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Assessing the Impact of the Digital Economy on Carbon Emission Reduction: A Test of the Mediation Effect Based on Industrial Agglomeration

Yuanlong Mao [1], Wenjing Dai [1], Yang Yang [1,*], Qiaoxia Liang [2,3] and Zichao Wei [4]

1 Wu Jinglian School of Economics, Changzhou University, Changzhou 213159, China; maoyuanlong@cczu.edu.cn (Y.M.); s24160254007@smail.cczu.edu.cn (W.D.)
2 College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China; liangqiaoxia@nieer.ac.cn
3 State Key Laboratory of Cryospheric Science and Frozen Soil Engineering, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou 730000, China
4 School of Cyber Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China; zcwei@hust.edu.cn
* Correspondence: yangyang@lzb.ac.cn

Abstract

As a pivotal engine of global economic growth, the digital economy provides nations with new momentum to achieve carbon neutrality. By driving inter-industry mobility and reallocation of production factors, the digital economy alters industrial agglomeration patterns, which ultimately influence carbon emissions. Understanding the intrinsic mechanisms through which the digital economy affects carbon emissions is therefore critical for both theoretical and practical significance in advancing green and low-carbon development. This study employs panel data from 278 Chinese cities (2011–2020) to investigate the mechanism by which the digital economy affects urban carbon emissions from the perspective of industrial agglomeration. Our findings indicate that the development of the digital economy significantly reduces urban carbon emissions; a one-percentage-point increase in digital economy development leads to a 0.091% decline in carbon emission intensity. Contrary to conventional expectations, however, higher levels of industrial agglomeration do not contribute to carbon reduction. Mediation analysis reveals that the digital economy enhances industrial agglomeration, which in turn weakens its direct carbon mitigation effect by approximately 6%. Furthermore, the impact varies across regions, city sizes, and industry sectors. These insights offer valuable policy implications for China's digital transformation, industrial agglomeration optimization, and energy-saving strategies to achieve its dual carbon goals.

Keywords: digital economy; industry agglomeration; carbon emission intensity; mediation effect; suppression effect

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1. Introduction

With the intensification of climate change, carbon dioxide emissions have become a major environmental concern worldwide. As a responsible major country, China is committed to fulfilling its international responsibilities under the Paris Agreement. Additionally, it aims to achieve a carbon peak before 2030 and carbon neutrality before 2060 [1]. This requires accelerating the adoption of resource-saving and environmentally friendly production methods, which means that China has entered a critical period of low-carbon economic transformation [2,3]. China's development trajectory since its reform and opening-up has been consistently accompanied by environmental challenges closely tied to urbanization. As the principal hubs of socioeconomic activity [4,5], cities serve dual roles as both engines of economic growth and primary sources of energy consumption and greenhouse gas emissions, particularly carbon dioxide. Empirical evidence indicates that urban areas may account for as much as 85% of China's total emissions [6], highlighting the critical importance of reducing urban carbon emissions in achieving the national dual carbon objectives.

In recent years, propelled by advancements in modern information and communication technologies (ICTs), such as big data analytics and artificial intelligence, digitization has been changing global production modes and lifestyles at a remarkable pace. The digital economy (DE) has emerged as a vital force for global economic growth [7]. According to the White Paper on Global Digital Economy (2023) [8], China's digital economy has consistently expanded since 2011, achieving an average annual growth rate of 16.4% that significantly outpaces GDP growth during the same period. It can offer solutions to mitigate climate change by optimizing resource allocation and fostering industrial integration and coordination [9–11]. Its transformative effect on traditional growth models plays a pivotal role in advancing low-carbon transitions in Chinese cities, which is essential for achieving sustainable development goals.

Meanwhile, industrial agglomeration (Agg) has played a crucial role in promoting China's economic growth while also leading to a series of environmental and climate issues [12–16]. On the one hand, Agg enhances resource utilization efficiency and fosters technological progress, which reduces energy intensity (energy consumption per unit of output) and indirectly contributes to energy conservation and emission reduction. On the other hand, it also expands production scale, which escalates carbon emissions and exacerbates regional pollution, thereby impeding the achievement of energy-saving targets. With the rapid advancement of industrial and digital industrialization, the digital economy fosters economic development by enhancing labor and capital productivity, reducing transaction costs, improving access to international markets [17], and serving as a key driver for accelerating China's economic transformation and development [11,18–21]. The development of the digital economy not only breaks through traditional limitations of space and time but also provides opportunities for the free flow and cross-border allocation of crucial industrial factors like capital and talent [22]. It can also integrate, empower, and combine industrial resources through data elements, thereby promoting technological and efficiency advancements [23–26]. These transformative shifts not only reshape the patterns of factor allocation but also drive adjustments in industrial production and business models. Such dynamics exert substantial moderating effects on both industrial agglomeration development and its environmental outcomes, thereby positioning them as a critical contributing factor to reducing regional carbon emission intensity (CI).

In this context, integrating industrial agglomeration factors into the analysis of the digital economy–carbon emissions nexus can not only promote the digital economy but also offer new solutions for reducing carbon emissions. This has significant practical implications for China to transform its economic development model and achieve green and low-carbon growth. Based on existing research, the primary contributions of this paper are as follows: Firstly, this article provides a new perspective for theoretical analysis of the digital economy and carbon emissions relationship. Secondly, unlike existing studies that focus on national and provincial levels, this paper uses Chinese prefecture-level cities as samples, thereby enriching related theoretical achievements. Thirdly, considering the varied performance of carbon emissions across regions and industries, we conduct comprehensive heterogeneity analyses to derive more actionable policy recommendations.

2. Literature Review and Hypothesis

2.1. Digital Economy and Carbon Emissions

With the advancement of information technology, the digital economy has grown significantly, becoming a crucial engine for economic development. Especially in the 21st century, the digital economy has reshaped the global competitive landscape and is a core driving force behind high-quality economic growth [27–29]. Consequently, many studies have explored the economic benefits of the digital economy, while recent research has begun to examine its impact on carbon emissions [30,31].

As a new form of economy [32], the digital economy, when combined with the real economy, can positively impact energy efficiency and green development by optimizing resource allocation, promoting technological innovation, and forming a diversified governance system. Studies have shown that the digital economy helps reduce carbon dioxide emissions and carbon emission intensity [33,34] and has a significant positive spatial spillover effect on carbon emissions [35,36]. This has an important positive impact on promoting high-quality regional economic development. However, some studies have found that the impact of the digital economy on carbon emissions is non-linear [37,38]. There is a threshold or inflection point where the digital economy can cause a "rebound effect," leading to increased energy use and worsening environmental quality instead of improving it [39,40].

Considering China's actual development trajectory, the digital economy, with its inherent advantages in information integration and unique capacity to synergize digital knowledge with modern information networks, demonstrates greater long-term efficiency and resilience in China. The digital economy exhibits high innovation potential, strong penetrative power, and extensive coverage, facilitating technological advancements and energy market upgrades [41,42]. Energy enterprises can leverage the digital economy to integrate traditional energy sectors with digital energy divisions, significantly enhancing operational and production efficiency through renewable energy sources and novel energy ecosystems [43,44].

