TECHNIUM
SOCIAL SCIENCES JOURNAL

www.techniumscience.com

Vol. 74/2025

A New Decade for Social Changes

PLUS COMMUNICATION

International
Communication & PR

Technium Social Sciences Journal
Vol. 74, 189-204, August, 2025
ISSN: 2668-7798
www.techniumscience.com

Digital Economy and Carbon Emissions Reduction: The Mediating Impact of Industrial Structure Transformation

Wang Kai[1*], Aza Azlina Md Kassim[2]

[1 2]Management and Science University, Malaysia

wangkaihngy@163.com

Abstract. This study investigates the impact of the digital economy on per capita carbon emissions across 30 Chinese provinces from 2013 to 2022, with a specific focus on the mediating role of industrial structure transformation. A composite index of digital economy development is constructed using the entropy weight method and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The Three-Stage Least Squares (3SLS) method is applied to examine both direct and indirect effects. The results show that a 0.119-unit increase in the digital economy index leads to a reduction of approximately 25,900 tons in per capita carbon emissions, representing around 21.8% of the sample mean. Furthermore, the digital economy significantly reduces emissions by promoting the upgrading of industrial structures. These findings provide valuable insights into the mechanisms through which digitalization supports low-carbon development and offer important policy implications for achieving carbon reduction targets.

Keywords. Digital Economy; Carbon Emissions; Industrial Structure

Introduction

With the rapid development of digital technologies such as the internet, artificial intelligence, and blockchain, traditional economic activities including production, distribution, and consumption have undergone profound transformations. This shift has given rise to the digital economy, which represents a new phase in global economic development. As an emerging driver of the Fourth Industrial Revolution, the digital economy is reshaping industrial structures, enhancing productivity, and contributing to sustainable growth. Recognizing its strategic potential, China has made digital economy development a national priority to foster innovation, improve resource allocation, and support industrial upgrading.

At the same time, China has committed to ambitious environmental targets, including achieving peak carbon emissions and carbon neutrality. International experience suggests that digitalization can play a pivotal role in supporting low-carbon transitions. In line with this trend, China seeks to leverage digital economy tools to decouple economic growth from carbon emissions and to advance green and sustainable development pathways.

Against this backdrop, this study aims to examine whether the growth of the digital economy in China contributes to the reduction of carbon emissions. Specifically, it explores the mediating role of industrial structure transformation in this process. Given that the secondary industry remains a major source of emissions, this study investigates whether the digital economy can indirectly reduce emissions by facilitating a shift toward cleaner and more service-oriented industries.

Literature Review

The Relationship Between the Digital Economy and Carbon Emissions.

The emergence of the digital economy has introduced data and digital technologies as new production factors, thereby moving beyond the limitations of traditional factor-driven growth models. This transformation creates new opportunities for sustainable economic development. According to the Global e-Sustainability Initiative (GeSI, 2015), digital technologies have the potential to reduce global carbon emissions by up to 20% by 2030 through their applications across various industries. As such, the influence of the digital economy on carbon emissions has become a widely studied topic in academic discourse.

However, some studies argue that digitalization may increase carbon emissions due to the "rebound effect," wherein improvements in energy efficiency lead to increased consumption. For example, the frequent upgrading and operation of digital infrastructure such as servers, network equipment, and data centers can significantly raise energy consumption (Salahuddin et al., 2016; Wang & Li, 2016).

Recent research suggests that evaluating the carbon mitigation potential of the digital economy requires a broader perspective beyond digital technologies alone. Scholars have emphasized the need to account for the structural and systemic transformations driven by digitalization (She & Wu, 2022; Sun et al., 2023). Therefore, it is essential to develop a comprehensive and multi-dimensional index to measure digital economy development and analyze its impact on carbon emissions.

Industrial Structure and Carbon Emissions

The link between industrial structure and carbon emissions is a central issue in environmental economics. Numerous studies confirm that industrial expansion, especially in energy-intensive sectors, significantly increases carbon emissions (Chen & Wu, 2022). The secondary industry—including sectors like steel, cement, and petrochemicals—relies heavily on fossil fuels and contributes disproportionately to emissions (IEA, 2017).

In contrast, the tertiary industry, which includes services such as finance, information technology, and education, typically exhibits lower carbon intensity. Shifting toward a service-oriented industrial structure is therefore considered a viable strategy for reducing emissions while maintaining economic growth (Ström, 2024; Batrancea et al., 2021).

However, the energy demands of digital services—such as data centers, logistics, and digital platforms—are also rising and may partially offset emission reductions. Thus, the net impact of industrial upgrading on emissions requires empirical validation.

In this study, industrial structure serves as a mediating variable. Following Yu et al. (2022), we use the ratio of tertiary industry value added to secondary industry value added to capture the level of industrial upgrading. A higher ratio reflects a greater orientation toward low-carbon service sectors.

