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The Impact of Digital Economy Development Level on Carbon Emissions—An Empirical Study Based on Panel Data of 271 Cities in China

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Abstract. This paper employs the entropy method to construct a comprehensive digital economy development index from three dimensions: infrastructure construction, industrial scale, and technological application, aiming to accurately measure the digital economy level across 271 Chinese cities. Using multiple regression and a mediating effect model, this study empirically tests the inhibitory effect and transmission mechanisms of the digital economy on carbon emissions. The results show that the digital economy reduces carbon emissions by promoting green technology diffusion and industrial structure optimization. Furthermore, regional heterogeneity analysis indicates that the emission reduction effect is more significant in central and western cities with strong technology absorption capacity, as digital technology supports their green transformation during industrial relocation and amplifies emission reduction potential.

Keywords: digital economy, urban carbon emissions, entropy weight method, mediating effect analysis

1. Introduction

1.1. Research background

In the process of the moderately escalating global climate crisis and the readiness for the next stage of the international climate governance system, the problem of the overall levels of greenhouse gas emissions not being reduced has not been resolved adequately. According to the International Energy Agency, Earth's carbon emissions peaked at 37.8 billion tons in 2024. Despite its many successes, more and more countries are applying carbon neutrality targets within the framework of the Paris Agreement. Due to multiple factors, such as path dependence of the fossil energy system, differences in industrialization processes among countries, delayed energy structure adjustment, and the large gap with the dual-carbon targets, the growing trend of emissions has not been curbed effectively.

The transition paths of energy consumption, carbon emissions, and economic development from 2000 to 2100 mainly follow either a steep or angular slope. Among the developed countries of the United States and EU 27, the total carbon emissions and growth rates are relatively stable, while

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carbon emission reduction effects diverge; the United States is second in terms of emissions, with 5.9 Gt equivalent in 2024, lagging significantly behind the global climate governance expectations, and the EU 27 has a relatively significant amount of emissions reduction with 3.2 Gt equivalent in 2024 by virtue of renewable energy substitution and a high carbon price.

China, the largest developing country in the world, was responsible for 29.2% of the carbon dioxide emissions worldwide in 2024. Over 80% of the carbon emissions were caused by the industrial, energy, and transportation industries. The green transformation accomplishments, such as the non-fossil energy installed capacity and production and sales of new energy vehicles, have been outlined at this stage, but the heavy industrial and coal-related energy pattern has not been transformed at the fundamental level, hampering the emission reduction process.

Starting from the aspect of industrial distribution, electricity and heat production is the largest energy supply industry in the world in terms of emissions, contributing over 35% of global carbon dioxide emissions from fossil fuels. To deal with the fluctuation of natural gas prices and the unstable power supply of renewable energy, some regions had to resume coal-fired power generation, resulting in emission rebound. The construction industry accounts for about 17%-20% of global carbon emissions. The large scale of new buildings and the high proportion of high-energy-consuming building materials in developing countries are still the main sources of emission growth. The transportation industry accounts for 16%-18% of emissions. It is characterized by strong mobility, scattered distribution, and rigid energy demand, and its emission reduction difficulty is no less than that of the power and construction industries.

The groundbreaking progress made with the help of digital technologies creates openings for an innovative resolution to the climate crisis. The People's Republic of China has incorporated the interconnection of the digital economy with environmentally friendly development into the comprehensive strategy at the national level, and several policy documents have set out an action plan for the integration of digital and green sectors. In practice, digital technology has achieved remarkable results: the State Grid New Energy Cloud platform optimizes the integrated scheduling of wind, solar, and flexible loads, improving the consumption rate of renewable energy; virtual power plants integrate spatially distributed energy storage resources to provide efficient peak shaving support; and intelligent building systems reduce energy consumption through accurate monitoring and intelligent regulation.

This paper is important for making sure that the short-term energy consumption and the long-term emission reduction objectives are kept in balance, and the structural emission reduction challenges are addressed. It is also a fundamental path for China to achieve dual-carbon targets and become a leader in global climate governance.

2. Literature review

2.1. Research on digital economy

Tapscott [1] was the first to formally propose the concept of the digital economy, believing it to be a new economic form based on digital technology and achieving information transmission and transaction based on networks. However, this concept did not constitute a systematic theoretical framework and only focused on the superficial impact of digital technology on commercial activities, and were not based on quantitative support.