Furthermore, the digital economy, which possesses distinctive characteristics, including information sharing and regional fluidity, strengthens social production and consumption systems by reducing information acquisition costs while exploiting the cross-regional nature of economic activities. This not only effectively mitigates the misallocation of production factors such as labor and capital, thereby significantly boosting production efficiency [45], but also facilitates real-time monitoring of critical input factors like energy, enabling more efficient intelligent matching. Through resource integration, it strengthens dynamic interlinkages, effectively guiding and achieving rapid optimal resource allocation. Consequently, while further stimulating economic expansion, it substantially elevates energy utilization efficiency, ultimately exerting a positive impact on reducing urban carbon emission intensity.

Based on this framework, we propose the following hypothesis:

H1: *The development of the digital economy exhibits a negative relationship with carbon emission intensity.*

2.2. Digital Economy and Industrial Agglomeration

Technological factors have consistently served as pivotal drivers in reshaping industrial geographic patterns. The rise of the digital economy has significantly reduced traditional production constraints, such as those tied to enterprise factor endowments and geographical location. This reduction in barriers facilitates firm relocation and migration while simultaneously fostering industrial agglomeration.

Firstly, the digital economy fundamentally reduces transaction costs, serving as a critical driver of industrial agglomeration. Enabled by advanced technologies such as 5G networks, big data analytics, and the Internet of Things (IoT) [46], the digital economy enhances the value, volume, variety, and velocity of big data, thereby improving data transparency and optimizing supply–demand matching [47]. By reducing spatial and temporal constraints on labor, which mitigates labor market asymmetries while expanding employment opportunities [48,49], this development attracts both technical talent and capital investment, thereby enabling related industries to agglomerate in regions where advanced digital ecosystems exist. According to transaction cost theory, which posits cost reduction as a critical for firms seeking external innovation resources and technologies, the digital economy's lower transaction costs not only release capital and management resources for innovation but also substantially enhance inter-firm information sharing and production coordination.

Secondly, knowledge spillover is crucial for industrial agglomeration. The digital economy's rapid development has intensified regional technological advantages and locational attractiveness, thereby generating significant knowledge spillover effects [50] and establishing efficient information exchange platforms. In contrast, the facilitation of new knowledge and technology diffusion among geographically proximate industries creates a chain reaction that attracts additional enterprises to co-locate, further reinforcing regional industrial agglomeration dynamics. Empirical studies show that information transmission still requires processing and response time [51]. This phenomenon is particularly observable in knowledge spillover effects, where a persistent tendency toward regional clustering characterizes enterprise location decisions [52]. To optimize innovation and technology spillovers in the digital economy, enterprises actively relocate toward counterparts with superior digital capabilities, thereby serving as catalysts for knowledge diffusion while simultaneously reinforcing industrial agglomeration dynamics.

Based on this framework, we propose the following hypothesis:

H2: *The digital economy significantly promotes industrial agglomeration.*

2.3. The Impact of the Digital Economy on Carbon Emissions: The Moderating Role of Industrial Agglomeration

In research on the impact of the digital economy on carbon emissions, most previous studies have focused on promoting green technology innovation and optimizing industrial structure [26,53,54]. These studies have shown that the digital economy facilitates the efficient dissemination and diffusion of knowledge and information, which improves regional resource utilization, breaks down innovation boundaries, and effectively promotes technological progress. At the same time, it can optimize and upgrade the industrial structure by improving resource allocation and enhancing communication and collaboration between industries. This reduces pollutant emissions and promotes green transformation [55,56]. For industrial agglomeration, an important form of industrial structural change [57], the development of the digital economy facilitates inter-industry cooperation, reduces transportation and transaction costs in agglomeration areas, and attracts production factors such as capital, labor, technology, and data. This strengthens the foundation of industrial agglomeration, affects its process and level in the region [58], and ultimately impacts regional carbon emissions.

However, the specific role that industrial agglomeration plays in the impact of the digital economy on carbon emission intensity is closely related to the relationship between industrial agglomeration and carbon emissions. There has been extensive research on this relationship, but the conclusions are not entirely consistent. There are three main views. One view is that industrial agglomeration leads to scale and congestion effects [59–61], which directly increase energy use and carbon emissions in production [62], and exacerbate environmental pollution in the agglomeration area [63,64]. Another viewpoint is entirely the opposite, arguing that industrial agglomeration plays a positive role by sharing infrastructure, enhancing industrial competitiveness, optimizing resource allocation, and encouraging technological innovation, thus fueling rapid national economic growth [65,66]. The continuous improvement of industrial agglomeration levels can generate significant externalities, improving production efficiency, reducing carbon emission intensity [67,68], and decreasing environmental pollution [69,70]. Another viewpoint suggests that the impact of industrial agglomeration on carbon emissions may be non-linear, with a certain critical value. Above and below this critical value, the effects can differ or even be completely opposite [71,72]. This non-linear impact is often closely related to specific regions, periods, and stages of economic development.

However, empirical observations of industrial agglomeration in China reveal persistent issues with homogenization in production/operational models and detrimental competition. Multi-industry participation in product manufacturing frequently disrupts market competition order. When cutthroat competition induces resource scarcity, it may inadvertently crowd out green innovation, creating a "congestion effect." The threshold level of agglomeration referenced in studies is often not easily achieved. Consequently, while the digital economy promotes greater industrial agglomeration, this agglomeration may predominantly exert a negative influence on the relationship between the digital economy and carbon emission intensity.

Based on this framework, we propose the following hypotheses:

H3: *Industrial agglomeration development generally exerts an adverse effect on the reduction of carbon emission intensity.*

H4: *Industrial agglomeration performs a suppression effect in the impact of the digital economy on carbon emission intensity.*

Empirical studies on Chinese cities reveal significant economic disparities across urban centers due to variations in city size, geographic location, and industrial structure. Consequently, the role of industrial agglomeration in the digital economy's impact on carbon emission intensity may also exhibit substantial heterogeneity. First, digital convenience incentivizes firms to locate in larger cities. Research by Wen et al. [73], Li et al. [74], and Zhang et al. [75] demonstrates that the economic effects of the digital economy display heterogeneity across city sizes. Second, the development level of the digital economy in China's eastern, central, and western regions generally follows an east-to-west gradient. This may lead to regional heterogeneity in how the digital economy and industrial agglomeration influence regional economic resilience. Liu et al. [76] confirm that China's digital economy development, industrial agglomeration, and green innovation efficiency exhibit spatial heterogeneity characterized by "higher in the east, lower in the west." Third, Zeng et al. [50] indicate that the digital economy exerts nonlinear threshold effects on industrial agglomeration, revealing sectoral heterogeneity. Wang et al. [77] further synthesize that the digital economy's promotional effect on manufacturing agglomeration is more pronounced in samples from small- to medium-sized cities, central-western regions, and high-technology industries.

