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Study on the effect of digital trade development on manufacturing carbon emissions

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ABSTRACT: *The rapid development of digital trade not only brings unlimited possibilities to business but also has a huge impact on the environment, especially playing an important role under the current dual carbon background. To provide a theoretical basis for giving full play to the carbon reduction of digital trade and promoting the outstanding growth of the manufacturing industry, and enhancing the competitive advantage of manufacturing enterprises, this paper uses the panel data of 30 provincial administrative regions in China from 2012 to 2021 to study the impact effect of the development level of digital trade on the carbon emissions of the manufacturing industry, and analyzes the spatial effect between digital trade and the carbon emission intensity of the manufacturing industry. It is found that the development level of digital trade has a nonlinear effect of first promoting and then suppressing the carbon emission intensity of the manufacturing industry, and there is heterogeneity in regions and sub-industries. The improvement of the development level of digital trade has a significant inhibitory effect on the carbon emission intensity of the manufacturing industry in neighboring regions. This might be related to the rapid development of digital trade driving the production efficiency of local manufacturing, the optimal allocation of resources, and the application and promotion of environmental protection technologies. Therefore, it is necessary to actively promote the development of digital trade and enhance the application of digital technology in the field of trade.*

KEY WORD*: Digital trade; Carbon emission intensity in the manufacturing industry; Inverted U-shaped curve; Spatial Durbin model*

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I. INTRODUCTION

At present, the challenges of global warming and the ecological environment are becoming increasingly severe.According to the "Global Sustainable Development Report 2023" released by the United Nations, the process of achieving the Sustainable Development Goals remains slow, and there is an even more urgent need to maintain a rapid development momentum.As carbon emissions are the main driver of global warming, reducing carbon emissions can help alleviate adverse climatic conditions and thereby promote the sustainable development of cities around the world[1].Therefore, governments and organizations around the world have committed to reducing emissions to address climate change and are actively seeking effective solutions to cut carbon emissions[2].As a major contributor to global carbon dioxide emissions, China's emissions in 2023 accounted for nearly one-third of the world's total, approximately 31% of global greenhouse gas emissions. The Chinese government has committed to striving to achieve carbon peaking before 2030 and carbon neutrality before 2060. This is a time-pressured, arduous and challenging task among the world's major economies[3].However, as China's economic growth and carbon reduction targets become increasingly strict, manufacturing, as the main source of China's carbon emissions, has become a key component in achieving the "dual carbon" goals[4]. In 2020, manufacturing accounted for 56% of China's total carbon emissions[5].From the perspective of industrial structure, China is more inclined towards manufacturing [6]. Therefore, as the international community pursues the sustainable development goals, China's manufacturing industry must take active measures to reduce carbon emissions. Carbon reduction in the manufacturing industry is crucial for maintaining high-quality economic development and achieving the goals of carbon peaking and carbon neutrality.

Given China's energy endowment and current stage of development, the transition from a "high-carbon society" to a "carbon-neutral society" requires the support of a technological system. Therefore, it is necessary to establish a green and low-carbon industrial system based on a large number of new technologies.Digital trade, as an emerging economic form, has transformed traditional trade practices by leveraging the most advanced innovative technologies such as big data analysis, cloud computing systems, and interconnected Internet of Things devices [7], characterized by the trading of goods and services through electronic platforms [8].With the continuous deepening of economic globalization, the position of digital trade is becoming increasingly important [9]. When deeply integrated with industries, it can effectively drive traditional industries to transform towards green[10][11] and low-carbon[12], empowering pollution reduction and carbon emission reduction. Meanwhile, digital technology can reduce energy consumption by improving the energy consumption structure and achieve the goal of carbon emission reduction [13].Therefore, against the backdrop of global warming and climate change, many countries have begun to attach importance to the development of digital trade, hoping to reduce carbon emissions through the development of digital trade. However, there are few existing literatures that conduct quantitative empirical analyses on the development of digital trade and carbon emission reduction in the manufacturing industry. Therefore, it is necessary for this paper to place digital trade and carbon emissions from the manufacturing industry in the same analysis, providing ideas for achieving carbon emission reduction and theoretical support for fully leveraging digital trade carbon emission reduction and promoting high-quality development in the manufacturing industry.

II. LITERATURE REVIEW

Research on trade and environmental issues can be traced back to the 1970s. With the acceleration of globalization, the rapid growth of international trade has had a profound impact on the environment.On the one hand, trade promotes economic development and technology dissemination, which may bring positive effects to environmental management. On the other hand, excessive development and resource consumption will lead to the deterioration of the ecological environment, climate change and the reduction of biodiversity.The relationship between trade and the environment has gradually attracted extensive attention from the academic community and policymakers. Currently, there are mainly three mainstream viewpoints in the academic circle:The first one is the "Polluted Paradise Hypothesis", namely the theory that trade is harmful. This view holds that trade may have a negative impact on environmental protection.The development of trade will promote economic growth. It may attract pollution-intensive industries due to relatively loose environmental policies, leading to environmental degradation (Taylor, 1994)[14].The second one is the "pollution halo Hypothesis", namely the theory that trade is beneficial. This view holds that trade is not the fundamental cause of environmental problems; instead, it contributes to environmental protection. Facing global market competition, trade liberalization may enable enterprises to adopt more environmentally friendly production methods, optimize the trade structure, and shift the space of polluting activities, thereby reducing pollutant emissions from the manufacturing industry (Cherniwchan, 2017) [15].The third is the theory of environmental complexity, namely the theory of trade neutrality. This view holds that there is a complex relationship between trade growth and energy consumption as well as pollution emissions. On the one hand, trade promotes the dissemination of environmental technologies. On the other hand, the spillover of high-pollution and high-energy-consuming output will lead to environmental deterioration (Anderson, 2005) [16].The complexity of trade to the environment lies in the sum of the scale effect, the structural effect and the technological effect. These three effects rise and fall alternately, causing complex results to the environment under the influence of different factors in different periods (Yu Zhuangxiong, 2024)[17].