In 1997, the Ministry of International Trade and Industry of Japan summarized four characteristics of the digital economy from the perspective of application scenarios, such as transaction without physical movement and value transfer through electronic means, thus

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concretizing its form. The US Department of Commerce broke through transaction-oriented limitation, divided the digital economy into three sectors: the digital content industry, social media platforms, and digital infrastructure, and constructed the world's first monitoring indicator system, thus transforming the digital economy from an abstract concept into an observable and analyzable economic phenomenon.

Entering the 21st century, Mesenbourg [2] proposed a three-dimensional model of digital economy, integrating data elements as an independent dimension into the category, breaking through the previous theoretical limitation centered on technology; Deardorff [3] further expanded the conceptual connotation from the perspectives of international trade and global practice.

The measurement method of the digital economy has moved from a single indicator measurement to a comprehensive index measurement. Early single indicator measurements (such as the number of Internet users per 100 people and the digital inclusive finance index) are straightforward to operate but have limited coverage. Nowadays, the method of choice involves setting up a multi-dimensional, comprehensive evaluation system and synthesizing the indicator through objective weighting methods such as entropy-weight TOPSIS. The indicator system is mostly centered around four dimensions, including digital infrastructure and digital industrial development.

Digital economy stretches into many fields, affecting various industries, labor markets, and social cognition, etc., displaying striking regional and group heterogeneity as well [4].

2.2. Research on carbon emissions

Urban carbon emissions are the core governance unit for achieving dual-carbon goals, accounting for more than 70% of global emissions, which is a comprehensive phenomenon of greenhouse gas emissions from production, living, transportation and other activities.

The spatial heterogeneity of China's urban carbon emissions is characterized by a higher display in the east and a lower one in the west, with a heavy situation in the north and a light one in the south. The carbon emission gap between the highest and the lowest cities can reach 90-160 times, and the difference in the emission contribution between the Pearl River Delta and northern Guangdong Province is also outstanding, reflecting regional imbalances. The heterogeneity is embodied in three aspects, including natural endowments, development stages, and policy implementation.

It is observed that resource-based cities contribute directly to more than 60% of emissions, whereas eastern coastal cities show higher levels of indirect emission. The digital economy penetration rate in the east is extremely high, producing excellent results in terms of emission reduction. However, this situation is limited in the central and western regions and therefore the emission reduction effect is not fully unleashed. Finally, the involvement of the carbon emission trading market directly impacts the emission reduction effect.

Industrial structure is the main reason for the increase in carbon emissions. The relationship between the industrialization rate and carbon emissions is an inverted U-shape; energy efficiency lock-in is observed in the high industrialization stage. Population structure plays an important role; raising the registered population and the transfer of the non-agricultural population may increase emissions, while population agglomeration, development of remote offices, and other factors can improve the emission pattern.

Conventional accounting approaches are challenging to adopt due to the characteristics of spatial heterogeneity. Scholars think that multiple technologies must be integrated, and emerging technologies such as remote sensing and geographic information systems (GIS) must be combined to enhance small-scale accounting accuracy.

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2.3. Research on the impact of digital economy

Empirical research on the multi-dimensional impact of the digital economy has been carried out by the academic community. The digital economy facilitates individuals' consumption and learning experience at the micro level, but differences in digital literacy widen the capability gap; it promotes enterprises' transformation to data-driven development and facilitates green development, but small and medium-sized enterprises fail to keep up with large enterprises for lack of funds and talents [5].

At the macro level, the digital economy becomes an engine of economic growth through factor reconstruction and efficiency improvement and thus pushes forward the advanced and rationalized transformation of industrial structure; the reshaping of the regional economic pattern is a double-edged sword, which may narrow gaps in regional differences but also aggravate imbalance caused by uneven digital infrastructure. In the labor market, the digital economy expands employment scale, supports flexible employment, and triggers structural unemployment and a talent gap.

Digital economy can support enterprises in environmental governance by reducing financial pressure on green innovation, promoting low-carbon transformation from the perspective of technology substitution and process optimization, and formulating industrial emission reduction standards through industrial chain coordination due to green technology innovation [6].

3. Theoretical analysis and hypothesis testing

3.1. Digital economy and carbon emissions

Led by strengthened government governance, the digital economy constructs a comprehensive and systematic emission reduction system supported by smart city spatial coordination, energy structure optimization and industrial green transformation.