Digital Economy and Industrial Structure

The development of the digital economy drives the restructuring and transformation of industrial systems. Emerging digital technologies such as artificial intelligence, 5G, and the Internet of Things facilitate the reallocation of resources from low-efficiency sectors to high-productivity industries (Li & Wang, 2021).

First, digitalization enhances coordination across the value chain and reduces information asymmetry, allowing production factors to shift toward advanced manufacturing and modern service sectors. This enables the rise of new business models and improves the efficiency and quality of industrial output (Ma & Ning, 2020).

Second, digital technologies reduce entry barriers, promote competition, and break technological monopolies. These dynamics stimulate innovation, generate scale effects, and accelerate industrial upgrading. The application of digital tools in traditional industries also enhances resource efficiency and lowers operational costs (Qi et al., 2020; Xiao & Qi, 2019). Overall, digital transformation supports a structural shift toward less carbon-intensive economic activities (Li & Han, 2021).

Theoretical Mechanism

The digital economy offers a platform for optimizing industrial structure and advancing sustainable development. By integrating digital infrastructure with advanced technologies such as cloud computing and big data, the digital economy facilitates higher productivity, reduced energy intensity, and new growth engines.

Experiences from developed countries demonstrate that internal restructuring of secondary industries—such as promoting high-tech manufacturing and green services—can effectively lower carbon emissions (Grossman & Krueger, 1991). The digital economy accelerates this shift by enabling more efficient allocation of production factors and supporting the expansion of low-carbon sectors (Qi et al., 2020).

Moreover, traditional industries are increasingly adopting digital tools to improve energy management and production efficiency. For instance, Germany's "Industry 4.0" and the United States' "Advanced Manufacturing Partnership" emphasize digitalization as a strategy for green industrial upgrading (Kagermann et al., 2016).

The digital economy also fosters new business models—such as e-commerce, telecommuting, and the sharing economy—that reduce reliance on physical infrastructure, lower transportation needs, and enhance energy efficiency (Shen & Huang, 2020). Collectively, these mechanisms underscore the role of digitalization in facilitating carbon reduction and sustainable industrial transformation.

Research Design

Variable Description

This study includes independent, dependent, and mediating variables. The independent variable is Digital Economy (DE); the dependent variable is Carbon Emissions (CE); and the mediating variable is Industrial Structure (IS). For carbon emissions, control variables include Gross Domestic Product (GDP, representing economic development), Regional Population Density (FD), Social Consumption Level (CL), and Foreign Direct Investment (FDI, representing the degree of openness).

For industrial structure transformation, control variables include the Level of Economic Development (GDP), Level of Industrialization (GIS), Social Consumption Level (CL), and Industrial R&D Investment (RD)..

Variable Measurement Methods

Measurement of Carbon Emissions

This study applies the emission factor method outlined in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Publications - IPCC-TFI, 2007). Carbon emissions are estimated using the carbon emission coefficients for fossil fuels, following established academic practices (Liu et al., 2019). This approach is widely used for macro-level estimation and offers practical convenience. Table 1 presents the carbon emission coefficients for nine types of fossil fuels.

Table 1.IPCC Energy Conversion Factors

Energy	Average Low Calorific Value	Conversion Factor	Carbon Value per Unit Calorie（t/kg ）	Carbon oxidation rate(%)
Coal	20 908 kjoule/kg	0.7143 kgce/kg	26.37	0.94
Coke	28 435 kjoule/kg	0.9714 kgce/kg	29.5	0.93
Crude Oil	41 816 kjoule/kg	1.4286 kgce / kg	20.1	0.98
Fuel Oil	41 816 kjoule/kg	1.4286 kgce/kg	18.9	0.98
Gasoline	43 070 kjoule/kg	1.4714 kgce/kg	19.5	0.98
Kerosene	43 070 kjoule/kg	1.4714 kgce/kg	20.2	0.98
Diesel	42 652 kjoule/kg	1.4571 kgce/kg	21.1	0.98
Liquefied	41 816 kjoule/kg	1.4286 kgce/kg	17.2	0.98
Petroleum Gas	50 179 kjoule/kg	1.7143 kgce/kg	17.2	0.98
Natural Gas	38 931 kjoule/kg	1.3300 kgce/kg	15.3	0.99

Source: 2006 IPCC Guidelines for National Greenhouse Gas Inventories (*Publications - IPCC-TFI*, 2007).

The carbon emissions are calculated using the following formula (Equation 3-1):

$$CE = \sum_{i=1}^{9} E_i \times NCV_i \times CEF_i \tag{1}$$

In this context, CE represents carbon emissions, i denotes the i-th type of fossil energy, $E_i$refers to the consumption of the$i$-th type of fossil energy, and NCV_i represents the lower calorific value of the i -th type of energy. CEF_i is the carbon dioxide emission factor for the i -th type of fossil energy.