Based on this framework, we propose the following hypothesis:

H5: *The effect of industrial agglomeration in the relationship between the digital economy and carbon emission intensity is subject to heterogeneous influences from city size, geographic location, and industrial structure types.*

Based on the analysis of the three aspects described above, this paper presents a theoretical mechanism map (Figure 1).

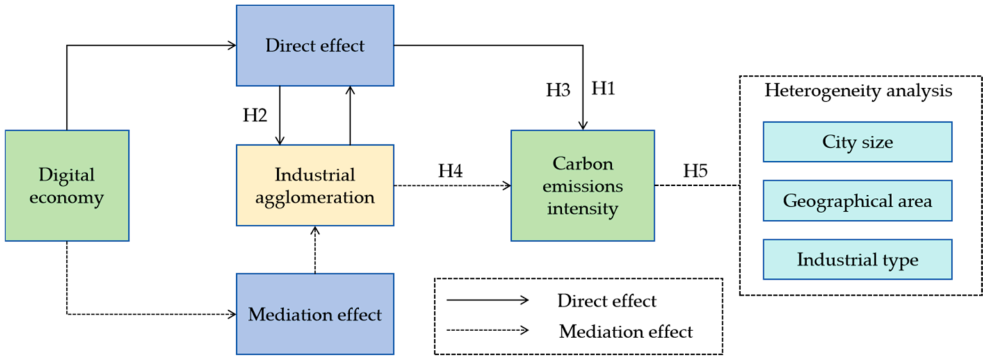

Figure 1. Theoretical mechanism framework.

3. Research Design

3.1. Model Construction

To explore the relationship among the digital economy, industrial agglomeration, and urban carbon emission intensity, this paper constructs a panel regression model proposed by Baron and Kenny [78] and applies the treatment approaches of Aguinis et al. and Shehzad et al. to test the mediation effect [79,80].

The first step is to examine the direct impact of the digital economy on carbon emission intensity.

$$\mathrm{lnCI_{it}} = \alpha_0 + \alpha_1 \mathrm{lnDE_{it}} + \alpha_2 \mathrm{Control} + \varepsilon_{it} \tag{1}$$

Here, i and t refer to city and year, respectively, CI represents the carbon emission intensity, DE represents the level of digital economy, Control represents the control variable, and ε is a random error term.

The second step is to examine the direct impact of industrial agglomeration on carbon emission intensity. At the same time, to verify that digital economy will indirectly affect carbon emission intensity through industrial agglomeration, industrial agglomeration is taken as a mediating variable, and the Sobel test is used to determine whether an intermediary effect exists. Since the mediating variables exhibit characteristics of endogenous explanatory variables to some extent, a simultaneous equation model is established.

$$\begin{cases} \mathrm{lnAgg_{it}} = \lambda_0 + \lambda_1 \mathrm{lnDE_{it}} + \lambda_2 \mathrm{Control} + \delta_{it} \\ \mathrm{lnCI_{it}} = \beta_0 + \beta_1 \mathrm{lnAgg_{it}} + \beta_2 \mathrm{Control} + \xi_{it} \end{cases} \tag{2}$$

Here, Agg represents the industrial agglomeration, and δ and ξ are random error terms.

The third step is to incorporate both the digital economy and industrial agglomeration into Equation (3) and analyze their impact on urban carbon emission intensity.

$$\mathrm{lnCI_{it}} = \gamma_0 + \gamma_1 \mathrm{lnDE_{it}} + \gamma_2 \mathrm{lnAgg_{it}} + \gamma_3 \mathrm{Control} + \mu_{it} \tag{3}$$

Here, μ is a random error term.

3.2. Variable Selection

3.2.1. Explained Variables

Carbon emission intensity (CI): This paper refers to the method adopted by Cong et al. [81] and Jing et al. [82] to calculate the annual total carbon dioxide emissions of each prefecture-level city. The carbon emission intensity is then calculated by dividing the total carbon dioxide emissions by the gross domestic product.

3.2.2. Explanatory Variables

Digital economy level (DE): At present, due to the strong penetration of the digital economy, it is difficult to accurately separate it from economic activities in statistics; therefore, it is not easy to calculate the development level of the digital economy, and there is no unified calculation standard. Most scholars choose to construct a multi-indicator evaluation system to measure the level of digital economy development in various regions. Based on this, this paper draws on the approach by Wang and Shao [83], then comprehensively calculates the digital economy development index using the number of mobile phone users per 100 people, the number of internet users per 100 people, the ratio of employees in information transmission, computer services, and software industries to all industries, and the digital inclusive financial index jointly compiled by Peking University and Ant Financial. The measurement employs the entropy weight method.

3.2.3. Mediating Variables

Industrial agglomeration level (Agg). There are several methods for measuring industrial agglomeration, among which location entropy is the most common method, having unique advantages in eliminating regional scale differences and reflecting spatial distribution characteristics. Therefore, this paper chooses the location entropy index to measure the degree of industrial agglomeration for each city. The calculation approach refers to the practice of O'Donoghue and Gleave [84], which has been widely adopted [85], and uses the number of employees in prefecture-level cities to calculate an entropy index that reflects the level of industrial agglomeration. The detailed formula is expressed as follows:

$$\mathrm{Agg}_{it} = \left(\frac{s_{ijt}}{\sum_i s_{ijt}}\right) / \left(\frac{\sum_j s_{ijt}}{\sum_i \sum_j s_{ijt}}\right) \tag{4}$$

where S_{ijt} is the proportion of the number of employees in industry j at the end of year t in city i to the total employment in city i.

3.2.4. Control Variables

According to the existing literature, the influencing factors of carbon emissions mainly include technological innovation, industrial structure, environmental regulations, openness, population density, energy consumption intensity, etc. [86–91]. Based on this, the following variables are used as control variables in this paper. The first is scientific and technological innovation (sci). Considering that financial support is an important guarantee for innovation, this paper selects the indicator of per capita scientific and technological investment in the financial expenditure of each city to measure it, with a unit of CNY per person. The second variable is industrial structure (str), which compares the ratio of the output value of the tertiary industry to that of the secondary industry to characterize the differences in industrial structure between different cities, with a unit of %. The third variable is environmental regulation intensity (ei). At present, there is still controversy over the measurement method for environmental regulation, and no unified indicator exists that can directly reflect the intensity of environmental regulation. Therefore, this paper selects indicators such as the comprehensive utilization rate of general industrial solid waste, the harmless treatment rate of household waste, and the centralized treatment rate of sewage treatment plants, and then uses the entropy method to calculate the environmental regulation index. The fourth variable is the degree of openness, measured by foreign direct investment (fdi), which is adjusted to CNY valuation based on the central parity rates of the USD/CNY in each year, with a unit of CNY 10,000. The fifth variable is population density (den), which is measured by the total number of people per square kilometer within the municipal district for each city. The sixth variable is energy consumption intensity (ec), which is measured as the amount of energy consumed (ton of standard coal) per CNY 10,000 of industrial added value.