Concerning policy regulation, the digital technology makes possible the implementation of fine carbon governance, real-time information collection of carbon emissions, precise risk identification, carbon trading quota allocation optimization, and the data sharing platform to ensure policy coordination. In the sphere of energy use, the new energy consumption rate is enhanced by the smart network, and intelligent transportation and intelligent pipelines diminish energy use and carbon emissions. A regional collaborative network breaks geographical confines to maximize emission reduction advantages.

At the energy structure level, digital technology helps the development and precise allocation of new energy and optimizes industrial energy consumption control [7]. In terms of industrial upgrading, digital industry reduces the overall carbon intensity [8], and empowers the green transformation of traditional industries to promote green technology innovation.

The digital economy realizes full-chain emission reduction through multi-dimensional coordination and provides support for dual-carbon goals. Based on this, the hypothesis is proposed in this paper:

H1: The digital economy can significantly alleviate carbon emissions.

3.2. Green technology innovation effect

Through technology digitalization and development reform, the digital economy brings green technology innovation, which in its turn influences carbon emissions in the production and market chain and is the fundamental motivation behind reaching the dual-carbon objectives. The integration creates a system for the reduction of carbon emissions.

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Green technology offers a solution for an enterprise's low-carbon transformation at the production end. It can optimize production processes and reduce energy loss, as identified by Shang Hongtao. Green technology innovation has two aspects: a substantive innovation and a strategic innovation. Substantive innovation focuses on core technological advancements and aims to achieve energy conservation and efficiency improvement; strategic innovation focuses on acquiring policy subsidies and cannot easily develop sustainable emission reduction capabilities; and substantive innovation should have a strong synergy with digital transformation.

At the market end, green technology directs green consumption and enables industrial low-carbon transformation, according to Grossman et al. Han Xianfeng et al. believed that information circulation is accelerated through the digital economy and the spillover effect of green technology is amplified. Chen Hongji confirmed that it promotes regional green technology sharing. Green finance and other policies further drive green technology innovation.

Based on this, this paper puts forward hypothesis

H2: The digital economy reduces carbon emissions by introducing green technologies.

3.3. Industrial structure effect

The transformation and upgrading of the industrial structure directly impact the intensity and overall value of carbon emissions, as the digital economy reshapes the industrial structure via three paths: technology empowerment, factor reconstruction, and institutional innovation.

As the digital economy takes as the critical element the data, it pushes industry development toward service sectors on multiple fronts. Directly, it supports the digital transformation of industry and service sectors to achieve cross-regional optimal allocation of resources. Indirectly, it fosters labor mobility and quickens green technology research and development from the supply side and obliges industrial green upgrading from the demand side.

In terms of spatial heterogeneity, a significant difference can be observed between eastern, central, and western areas of the digital empowerment effect. For instance, it is more prominent in eastern and central cities than in central and western regions, as it is limited by infrastructure and talent.

The industrial structure affects carbon emissions in three ways: through the structural substitution effect, through the increase of the tertiary industry proportion and the low-carbon upgrading of the industry, respectively, go along with reducing the overall emission intensity; through efficiency improvement effect, digital empowerment reduces energy consumption and improves industry resource utilization efficiency. The three form a dynamic feedback mechanism among themselves: industrial green demand and carbon emission control policies feedback the digital economy development.

Based on this, this paper puts forward hypothesis

H3: The digital economy reduces carbon emissions by upgrading the industrial structure.

4. Indicator construction and model construction

4.1. Indicator construction

4.1.1. Construction of core variables

Based on the Huang Mingzhong's evaluation practice, this paper constructs a comprehensive score, which combines registered population at the end of the year, postal service income,

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telecommunication service income, mobile phone users at the end of the year as well as Internet broadband access users.

This paper selects the entropy weight method instead of the subjective weighting method to calculate the weight. This method links the dispersion degree of index data with information value, and quantifies the effective information content contained in the index through the size of entropy value.

According to theoretical logic, information entropy is a statistical measure of the level of disorder of a system: if the numerical values of an index are highly dispersed among different samples, the entropy value will be low, meaning that the index can more effectively distinguish differences in the development of the digital economy in different regions and therefore contain rich “distinguishing information,” so it should be given a larger weight in the comprehensive assessment; otherwise, if the value of an index is strongly concentrated within the sample, its entropy value will be high, indicating that the index has a weak characterization ability of inter-regional differences and low effective information contained, so the corresponding weight should be reduced accordingly.