To enhance the robustness of the empirical analysis, this study normalizes the calculated carbon emission equivalents by population, deriving per capita carbon emissions, which are then used as the dependent variable.

Measurement of the Digital Economy

At present, there is no unified consensus in the academic community regarding a comprehensive system for measuring the digital economy. Although various research institutions have developed their own digital economy evaluation frameworks, the original data from these institutions are not publicly accessible and thus cannot be applied in this study.

To ensure the scientific rigor of this research, we draw upon existing literature and strike a balance between data availability and the comprehensiveness of the indicator system. Specifically, we collect provincial-level data from 2013 to 2022 across four key dimensions—digital finance, digital infrastructure, digital industrialization, and enterprise digitalization—to construct the digital economy evaluation index system (as shown in Table 2).

Table 2. Indicator system of digital economy development level

Level 1 Indicators	Level 2 Indicators	Level 3 Indicators
Digital economy	Digital finance	Breadth of digital financial coverage
		Depth of use of digital finance
		Level of online mobile payment
		Level of digital finance digitisation
	Digital infrastructures	Length of fiber optic lines
		Number of mobile phone subscribers
		Number of Internet broadband access
		Mobile phone penetration rate
		Mobile phone base stations
	Digital Industry	Software Business Revenue
		Telecommunication Revenue
		Employees in digital industry
	Enterprise Digitisation	Number of websites owned by enterprises
		Number of computers in use at the end of the period
		Number of e-commerce enterprises
		E-commerce sales

The measurement method combines the Entropy Weight Method and the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach. This integrated method is particularly advantageous when evaluating multidimensional economic indicators, as it allows for objective weighting based on data variability and provides a comprehensive ranking based on relative closeness to an ideal solution.The calculation process is as follows:

Positive indicators:

$$DE_{ij} = \frac{DE_{ij} - \min(DE_{ij})}{\max(DE_{ij}) - \min(DE_{ij})} \tag{2}$$

Negative indicators:

$$DE_{ij} = \frac{\max(DE_{ij}) - DE_{ij}}{\max(DE_{ij}) - \min(DE_{ij})} \tag{3}$$

The basic steps involve assuming there are m regions and n digital economy evaluation indicators, and the judgment matrix is constructed as follows:

$$DE_{ij} = (DE_{ij})_{mn} = \begin{bmatrix} DE_{11} & \cdots & DE_{1n} \\ \vdots & \vdots & \vdots \\ DE_{m1} & \cdots & DE_{mn} \end{bmatrix} \tag{4}$$

In the formula, X_{ij}represents the standardized value of the jth digital economy indicator for the ith region, and x_{ij} is the initial value of the jth digital economy indicator for the ith region.

The calculation of the share of the jth digital economy indicator in the ith region is represented by the formula:

$$P_{ij} = DE_{ij} \Big/ \sum_{i=1}^{M} DE_{ij} \tag{5}$$

Calculate the entropy value, Eq:

$$E_j = -K\left(\sum_{i=1}^{m} P_{ij} ln\, P_{ij}\right) \quad K = \frac{1}{lnm} \tag{6}$$

Determine the weights of the indicators using the formula:

$$W_j = 1 - E_{ij} \Big/ \sum_{i=1}^{m} (1 - E_{ij}) \tag{7}$$

TOPSIS Basic steps: Calculate the weighting matrix:

$$R = (r_{ij})_{mn} = \begin{bmatrix} W_1X_{11} & \dots & W_nX_{11} \\ \vdots & \vdots & \vdots \\ W_1X_{m1} & \dots & W_nX_{mn} \end{bmatrix} \tag{8}$$

Calculate positive and negative ideal solutions

$$\begin{cases} S_j^+ = \max(r_{1j}, r_{2j,} \dots r_{nj}) \\ S_j^- = \min(r_{1j,} r_{2j,} \dots r_{nj}) \end{cases} \tag{9}$$

Calculate the Euclidean distance between the indicator values of the area and the positive and negative ideal solutions:

$$D_i^+ = \sqrt{\sum_{i=1}^{n} (S_j^+ - r_{ij})^2}, \quad D_i^- = \sqrt{\sum_{i=1}^{n} (S_j^- - r_{ij})^2} \tag{10}$$

Relative proximity of indicator values to the optimal solution in each region C_i:

$$C_i = \frac{D_i^-}{D_i^- + D_i^+}, \quad C_i \in [0,1] \tag{11}$$

The regions are ranked based on the C_i value, where a larger C_i indicates that the digital economy development in the region is closer to the optimal value, reflecting a higher level of digital economy development, and vice versa.

