constructs a spatial weight matrix (SWM) and SDM, and introduces a mediation effect test method to deeply analyze the multidimensional impact of DE on CE efficiency through technological innovation and industrial structure optimization, as well as its spatial spillover effects.

3.1 Impact and mechanism of the DE on CEE

The DE mainly contributes to the progression of carbon neutrality through “controlling increment” and “reducing stock” (Nizametdinov 2022). “Incremental control” refers to reducing CEs from the source. First, through the “dematerialization” and “light asset” characteristics of the Internet, material consumption and unnecessary offline activities are reduced, and travel related CEs are also reduced. The second is to use information technology innovation to improve energy efficiency and reduce unit energy consumption, which is an important path for future emissions reduction. “Reducing stock” focuses on reabsorbing already emitted carbon dioxide (Kobilov et al. 2022). The profound combination between DE and real economy optimizes traditional industries through digital technology, reduces costs, improves efficiency, and promotes economic development and CEE improvement (Tan et al. 2024a).

Based on the aforementioned information, hypothesis H1 is proposed: The DE acts beneficially on CEE.

Figure 1 illustrates the direct impact mechanism of the DE on CEE. Its main path includes two aspects: “integrated development with the real economy” and “the government strengthened the regulation of energy”. Firstly, the DE promotes the improvement of CEE through its integration with the real economy. Specifically, it is manifested in the promotion of industrial upgrading

and innovation to optimize production methods, cross-border integration and synergistic effects to improve resource utilization, and the promotion of low-carbon production and consumption models to achieve green transformation. Secondly, the government utilizes digital technology to strengthen energy regulation and further improve CEE. This is reflected in data collection and analysis helping optimize energy management, real-time monitoring and feedback improving the ability to regulate energy use, and digital interaction and communication promoting collaboration among all parties to jointly promote carbon reduction.

Firstly, the DE promotes digital transformation by optimizing production processes and equipment management to improve production efficiency and assist in energy conservation and emission reduction. High energy consuming enterprises utilize green technology transformation and digital management to achieve investment optimization and equipment updates, while promoting industrial structure upgrading. Secondly, digital technology supports the intelligence of devices, optimization of transportation, and efficient utilization of energy in the primary industry.

The advancement of the DE has a notable impact on energy consumption and CEE. The research investigates the path of how the DE affects CEE from multiple perspectives and proposes hypothesis H2: China’s urban DE can use green innovation technologies to promote CE rates.

Figure 2 shows the mechanism by which the DE improves urban CEE through GTI, mainly including three aspects: enterprise green innovation, industrial structure upgrading, and alleviating energy mismatch. Firstly, the DE promotes green innovation in enterprises, eliminating technological barriers and achieving technology spillover effects through low-carbon production technology exchange and technological innovation improvement, thereby promoting the improvement of CEE. Secondly, upgrading the industrial structure is an important path for the DE to promote CEE. Digital means accelerate the flow of production factors and optimize resource allocation, facilitate the shift of high-energy-consuming industries towards a low-carbon path, and achieve efficient operation and upgrading of industries. Finally, the DE plays a role in mitigating energy mismatches.

The DE helps upgrade through two paths: digital industrialization and industrial digitization. The former refers to the emerging industries such as electronic information manufacturing and communication, which are developing towards technology intensive and environmentally friendly industries through information technology. The latter combines digital technology with traditional