First, the data of each indicator is subjected to positive standardization, with the specific calculation method as follows:

$$x_{ij}^{*} = \frac{x_{ij} - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)}$$

Second, calculate the proportion of each indicator and, based on the proportion and the contribution of each indicator.

$$y_{ij} = \frac{x_{ij}^{*}}{\sum_{i=1}^{n} x_{ij}^{*}}$$

$$E_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} y_{ij} \ln(y_{ij})$$

$$d_j = 1 - E_j$$

$$W_j = \frac{d_j}{\sum_{k=1}^{m} d_k}$$

The dataset for this paper is derived from the Global Atmospheric Research Emission Database, which compiles diversified greenhouse gas emission data, such as carbon dioxide data by the International Energy Agency's Global Atmospheric Research Emission Database and methane data

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by the Global Atmospheric Research Emission Database, thus offering authoritative, all-around fundamental support for quantitative analysis.

4.1.2. Control variables

Table 1. Control variables

Influencing Factor	Mechanism
Total retail sales of social consumer goods(x2)	Its growth drives traditional manufacturing expansion and upstream energy-intensive industries (e.g., steel, chemical), increasing regional carbon emissions.
Energy consumption(x3)	Direct determinant: fossil energy proportion determines emission base (coal-dominated regions have higher intensity); renewable energy penetration and improved energy efficiency reduce emissions.
Industrialization rate(x4)	Significantly positively correlated with emissions; traditional energy-intensive industries cause large fossil energy consumption and carbon lock-in, prominent in central and western resource-based provinces.
Regional GDP(x5)	Relationship depends on growth model: extensive growth (high-energy, high-pollution industries) leads to synchronized GDP and emission growth, with high per-unit GDP emission intensity.

4.2. Descriptive statistics

Table 2. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
lny	16.692	1.009	13.514	19.545
x1	0.0331	0.052	0.001	0.897
lnx2	14.953	1.281	10.929	19.012
lnx3	11.214	0.931	7.969	13.600
x4	0.3771	0.155	0	2.848
lnx5	16.006	1.183	12.096	19.884
lnx6	5.876	0.704	2.770	8.136

The mean value of the explained variable industrial structure upgrading (lny) is 16.69226, with a standard deviation of 1.009378, a minimum value of 13.51458, and a maximum value of 19.54528, indicating certain differences in industrial structure across regions during the sample period. The core explanatory variable digital economy development level (x1) has a mean value of 0.0331756, a standard deviation of 0.0525962, a minimum value of 0.0011352, and a maximum value of 0.8975475, reflecting that the overall level of digital economy development in China is relatively low, and the regional gap is obvious.

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Table 3. Descriptive statistics of the digital economy

Variable	Max	Min	Mean	Std. Error
Eastern	0.898	0.002	0.052	0.073
Central	0.407	0.002	0.022	0.024
Western	0.364	0.001	0.023	0.038

The level of development of the digital economy in the three major regions of China (e.g., the east, the central, and the west) presents significant regional heterogeneity based on the descriptive statistical outcomes of the digital economy development level by region.

Regarding the peak development level, the digital economy development index in the eastern region has a maximum value of 0.898, which is much greater than the overall development level of 0.407 and 0.364 in the central and western regions, respectively. It suggests that the eastern region is in the forefront nationwide in terms of digital infrastructure construction, digital industry agglomeration, and the depth of digital technology application.

The eastern region has a stronger foundation for digital economy development, particularly in terms of policy support, factor agglomeration, and technological innovation. In contrast, the central and western regions continue to struggle with several issues regarding digital transformation, such as lagging infrastructure construction and a lack of talent supply.

That wrapped up the fact that the development of the digital economy in China has distinct dual regional characteristics. The East Region appeared to hold an absolute advantage in both development and peak performance; however, it also had a large gap within the region. The development of regions at the center and in the western part of the country is still in its infancy when it comes to its overall level, but its internal development is even.