The relative closeness C of the digital economy index values for the 30 provinces to the ideal solution has been calculated, and the scores have been ranked accordingly. Due to space limitations, only the average digital economy scores for the 30 provinces are presented. The results are shown in Table 3.

Table 3. Level of development of the digital economy

Rank	Province	Digital Economy Development Index
1	Beijing	0.5174
2	Guangdong	0.3993
3	Jiangsu	0.3099
4	Shanghai	0.2956
5	Zhejiang	0.2753
6	Shandong	0.2246
7	Sichuan	0.1812
8	Tianjin	0.1516
9	Fujian	0.1456

10	Liaoning	0.1442
11	Shaanxi	0.1333
12	Henan	0.1276
13	Hubei	0.1269
14	Chongqing	0.1226
15	Anhui	0.1198
16	Hunan	0.1040
17	Hebei	0.1002
18	Yunnan	0.0847
19	Guizhou	0.0819
20	Jiangxi	0.0797
21	Guangxi	0.0769
22	Jilin	0.0699
23	Hainan	0.0674
24	Gansu	0.0663
25	Shanxi	0.0656
26	Qinghai	0.0644
27	Heilongjiang	0.0562
28	Xinjiang	0.0558
29	Inner Mongolia	0.0540
30	Ningxia	0.0503

Measurement of Industrial Structure

Based on previous research, this study measures industrial structure using the ratio of the value added by the tertiary industry to that of the secondary industry in each region. Industrial structure plays a crucial role in the transmission mechanism through which the digital economy affects carbon emissions. By adjusting the proportional distribution among different industries, carbon emissions can be effectively controlled (Herrendorf et al., 2014).

The development of the tertiary sector (services) is generally associated with lower carbon emissions. Therefore, a higher ratio of tertiary to secondary industry value added often indicates lower overall carbon intensity (Felipe et al., 2019).

Introduction to the model

Basic Model Specification

The aim of this study is to investigate the impact of digital economy development on carbon emissions. The basic econometric analytical model chosen is expressed below:

$$CE_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_c X_{it} + \mu + \sigma_i + \varepsilon_i \quad (12)$$

Where CE_{it} represents the peak carbon of province i in period t; DE_{it} represents the level of digital economy development of province i in period t; X_{it} reflects a series of control variables that may affect the carbon emissions of provinces; ε_i represents the random disturbance term; α_1 is the coefficient of digital economy development, the value of which reflects its impact on the quality of the environment; and α_c is the estimation coefficient of the control variables. On this basis, the cyclical fluctuations of the economy and macroeconomic policies, which are unpredictable factors that change over time, may affect natural emissions, and in order to prevent them from leading to estimation bias, time-fixed effects σ_i are included; at the same time, there may be factors that do not change over time, such as geographic location, regional culture, and so forth, between provinces, and for this reason, provincial and municipal individual fixed effects μ are included in the model.

Model Specification for the Relationship between Independent Variables and Mediating Variables

This study further analyzes the impact of the mediating variable on carbon emissions, which helps to better understand the mechanism through which the digital economy influences carbon emissions. The following is the regression model illustrating the effect of the mediating variable on carbon emissions:

$$PC_{it} = \alpha_0 + \alpha_1 IS_{it} + \alpha_c X_{it} + \mu + \sigma_i + \varepsilon_i \quad (13)$$

In this context, IS_{it} represents the proportion of the tertiary industry structure in province i during period t ; DE_{it} denotes the level of digital economy development in province i during period t; V_{it} encompasses a series of control variables that may influence the development of the tertiary industry; ε_i indicates the random disturbance term. The coefficient α_1 pertains to digital economy development, reflecting the impact of digital economy growth on the upgrading of industrial structure, while α_c represents the estimated coefficients for the control variables. To prevent potential estimation bias, time fixed effects σ_i are incorporated. Additionally, since provinces may exhibit time-invariant factors such as geographical location and regional culture, province-specific fixed μ are included in the model.

Model Specification for the Mechanism of the Digital Economy's Impact on Carbon Emissions

Based on relevant theories and literature, this study further investigates the mediating mechanism through which the digital economy affects carbon emissions via industrial structure. Given that simultaneous equation modeling can eliminate potential correlations among the disturbance terms of different equations—thereby addressing the endogeneity issues that may arise from neglecting interdependencies in single-equation models—this study constructs a system of equations involving the digital economy, industrial structure, and carbon emissions.