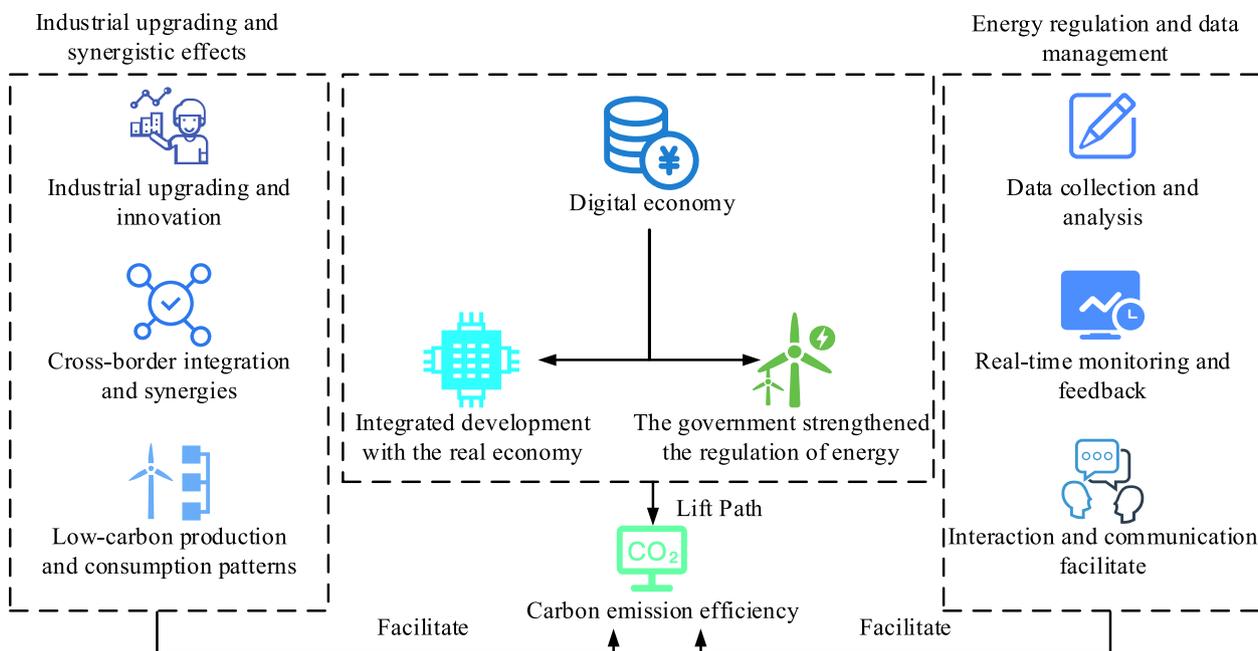


Fig. 1 Direct impact of DE on CEE

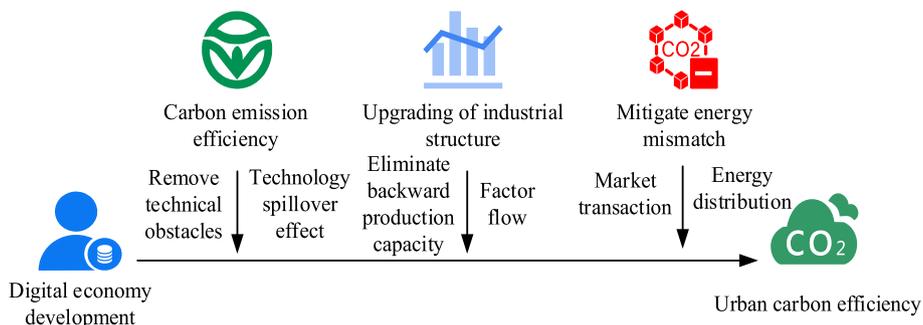


Fig. 2 The mechanism of GTI in DE to enhance urban CEE

industries to achieve production and operational transformation. The upgrading of industrial structure not only optimizes resource allocation, promotes coordinated development of various industries, but also achieves industrial high-end development. China’s current industrial development faces problems such as unreasonable layout and high energy consumption and pollution in the secondary industry.

Therefore, hypothesis H3 is proposed: the enhancement of the industrial structure of China’s urban DE has a positive promoting effect on urban CEE.

The DE has broken through the temporal and spatial limitations of traditional economies, strengthened inter regional factor connections, and has regional spillover effects on CEE. Hypothesis H4 is proposed: the

advancement of the DE has SSEs on CEs in neighboring cities.

In Fig. 3, the mechanism path of SSE is as follows. From one perspective, the DE promotes resource integration and factor sharing between regions through the popularization of digital information technology, optimizes production layout and energy utilization efficiency, reduces fossil energy consumption in neighboring areas, and improves regional and peripheral carbon productivity. Digital technology serves as a catalyst for the widespread dissemination of green knowledge and innovations, amplifying technology spillover effects. It fosters enhanced innovation capabilities and facilitates the upgrading of industrial structures in neighboring regions. This dynamic process enables the efficient flow of