Global climate change poses a serious threat to human survival and sustainable development. Therefore, carbon emissions have become a central issue of concern for governments around the world and the international community, promoting extensive research on their impacts.The research of Yang,Y, &Zhuangxiong,Y. (2024) holds that enterprise digitalization can not only enhance enterprise efficiency but also effectively suppress carbon emissions. Moreover, the higher the degree of digitalization, the lower the level of carbon emissions[18].This is similar to the viewpoint of Chen,K, &Lei,Z. (2024), who believes that enterprise technological transformation significantly promotes the reduction of carbon emissions, and enterprise technological innovation plays a mediating role between digitalization and carbon emissions [19].The difference is that Chinese scholar Liu Pengfei (2024) holds that what plays a mediating role between digital technology and carbon reduction is the upgrading of industrial structure and the improvement of energy utilization efficiency[20].However, the key factors influencing carbon emission intensity vary in different economic cycles. Among them, the energy structure is a key factor for carbon reduction throughout the economic cycle (Xie Pinjie, 2024)[21].On this basis, Grossman & Krueger proposed the viewpoint that economic growth can deteriorate the environment through scale effects, while economic growth can improve the environment through technological effects and structural effects [22].Furthermore, the intensification of competition among banks can promote technological progress and industrial structure. Initially, both the increase in fixed assets and residents' consumption contributed to carbon emissions. However, through the threshold model, it was found that as the degree of competition increased, carbon emissions showed a downward trend (Zhu,Y, &Shanxing,D., 2024)[23].

Some scholars also hold that public environmental participation driving the public's low-carbon consumption choices at the consumption end and optimizing the energy structure at the production end can promote the low-carbon transformation of household consumption (Tian Shuying, 2024)[24].Of course, carbon reduction cannot do without the support of government policies. Public finance support for research and development (R&D) projects can reduce carbon emission intensity, especially in regions with lower economic growth efficiency. Moreover, investment in scientific research can promote the development of digital green technologies and further drive low-carbon innovation (Jiandong Chen, 2023) [25].Meanwhile, the pilot policy of integrating science and technology with finance can promote energy conservation and emission reduction in cities through three approaches: resource effect, human capital effect and innovation effect. Compared with other non-pilot cities, the carbon emission intensity of the cities piloted by the policy is significantly reduced (Wang Haojie, 2024) [26].Furthermore, different tax policy situations have different influences on enterprises' financing decisions. The availability of bank financing and the preferential tax policies can promote the carbon emission reduction investment of small and medium-sized enterprises. Especially, small and medium-sized enterprises are more inclined to choose carbon emission reduction investments with higher risks but greater potential returns when obtaining tax preferences, promoting carbon emission reduction (Luo,P., 2024)[27].With the acceleration of global integration and digitalization, digital trade has become a new form of economic activity. From e-commerce to digital services, its rise has had a profound impact on the economic, social and environmental patterns of countries around the world. With the challenges of global climate change and the enhancement of environmental awareness, it is becoming increasingly important to study the relationship between digital trade and regional carbon emissions.Some scholars have conducted research on the environmental effects between digital trade and carbon emissions. Hong Ji&Baocheng Xiong (2023) found that the growth of digital trade, especially in high-tech regions, can promote the efficient utilization of resources and thereby reduce carbon emissions [28].Among them, energy utilization efficiency, scale effect, technological innovation and structural optimization can all achieve pollution reduction and carbon reduction, and there is a negative inhibitory effect of reducing the nonlinear marginal effect of marketization degree (Liu Hong, 2024) [29].Meanwhile, digital trade can affect carbon emissions through both supply (enterprises) and demand (residents) aspects. The green innovation activities of enterprises and the improvement of residents' consumption behaviors are the main driving forces for digital trade to reduce carbon emissions [30][31].Among them, digital trade promotes carbon emission reduction more effectively through technological effects than through structural effects, while the structural upgrading of rural residents has an inhibitory effect on emission reduction, while urban residents have a promoting effect on emission reduction (XiangyuShi·YanLiu·Zefen Yu.,2024)[32].Shi Xiongtian (2024) holds a different view from this. He believes that on the production side, the scale effect and technological effect have a greater promoting effect on carbon emissions than the structural effect [33].However, there are regional differences in the carbon reduction potential of digital trade. For instance, in China, the northern region shows a more obvious emission reduction effect than the southern region, while the central and western regions perform better than the eastern region in this regard (Wang Y et al., 2023) [34].