By establishing a panel-based system of simultaneous equations, the digital economy, industrial structure, and carbon emissions are jointly estimated as interlinked components. Following the methodological approaches of Mobarak (2005) and Chen Honghui et al. (2012), the system of equations is constructed as follows:

$$\begin{cases} PC_{it} = a_0 + a_1 DE_{it} + a_2 IS_{it} + a_c X_{it} + \mu + \sigma_i + \varepsilon_{it} \\ IS_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 FDI_{it} + \beta_c V_{it} + \mu + \sigma_i + \varepsilon_{it} \end{cases} \quad (14)$$

Here, X_{it} represents the control variables that influence carbon emissions, while V_{it} denotes the control variables that affect industrial structure. The coefficient a_1 indicates the direct effect of the digital economy on carbon emissions, and the product $\beta_1 \times a_2$ represents the indirect effect of the digital economy on carbon emissions through industrial structure. The total effect is given by $a_1 + \beta_1 \times a_2$.

Analysis of empirical results

Before conducting the empirical analysis, the correlation coefficients and variance coefficients among variables are examined to assess potential multicollinearity issues. The correlation matrix in Table 4 presents the correlation coefficients between variables, with most values below 0.7, indicating relatively low linear correlation among the variables.

Table 4. Matrix of correlations

Variables	CE	DE	FDI	LNCL	LNGDP	LNFD	IS
CE	1.000						
DE	-0.252	1.000					
FDI	-0.207	0.673	1.000				
LNCL	-0.480	0.240	0.204	1.000			
LNGDP	-0.022	0.752	0.819	0.007			
LNFD	-0.352	0.604	0.653	0.424	0.602	1.000	
IS	-0.169	0.595	0.458	0.118	0.565	0.322	1.000

Although the correlation between the digital economy (de) and per capita GDP (lngdp) is relatively high, reaching 0.752, this likely reflects the strong association between economic development and digital economy advancement. However, this level of correlation remains within an acceptable range and is unlikely to cause significant multicollinearity problems.

Overall, the correlation matrix suggests that linear correlations among the variables are generally low, indicating that the variable selection is appropriate and that there are no evident multicollinearity issues.

OLS regression analysis

To eliminate the influence of outliers, all continuous variables are winsorized at the 1% upper and lower tails. To address potential endogeneity issues caused by omitted variables, both Fixed Effects and Random Effects models based on panel data are employed. The specific regression results are presented below.

The analysis begins with an OLS regression to preliminarily examine the impact of digital economy development on carbon emissions. As shown in Column (1) of Table 5, the regression coefficient of the digital economy is -21.80 and is significant at the 1% level, indicating a significant negative relationship between digital economy development and carbon emissions. This coefficient implies that when the digital economy index increases by 0.119, per capita carbon emissions decrease by approximately 25,900 tons, accounting for about 21.8% of the average emission level.

Table 5. Regression results

Variable	CE (1)	CE (2)	CE (3)
CE	-21.80*** (-4.50)	-24.76*** (-3.64)	-19.90** (-2.09)
DE		-10.12*** (-2.79)	5.386 (-1.45)
FDI		-38.63*** (-4.50)	-16.94*** (-2.61)

LNCL		11.91*** (-5.08)	5.716* (-1.74)
LNGDP		-1.783*** (-3.07)	-1.764 (-0.16)
Con	3.462*** (14.00)	-17.004*** (-2.57)	-26.627 (-0.50)
ID	NO	NO	YES
Year	NO	NO	YES
Obs	300	300	300
R^2	0.06	0.30	0.30

* p<0.1 ** p<0.05 *** p<0.01

In Column (2), carbon emission-related control variables are added to mitigate potential confounding effects on the causal estimation. The result shows that the negative impact of the digital economy on carbon emissions becomes even stronger, with a regression coefficient of -24.76, still significant at the 1% level.

In Column (3), both province and year fixed effects are included. The regression coefficient of the digital economy on carbon emissions is -19.90, and remains significant at the 5% level.

Among the control variables, the degree of openness (FDI), social consumption level, and population density all show significantly negative effects on carbon emissions, suggesting that these factors contribute positively to emission reduction. However, the coefficient for economic development is significantly positive, indicating that during the sample period, higher economic levels were associated with an increase in carbon emissions.

The regression results in Table 6 show that the coefficient of the tertiary industry's share in the industrial structure on carbon emissions is -9.357, which is statistically significant at the 1% level. This indicates that an increase in the share of the tertiary sector contributes to the reduction of carbon emissions. As the service sector forms the core of the tertiary industry, it is characterized by relatively low energy consumption. Furthermore, with the advancement of informatization and digitalization, the carbon emission intensity per unit of GDP has decreased even further. This result suggests that promoting industrial structure optimization and fostering the development of the tertiary sector—particularly green service industries—is a crucial pathway toward achieving a low-carbon economic transition.