3.3. Data Resources

Considering the availability and completeness of data for the selected variables, this paper excluded cities with severe data gaps, ultimately selecting 278 prefecture-level cities for the study. The data are primarily sourced from the China Urban Statistical Yearbook, the China Energy Statistical Yearbook, the China Regional Economic Yearbook, the China Environmental Statistical Yearbook, the China Environmental Yearbook, and various provincial and city statistical yearbooks and bulletins. A small number of missing values were filled using interpolation. Additionally, to avoid heteroscedasticity, all variables (except for industrial structure variables expressed as percentages) are logarithmically transformed. Descriptive statistics of the variables are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variables	Description	Mean	Std. Dev.	Min	Max
lnCI	carbon emission intensity	0.679	0.876	−1.954	3.208
lnDE	digital economy level	−3.186	0.687	−5.976	−0.236
lnAgg	industrial agglomeration level	2.904	0.241	2.176	4.048
lnsci	scientific and technological innovation	4.538	1.204	1.667	10.033
str	industrial structure	1.026	0.580	0.114	5.348
lnei	environmental regulation intensity	−0.663	0.139	−1.568	−0.376
lnfdi	foreign direct investment	6.458	1.723	0.000	7.762
lnden	population density	5.758	0.896	1.609	7.882
lnec	energy consumption intensity	−2.871	0.768	−5.499	2.705

Note, Std. Dev. refers to standard deviation.

4. Empirical Analysis

4.1. Panel Unit Root Tests and Multicollinearity Test

For panel data with extended time series, variables often exhibit shared trends despite lacking inherent causal relationships. Regressing such data may yield high R-squared values but statistically meaningless results. This phenomenon is known as spurious regression [92]. To ensure estimation validity and avoid spurious regression, testing the stationarity of panel series is essential. Given the dual possibilities of common or individual unit root processes across cross-sectional sequences, this study employs two methodological groups to ensure robustness: homogeneous unit root tests using the LLC and Breitung methods and heterogeneous unit root tests using the IPS and Fisher-ADF methods. A series is conclusively deemed stationary only if both test groups reject the null hypothesis of unit root presence. Conversely, failure to reject in either group indicates non-stationarity. The results of these panel unit root tests are reported in Table 2.

The test results show that all variables strongly reject the null hypothesis that there is a unit root, that is, all variables are stationary. Regression analysis conducted on stationary variables will yield valid results, effectively avoiding spurious regression. Meanwhile, prior to conducting regression analysis on the variables, a correlation analysis must be performed to assess their interrelationships. If multicollinearity exists, it may lead to statistically inefficient parameter estimates, resulting in model distortion or inaccurate estimations. Here, we employ the Pearson correlation coefficient for assessment, with results presented in Figure 2.

Table 2. Panel unit root tests.

Variables	LLC	Breitung	IPS	Fisher-ADF
lnCI	−13.2469 *** (0.0000)	−3.0114 *** (0.0013)	−14.1226 *** (0.0000)	41.2567 *** (0.0000)
lnDE	−28.034 *** (0.0000)	−6.8489 *** (0.0000)	−12.8414 *** (0.0000)	49.8142 *** (0.0000)
lnAgg	−35.2644 *** (0.0000)	−3.8626 *** (0.0001)	−9.0141 *** (0.0000)	84.1622 *** (0.0000)
lnsci	−13.2429 *** (0.0000)	−2.2599 ** (0.0119)	−6.9593 *** (0.0000)	52.0277 *** (0.0000)
str	−11.1849 *** (0.0000)	−2.4296 *** (0.0076)	−3.3723 *** (0.0004)	34.8830 *** (0.0000)
lnei	−45.7399 *** (0.0000)	−3.0570 *** (0.0011)	−14.4470 *** (0.0000)	47.2148 *** (0.0000)
lnfdi	−60.6075 *** (0.0000)	−2.6581 *** (0.0039)	−12.9011 *** (0.0000)	66.6766 *** (0.0000)
lnden	-2.7×10^2 *** (0.0000)	−2.3497 *** (0.0094)	−6.0179 *** (0.0000)	114.2309 *** (0.0000)
lnec	−19.2647 *** (0.0000)	−2.7955 *** (0.0026)	−10.1035 *** (0.0000)	77.2898 *** (0.0000)

Note, ** and *** represent the 5% and 1% significance levels, respectively.

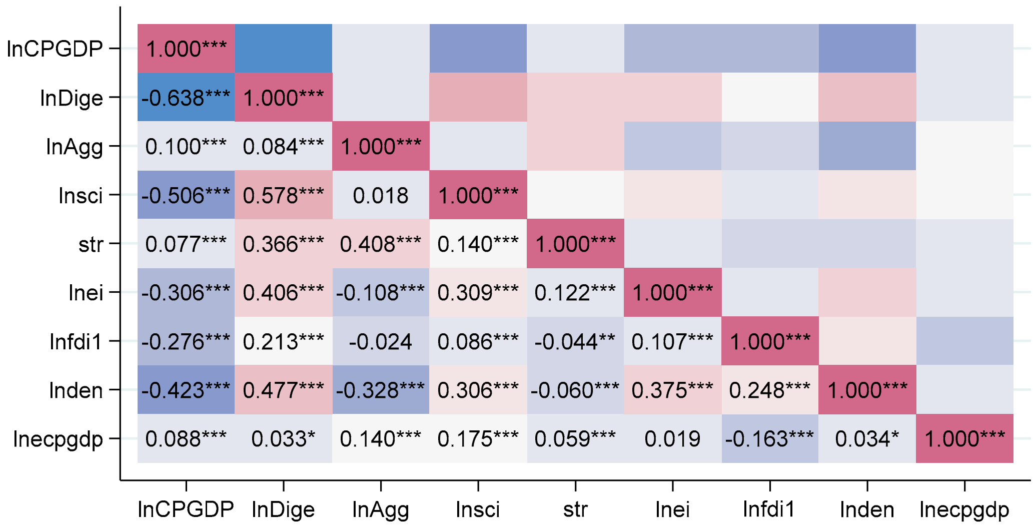

Figure 2. Correlation heatmap. The intensity of color represents the strength of correlation. *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively.

Conventionally, a Pearson correlation coefficient that exceeds 0.8 indicates potential multicollinearity. As shown in Figure 2, multicollinearity can be reasonably neglected in subsequent regression analysis. Moreover, the heatmap reveals: a significant negative correlation between carbon emission intensity and the digital economy, a significant positive correlation between carbon emission intensity and industrial agglomeration, and a significant positive correlation between the digital economy and industrial agglomeration. These statistically robust relationships establish a solid foundation for subsequent hypothesis testing. Additionally, by calculating the variance inflation factor (VIF) of the variable, it was found that the average VIF value was 1.505, and the highest and lowest VIF values were 2.327 and 1.34, respectively. These values are also far below the threshold usually used to judge multicollinearity problems, indicating that the multicollinearity problem is not significant in the constructed econometric model and thus will not affect subsequent estimation results.

4.2. Benchmark Model Regression Results and Discussion

After conducting Hausman tests and time fixed effects tests on Equations (1)–(3), a double fixed effects model was selected for linear regression analysis. The regression results of each model are shown in Table 3.