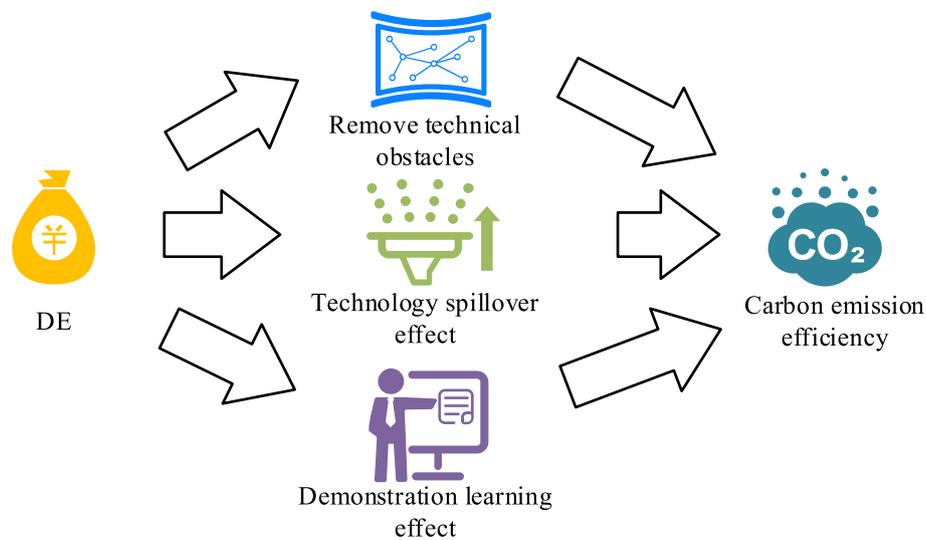


Fig. 3 SSE and path mechanism

resources from low-income to high-income areas, thereby further elevating carbon productivity. In addition, the DE attracts surrounding areas to participate in digital construction through demonstration effects, promotes the transformation of traditional industrial chains and green low-carbon transformation, optimizes regional energy consumption, and improves overall production efficiency. The technology spillover effect refers to the development of DE promoting technological innovation and knowledge dissemination, and the diffusion of technological achievements between regions. The demonstration learning effect refers to the fact that after DE achieves success in a certain city, other cities will learn from its development model and experience. This division helps to deepen the understanding of the impact mechanism of DE on CEE in the spatial dimension, indicating that DE not only has an impact through direct technology dissemination, but also stimulates learning and innovation in other cities through demonstration, thereby achieving the overall improvement of CEE in the region.

3.2 Calculation methods for DE index and CEE

Due to the study covering 259 different cities, there are inherent differences in resource endowment, initial environmental regulation intensity, and other aspects that do not change over time. Ignoring these individual effects will lead to omitted variable bias. Therefore, this study adopts a panel fixed effects model to measure the urban DE index, in order to effectively control the omitted variable bias caused by such individual heterogeneity, thus more clearly identifying the causal relationship between the digital economy and carbon

emission efficiency. The study data was sourced from the National Bureau of Statistics and provincial statistical yearbooks. Missing data was supplemented through interpolation. To evaluate the influence of DE development on CEE, a benchmark regression model was built and a panel fixed effects model was adopted to comprehensively consider the differences between cities and overcome the limitations of mixed regression in handling dynamic changes (Hu et al. 2023; Wang et al. 2024a). Simultaneously controlling the bidirectional fixed effects of cities and years, the system analyzed the influence of the level of digital economic advancement on CEE. The particular formula is presented in Eq. (1).

$$CE_{i,t} = \alpha_0 + \alpha_1 Dige_{i,t} + \alpha_2 Control_{i,t} + \mu_i + \delta_i + \varepsilon_i \tag{1}$$

In Eq. (1), $CE_{i,t}$ is the CEE of a city i in the given year t . $Dige_{i,t}$ indicates the level of DE development in a city. $Control_{i,t}$ represents control variables, used to control other factors that may influence CEE, such as industrial structure, energy structure, technological progress, etc., to avoid interference from these factors. α_0 represents the baseline value of CEE when all independent variables are zero. α_1 indicates the marginal impact of the DE on CEE. α_2 represents the regression coefficient of the control variable $Control_{i,t}$. μ_i is the fixed effects of city i . δ_i is the fixed effect of year i . ε_{it} is an error term, it represents the unexplained part of the model. Based on the perspective of the Internet, this study selects four basic indicators: Internet penetration rate, the proportion of digital industry practitioners, mobile phone penetration rate and the development level of digital finance to evaluate the development level of DE.

To construct a comprehensive "Digital Economy Development Level (Dige)" index, this study used Principal Component Analysis (PCA) to reduce and synthesize the dimensions of the four indicators mentioned above, in order to eliminate multicollinearity among the indicators and determine the weights of each indicator. Finally, the comprehensive index of digital economy development at the city level was calculated. The index is then processed using the natural logarithm in regression analysis, which is the core independent variable *lnDige* in the model. Figure 4 indicates the meaning and observation objects of urban CEE indicators.

To improve the accuracy of research conclusions, the Slack-Based Measure (SBM) model proposed by Andersen was used to measure CEE. This model overcomes the limitations of traditional SBM models, which tend to have efficiency values close to 1 when studying a large number of cities, and incorporates unexpected outputs to more accurately measure CEE (Joseph and Mustaffa 2023; Xu et al. 2023). Meanwhile, considering that CEE is affected by the DE and various complex factors, to prevent endogeneity issues stemming from omitted variables, multiple control variables were selected based on literature review, as shown in Fig. 5.