Table 6. Regression results

Variable	CE
IS	-9.357*** (-6.67)
FDI	2.437 (0.81)
LNCL	-20.229** (-3.34)
LNGDP	2.450 (0.79)
LNFD	-10.820 (-1.06)

YEAR/ID	YES
Con	62.432 (1.22)
obs	300
R 2	0.303

* p<0.1 ** p<0.05 *** p<0.01

Stability test

To verify the robustness of the carbon reduction effect of the digital economy, this study replaces the dependent variable with the natural logarithm of total carbon emissions (LNPC) for regression testing. Compared to the "per capita carbon emissions" indicator, the logarithmic transformation of total carbon emissions helps mitigate potential bias caused by regional differences in population size. Specifically, per capita carbon emissions are easily influenced by population base—regions with large populations may still exhibit high absolute emissions despite low emission intensity, which can distort the consistency of regression results. By introducing the natural logarithm of total carbon emissions, differences in sample magnitude can be better controlled, thereby enhancing the robustness and reliability of the regression analysis.

According to the regression results in Table 7, when the dependent variable is replaced with LNPC, the regression coefficient of the digital economy index (DE) is -1.099 in Column (1) and -1.093 in Column (2), both of which are statistically significant at the 1% level. This suggests that a one-unit increase in the digital economy index is associated with an average reduction of approximately 66.2% in total carbon emissions (as a rough interpretation of the coefficient).

Table 7. Stability test -Regression results

Variable	LNCE (1)	LNCE (2)
DE	-1.099*** (-5.07)	-1.093*** (-4.19)
FDI		.162 (1.60)
LNCL		-.415** (-2.34)
LNGDP		.077 (0.86)
LNFD		1.26*** (4.23)
Year/ID	YES	YES
Obs	300	300
Constant	5.901*** (215.14)	-1.648 (-1.13)
R	0.290	0.366

* p<0.1 ** p<0.05 *** p<0.01

Further analysis reveals that whether the dependent variable is per capita carbon emissions or total carbon emissions, the digital economy consistently exhibits a significant negative effect on carbon emissions, confirming its important contribution to emission reduction.

In summary, by replacing the dependent variable with total carbon emissions for robustness testing, the negative impact of the digital economy on carbon emissions remains significant, indicating strong robustness of the results and providing greater support for the baseline regression model.

Mediation effect test

This section empirically examines the transmission pathways among the digital economy, industrial structure, technological innovation, and carbon emissions using a panel Three-Stage Least Squares (3SLS) estimation of simultaneous equations. The 3SLS method helps mitigate potential endogeneity issues in the model, effectively identifying the interrelationships between variables and disturbance terms, thereby enhancing the accuracy and validity of the simultaneous equation estimation.

According to the regression results in Table 8, the impact of the digital economy on carbon emissions through the industrial structure transmission pathway is analyzed. The table shows that the direct effect of the digital economy on carbon emissions has a coefficient of -14.898, which is significant at the 1% level. This indicates that an increase of 0.119 in the digital economy index directly reduces per capita carbon emissions by approximately 15%. Although the magnitude may not seem extremely large, in real-world settings, the development of the digital economy is a cumulative process, and its emission reduction effect tends to accumulate over time.

Moreover, the digital economy has a positive and significant effect on industrial structure (IS), with a coefficient of 3.442, meaning that for every one-unit increase in the digital economy index, the ratio of the tertiary industry to the secondary industry increases by 3.442. In addition, the regression coefficient of industrial structure on carbon emissions is -3.632 (also significant and negative), indicating that a higher proportion of the tertiary industry contributes to lower per capita carbon emissions. Based on the coefficient calculations, the indirect effect of the digital economy on carbon emissions via industrial structure is -12.5, and the total effect is -27.398. This suggests that when the digital economy index increases from its mean value of 0.145 to approximately 0.264, it could theoretically result in a more than 25% reduction in per capita carbon emissions—a considerable mitigation potential.

Table 8. IS Mediated effects Regression results

Variable	CE	IS
DE	-14.898** (-2.1)	3.442*** (11.89)
IS	-3.632*** (-3.75)	
FDI	-9.355*** (-2.73)	
LNCL	-31.485*** (-3.74)	1.652*** (5.73)
LNGDP	14.493*** (6.2)	0.349*** (5.52)
LNFD	-2.742*** (-4.9)	
GIS		-4.633*** (-15.08)

RD		-0.175*** (-7.78)
YEAR/ID	YES	YES
Con	-87.047*** (-4.03)	0.9411 (.49)
obs	300	300
R 2	0.321	0.808

* p<0.1 ** p<0.05 *** p<0.01

Overall, both the total and indirect effects of the digital economy on carbon emissions are significantly negative. This confirms the transmission pathway of “Digital Economy ↑ → Industrial Structure Upgrading ↑ → Carbon Emissions ↓”—indicating that the digital economy reduces carbon emissions not only directly, but also indirectly by promoting industrial structure optimization and upgrading. This result supports the original hypothesis H9, demonstrating that the digital economy contributes to carbon mitigation through both direct and indirect pathways. These two effects form a virtuous cycle: industrial upgrading further stimulates demand for digital technologies and markets, while the expansion of emerging service industries provides new platforms for technological innovation.