Table 3. Benchmark model regression results.

Explanatory Variables	Explained Variables			
	(1) lnCI	(2) lnAgg	lnCI	(3) lnCI
lnDE	−0.091 *** (0.000)	0.082 *** (0.000)		−0.097 *** (0.000)
lnAgg			0.066 ** (0.019)	0.080 *** (0.004)
lnsci	−0.101 *** (0.000)	−0.010 ** (0.030)	−0.101 *** (0.000)	−0.100 *** (0.000)
str	0.178 *** (0.000)	−0.007 (0.444)	0.175 *** (0.000)	0.178 *** (0.000)
lnei	−0.089 *** (0.007)	−0.043 * (0.071)	−0.115 *** (0.000)	−0.086 *** (0.010)
lnfdi	−0.007 *** (0.003)	−0.003 (0.137)	−0.008 *** (0.003)	−0.007 *** (0.004)
lnden	−0.584 *** (0.000)	−0.100 (0.208)	−0.579 *** (0.000)	−0.576 *** (0.000)
lnec	0.108 *** (0.000)	−0.001 (0.907)	0.108 *** (0.000)	0.108 *** (0.000)
Intercept	4.216 *** (0.000)	3.463 *** (0.000)	4.242 *** (0.000)	3.916 *** (0.000)
City fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Sobel Z				−11.284 *** (0.000)
Observations	2780	2780	2780	2780
R-squared	0.499	0.019	0.496	0.501
F-Statistic	154.72 *** (0.000)	2.930 *** (0.000)	153.10 *** (0.000)	146.51 *** (0.000)

Note, *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. Based on the R-squared, F-statistic, and overall results, the model demonstrates goodness-of-fit, proves statistically significant, and yields robust findings.

According to the empirical results of Equation (1), the coefficient of the impact of digital economy development on urban carbon emission intensity is −0.091, significant at the 1% level. This means that for every 1 unit increase in digital economy development, urban carbon emission intensity decreases by 9.1%, thereby providing empirical support for Hypothesis H1. This indicates that the development of the digital economy helps reduce urban carbon emission intensity and promotes the low-carbon transformation of Chinese cities. The reason may be that as the digital economy develops, technologies such as big data and cloud computing increasingly penetrate various aspects of enterprise production, operation, and service. This optimizes the overall allocation of factor resources in the industry, fosters technological innovation, and improves energy utilization efficiency, thereby reducing urban carbon emission intensity. This dynamic is vividly demonstrated in China's zero-carbon smart park initiatives, now pivotal catalysts for urban green transformation. Leveraging digital advantages, on the one hand, governments deploy integrated solutions, including AI-optimized design, large-model development, and energy mechanism innovation, to establish full-chain governance systems with smart energy platforms that enable dynamic carbon accounting. On the other hand, enterprises utilize IoT-driven carbon management platforms, employing big data analytics to enhance environmental efficiency and achieve lifecycle emission tracking. Driven by policy–technology synergy, digital economy standardizes environmental governance and accelerates low-carbon urbanization.

According to the empirical results of Equation (2), the coefficient of the impact of digital economy development on industrial agglomeration is 0.082, significant at the 1% level, thereby providing empirical support for Hypothesis H2. This means that for every 1 unit increase in digital economy development, the degree of industrial agglomeration increases by 8.2%. This indicates that the digital economy positively influences the agglomeration of regional industries. There may be two reasons for this. First, as the digital economy develops, technologies like 5G and blockchain are increasingly applied to existing industries, transforming traditional sectors, enhancing inter-industry division of labor and cooperation, and boosting the spillover effects of knowledge and technology, thus revitalizing industrial clusters. Second, as the digital industry matures, it tends to cluster, promoting economies of scale, knowledge sharing, and technology spillovers, which further enhance regional industrial agglomeration.

The empirical results of Equation (2) also show that the impact of industrial agglomeration on urban carbon emission intensity is significantly positive, with a regression coefficient of 0.066, thereby providing empirical support for Hypothesis H3. This indicates that industrial agglomeration has increased urban carbon emission intensity during the sample period. There may be two reasons for this. Firstly, the process of optimizing and upgrading the industrial structure is relatively slow. The secondary industry, as the pillar of the regional economy, still heavily relies on low-tech industries with "high energy consumption and heavy pollution," especially given the overall decline in national economic growth. Therefore, energy efficiency constraints in related fields are insufficient. Secondly, after years of development, industrial agglomeration in most cities has progressed beyond the initial stage, and further concentration of enterprises leads to more traffic congestion, energy consumption, and pollutant emissions. The "congestion effect" of industrial agglomeration exceeds the "scale effect," resulting in a decline in the net effect of energy conservation and emission reduction.

In Equation (3), both the digital economy and industrial agglomeration are included in the regression equation, and the Sobel test results show a significant mediating effect of industrial agglomeration. The regression results indicate that the impacts of the digital economy and industrial agglomeration on urban carbon emission intensity are still significant separately. However, the coefficient of digital economy development on carbon emission intensity is -0.097, while the coefficient of industrial agglomeration on carbon emission intensity is 0.080, showing opposite direct and indirect effects, thereby providing empirical support for Hypothesis H4. This means that industrial agglomeration has a suppression effect, a special form of mediation, on the impact of the digital economy on urban carbon emission intensity. By calculation, this degree of suppression effect is approximately 6%. The development of the digital economy not only promotes further industrial agglomeration but also indirectly strengthens the "congestion effect" of industrial agglomeration, hindering the reduction of urban carbon emission intensity. These results indicate that there is still much room to explore the potential of the digital economy to reduce urban carbon emissions.

4.3. Robustness Test and Endogenous Treatment

4.3.1. Robustness Test

To verify the robustness of the empirical results described above, this paper uses the following three methods to carry out the necessary tests.

Firstly, variable substitution. In order to avoid bias caused by variable selection, the digital economy level index (DE′) was recalculated using principal component analysis, and the regression results were consistent with the previous results, as shown in column 1 of Table 4. Secondly, sample change. Some cities such as Beijing, Shanghai, Guangzhou, and Shenzhen are all types of municipalities directly under the Central Government, provincial capital cities, or cities specifically designated in the state plan. These cities are usually the political or economic centers of the surrounding areas, with outstanding policy and capital advantages that provide obvious resource advantages in the development of the digital economy. Therefore, this paper excluded corresponding special samples and conducted a regression analysis, with the results shown in column 2 of Table 4. Thirdly, winsorization was performed. To eliminate the influence of outliers on the whole sample, variables were truncated at the 99th and 1st percentiles, and the model was re-estimated. The regression results were consistent with the previous results, as shown in column 3 of Table 4. Fourthly, model transformation. To reduce the interference of potential bias from functional form misspecification in the baseline model on the conclusions, first-order and second-order lag terms of the dependent variable are introduced to convert the static model into a dynamic panel model, with the Generalized Method of Moments (GMM) used for estimation and testing. The test results show that the *p*-value of the Hansen J statistic test is greater than 10%, failing to reject the null hypothesis that instrumental variables satisfy exogeneity. In the autocorrelation test results, AR(1) and AR(2) indicate rejecting the null hypothesis that there is no autocorrelation in the first-order difference and failing to reject the null hypothesis that there is no autocorrelation in the second-order difference, respectively. Therefore, it can be seen that the GMM model estimation method is reasonable, and the regression results are consistent with the previous results, as shown in column 4 of Table 4. The three methods described above further validate the robustness of the regression results.