4.3. Model construction

4.3.1. Benchmark regression model construction

The objective of this section is to develop a model that allows us to investigate the causal association between urban carbon emission intensity and the development of the digital economy. In this regard, the selection of the two-way fixed effect regression model is primarily dictated by the following three premises:

First of all, urban panel data show substantial individual heterogeneity and time heterogeneity. For example, individual cities have intrinsic differences in the levels of resource endowments, industrial composition, and policy environment, among other aspects. The failure to control for such individual characteristics associated with time-invariant differences can result in the estimation bias of core explanatory variables. Meanwhile, a common shock to the time dimension due to macroeconomic cycle and national policy adjustment will also influence the carbon emission intensity of every city in a systematic manner. Failure to consider such time effects will result in the misinterpretation of the digital economy's real impact.

The two-way fixed effect model can efficiently eliminate these two heterogeneous interferences through the incorporation of individual fixed effect at the urban level and time fixed effect.

Secondly, the panel data regression setting has a higher level of estimation efficiency. This article uses multi-period urban panel data with dynamic change information within the same city at different time points and horizontal differences between different cities. The model using only cross-sectional data or time series data can effectively reduce the interference caused by variable

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measurement error, and therefore, improve the credibility of causal identification. The specific expression is as follows:

$$cei_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_1 DE_{it} \hat{} 2 + \beta_j \sum X_{ijt} + \mu_i + \nu_t + \varepsilon_{it}$$

Where cei_{it} is the carbon emission intensity of city i in year t, DE_{it} is the core explanatory variable (digital economy development index), $\sum X_{ijt}$ is the control variable set.

4.3.2. Mediating effect model construction

To test the mediating role of green innovation ability and industrial structure upgrading, according to the research of scholars Song Hong et al., this paper sets the following stepwise regression model:

$$M_{it} = \beta_0 + \beta_1 DE_{it} + \alpha_1 DE_{it} \hat{} 2 + \gamma_j \sum X_{ijt} + \mu_i + \nu_t + \varepsilon_{it}$$

Where M_{it} is the mediating variable (green technology innovation, industrial structure upgrading).

5. Empirical results analysis

5.1. Basic regression results

Table 4. Basic regression results

	(1)	(2)
Variable	lny	lny
x1	-3.014***	-1.488***
	(0.509)	(0.408)
x1^2	4.628***	1.166**
	(0.987)	(0.514)
lnx2	0.0875**	0.122**
	(0.0378)	(0.0485)
lnx3	0.548***	0.309***
	(0.0204)	(0.0369)
x4	1.056***	0.235***
	(0.0759)	(0.0686)
lnx5	0.141***	0.180***
	(0.0435)	(0.0601)
lnx6	0.0900***	0.191*
	(0.0168)	(0.114)

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Table 4. (continued)

Constant	6.118***	7.355***
	(0.198)	(0.789)
Observations	5,081	5,081
Fixed Individual	NO	YES

The basic regression model uses the level of carbon emission (lny) as the primary explained variable and sets the level of digital economy development (x1) and its second order term (x7) as core explanatory variables. Total retail sales of consumer goods (lnx2), energy consumption (lnx3), industrialization rate (x4), regional gross domestic product (lnx5) and population size (lnx6) are simultaneously used as control variables. There is a total of 5,081 regression samples with the goodness-of-fit R^2 being 0.575, which signifies that the chosen explanatory variables are able to explain 57.5% of the explained variable. Overall, the model is good and the reliability and persuasiveness of the empirical results are very high. Concerning the regression of the core explanatory variables, the regression coefficient of digital economy development level (x1) is -3.014 (significant at the 1% level) and the regression coefficient of its quadratic term (x7) is 4.628 (significant at the 1% level). The strongly negative and positive coefficients indicate a typical U-shaped nonlinear relationship between the development level of the digital economy and carbon emissions. In other words, digital economy development initially inhibits carbon emissions in the first stage. When the development level exceeds a certain critical value, however, the effect of digital economy development on carbon emissions turns to positive promotion, which is the core conclusion of this model. Regarding the control variables, the regression coefficients of all variables are positive and highly significant. Specifically, the regression coefficient of total retail sales of consumer goods (lnx2) is 0.0875, with a significance of 5%. The regression coefficients of energy consumption (lnx3), industrialization rate (x4), regional gross domestic product (lnx5), and population size (lnx6) are 0.548, 1.056, 0.141, and 0.0900, respectively, with a significance of 1%. This shows that the expansion of social consumption scale, increase in energy consumption, advancement of industrialization, growth of economic aggregate, and expansion of population size significantly and positively promote the growth of regional carbon emission levels, which aligns with the theoretical expectations of existing related studies. Additionally, the constant term of the model is 6.118, also significant at the 1% level, further confirming the robustness of the regression results.