The primary reason behind this mechanism is that the digital economy relies heavily on network effects—in the process of industrial digitalization, the larger the enterprise scale and the more developed the data-sharing and collaboration platforms, the stronger the positive feedback loop. Furthermore, network effects not only drive market expansion but also promote the upgrading of traditional industries.

Conclusion

First, the digital economy index, constructed via the entropy-TOPSIS approach, reveals marked regional disparities, with eastern provinces exhibiting much higher digitalization levels than western provinces. This east–west divide has important implications for the effectiveness of digital-driven green transformation.

Second, the empirical evidence indicates that the digital economy exerts both direct and indirect negative effects on carbon emissions. Notably, the mediation analysis confirms that industrial structure upgrading—shifting from energy-intensive secondary industries to lower-emission tertiary sectors—serves as a key transmission channel for carbon mitigation. These findings highlight the multi-layered mechanisms through which digitalization supports sustainable development and inform the policy design for achieving carbon reduction targets.

Policy Implications

This study enriches the theoretical and empirical literature on the environmental impacts of digital transformation. The construction of a multi-dimensional digital economy index, and its integration with mediation analysis, provides a replicable framework for future research. Moreover, identifying the indirect effect via industrial structure advances the understanding of the complex pathways linking digitalization and low-carbon transition.

Implications for Government Regulation

Given the significant role of the digital economy in reducing carbon emissions, policymakers should:

Narrow the Digital Divide: Prioritize investment in digital infrastructure and talent development in central and western provinces to ensure nationwide benefits of digitalization.

Promote Industrial Upgrading: Design and implement policies that encourage the transition from energy-intensive manufacturing to service-oriented and high-tech industries. Pilot programs such as digital demonstration cities and digital industry clusters can help less-developed regions leapfrog toward green growth.

Support Digital Transformation of Enterprises: Incentivize traditional enterprises to adopt digital tools for improving resource allocation, production efficiency, and environmental performance.

Enhance Cross-regional Collaboration: Facilitate knowledge and technology transfer from leading eastern digital enterprises to less-developed regions, building an integrated digital ecosystem with strong emission-reduction spillover effects.

Research Limitations and Future Directions

The analysis relies primarily on provincial-level panel data; city-level or firm-level microdata are not included. Future research could explore finer spatial granularity and firm-level heterogeneity.

Some indicators of the digital economy and carbon emissions are limited by data availability and may not fully capture the dynamic evolution of digital transformation. As more data become available, alternative indicators and new digital economy dimensions can be incorporated.

With the ongoing rapid advancement of digital technologies, the measurement framework for the digital economy will require periodic updating to reflect emerging trends (e.g., AI, blockchain, green computing).

Further research is encouraged to investigate the micro-mechanisms at the enterprise level and the potential heterogeneity of digital economy effects across sectors and regions.

References

[1] OECD. (2015). OECD Digital Economy Outlook 2015. Paris: OECD Publishing.

[2] Wang, Y. (2023). New trends and characteristics in digital economy development. New-Type Urbanization, 7, 14.

[3] Global e-Sustainability Initiative (GeSI). (2015). SMARTer2030 ICT Solutions for 21st Century Challenges. https://smarter2030.gesi.org/downloads/Full_report.pdf

[4] Salahuddin, M., Alam, K., & Ozturk, I. (2016). The effects of Internet usage and economic growth on CO2 emissions in OECD countries: A panel investigation. Renewable and Sustainable Energy Reviews, 62, 1226–1235.

[5] Wang, Z., & Li, C. (2016). An empirical study on the energy-saving and emission-reduction effects of internet development in China: A regional perspective. Journal of China University of Geosciences (Social Sciences Edition), 16(6), 54–63+152.

[6] Shen, Y., & Huang, H. (2020). A study on the impact of digital economy development on the optimization and upgrading of the manufacturing industry structure: Based on panel data from Zhejiang Province, 2008–2017. Science and Technology Management Research, 40(3), 147–154.

[7] She, Q., & Wu, L. (2022). The carbon reduction effect of digital economy development. Economic Survey, 39(5), 14–24.