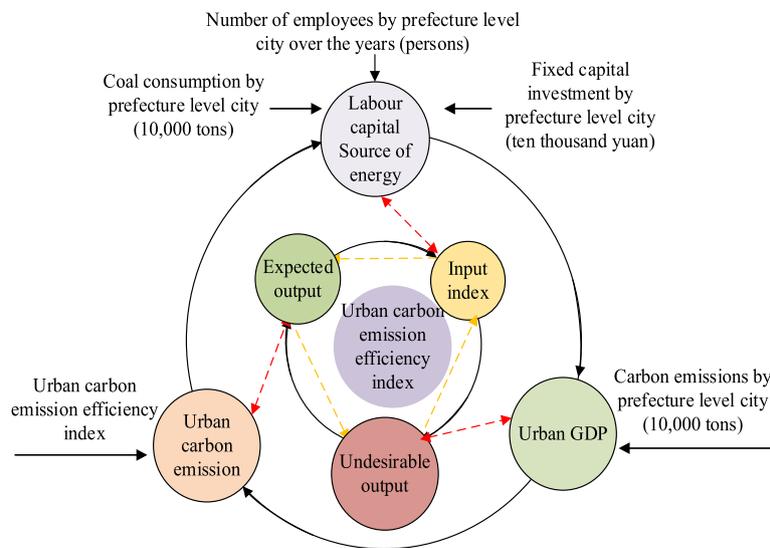


Fig. 4 Meaning and observation objects of urban CEE index

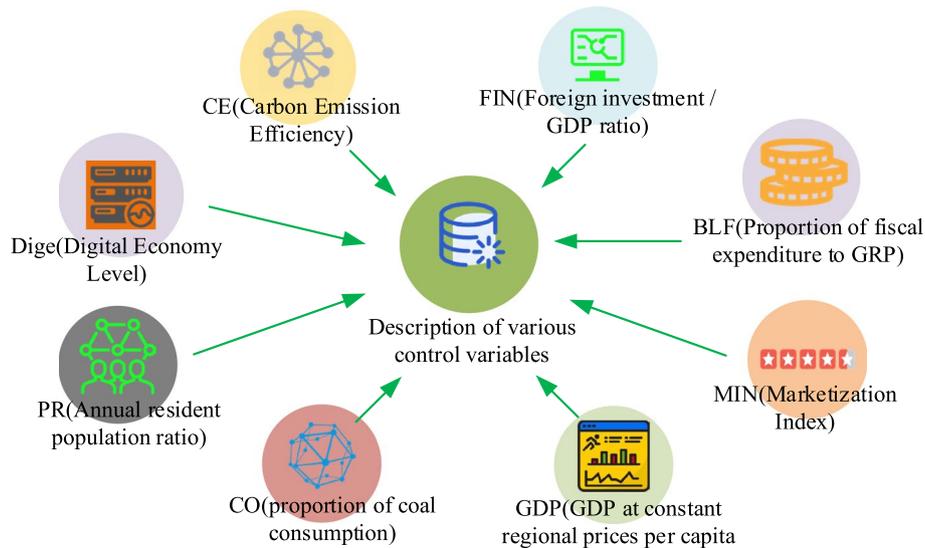


Fig. 5 Description of various control variables

In Fig. 6, the testing process is as follows. Firstly, the existence of mediation effect is determined by testing the coefficient α_1 . If notable, the coefficients γ_1 and δ_1 are further tested to determine complete mediation, partial mediation, or the existence of other mediation effects. If α_1 is not notable, there may be a masking effect, and the Bootstrap method needs to be used to verify the significance of γ_1 and δ_1 . If the indirect effect is notable while the direct effect is not notable, it represents a full mediation effect. If both are notable, it indicates partial mediation or other mediation. If the indirect effect is not notable and the direct effect is notable, it may be a case of no mediating effect or other complex situations. To analyze the spatial effects of the DE on CEE, the study constructs a Global Namespace (GNS) model (Lee et al. 2024). The specific calculation formula is shown in Eq. (3).

$$\begin{cases} \ln CE_{i,t} = \theta_0 + \omega W \ln CE_{i,t} + \gamma \theta_1 \ln Dige + \theta_2 Control_{i,t} + \theta_3 W \ln Dige_{i,t} + \theta_4 WX_{it} + \mu_{1i} \\ \mu_{1i} = \eta W \mu_{1i} + \varepsilon_{1i} \end{cases} \quad (3)$$

In Eq. (3), W represents the SWM. ω and η both are spatial autoregressive coefficients. $\theta_1, \theta_2, \theta_3,$ and θ_4 all represent spatial autocorrelation coefficients. Spatial autocorrelation analysis aims to ascertain whether a variable exhibits spatial dependency and the degree of such dependency. The Local Indicators of Spatial Association (LISA) coefficient is a statistical measure used to measure local spatial autocorrelation, primarily for analyzing spatial non stationarity in geographic data. The study measures global features through Moran's I and analyzes the degree of local spatial clustering by combining LISA coefficients. The detailed computational procedure is outlined in Eq. (4).

$$Moran's\ I = \frac{n(z_i - \bar{z}) \sum_{i^l j} W_{ij} (z_j - \bar{z})}{\sum_{i=1}^n (z_i - \bar{z})^2} \quad (4)$$