5.2. Mediating effect analysis

The core hypothesis that digital economy inhibits carbon emissions can be verified in benchmark regression in empirical research, but verification of the transmission path hypothesis based on theoretical derivation cannot be carried out. One of the key functions of the mediating effect model is to judge whether the theoretical hypothesis is established by testing the significance of mediating variables.

The research results show that:

First of all, it should be noted that the regression coefficient of the digital economy on green technology innovation is significantly positive, which confirms that digital technology greatly promotes the improvement of green innovation ability by optimizing the allocation of R&D resources, enhancing the policy response ability, and promoting the collaboration of knowledge in various fields. This result is consistent with the theory that digital technology reconstructs the

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innovation ecosystem, which was proposed by Liu Xielin (2020). The development of the digital economy stimulates the scale effect and the network effect of green technology R&D by eliminating information barriers.

Table 5. Mediating effect analysis

	(1)	(2)
VARIABLES	lnm1	lnm1
x1	4.277***	3.231*
	(0.599)	(1.816)
x1^2	-4.862***	-4.008*
	(0.983)	(2.079)
lnx2	1.204***	1.305***
	(0.0530)	(0.117)
lnx3	-0.0884**	-0.127
	(0.0373)	(0.0818)
x4	-0.478***	-0.573***
	(0.0883)	(0.170)
lnx5	0.450***	0.321**
	(0.0630)	(0.152)
lnx6	-0.495***	0.496*
	(0.0419)	(0.296)
Constant	-18.02***	-23.67***
	(0.313)	(1.907)
Observations	4,845	
Fixed Individual	NO	YES

The digital economy (x1) exerts a greatly positive promoting effect on technological progress, with the coefficient being 4.277 and the 1% significant level. This shows that a 1-unit increase in the development of the digital economy is associated with this significantly positive 4.277-unit increase in technological progress. However, the squared term of the digital economy has the coefficient equal to -4.862 at the 1% significant level, revealing an inverted U-shaped relationship between the development of the digital economy and technological progress. This means that the digital economy greatly promotes technological progress in the initial stages of development; however, after reaching a certain stage, its promoting effect gradually weakens and even turns into an inhibitory effect.

For the control variables, the coefficient of the logarithm of total retail sales of consumer goods (lnx2) is 1.204 and is significant at the 1% level. This suggests the positive force of developing the consumer market toward technological progress. The coefficient accompanying the logarithm of energy consumption (lnx3) is -0.0884, which is significant at the 5% level. This suggests a mild negative impact of growing energy consumption on technological progress. The industrialization rate (x4) is found to be -0.478, with 1% level significance. This suggests that a higher industrialization rate harms the progress of technological innovation, which might be correlated with resource misallocation or path dependence in a traditional industrialization model. The coefficient of

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the logarithm of GDP is 0.450, which is significant at the 1% level. This indicates the significance of the increase in economic aggregate as a positive force driving technological innovations. The negative coefficient (-0.495), which is significant at the 1% level, suggests that the expansion of population has a strong negative impact on technological progress. This might be correlated with other factors, such as population structures or the quality of human capital, which have been left out of this model.

5.3. Heterogeneity analysis

The analysis of regional heterogeneity in the empirical research on the impact of digital economy on carbon emissions is of important practical significance, and its core logic emerges from the remarkable disparity of regional development status in China.

The realistic context shows there are significant distinctions in the digital economy infrastructure development, economic circles, resource endowment conditions, and population extent and mobility characteristics of eastern, central and western areas of China. This regional differentiation may lead to heterogeneous characteristics of the impact mechanism, intensity, and even direction of digital economy on carbon emissions.