[8] Sun, X., Wang, Y., & Wang, Y. (2023). The development level of China's digital economy: Indicator system, regional disparities, and spatiotemporal evolution. Journal of Dalian University of Technology (Social Sciences Edition). Advance online publication. https://doi.org/10.19525/j.issn1008-407x.2023.06.005

[9] Chen, Y., & Wu, J. (2022). Changes in carbon emission performance of energy-intensive industries in China. Environmental Science and Pollution Research, 29(29), 43913–43927. https://doi.org/10.1007/s11356-021-18354-w
[10] International Energy Agency. (2017). Energy Technology Perspectives 2017.
[11] Zhao, X., Ma, X., Chen, B., Shang, Y., & Song, M. (2022). Challenges toward carbon neutrality in China: Strategies and countermeasures. Resources, Conservation and Recycling, 176, 105959.
[12] Ström, P. (2024). Services and the green transition in developing countries. In Rethinking Economic Transformation for Sustainable and Inclusive Development (pp. 123–142). Edward Elgar Publishing. https://www.elgaronline.com/edcollchap-oa/book/9781035348466/book-part-9781035348466-10.xml
[13] Batrancea, L., Pop, M. C., Rathnaswamy, M. M., Batrancea, I., & Rus, M.-I. (2021). An empirical investigation on the transition process toward a green economy. Sustainability, 13(23), 13151.
[14] Yu, Z., Fan, Y., & Luo, H. (2022). The impact of industrial structure upgrading on carbon emission intensity in China. East China Economic Management, 36(1), 78–87.
[15] Li, Z., & Wang, J. (2021). Development of the digital economy, allocation of data factors, and improvement of manufacturing productivity. Economist, 10, 41–50. https://doi.org/10.16158/j.cnki.51-1312/f.2021.10.005
[16] Ma, Z., & Ning, Z. (2020). Digital economy, factor allocation, and quality upgrading of manufacturing. Economic System Reform, 3, 24–30.
[17] Qi, Y., Xiao, X., & Cai, C. (2020). The digital restructuring of industrial organization. Journal of Beijing Normal University (Social Sciences), 2, 130–147.
[18] Xiao, X., & Qi, Y. (2019). The value dimensions and theoretical logic of industrial digital transformation. Reform, 8, 61–70.
[19] Li, Y., & Han, P. (2021). The impact of digital economy development on the optimization and upgrading of China's industrial structure: An empirical analysis based on provincial panel data. Commercial Economy Research, 6, 183–188.
[20] Grossman, G., & Krueger, A. (1991). Environmental Impacts of a North American Free Trade Agreement (No. w3914; p. w3914). National Bureau of Economic Research. https://doi.org/10.3386/w3914
[21] Kagermann, H., Anderl, R., Gausemeier, J., Schuh, G., & Wahlster, W. (2016). Industrie 4.0 in a Global Context: Strategies for cooperating with international partners. Herbert Utz Verlag. https://books.google.com/books?hl=zh-CN&lr=&id=6BidDQAAQBAJ&oi=fnd&pg=PA5&dq=Recommendations+for+Implementing+the+Strategic+Initiative+INDUSTRIE+4.0.+Final+Report+of+the+Industrie+4.0+Working+Group.&ots=EzRClmKmp-&sig=UpN_vfWyx-eXa28m_8RTwGxp-Oc
[22] Liu, C., Sun, Z., & Zhang, J. (2019). Policy effects of China's carbon emissions trading pilot on emission reduction. China Population, Resources and Environment, 29(11), 49–58.
[23] Shen, Y., & Huang, H. (2020). A study on the impact of digital economy development on the optimization and upgrading of the manufacturing industry structure: Based on panel data from Zhejiang Province, 2008–2017. Science and Technology Management Research, 40(3), 147–154.
[24] Institute of Digital Finance Peking University. (2024). https://en.idf.pku.edu.cn/
[25] National Bureau of Statistics of China of Yearbook. (2024).

https://www.stats.gov.cn/english/Statisticaldata/yearbook/
[26] Publications—IPCC-TFI. (2007). https://www.ipcc-nggip.iges.or.jp/public/2006gl/chinese/index.html
[27] Herrendorf, B., Rogerson, R., & Valentinyi, A. (2014). Growth and structural transformation. Handbook of Economic Growth, 2, 855–941.
[28] Felipe, J., Widyasanti, A., Foster-McGregor, N., & Sumo, V. (2019). Policies to support the development of Indonesia's manufacturing sector during 2020–2024: A joint ADB–BAPPENAS report. Asian Development Bank. https://books.google.com/books?hl=zh-CN&lr=&id=D-mGDwAAQBAJ&oi=fnd&pg=PT15&dq=Felipe+++industrial+structure&ots=nBovupDNK_&sig=Tnv2OdN73v9HFPh0CoLwz8kZHaM
[29] Xu, W., Zhou, J., & Liu, C. (2022). Spatial effects of digital economy development on urban carbon emissions. Geographical Research, 41. https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFQ&dbname=CJFDLAST2022&filename=DLYJ202201009&v=