In Eq. (4), n is the total number of observed samples. z_i is the variable value representing the observation point. \bar{z} represents the average value of variables for all observation points. To improve the descriptive ability and analytical accuracy of the SWM for actual situations, the particular expression of the economic distance matrix constructed based on geographic distance is studied as shown in Eq. (5).

$$w'_{ij} = \begin{cases} \frac{E_i E_j e^{-\alpha}}{\sum_j w'_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \quad (5)$$

In Eq. (5), w'_{ij} represents the economic weight value between points i and j after the standardization. $e^{-\alpha}$ represents the exponential decay factor. E_i and E_j are the economic characteristic values of point i and point j , respectively. The nested matrix is shown in Eq. (6).

$$w''_{ij} = \begin{cases} \left(\frac{1}{|v_i - v_j + 1|} \right) e^{-\alpha} \\ \sum_j w''_{ij} \end{cases}, i \neq j \quad (6)$$

$$0, i = j$$

In Eq. (6), v_i is the economic indicator of the spatial unit city i . Data Envelopment Analysis (DEA) serves as a non-parametric approach for assessing efficiency, and traditional DEA models are difficult to accurately handle slack variables. To address the impact of unexpected

output on efficiency evaluation, this study combines the super efficiency DEA model, adopts the super efficiency SBM model, and utilizes the super efficiency SBM model based on unexpected output. The calculation process of this model is shown in Eq. (7).

$$\begin{cases} \text{Min } \theta = \frac{1}{m} \sum_{i=1}^m \frac{\bar{z}_i}{x_{i0}} / \left[\frac{1}{S_1 + S_2} \left(\sum_{q=1}^{S_1} \frac{p_q^w}{\gamma_q^w} + \sum_{q=1}^{S_2} \frac{p_q^b}{p_q^b} \right) \right] \\ z_0 = z_\alpha + n^-, p_0^w = p^w \alpha - n^w, p_0^b = p^b \alpha + n^b \\ \bar{z} \geq \sum_{j=1, \neq k}^n \alpha_j z_j, \bar{p}^w \leq \sum_{j=1, \neq 0}^n \alpha_j p_j^w, \bar{p}^b \leq \sum_{j=1, \neq 0}^n \alpha_j p_j^b \\ \sum_{j=1, \neq 0}^n p_j = 1, s^- \geq 0, s^\alpha \geq 0, s^+ \geq 0, \alpha \geq 0 \end{cases} \quad (7)$$

In Eq. (7), m represents the number of input indicators. n^- represents a slack variable. S_1 and S_2 indicate the number of expected output variables. P^w is the expected output slack variable. P^b indicates an unexpected output slack variable. P_q^b indicates the adjusted expected output. In summary, to effectively address potential econometric issues in empirical analysis, this study first introduced a bidirectional fixed effect between city and year to control for omitted variable bias caused by individual heterogeneity (such as geographic features) that does not change over time and time trends (such as macro policies) that do not change over time. Secondly, in order to prevent endogeneity bias caused by omitted variables, multiple control variables were selected based on the literature review. Finally, SDM is adopted and incorporated into the spatial weight matrix to directly estimate and separate the impact of the DE on CE efficiency in the local and neighboring regions, thereby correcting estimation errors caused by spatial dependence.

4 Results and discussion

The experiment was based on panel data from 259 prefecture level and above cities in China from 2015 to 2022, and indicator data were obtained through principal component analysis for measurement. The dependent variable was CEE, which was calculated using the super efficiency SBM model. To reflect the spatial correlation between cities, an SWM based on geographic distance was constructed. The observed values of all variables were set to 3995, and Table 1 indicates the statistical results of variable values.

As per Table 1, notable variations existed in the distribution range and dispersion degree of each variable, reflecting the diversity of regional economic and environmental indicators. To verify the rationality of the model setting, this study further adopted the instrumental variable method, using the telephone penetration rate in 1984 as the instrumental variable. The DE coefficient remained significantly positive ($\beta=0.018$, $t=3.82$, $p<0.001$), excluding reverse causal interference. After sequentially adding ESG, AI, DC, and Crypto variables,

the core variable $\ln Dige$ coefficient remained stable at 0.014–0.017 ($p<0.001$), with a volatility of less than 15%. Breaking down GDP into digital industry added value (DE-GDP) and traditional industry added value (NonDE-GDP), it was found that only DE-GDP had a significant positive impact on CEE ($\beta=0.182$, $p<0.01$). The regression analysis outcomes of the DE on CEE are presented in Table 2.