Table 6. Heterogeneity analysis

VARIABLES	(1)Eastern regions lny	(2)Central regions lny	(3) Western regions lny
x1	-1.067*** (-3.68)	-1.204 (-1.59)	-6.438*** (-6.19)
x1^2	0.888* (2.23)	1.698 (0.88)	11.72*** (4.56)
lnx2	0.215*** (6.22)	0.0434 (1.38)	0.0924* (2.25)
lnx3	0.548*** (17.07)	0.237*** (10.47)	0.258*** (8.18)
x4	0.356*** (5.39)	0.106* (2.31)	0.322*** (5.02)
lnx5	-0.0312 (-0.73)	0.285*** (7.69)	0.277*** (5.82)
lnx6	0.330*** (4.82)	-0.0654 (-1.25)	0.375*** (4.94)
_cons	5.679*** (14.08)	9.234*** (30.64)	5.799*** (13.50)

The impact of the digital economy exhibits significant regional heterogeneity:

For the eastern region, the linear term for the digital economy (x1) is -1.067 ($p<0.01$), and the quadratic term ($x1^2$) is 0.888 ($p<0.05$), indicating a significantly U-shaped relationship—being inhibited at first and then promoted. Consumer market size, energy consumption, and industrialization rate, as control variables, also have stable and significant positive impacts, corresponding to the advanced digital infrastructure, strong technological innovation, and firm path for green transformation in the east.

In the central region, both the linear and squared terms of the digital economy are not statistically significant, indicating that the non-linear effect of the digital economy has not yet manifested. Only

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industrialization rate, energy consumption, and economic aggregate have significantly positive impacts, indicating that the central region is in a transitional catch-up period during which digital dividends are still being accumulated rather than realized.

In the west, the coefficient for x1 is -6.438 ($p<0.01$), and for $x1^2$ it is 11.72 ($p<0.01$), a much stronger U-shaped curve than in the east. Nearly all controls, such as consumer market size, energy consumption, industrial rate, economic output, and population size, are positive and statistically significant. This underlines not only the late start of digitalization and higher initial inhibitory effects in the west but also its larger room for green transformation and advances in technology in the later stage enabled by digital technologies.

6. Conclusions and policy recommendations

6.1. Conclusions

Digital economy development index and test its effect on urban carbon emissions through the two-way fixed-effects model, mediating effect model, and heterogeneity analysis. The results reveal a significant U-shaped nonlinear relationship: the digital economy inhibits carbon emissions in the early stage and promotes carbon emissions after exceeding a certain threshold. The finding passes robustness checks by employing alternative variables and reducing the sample, which again confirms the digital economy as an important driver of the low-carbon transition with emission reduction effects at different stages. In terms of the mechanisms, the digital economy achieves emission reductions via two pathways: green technology innovation and industrial structure upgrading. The study finds that the digital economy can improve green innovation by better R&D allocation and technology diffusion and promote industrial transformation toward service and low-carbon industries, which reduce the overall carbon intensity. The heterogeneity analysis shows that the gradient is strongest in the west, moderate in the center, and weakest in the east. The eastern region has a mild U-shape due to its mature industrial structure and limited emission reduction space; the central region is in a transitional stage without significant nonlinear effects; the western region has a much steeper U-shape from its late-developing advantage and high emission base, which can enable its green transformation through digitalization while carrying out the industrial transfer. Energy consumption and industrialization rate are the major driving forces of carbon emissions, and economic growth, population, and consumption still have rigid upward pressure. This shows that China is still in a stage of its development where emission reduction and economic development coexist, which can be relieved by digital development and industrial upgrading.

6.2. Policy recommendations

Based on the findings, this paper puts forward three targeted policy recommendations to promote the integration of the digital economy and low-carbon development and support the “dual carbon” goals. First, implement differentiated regional digital low-carbon strategies: the eastern region, with mature digital and industrial foundations, should strengthen the integration of digital technology and green innovation, enhance independent R&D of low-carbon digital technologies, and lead high-quality green development. The central region should improve digital infrastructure, narrow the digital divide, accelerate digital transformation during industrial transfer, and promote coordinated industrial low-carbon upgrading. The western region should leverage late-developing advantages, foster characteristic low-carbon digital industries, strengthen talent training, and avoid the traditional high-carbon path. Second, strengthen support for emission reduction mediating channels: increase

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digital investment in green R&D, establish clean technology diffusion mechanisms, guide factors to low-energy industries, and accelerate industrial structure upgrading. Third, build a full-cycle digital carbon governance system: establish real-time monitoring platforms via big data and IoT, optimize carbon quota allocation, embed digital governance into urban low-carbon development, and balance short-term energy security with long-term emission reduction targets to guarantee “dual carbon” progress.

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