In conclusion, although the academic community has conducted a certain degree of exploration on the impact of digital trade on carbon reduction, most of the existing literature is a macro study of digital trade and carbon emissions, and there are few quantitative empirical analyses of digital trade and carbon emissions from the manufacturing industry.Against this backdrop, this paper incorporates carbon emissions from digital trade and manufacturing into the same analysis to draw on ideas for achieving the "dual carbon" goals.The main contributions of this paper are as follows: First, a comprehensive evaluation index system for digital trade is constructed, and the entropy method is used for measurement to obtain the development level index of digital trade, providing a new idea for the theoretical research related to the measurement of digital trade.Second, from the perspective of manufacturing, the relationship between digital trade and carbon emissions was analyzed. For the first time, the nonlinear impact of digital trade on manufacturing carbon emissions was systematically verified, and the specific differences between the two in regions and manufacturing sub-sectors were analyzed.Thirdly, a bidirectional fixed-space Durbin model was constructed to further analyze the spatial effect between digital trade and carbon reduction in manufacturing, providing a scientific basis for formulating more environmentally friendly policies.

III. Materials and Methods

3.1 Research Objectives

Based on the research method proposed by Song Min (2024), this paper constructs a benchmark regression model. Considering the potential non-linear relationship be-tween the development level of digital trade and the carbon emission intensity of manufacturing, the quadratic term of the core explanatory variable is introduced into the linear benchmark regression model to discussion. The following non-linear regression models are constructed:

First, Model (1) examines the direct impact of digital trade on manufacturing car-bon emissions:

$$CEI_{it} = \alpha_0 + \alpha_1 DC_{it} + \alpha_2 DC_{it}^2 + \alpha_3 Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

Second, Models (2) and (3) are constructed to examine the mechanisms of digital trade affecting manufacturing carbon emissions:

$$med_{it} = \beta_0 + \beta_1 DC_{it} + \beta_2 DC_{it}^2 + \beta_3 Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

$$CEI_{it} = \delta_0 + \delta_1 DC_{it} + +\delta_2 DC_{it}^2 + \delta_3 med_{it} + \delta_4 Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{3}$$

Finally, the dual fixed spatial Durbin model (4) is constructed to test the spatial effect of the development level of digital trade on the carbon emission intensity of the manufacturing industry:

$$CEI_{it} = \varphi_0 + \varphi_1 DC_{it} + \varphi_2 DC_{it}^2 + \varphi_3 Control_{it}$$
$$+\rho_1 \sum_{j=1}^{n} W_{ij} CEI_{it} + \rho_2 \sum_{j=1}^{n} W_{ij} DC_{it} + \rho_3 \sum_{j=1}^{n} W_{ij} DC_{it}^2 + \rho_4 \sum_{j=1}^{n} W_{ij}\, Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (4)$$

3.2Variable Selection

Explained variable: Carbon Emission intensity (CEI) of the manufacturing industry. This paper adopts the carbon dioxide emissions in the China Carbon Accounting Database (CEADS) as the measurement standard of carbon emissions. And drawing on the practice of Fu Hua (2021), according to the "Classification of Industries of National Economic Activities" (GB/T 4754-2017) released by the National Bureau of Statistics in 2017, after eliminating discontinuous data, this study covered 28 sub-industries of the manufacturing industry [35]. The carbon emission intensity of the manufacturing industry is expressed by the ratio of the carbon emissions of each province's manufacturing industry to its GDP.

Explanatory variable: Level of Digital Trade Development (DC). The application of digital technology in the field of trade can promote the transformation and upgrading of trade. The development of digital technology is also inseparable from the construction of digital infrastructure. Therefore, digital technology and digital infrastructure are the foundation for the development of digital trade. The scale of digital trade reflects the overall scale and vitality of the digital trade market. The potential for digital development reflects the potential for the future development of digital trade and can predict the future development trend and prospects of digital trade. To this end, this paper constructs a comprehensive evaluation index system from four dimensions: digital innovation ability, digital infrastructure, digital trade ability and digital development potential (Table 1).

Table 1. Comprehensive evaluation index system of digital trade development level.

Primary index	Secondary index	Three-level index	direction
Digital trade development level	Digital innovation capability	R&d personnel	+
		R&d expenditure as a percentage of GDP	+
		Number of patent applications accepted	+
		Scientific journal articles	+
	Digital infrastructure	Length of long distance optical cable line	+
		Number of Domains	+
		Number of pages	+
		Internet broadband access port	+
		Mobile phone penetration	+
		Number of mobile Internet users	+
	Digital trade capability	Software revenue	+
		E-commerce sales	+
		E-commerce purchases	+
		Added value of the tertiary industry	+
	Digital development potential	Post and telecommunications business volume	+
		Number of enterprises with e-commerce trading activities	+
		Per capita GDP	+
		Market openness	+

Control variables: Drawing on the research of Liu Xiaoli (2020), Ma Zihong (2019), etc., this paper controls for other factors affecting carbon emissions in the manufacturing industry: the level of economic development (GDP), expressed as per capita GDP; The degree of opening up to the outside world is expressed as the proportion of the total volume of imports and exports of goods to GDP. The level of financial development (FD) is expressed as the proportion of the year-end deposit balance of financial institutions in each province to GDP. Research and development intensity (RD) is expressed as the proportion of R&D expenditure to the output value of the manufacturing industry. The level of urbanization (City) is expressed by the proportion of the urban population. The energy consumption structure (ES) is represented by the ratio of coal to the total energy consumption of each province.

Mediating variable: Output size (SC), expressed in terms of manufacturing output value; Technological progress (TA) is expressed by the number of patent applications accepted.