From Table 2, the impact of the DE on CEE was significant and positive, which confirmed hypothesis H1, that DE can directly promote the improvement of CEE through two core paths: "incremental control" and "inventory reduction", providing strong empirical support for DE to assist in green and low-carbon transformation. The coefficient was positive in multiple models and reached the highest value of 0.0167 in the seventh column model, demonstrating that the expansion of the DE helped to improve CEE. The impact of $\ln GDP$ on CEE was positive and significant in all models. Its impact was gradually increasing, with a coefficient of 0.2567 in column (7), indicating that economic development occupied a key position in improving CEE. The coefficient of influence of population variables was positive and significant, especially in column (3) where the coefficient was as high as 1.403, indicating that population size promoted CEE through optimization of production or consumption structure. The influence direction and significance of other control variables varied. Among them, $\ln BLF$ was significantly negative in some models, while $\ln MIN$ and $\ln CO$ both showed negative effects, reflecting the inhibitory effect of traditional industries on CEE. To verify hypothesis H2, GTI was selected as the measurement indicator, and the regression outcomes are in Table 3.

From Table 3, the impact coefficient of green innovation technology on CEE in model (7) was 0.002, but it did not reach a significant level, indicating that the direct impact of GTI in separate analysis was weak and may have needed to be indirectly influenced through other pathways. The impact of the DE on CEE was positive and significant in all

Table 1 Numerical statistics of variables

| Variable | Mean value | Standard deviation | Min value | Max value |
|----------|------------|--------------------|-----------|-----------|
| CE | 0.218 | 0.116 | -0.749 | 1.311 |
| Dige | -0.199 | 0.807 | -5.538 | 2.612 |
| GDP | 1.391 | 0.483 | 0.008 | 3.697 |
| PR | 1.923 | 0.105 | 1.415 | 2.202 |
| BLF | 14.318 | 0.895 | 10.958 | 18.005 |
| FIN | 13.583 | 2.098 | 5.992 | 19.495 |
| MIN | 2.435 | 0.248 | 1.507 | 2.979 |
| CO | 4.377 | 0.286 | -3.792 | 4.938 |
| ESG | 52.302 | 12.734 | 26.625 | 86.207 |
| AI | 6.723 | 3.154 | 0.118 | 19.842 |
| DC | 4.381 | 2.059 | 0.032 | 12.910 |
| Crypto | 1.174 | 0.892 | 0.002 | 5.345 |

Table 2 Basic regression outcomes (H1)

| Variable | LnCE (1) | LnCE (2) | LnCE (3) | LnCE (4) | LnCE (5) | LnCE (6) | LnCE (7) |
|----------------|-------------------------------|------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| $\ln Dige$ | 0.020 ^c (0.0036) | 0.009 ^c (0.0034) | 0.014 ^c (0.0035) | 0.014 ^c (0.0035) | 0.014 ^c (0.0035) | 0.014 ^c (0.0035) | 0.016 ^c (0.0036) |
| $\ln GDP$ | / | 0.230 ^c (0.0116) | 0.250 ^c (0.0118) | 0.254 ^c (0.0123) | 0.254 ^c (0.0123) | 0.249 ^c (0.0114) | 0.262 ^c (0.0118) |
| $\ln PR$ | / | / | 1.403 ^c (0.1326) | 1.412 ^c (0.1323) | 1.412 ^c (0.1323) | 1.384 ^c (0.1333) | 1.426 ^c (0.1290) |
| $\ln BLF$ | / | / | / | -0.009 ^c (0.0094) | -0.009 ^c (0.0094) | -0.008 ^c (0.0098) | -0.014 ^c (0.0094) |
| $\ln FIN$ | / | / | / | / | 0.001 ^c (0.0022) | -0.002 ^c (0.0023) | -0.0023 ^c (0.0024) |
| $\ln MIN$ | / | / | / | / | / | -0.0980 ^c (0.0240) | -0.1101 ^c (0.0234) |
| $\ln CO$ | / | / | / | / | / | / | -0.0889 ^c (0.0060) |
| Constant | -0.3110 ^c (0.0059) | 0.0839 ^c (0.0128) | -2.6240 ^c (0.2568) | -2.5201 ^c (0.2771) | -2.5201 ^c (0.2776) | -2.2569 ^c (0.2842) | -1.8568 ^c (0.2770) |
| R ² | 0.065 | 0.152 | 0.178 | 0.178 | 0.178 | 0.180 | 0.229 |