4.3.2. Endogenous Treatment

Considering that the endogeneity of variables may compromise the consistency of estimation results, the instrumental variable method is used to deal with the endogeneity problem.

Based on the research methods adopted by Nunn and Qian [93] and Gao et al. [94], this paper selects the interactive term of the number of mobile internet users per 100 people in each city last year and the number of fixed telephones per 10,000 people in 1984 as the instrumental variable of the level of the digital economy. This instrumental variable satisfies the constraints of correlation and exclusivity. On the one hand, the development of the digital economy depends on the application and popularization of internet technology, and the internet's emergence as a publicly recognized technology originated from the Public Switched Telephone Network (PSTN), which is a foundational infrastructure of traditional telecommunications. Regions exhibiting higher PSTN penetration historically possessed more advanced information infrastructure, conferring structural advantages in contemporary digital economy development. Consequently, this variable meets the correlation constraints. On the other hand, the number of fixed telephones per 10,000 people in 1984 is a historical figure; with the rise and development of the Internet and mobile communication equipment, the impact of traditional communication facilities on economic and social development has gradually declined. Therefore, this variable meets the exclusive constraints. In addition, this instrumental variable is cross-sectional data and cannot be directly incorporated into the model. Here, referring to the practices of Duflo and Pande [95], the instrumental variable is multiplied by the time trend term and then incorporated into the regression model. Meanwhile, considering that the development of the digital economy may have a certain time lag effect on industrial agglomeration and urban carbon emissions, the explained variables lagged by one, and two periods are added as instrumental variables.

Table 4. Robustness and endogeneity tests.

Explanatory Variables	Explained Variables				
	lnCI	**lnCI**	**lnCI**	**lnCI**	**lnCI**
$lnCI_{t-1}$				0.594 *** (0.005)	
$lnCI_{t-2}$				0.083 (0.518)	
lnDE′	−0.087 *** (0.000)				
lnDE		−0.128 *** (0.000)	−0.097 *** (0.000)	−0.450 * (0.060)	−0.233 *** (0.000)
lnAgg	0.083 *** (0.003)	0.097 *** (0.002)	0.080 *** (0.004)	0.572 * (0.082)	0.094 *** (0.003)
Control	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
Observations	2780	2590	2780	2224	2502
R-squared	0.505	0.490	0.501	0.346	0.406
AR (1)				−3.500 *** (0.000)	
AR (2)				0.660 (0.561)	
Hansen J Statistic				12.84 (0.381)	4.534 (0.104)
Kleibergen-Paaprk LM Statistic					163.707 *** (0.000)
Cragg-Donald Wald F Statistic					280.114 [22.30]
F-Statistic	149.03 *** (0.000)	131.00 *** (0.000)	146.51 *** (0.000)	355.36 *** (0.000)	131.00 *** (0.000)

Note, * and *** represent the 10% and 1% significance levels, respectively. The robustness test only lists the estimated results of the mediation effect Equation (3), omitting the estimated results of Equations (1) and (2). The values in brackets represent the critical values of the Stock–Yogo test at a true significance level that does not exceed 10%.

On this basis, this paper uses the two-stage least squares (2SLS) method to re-estimate the model, and the regression results are shown in column 5 of Table 4. The Kleibergen–Paaprk LM statistic is significant at the 1% level, indicating that the hypothesis that the instrumental variables are not identifiable is rejected, and the instrumental variables are set reasonably. The Cragg–Donald Wald F statistic is 536.770, which is greater than the critical value of 19.98 for a 10% significance level of the weak instrumental variable test. The weak instrumental variable hypothesis is rejected, and the instrumental variable selection is effective. The p-value of Hansen's J statistic is greater than 10%, indicating that it cannot reject the null hypothesis that instrumental variables are exogenous; there is also no overidentification of the instrumental variable. Overall, after alleviating endogeneity issues, industrial agglomeration also has a significant suppressing effect on the impact of digital economy on urban carbon emission intensity, which proves the reliability of the benchmark regression conclusion.

4.4. Further Discussion: Heterogeneity Analysis

4.4.1. City Size Heterogeneity

In 2014, the State Council of China issued Notice of the State Council on Adjusting the Standards for Categorizing City Sizes, which classified city size based on the number of permanent residents in urban areas. The size of a city directly determines the number of talent, capital, and other factor resources [96], which to some extent affects the foundation of digital economy development and the trend of industrial agglomeration. Based on this, this paper divides all cities into large cities and small- and medium-sized cities, and conducts regression analyses separately. The results are shown in columns 1 and 2 of Table 5.

Table 5. Regression results for city size heterogeneity and geographical region heterogeneity.

Explanatory Variables	Explained Variables				
	Large Cities	**Small- and Medium-Sized Cities**	**Eastern Cities**	**Central Cities**	**Western Cities**
	lnCI	**lnCI**	**lnCI**	**lnCI**	**lnCI**
lnDE	−0.051	−0.166 ***	−0.007	−0.015	−0.082 **
	(0.202)	(0.000)	(0.840)	(0.729)	(0.046)
lnAgg	0.065	0.098 ***	0.030	0.033	0.127 **
	(0.166)	(0.005)	(0.511)	(0.394)	(0.030)
Control	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
Observations	1000	1780	1190	770	820
R-squared	0.590	0.489	0.534	0.695	0.438
F-Statistic	74.78 ***	89.06 ***	71.12 ***	90.51 ***	33.02 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note, ** and *** represent the 5% and 1% significance levels, respectively. This paper follows the classification criteria in the "Notice of the State Council on Adjusting the Standards for Categorizing City Sizes" issued by the State Council of China in 2014. The cities with a permanent population of more than 1 million in urban areas are classified as large cities, cities with a permanent population between 500,000 and 1 million are classified as medium-sized cities, while cities with a permanent population below 500,000 are classified as small cities. In the analysis process, the sample of small cities is relatively small, so the small cities and medium-sized cities were merged into one category for regression analysis.

The results show that industrial agglomeration only in small- and medium-sized cities has a significant suppressing effect on the impact of the digital economy on urban carbon emission intensity; however, this effect is not obvious in large cities. The possible reason is that, under the influence of human capital, technological level, and industrial structure, most industrial agglomerations in small- and medium-sized cities are still formed through factors such as cheap labor, cheap land supply, relaxed tax policies, and low environmental protection costs. In this case, the driving force of green and low-carbon technological innovation is insufficient. In fact, compared to large cities, small- and medium-sized cities generally lack innovation capabilities, and part of the driving force behind their economic development comes from the transfer of heavy-polluting industries from large cities. As a result, small- and medium-sized cities rely too much on large cities in terms of space and lag behind them in terms of time during the process of industrial structure optimization and upgrading. In recent years, with the continuous development and expansion of the digital economy, the reasons described above have made the suppressing effect of industrial agglomeration on carbon emission intensity in small- and medium-sized cities more obvious compared to large cities.