3.3Data sources and descriptive statistics

Considering the availability of data, this paper selects panel data from 30 provincial-level administrative regions in China (excluding the Tibet Autonomous Region and the Hong Kong, Macao, and Taiwan regions) for the period 2012–2021 as the sample for the empirical study. The data for the study are primarily sourced from the China Statistical Yearbook, China Environmental Statistics Yearbook, China

Industrial Statistics Yearbook, and the EPS database, among others. Descriptive statistics for the variables are presented in Table 2.

Table 2. Descriptive statistics of relevant variables.

	N	mean	sd	min	median	max
CEI	300	0.027	0.027	0.003	0.020	0.174
DC	300	0.131	0.134	0.009	0.081	0.818
ES	300	0.007	0.004	0.000	0.007	0.025
FD	300	1.916	0.728	0.198	1.736	5.233
Urban	300	0.600	0.121	0.146	0.587	0.896
Open	300	0.007	0.033	0.000	0.003	0.451
RD	300	0.011	0.004	0.003	0.010	0.026
HC	300	0.013	0.004	0.006	0.012	0.027
Scale	300	9.830	1.143	7.193	9.984	11.976
Tech	300	1.283	0.711	0.549	1.120	5.297

Source: Compiled and calculated by the authors.

IV. Results

4.1 Baseline Regression

This paper selects the time and individual bidirectional fixed effects for nonlinear benchmark regression analysis, and the results are shown in Table 3. The R-squared was 0.968, very close to 1, indicating that the model explained 96.8% of the variability in the data and the fitting effect was very good.Columns (1) and (2) in the table respectively represent the estimation results without added control variables and with added control variables. It was found that the coefficient of the primary term (DC) of the development level of digital trade was always significantly positive, and the coefficient of the secondary term (DC2) was always significantly negative. This indicates that with the development of digital trade, the carbon emission intensity of the manufacturing industry shows a nonlinear effect of first promoting and then suppressing.Column (2) represents the regression results after adding relevant control variables. The estimated parameter of the first term of the explanatory variable digital trade development level is 0.204 ($p<0.01$), and the coefficient of the second term is -0.149 ($p<0.01$).It indicates that in the early stage of the development of digital trade, for every one-unit increase in digital trade, the carbon emission intensity of the manufacturing industry will increase by 0.204 units. With the development of digital trade, the promoting effect on the carbon intensity of the manufacturing industry gradually turns into an inhibitory effect. At this time, for every one-unit increase in digital trade, the carbon intensity of the manufacturing industry will decrease by 0.149 units.This might be because in the early stage of digital trade, the costs of infrastructure construction and transformation led to an increase in carbon emissions from the manufacturing industry. Moreover, in the initial stage of digital transformation, the efficiency improvement of the manufacturing industry might not be significant, or there might be a period of technological adaptation, resulting in insufficient optimization of resource utilization and an increase in carbon emissions instead. With the improvement of the development level of digital trade, technological optimization may promote the application of clean technologies, and the improvement of production efficiency may reduce the waste of resources and enhance the efficiency of resource utilization, thereby achieving low-carbon emissions.

Table 3. Baseline regression results.

	(1)	(2)
	CEI	**CEI**
DC	0.185***	0.204***
	(0.034)	(0.037)
DC2	-0.118***	-0.149***
	(0.028)	(0.034)
ES		-0.018
		(0.223)
FD		0.009***
		(0.003)
Urban		-0.029***
		(0.010)
Open		0.006
		(0.013)
RD		0.129
		(0.179)
HC		1.749**
		(0.795)
_cons	0.007**	-0.018
	(0.003)	(0.015)
ID	Yes	Yes

Year	Yes	Yes
r2	0.968	0.973
N	300	300

Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in parentheses. Source: Calculated by Stata17.0 software.

This paper adopts the U-shaped test to verify the inverted U-shaped relationship between digital trade and the carbon emission intensity of the manufacturing industry. The test results are shown in Table 4, confirming that the marginal effect is statistically significant. It can be known from Figure 1 that the extreme point 0.685 (- [0.024/(2*(-0.018))≈0.685) is between [0.009,0.818]. The slope of the curve is positive on the left side of the extreme point and negative on the right side. The slopes of the curve are opposite signs, and the extreme point is within the 95% confidence interval, indicating that the estimation of the extreme point is reliable. It can be considered that there is an obvious inverted "U" shaped relationship between digital trade and the carbon emission intensity of the manufacturing industry. The results show that when it is below the extreme point of 0.685, the carbon emission intensity of the manufacturing industry will increase with the rise of the development level of digital trade, reaching the maximum at the extreme point. When the development level of digital trade is below 0.685, the carbon emission intensity of the manufacturing industry will decrease. Research Hypothesis 1 has been verified.

Table 4. Utest results.