^a: $p<0.05$, ^b: $p<0.01$, ^c: $p<0.001$

Table 3 Basic regression outcomes (H2)

| Variable | LnCE (5) | LnCE (6) | LnCE (7) |
|----------------|------------------------------|-------------------------------|------------------------------|
| lnDige | 0.016 ^c (0.0036) | 0.056 ^c (0.0235) | 0.016 ^c (0.0036) |
| lnGDP | 0.262 ^c (0.0120) | 0.391 ^c (0.0832) | 0.262 ^c (0.0118) |
| lnPR | 1.426 ^c (0.1292) | 6.670 ^c (0.9016) | 1.415 ^c (0.1304) |
| lnBLF | -0.001(0.0022) | -0.091 ^c (0.0152) | -0.002(0.0020) |
| lnFIN | -0.015(0.0093) | -0.138 ^b (0.0654) | -0.0016(0.0094) |
| lnMIN | -0.112(0.0233) | -0.610 ^c (0.1640) | -0.108 ^c (0.0234) |
| lnCO | -0.089 ^c (0.0061) | -0.050(0.0410) | -0.089 ^c (0.0058) |
| lnGTI | / | / | 0.002(0.0026) |
| Constant | -1.856 ^c (0.2776) | -12.943 ^c (0.2842) | -1.841 ^c (0.2793) |
| R ² | 0.232 | 0.814 | 0.223 |

^a: $p < 0.05$, ^b: $p < 0.01$, ^c: $p < 0.001$

models, with coefficients ranging from 0.016 to 0.056, indicating the promoting role of digital development in green transformation and verifying hypothesis H2. The impact of economic development was significant and positive, especially in model (6), where the coefficient increased to 0.391, indicating a robust relationship between economic growth and the improvement of CEE. Other variables were negative in some models, indicating that human resource allocation may not have fully utilized its role in promoting CEE. LnMIN had a significant negative impact on CEE, indicating that resource-intensive industries were an important obstacle to efficiency improvement. The R² of the model rose from 0.232 to 2.234, revealing a notable enhancement in the explanatory power of the model for CEE after gradually introducing variables. To verify hypothesis H3, the proportion of the tertiary industry to the secondary industry was chosen as the indicator for (TS), and the regression outcomes are in Table 4.

From Table 4, the impact of lnTS on CEE was significant and negative in model (6), but not significant in other models. The impact of the DE on CEE was beneficial and notable in all models, with a coefficient range of 0.006–0.016 and $p < 0.001$, indicating that the DE had a

Table 4 Basic regression outcomes (H3)

| Variable | LnCE (5) | LnCE (6) | LnCE (7) |
|----------------|------------------------------|-------------------------------|------------------------------|
| lnDige | 0.016 ^c (0.0036) | 0.006 ^c (0.0005) | 0.016 ^c (0.0036) |
| lnGDP | 0.264 ^c (0.0119) | 0.006 ^c (0.0023) | 0.260 ^c (0.0118) |
| lnPR | 1.428 ^c (0.1294) | -0.248 ^c (0.0239) | 1.548 ^c (0.1308) |
| lnBLF | -0.001(0.0021) | -0.002 ^c (0.0003) | -0.003(0.0022) |
| lnFIN | -0.015(0.0093) | -0.0004 ^c (0.0016) | -0.003(0.0022) |
| lnMIN | -0.111 ^c (0.0234) | -0.016 ^c (0.0042) | -0.102 ^c (0.0234) |
| lnCO | -0.088 ^c (0.0058) | -0.003 ^c (0.0012) | -0.089 ^c (0.0058) |
| lnTS | / | / | 0.490 ^c (0.0884) |
| Constant | -1.857 ^c (0.2770) | 2.382 ^c (0.0512) | -3.028 ^c (0.3466) |
| R ² | 0.229 | 0.716 | 0.236 |

^a: $p < 0.05$, ^b: $p < 0.01$, ^c: $p < 0.001$

stable influence on improving CEE. The influence of economic development on CEE was significantly positive, with the coefficient decreasing to 0.006 in model (6), but still maintaining a positive effect, indicating that economic growth had a strong driving effect on improving CEE in industrial restructuring. The negative significant impact of other variables in model (6) was -0.248, which may have been due to the increasing effect of population size on energy consumption. The negative significance of lnMIN (mining) indicated the constraining effect of resource-intensive industries on CEE. The explanatory power R² of the model rose to 0.716, demonstrating a substantial enhancement in the explanatory power of the model for CEE after the addition of lnTS. The above results validated H3. The results indicate that DE not only directly enhances CEE, but also plays a role through two indirect pathways: promoting GTI and optimizing industrial structure. Among them, the mediating effect coefficient of technological innovation is 0.002, indicating that its contribution is relatively small. The intermediary effect coefficient of industrial structure optimization is as high as 0.490. This mechanism discovery is consistent with the conclusion of Chen et al. (2022) on the role of industrial structure optimization in emission reduction. Before conducting spatial econometric analysis, the global spatial autocorrelation test was used to find out whether there was correlation in the overall spatial distribution. Next, local spatial autocorrelation testing was performed to identify the clustering patterns or distribution of outliers in local spatial units. The relevant inspection outcomes are in Table 5.