4.4.2. Geographical Region Heterogeneity

According to the classification standards of the National Bureau of Statistics of China, all cities are categorized according to different geographical regions. At present, China's economy, especially the digital economy, still exhibits significant differences among the eastern, central, and western regions [97]. The closer a city is to the eastern coastal areas, the earlier its historical development and the better its technological conditions are. As a result, the corresponding regions have accumulated a large amount of population, capital, and other resources in a relatively small geographical area, and created huge national wealth. It follows that the imbalance of regional economic development also affects the foundation of digital economy development and the evolution of industrial agglomeration trends. Based on this, this paper divides all cities into eastern, central, and western regions and conducts regression analyses separately. The results are shown in columns 3, 4, and 5 of Table 5.

The results show that industrial agglomeration only in the western region has a significant suppression effect on the impact of the digital economy on urban carbon emission intensity, while this effect is not obvious in the eastern and central regions. This result may be closely related to the sustained industrial gradient transfer in geographical space over recent years. In the past decade or so, China's economy has entered the "New Normal," characterized by economic growth that has shifted from high-speed to medium-high-speed and has been driven by factors and investments related to innovation. Against this background, the developed eastern regions have accelerated the pace of industrial structure adjustment due to factors such as tightening industrial land, rising labor costs, and higher environmental protection thresholds. However, the main way to optimize the structure is to relocate low-end industries and replace them with high-end industries. As a result, in the process of industrial gradient transfer from east to west, the phenomenon of synchronous transfer of many traditional polluting enterprises often occurs. In this case, although the development of the digital economy has greatly promoted the expansion of output scale in the transferred cities, at the same time, it has further exacerbated pollution emissions in the corresponding cities. Finally, the improvement of industrial agglomeration partially offsets the positive effect of the digital economy on the reduction of urban carbon emission intensity.

4.4.3. Industry Type Heterogeneity

Given the complexity and diversity of industrial classification, as well as the availability of data, this paper selects the primary, secondary, and tertiary industry as the types of agglomeration division. Generally, the impact of different industries on the national economy's energy consumption varies, and the impacts of climate change and carbon emissions vary across different industrial sectors [98,99]. Therefore, different types of industrial agglomeration often have distinct impacts on urban carbon emissions. Based on this, this paper separately calculated the agglomeration levels of the primary, secondary, and tertiary industries in each city according to the calculation formula mentioned in the section above of the mediating variables, with variable names of Agg1, Agg2, and Agg3, respectively. The regression analysis results are shown in Table 6.

The results show that only the agglomeration of the tertiary industry has a significant suppressing effect on the impact of the digital economy on urban carbon emission intensity; however, it is not clear whether the primary or secondary industries exhibit such an effect. There may be two reasons for this result. Firstly, in China's national economic development process, the agglomeration of the tertiary industry lags behind that of the secondary industry, most of which are still in the initial stage of agglomeration, and the utilization of factor resources is relatively extensive. Therefore, the spillover effect of improved resource utilization efficiency is not significant. Secondly, the scientific and technological level of the tertiary industry itself is relatively low, and most industries are still in the low-tech expansion stage, lacking support from emerging and high-tech industries. In this case, factors such as low production technology, low production efficiency, and low resource utilization rate lead to excessive consumption of regional resources and energy, which deepens environmental pollution and hinders the reduction of urban carbon emission intensity.

Table 6. Regression results of industrial type heterogeneity.

Explanatory Variables	Explained Variables		
	Primary Industry lnCI	**Secondary Industry lnCI**	**Tertiary Industry lnCI**
lnDE	−0.089 *** (0.000)	−0.090 *** (0.000)	−0.097 *** (0.000)
lnAgg1	0.005 (0.236)		
lnAgg2		−0.013 (0.568)	
lnAgg3			0.053 ** (0.015)
Control	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
Observations	2780	2780	2780
R-squared	0.496	0.499	0.500
F-Statistic	145.00 *** (0.000)	145.49 *** (0.000)	146.15 *** (0.000)

Note, ** and *** represent the 5% and 1% significance levels, respectively.

The three heterogeneity analyses described above jointly provide empirical support for Hypothesis H5.

5. Discussion

This study contributes to the burgeoning literature that examines the ecological implications of both the digital economy and industrial agglomeration. While existing research has investigated the individual direct and indirect effects of digital economic and industrial agglomeration on carbon emissions, there remains a gap in systematically examining their combined influence, particularly regarding how digital transformation transforms industrial agglomeration patterns. Our research extends previous work by revealing the mediation role of industrial agglomeration in the relationship between the digital economy and urban carbon emission intensity. Although our findings corroborate the negative correlation between the digital economy and carbon emission intensity observed in earlier studies, we further elucidate the complex causal relationship by which digitalization affects emission intensity through its restructuring effects on industrial agglomeration patterns.

The complexity described above is inherently rooted in China's unique industrial development context, where urban industrial agglomeration patterns have been profoundly shaped by dual mechanisms of cross-border and domestic industrial gradient transfers. Regions receiving these transfers typically specialize in energy-intensive, low-end industries; while serving as an engine for local economic growth, it has simultaneously produced substantial environmental externalities. Notably, the higher agglomeration levels in these regions substantially complicate the low-carbon transition. Conversely, regions that transfer industries outward face their distinct challenges. While these highly clustered regions benefit from agglomeration, their marginal revenue in energy conservation and emission reduction is diminishing. Meanwhile, the nascent industries they develop, such as the digital economy, generate unforeseen carbon emissions. For instance, data storage platforms, computing centers, and 5G infrastructure require massive energy inputs; manufacturing industries like computers, communications, and electronic equipment also exhibit high electricity consumption, leading to elevated emissions. This reveals a significant masking effect of industrial agglomeration on the digital economy's emission reduction potential. Importantly, the finding remains robust and consistent across rigorous endogeneity treatments and multiple robustness checks.

This study departs from conventional research focused on resource allocation efficiency and technological innovation, instead interrogating how industrial spatial organization and urban heterogeneity critically shape the effectiveness of digital economy policies. Our findings demonstrate that the success of digital economy initiatives and associated industrial policies is fundamentally contingent upon broader urban characteristics, including city size, geographic location, and industrial structure. This approach resonates with contemporary discussions in carbon emission governance research, underscoring the need for more nuanced analytical frameworks. Together, these insights illuminate a strategic pathway for policymakers to amplify synergistic emission-reduction outcomes through the coordinated development of the digital economy and industrial agglomeration.