Lower bound	Upper bound	
Interval	0.009	0.818
Slope	0.202	-0.040
t-value	5.580	-1.803
P>t	0.000	0.036

Source: Calculated by Stata17.0 software

Figure 1. utest results

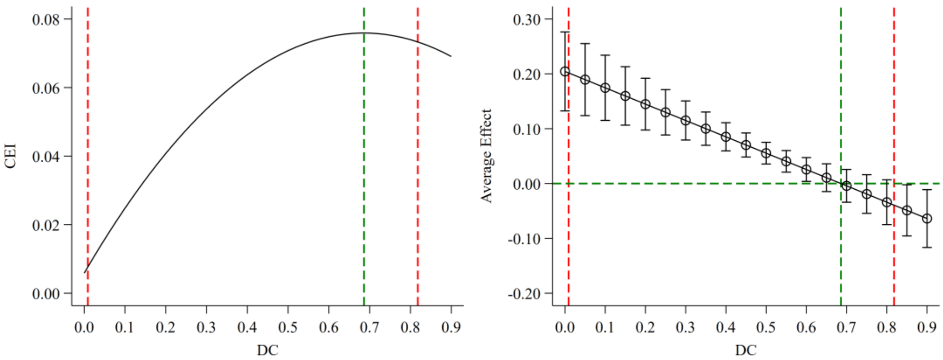

Figure 1. utest results:(a) Inverted U-shaped diagram;(b) Marginal effect graph (95% confidence interval). source: Calculated by Stata17.0 software.

4.1 Baseline Regression

This paper adopts four methods, namely tailing processing, removing municipalities directly under the Central Government, lagging the independent variable by one period, and eliminating the data of epidemic years, to verify the robustness of the benchmark regression results.

Firstly, in Model (1), the data is tailing to a 1% degree to reduce the influence of outliers on the regression results and improve the robustness of the results. The results are shown in column (1) of Table 5. The coefficient of the primary term of digital trade obtained by tailing is 0.180 (p<0.01), and the coefficient of the secondary term is -0.135 (p<0.01). They are consistent with the benchmark regression results in terms of coefficient symbols, significance levels, and the existence of inverted U-shaped relationships. It indicates that tailgating treatment has not changed the fundamental trend and significance level of the impact of digital trade development on the carbon emission intensity of the manufacturing industry.

Secondly, this paper examines the impact of the development level of digital trade on the carbon intensity of the manufacturing industry in the remaining samples by eliminating samples (i.e., municipalities directly under the Central Government) that may have special economic, policy or geographical characteristics. The results are shown in List (2). The coefficient of the primary term of digital trade is 0.260 (p<0.01), and the coefficient of the secondary term is -0.196 (p<0.01). The results of the robust test are consistent with those of the benchmark regression in terms of coefficient signs, significance levels, and the existence of the inverted U-shaped relationship. This indicates that the benchmark regression results have high robustness and are not affected by the special factors of municipalities directly under the Central Government.

Table 5. Robustness test results.

	(1)	(2)	(3)	(4)
	Data indentation 1%%	**de-municipalities**	**Lag one stage independent variable**	**Eliminate the impact of the epidemic**
DC	0.180***	0.260***		0.182***
	(0.031)	(0.039)		(0.043)
DC2	-0.135***	-0.196***		-0.137***
	(0.031)	(0.036)		(0.041)
LDC			0.176***	
			(0.033)	
LDC2			-0.133***	
			(0.033)	
_cons	-0.004	-0.012	-0.018	0.028
	(0.011)	(0.015)	(0.014)	(0.027)
ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
r2	0.980	0.976	0.978	0.979
N	300	260	270	240

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, Standard errors in parentheses. Source: Calculated by Stata17.0 software.

Again, in this paper, the development level of the independent variable digital trade lags behind by one period to examine its impact on the carbon intensity of the manufacturing industry. While verifying the robustness, it also reduces the influence of the endogeneity problem in the study. The results are shown in Column (3). The primary term of digital trade with a lag of one period is 0.176 ($p<0.01$), and the secondary term is -0.133 ($p<0.01$). This indicates that there is a certain time lag effect in the impact of digital trade on the carbon intensity of the manufacturing industry, that is, digital trade does not immediately lead to a significant reduction in carbon emissions from the manufacturing industry. Rather, it takes a certain amount of time for its emission reduction effect to gradually emerge. Moreover, the further improvement of the development level of digital trade gradually weakens its promoting effect on the carbon intensity of the manufacturing industry and may turn into an inhibitory effect. This result is consistent with the benchmark regression in terms of coefficient sign, significance level and inverted U-shaped relationship, enhancing the robustness of the conclusion that digital trade nonlinearly affects the carbon emission intensity of the manufacturing industry.

Finally, in this study, the data of epidemic years were excluded to eliminate the possible interference of this special event, the epidemic, on the regression results. As shown in column (4) of Table 5, the primary term of digital trade is 0.182 ($p<0.01$), and the secondary term is -0.137 ($p<0.01$). These are consistent with the benchmark regression results in terms of coefficient sign, significance level, and the existence of an inverted U-shaped relationship, indicating that after excluding the short-term fluctuations and uncertainties brought about by the epidemic, The result of the impact of digital trade on the carbon emission intensity of the manufacturing industry remains robust.

This verification not only strengthens the robustness of the initial research results, but also enhances the universality and reliability of the research results, thereby providing a more solid foundation for policy-making.

4.3 Endogeneity test

The benchmark regression model may be affected by endogeneity problems, causing deviations in the regression results. First, digital trade is influenced by numerous factors. Although several variables were controlled in this study, the existence of omitted variables cannot be completely ruled out. Second, while the development level of digital trade promotes carbon reduction in the manufacturing industry, carbon reduction in the manufacturing industry will also force the improvement of the development level of digital trade.Therefore, this paper draws on the approach of Nunn Qian (2014), selects the number of mobile phone users in each province at the end of 2000 as the instrumental variable, and considers the time trend [36].This choice is based on theoretical rationality and the availability of actual data, aiming to capture the potential connection between the development level of digital trade and the early communication technology foundation. In order to be consistent with the number of endogenous variables, this paper refers to the practice of Wang Pengfei et al. (2023) and squares the instrumental variable 1 to obtain the instrumental variable 2[37].