From Table 5, both spatial global autocorrelation and local autocorrelation showed significant differences between 2015 and 2022. The Moran's I rose annually, rising from 0.055 in 2015 to 0.152 in 2022, revealing that spatial clustering is gradually strengthening. At the same time, Geary's C value indicated a downward trend, dropping from 0.932 in 2015 to 0.811 in 2022, suggesting a

Table 5 Regression outcomes of spatial econometric model from 2015 to 2022

| Year | Moran's I | Geary's C |
|------|--------------------|--------------------|
| 2015 | 0.055 ^c | 0.932 ^c |
| 2016 | 0.094 ^c | 0.924 ^c |
| 2017 | 0.076 ^c | 0.882 ^c |
| 2018 | 0.104 ^c | 0.883 ^c |
| 2019 | 0.156 ^c | 0.876 ^c |
| 2020 | 0.124 ^c | 0.845 ^c |
| 2021 | 0.138 ^c | 0.828 ^c |
| 2022 | 0.152 ^c | 0.811 ^c |

^a: $p < 0.05$, ^b: $p < 0.01$, ^c: $p < 0.001$

gradual weakening of spatial heterogeneity. This indicates that the research object gradually tends towards a significant clustering state in spatial distribution. The significance of both global and local autocorrelation tests met $p < 0.001$, further confirming the existence of spatial effects and indicating that conducting spatial econometric analysis is reasonable and necessary. Partial decomposition can better test the hypothesis H4 of the existence of SSEs, and the decomposition data of the spatial econometric model are in Table 6.

From Table 6, there were differences in the direct effects and SSEs of each variable. The advancement of the DE had a significant promoting effect in space. The direct effect of lnPR was positive, while the spillover effect was negative, indicating that population variables had a notable influence on local advancement, but may have inhibited the development of adjacent areas. The direct and spillover effects of lnMIN and lnCO were both negative, indicating that energy and environmental factors had inhibitory effects in both local and neighboring regions. Partial differential decomposition confirmed hypothesis H4 that SSEs exhibited heterogeneity. In addition, for every 1% increase in the level of the urban DE, the CEE of neighboring cities increased by 0.065%. This discovery reveals the diffusion of DE emission reduction effects in geographical space, indicating that the digital development of cities is not only beneficial to themselves, but also radiates and improves the carbon efficiency of surrounding areas through mechanisms such as technology spillover, knowledge dissemination, and demonstration effects.

5 Conclusion

To explore in depth the impact and potential mechanisms of China’s urban DE development on CEE, the research used panel data from 259 prefecture level and above cities in China from 2015 to 2022, and conducted regression analysis using an SDM. Meanwhile, Moran’s I and Gearys C were utilized to test spatial correlation and analyze the SSEs of the DE. The role of the DE in facilitating the shift towards green and low-carbon practices was verified from both a theoretical standpoint and through empirical analysis. The

spatial econometric model and mediation effect testing method used in the framework proposed by this research were based on general statistical and economic theories, which can effectively capture spatial correlations and causal relationships between variables. It has a certain universality and can provide useful reference for other countries and regions. Due to significant differences in economic development levels, industrial structures, energy efficiency, and environmental policies among different countries and regions, the application of this framework in other regions may need to be adjusted appropriately based on local conditions. In addition, differences in policy environments and market mechanisms among countries can also affect the effectiveness of DE.

However, this study also has certain limitations, such as a short data time span and only covering Chinese cities, which limits the judgment of long-term trends and cross-border applicability. In addition, the measurement index system for digital economy and carbon emission efficiency still needs to be improved. Therefore, future research should further consider expanding the data time range, conducting cross-border comparative analysis, and adopting a more comprehensive DE indicator system. At the same time, conduct in-depth research on other potential mediating variables such as policies and social factors to fully understand the impact mechanism of DE on CEE.

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Authors’ contributions

The author confirms being the sole contributor of this work and has approved it for publication.

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Data availability

The data used to support the findings of this study are available from the corresponding author upon request.

Declarations

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

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Table 6 Decomposition of spatial metrology model (H3)

| Variable | Direct effect | Spillover effect | Total effect |
|----------|-----------------|------------------|-----------------|
| lnDige | 0.012c(0.0032) | 0.064c(0.0178) | 0.080c(0.0182) |
| lnGDP | 0.264c(0.0132) | 0.062c(0.0422) | 0.206c(0.0384) |
| lnPR | 1.572c(0.1262) | -1.290c(0.5640) | 0.282c(0.5424) |
| lnBLF | -0.001(0.0096) | -0.072c(0.0394) | -0.071c(0.0371) |
| lnFIN | -0.002a(0.0018) | -0.001(0.0112) | -0.003(0.0112) |
| lnMIN | -0.086c(0.0226) | -0.514c(0.1236) | -0.604c(0.1284) |
| lnCO | -0.092c(0.0058) | -0.074c(0.0288) | -0.115c(0.0301) |

^a: $p < 0.05$, ^b: $p < 0.01$, ^c: $p < 0.001$

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