6. Conclusions and Policy Implications

6.1. Conclusions

Based on panel data from 278 Chinese cities spanning 2011 to 2020, this paper examines the influence and mechanism of the digital economy on carbon emission intensity in Chinese cities from the perspective of industrial agglomeration. We have drawn the following conclusions:

Firstly, there is a significant negative relationship between the digital economy and carbon emission intensity, but a significant positive relationship between industrial agglomeration and carbon emission intensity. Secondly, the mediation effect test found that industrial agglomeration suppresses the reduction of urban carbon emission intensity driven by the digital economy. This means that the digital economy's promotion of industrial agglomeration hinders the reduction of urban carbon emission intensity. After controlling for industrial agglomeration, the digital economy's effect on reducing urban carbon emission intensity increases. Thirdly, heterogeneity analysis indicates that in comparisons between small- and medium-sized cities and large cities, central and western cities and eastern cities, and the tertiary industry and the primary and secondary industries, the former show a significant suppression effect on reducing urban carbon emission intensity driven by the digital economy, while the latter do not.

6.2. Policy Implications

Based on the conclusions outlined above, the following suggestions are put forward: Firstly, China should deepen the digital transformation of industries, strengthen and optimize the digital economy, and create sufficient driving force to reduce urban carbon emission intensity. Specifically, it is necessary to accelerate the construction of data space and information infrastructure, enhance the application of digital technologies, such as the internet, big data, and artificial intelligence, and optimize industrial resource allocation through the digitalization of the entire industrial chain to promote the green and low-carbon transformation of traditional industries. Especially for medium- and small-sized cities, as well as those in the western region, the government needs to prioritize and guarantee digital investment as a key area of fiscal, taxation, and financial support. Additionally, policymakers should steadily advance the deep integration and innovative application of data elements within capital markets. By synthesizing multi-dimensional datasets such as environmental protection, meteorology, and finance, they can amplify the capital markets' pivotal role in resource mobilization. This integration unlocks the full potential of data resources through efficient utilization, enables cross-factor interoperability, and channels production elements toward green and low-carbon sectors, thereby propelling the real economy's green transition and low-carbon sustainable development. Moreover, local governments should utilize the linking role of internet platform enterprises to guide enterprises to carry out digital intelligent transformation and continuously enhance their digital capabilities. Through integrated online–offline approaches, they will foster highly coordinated collaboration across industrial chains and advance the convergence of digital technologies with the real economy, particularly green and low-carbon industries. A critical pathway is that policymakers can draw on the radiation and driving effect of constructing zero-carbon digital intelligence parks to achieve the sharing of data dividends and the expansion of the scope of carbon reduction, with the application and promotion of its replicable practical experience to other regions, thereby more effectively leveraging the green innovation and driving functions of data in traditional industries. This enables data dividend sharing and expands carbon reduction coverage, ultimately empowering data resources to drive green innovation in traditional industries.

Secondly, China should promote high-quality industrial agglomeration to provide an efficient means for reducing urban carbon emission intensity. Specifically, local governments should prioritize ecological and green development, accelerate the high-end and intelligent development of industries, and enhance the role of scientific and technological innovation and high-tech industries. This will facilitate the shift from a labor-intensive and resource-intensive economy to a modern industrial cluster dominated by a green and low-carbon economy. The knowledge spillover effect of high-tech industry agglomeration will promote industrial upgrading and improve the quality and efficiency of the agglomeration economy. However, it should be noted that the development strategies of regions with remarkable carbon reduction effects should not be blindly copied. Especially for regions that focus on the coordinated development of new infrastructure, their carbon emissions may increase at the present stage. However, from a perspective that takes into account the overall situation and long-term prospects, they still have considerable potential for carbon reduction. Additionally, policymakers should continuously optimize the division of labor, coordination, and organizational structure of industries within the agglomeration area. Enhancing the correlation and spatial pattern interaction between upstream and downstream industries will promote collaborative agglomeration and improve agglomeration levels. This will maximize economies of scale, reduce crowding effects, improve resource conservation and intensive utilization, and ultimately promote the green and low-carbon transformation of regional economies.

Thirdly, China should implement differentiated countermeasures based on city size, geographical region, and industry type. Specifically, it is essential to focus on optimizing and upgrading industries in small- and medium-sized cities, deepen the reform of agglomeration modes, and shift from an extensive model of "high input, high consumption, high emissions, and low efficiency" to an intensive model of "low input, low consumption, low emissions, and high efficiency." This should be accomplished while improving labor quality and economic benefits to enhance the green level of industrial agglomeration. Moreover, policymakers should emphasize the coordinated development of cities in the western and central eastern regions. Accelerating the construction of a green and modern industrial system in western cities requires establishing an ecological environment constraint mechanism, improving industrial transfer mechanisms, and building a regional coordinated development network. Additionally, policymakers should leverage the spillover effects of the digital economy on regional economic development to ensure that the diffusion effect of green and low-carbon technology innovation in the domestic industrial gradient transfer process is fully utilized. This will prevent digital technologies from becoming a means for unfair competition in individual regions due to access threshold restrictions during ecological transformation, which would hinder the progress and quality improvement of the coordinated development of digitalization and greening.

In addition, local governments should seize the new opportunities presented by the technological revolution and the development of the digital economy. They should focus on technological innovation, improve the overall technological content and level of the tertiary industry, and promote the advanced and high-end development of tertiary industry agglomeration. This will accelerate the implementation of renewable energy utilization and energy conservation and carbon reduction transformation of energy-consuming equipment and promote the agglomeration and high-end and green development of the tertiary industry. It will also create a positive feedback loop between industrial agglomeration and technological innovation, effectively improving regional energy utilization efficiency and reducing carbon emission intensity. Ultimately, these measures will lay a solid foundation for China to achieve a win–win situation characterized by stable economic growth and steady progress in the low-carbon transformation.

6.3. Limitations and Future Research

A key limitation of this study is its exclusive focus on China, which may restrict the generalizability of the findings to other countries, particularly those at varying stages of digital transformation and industrial development. Moreover, this study predominantly utilizes macro-level statistical data and secondary sources, which may not adequately capture the rapid evolutionary dynamics of the digital economy. The lack of real-time, high-resolution data could impair the accuracy and timeliness of tracking digitalization's dynamic shifts, thereby limiting a more nuanced assessment of its interaction with industrial agglomeration and variations in carbon emission intensity.

To advance and enrich this line of inquiry, future research should embrace a multidimensional analytical framework. First, conducting cross-national comparative analyses would enhance the generalizability of findings while generating actionable insights for global best practices, particularly examining countries with heterogeneous economic structures, policy frameworks, and industrialization stages. Second, for research constrained by macro-level statistics and secondary data, methodological rigor can be enhanced by applying bootstrapping estimation or Monte Carlo resampling techniques to mediation effect testing, thereby significantly bolstering the robustness and precision of empirical inferences. Third, leveraging big data technologies through strategic collaborations with platform enterprises would enable integrated management of massive data resources, thereby securing real-time, high-granularity data support to further elevate inferential precision. Finally, further research can explore the specific role of digital industry agglomeration, study how the development of these emerging industries affects the impact of the digital economy on carbon emission intensity, and thereby gain a broader understanding of the role of industrial agglomeration in influencing the carbon emission intensity of the digital economy.

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