Table 6. Results of endogeneity test.

	(1)	(2)	(3)
	First_stage	**First_stage**	**Second_stage**
�IVdigital	-20.504**	-40.270***	
	(8.939)	(12.901)	
IVdigitalsq	0.737***	1.189***	

	(0.242)	(0.351)	
DC			0.580***
			(0.168)
DC2			-0.486***
			(0.172)
ID	Yes	Yes	Yes
Year	Yes	Yes	Yes
Sanderson_Windmeijer_Chi	58.52	36.17	
Sanderson_Windmeijer_Chi_P	[0.000]	[0.000]	
Sanderson_Windmeijer_F	53.55	33.10	
Stock_Yogo	[7.03]	[7.03]	
N	300	300	300

Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in parentheses. Source: Calculated by Stata17.0 software.

Table 6 presents the results of the two-stage least squares (2SLS) regression. As shown in columns (1) and (2), the first-stage regression analysis indicates that the Sander-son-Windmeijer-Chi statistic achieves significance at the 1% threshold, rejecting the null hypothesis that the instrumental variable has heteroscedasticity. The F-statistical values were 53.55 and 33.10, both greater than 10. The null hypothesis of weak instrumental variables was rejected. This result emphasizes the suitability and validity of the instrumental variables selected in this study. Meanwhile, the endogeneity test results are consistent with the regression results in terms of coefficient signs, significance levels, and the existence of inverted U-shaped relationships. This indicates that even after considering endogeneity factors, the initial manifestation of the impact of digital trade development on the carbon emission intensity of the manufacturing industry is a promoting effect, and then it turns into an inhibitory effect. This result enhances the robustness and credibility of the study.

4.4 Analysis of intermediary effect

To verify whether the scale effect and the technology effect play a mediating role in the relationship between the development of digital trade and the carbon emission intensity of the manufacturing industry, this study uses models (2) and (3) for regression analysis.

Table 7. Results of mediation effect analysis.

	(1) Scale	(2) Tech
DC	2.184***	2.164**
	(0.674)	(0.872)
DC2	-1.351**	-2.125***
	(0.586)	(0.713)
_cons	10.993***	0.905**
	(0.362)	(0.385)
ID	Yes	Yes
Year	Yes	Yes
r2	0.989	0.968
N	300	300

Note: *** p<0.01, ** p<0.05, * p<0.1, Standard errors in parentheses. Source: Calculated by Stata17.0 software.

According to columns (1) and (2) in Table 7, it can be known that the regression results of the development level of digital trade on the carbon emission intensity of the manufacturing industry through scale effect and technology effect show that the primary term coefficients of digital trade are significantly positive and the secondary terms are significantly negative. This indicates that in the early stage of the development of digital trade, scale effect and technology effect have a significant positive impact on the carbon emission intensity of the manufacturing industry. With the further improvement of the development level of digital trade, the promoting effect of scale effect and technological effect on the carbon emission intensity of the manufacturing industry gradually weakens and turns into an inhibitory effect after reaching a certain extent. Furthermore, by comparing with the benchmark regression results in the previous text, it is known that the direction of the direct effect coefficient is consistent with that of the scale effect and the technology effect coefficient, indicating that the scale effect and the technology effect play a partial mediating role in the relationship between the development of digital trade and the carbon emission intensity of the manufacturing industry. The research hypotheses 3 and 4 have been verified.

4.5 Heterogeneity Analysis

In the heterogeneity analysis, this study delved deeply into the regional and industry differences in the impact of digital trade development on manufacturing carbon emissions. For this purpose, this paper divides the samples into the eastern region and the central and western regions. Drawing on the methods of Wang Zhihua et al., it classifies each industry of the manufacturing sector and conducts regression analysis by dividing each industry of the manufacturing sector into three categories: labor-intensive, resource-intensive and technology-intensive. The results are shown in Table 8.

Table 8. Results of regional and subdivision industry heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)
	East	**Midwest**	**labor-intensive**	**resource-intensive**	**technology-intensive**
DC	0.005	0.622***	0.586***	0.711***	0.466***
	(0.013)	(0.095)	(0.112)	(0.121)	(0.067)
DC2	0.012	-1.253***	-1.090***	-1.399***	-0.580***
	(0.010)	(0.270)	(0.307)	(0.318)	(0.119)
_cons	0.008	0.095***	0.173***	0.144***	0.166***
	(0.008)	(0.031)	(0.046)	(0.023)	(0.034)
ID	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
r2	0.984	0.985	0.979	0.981	0.983
N	110	190	150	150	150

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.Source: Calculated by Stata17.0 software.

According to the results in columns (1) - (2) of Table 8, both the primary term coefficient and the secondary term coefficient of digital trade in the eastern region are not significant, indicating that the direct effect of the development level of digital trade in the eastern region has no obvious impact on the carbon emission intensity of the manufacturing industry, and there is no obvious inverted U-shaped relationship between the two. On the contrary, in the central and western regions, the primary term coefficient of digital trade is significant and positive, and the secondary term coefficient is significant and negative. This indicates that in the central and western regions, digital trade still has an inverted U-shaped effect of first promoting and then suppressing the carbon emission intensity of the manufacturing industry. This might be because the eastern region has a higher level of digital trade development than the central and western regions. Its digital infrastructure is more complete and the atmosphere of scientific and technological innovation is stronger. Therefore, the carbon emission reduction effect of digital trade in the central and western regions is more significant than that in the eastern region.

Industrial heterogeneity: According to columns (3) - (5) in Table 8, the primary term coefficients of digital trade in each sub-industry are significantly positive, and the secondary term coefficients are significantly negative. It indicates that the development of digital trade has an influence relationship of promoting first and then suppressing the carbon emission intensity of each sub-industry in the manufacturing industry, presenting an inverted U-shaped curve relationship. From the perspective of the impact coefficient of digital trade on the carbon emission intensity of various sub-sectors in the manufacturing industry, in the early stage of the development of digital trade, the promoting effect of digital trade on resource-intensive industries was the most significant, followed by laborintensive and technology-intensive industries. In the later stage of the development of digital trade, the emission reduction effect of digital trade on technology-intensive industries is more significant, followed by resource-intensive and laborintensive industries.

4.6 Spatial Effect Analysis

This paper uses a spatial econometric model to test the spatial effect of the development level of digital trade on the carbon emission intensity of the manufacturing industry. To understand the spatial autocorrelation of carbon emission intensity in the manufacturing industry of various provinces in China, this paper conducts the Moran's I index model for testing. The test results are shown in Table 9. The results show that the global Moran index of manufacturing carbon emission intensity in each year has passed the significance level of 1%, and the global Moran index within the selected years is all positive. This indicates that there is a significant positive correlation in the manufacturing carbon emission intensity of each province in China, that is, regions with high manufacturing carbon emission intensity are clustered together with regions with high carbon emission intensity. Regions with low carbon emission intensity in the manufacturing industry are clustered together.

Table 9 Global Moran Index Results of Carbon Emission Intensity in the manufacturing industry

year	I	E(I)	Sd(I)	Z	P-value
2012	0.149	-0.035	0.065	2.825	0.005
2013	0.140	-0.035	0.066	2.668	0.008
2014	0.141	-0.035	0.065	2.695	0.007
2015	0.147	-0.035	0.065	2.789	0.005
2016	0.152	-0.035	0.065	2.853	0.004
2017	0.150	-0.035	0.068	2.732	0.006
2018	0.139	-0.035	0.068	2.563	0.010

2019	0.137	-0.035	0.068	2.527	0.011
2020	0.139	-0.035	0.068	2.569	0.010
2021	0.137	-0.035	0.067	2.555	0.011

Data source: Calculated by Stata17.0 software.

To present the spatial agglomeration state of carbon emission intensity in the manufacturing industry more intuitively, this paper plots the corresponding Moran scatter plots of carbon emission intensity in the manufacturing industry in 2012 and 2021 based on the verification results of the Moran Index, as shown in Figure 2. It is not difficult to see that compared with the Moran scatter plot in 2012, the number of regions clustered at the origin in 2021 was smaller, indicating that the spatial agglomeration effect of manufacturing carbon emission intensity in various provinces of our country is more obvious. The data points of the past two years are mainly concentrated in the first quadrant and the third quadrant, indicating the trend of high-emission areas aggregating with other high-emission areas and low-emission areas aggregating with other low-emission areas. This mode emphasizes the existence of positive spatial correlation. Therefore, the research results confirm that the carbon emission intensity of the manufacturing industry in various provinces of China shows a significant spatial interdependence, verifying the application of regression analysis of the spatial econometric model.

Figure 2. Moran scatter plot

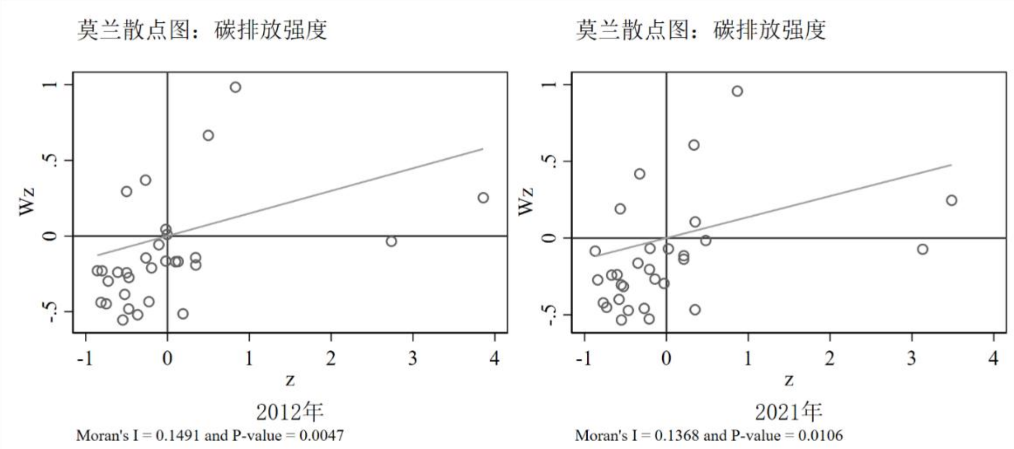

Figure 2. Moran scatter plot:(a)2012;(b)2021. Source: Calculated by Stata17.0 software.

Further LM test revealed that the P-values of both the Spatial Error Model (SEM) and the Spatial Lag model (SAR) were less than 0.1. Through the significance test, it was initially determined to use the Spatial Durbin Model (SDM). Then, the LR test and Wald test were conducted. The results showed that the statistical results of both tests were significant, indicating that the Spatial Durbin Model (SDM) should be selected.

The regression of the SDM model yields Tables 10. It can be seen from the table that under the direct effect, the coefficient of the primary term of the development level of digital trade is significantly positive, and the coefficient of the secondary term is significantly negative. That is, the development level of digital trade has a nonlinear impact of first promoting and then inhibiting the carbon emission intensity of the manufacturing industry in each province. This might be related to the rapid development of digital trade driving the production efficiency of local manufacturing, the optimal allocation of resources, and the application and promotion of environmental protection technologies. In terms of the spatial spillover effect, the coefficient of the primary term of the development level of digital trade is significant and negative, while the coefficient of the secondary term is not significant and positive. This indicates that the improvement of the development level of digital trade has a significant inhibitory effect on the carbon emission intensity of the manufacturing industry in neighboring regions. This might be related to the differences in digital trade development, industrial structure and other aspects among neighboring regions.

Table 10. Regression results of spatial econometric model.

	(1) SDM
Main	
DC	0.177*** (0.025)
DC2	-0.123*** (0.026)
Wx	
DC	-0.122*

	(0.071)
DC2	0.088 (0.089)
Spatial	
rho	0.238** (0.115)
ID	Yes
Year	Yes
r2	0.010
N	270

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.Data source: Calculated by Stata17.0 software.

V. Conclusion and Recommendations

5.1 Conclusion

This study, based on panel data from 30 provinces in China, deeply explores the impact of the development level of digital trade on the carbon intensity of the manufacturing industry. Findings: (1) The development of digital trade has a nonlinear effect of first promoting and then inhibiting the carbon intensity of the manufacturing industry. Moreover, the impact of digital trade on the carbon emission intensity of the manufacturing industry shows regional and sub-industry differences. Specifically, the emission reduction effects in the eastern region and the central and western regions are significantly different, and the emission reduction effect in the central and western regions is more obvious. Within the manufacturing industry, the development of digital trade has an inverted U-shaped relationship with the carbon intensity of various industries. The impact on technology-intensive industries is the most significant, followed by resource-intensive industries, and finally labor-intensive industries. (2) Digital trade can have a promoting and then restraining effect on the carbon intensity of the manufacturing industry through scale effects and technological effects, and the inverted U-shaped relationship is equally obvious. (3) The spatial agglomeration effect of carbon emission intensity in the manufacturing industry of various provinces in China is obvious, showing the characteristics of high-value and high-value or low-value and low-value aggregation, and there is a spatial positive correlation. Under the direct effect, the development of digital trade has a nonlinear impact on the carbon intensity of the manufacturing industry in each province. In terms of spatial spillover effects, the development of digital trade has a significant inhibitory effect on the carbon intensity of manufacturing in neighboring regions.

5.2 Suggestions

Based on the above conclusions, this paper focuses on the five-dimensional system of regional coordination, industrial adaptation, policy precision, educational transformation and spatial linkage, and puts forward the following suggestions:

First of all, the government should increase its support for digital trade and green and low-carbon technologies to promote the transformation and upgrading as well as green development of the manufacturing industry. Policy makers should also recognize the regional differences in digital trade in promoting the green and low-carbon transformation of the manufacturing industry and formulate corresponding policy measures to narrow this gap. First of all, enhance innovation capabilities and technological levels to improve core competitiveness. On the one hand, the government can offer policy preferences and financial support to scientific research undertakings, encouraging enterprises to increase investment in research and development and carry out technological innovation. On the other hand, increase investment in basic research and applied basic research, optimize the structure of R&D expenditure, encourage enterprises and all sectors of society to increase investment in R&D, form diversified sources of R&D funds, enhance the capacity for original innovation, and lay a solid foundation for long-term development.

Secondly, as the carbon emission reduction effects of digital trade vary among different manufacturing industries, it is necessary to implement precise regulation among various industries to unleash the emission reduction potential of different sub-sectors. First of all, formulate the adaptation list of "industry - technology - carbon emissions". For instance, in technology-intensive industries, leading enterprises can be compelled to open green digital technology interfaces and establish industry-level industrial Internet emission reduction platforms. In resource-intensive industries, the "digital twin + process optimization" model can be promoted, and enterprises that have completed the full-process digital transformation can be given the preferential policy of immediate refund of value-added tax upon collection. In labor-intensive industries, an ecosystem of "cross-border e-commerce + localized green manufacturing" can be developed, and tariffs can be reduced or exempted for enterprises that use digital short-chain logistics.

Finally, the government should also adjust the degree of intervention in a timely manner in accordance with the different stages of digital trade development and changes in the carbon emission intensity of the manufacturing industry. At the stage of low digital trade level, that is, when the critical value is lower than 0.436, strengthen the linkage between green technology subsidies and carbon quota allocation; During the high digital trade level stage, that is, when the critical value is higher than 0.436, administrative intervention will be gradually withdrawn, market-oriented trading of "digital carbon tickets" will be promoted, and enterprises will be allowed to exchange their digital emission reduction achievements for foreign trade qualifications.

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