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The impact of digital transformation on low-carbon development of manufacturing

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Objective: To measure the low-carbon development level and digital transformation degree of China's manufacturing industry, and to examine the impact of digital transformation on low-carbon development.

Methods: This paper uses Super Slack Based Measure (SBM) model and multi-regional input-output model to measure the low-carbon development level and digital transformation degree of 17 manufacturing industries in 30 provinces of China from 2012 to 2018, and uses high-dimensional fixed effect model and mediation model to study the impact of digital transformation on low-carbon development.

Results: 1) During the study period, China's manufacturing industry showed an upward trend in terms of low-carbon development level and digital transformation, but there were significant regional and industrial disparities. 2) Digital transformation can significantly promote the low-carbon development of manufacturing industry, which is still valid in the robustness test. 3) For sub-indicators, digital industrialization has the most obvious effect on the low-carbon development of manufacturing industry, and the improvement of digital development environment also has a positive impact on low-carbon development. 4) The heterogeneity analysis indicate that digital transformation has a greater impact on promoting low-carbon development of manufacturing in underdeveloped regions, and the positive effect is obvious in medium-low-energy-consuming industries, but not in high-energy-consuming industries. 5) The mechanism test shows that technological innovation is a channel for digital transformation to promote low-carbon development.

Value: This paper provides empirical evidence for the environmental impact of digital transformation, and offers a scientific basis for relevant departments to formulate low-carbon development policies from the perspective of digital transformation.

KEYWORDS

digital transformation, manufacturing, low-carbon development, multi-regional input-output model, high-dimensional fixed effects model

1 Introduction

After more than 40 years of reform and opening up, China's manufacturing industry has achieved leapfrog development. However, due to the long-term extensive production mode oriented by high energy consumption and high pollution in China's traditional manufacturing industry, environmental problems have also expanded rapidly with the development of traditional manufacturing industry (Peng et al., 2022). According to data from CEADs, the energy consumption of 30 manufacturing industries in China increased from 0.61 billion tons of standard coal in 2000 to 2.3 billion tons of standard coal in 2019, an increase of nearly

2.8 times in 20 years; at the same time, carbon emissions increased from 1.12 billion tons to 3.51 billion tons, an increase of 2.1 times in 20 years. The continuous increase in energy consumption and carbon emissions not only has a negative impact on the sustainable development of China's economy, but also seriously hinders China's progress towards its peak carbon and carbon neutrality goals (Ge et al., 2022). Therefore, it is an urgent and practical issue to be studied how to break the crude development mode of some industries and realize the low-carbon development of China's manufacturing industry.

At present, digital technologies represented by the Internet, artificial intelligence and big data are deeply integrated with various fields of economic and social development, gradually becoming a strong engine for the transformation of new and old kinetic energy in China (Zhang C et al., 2022). According to the "China Digital Economy Development Report (2022)" released by the China Academy of Information and Communications Technology, the scale of China's digital economy reached 7.1 trillion US dollars in 2021, accounting for 39.8% of Gross Domestic Product (GDP), which shows that the digital economy has changed from an important component of China's economy to a key leading force for economic development. In the critical period of China's economic transformation, the application of digital technology will undoubtedly affect the mode of industrial production, and will also have a profound impact on the industry's energy demand and carbon emissions (Ren et al., 2021; Wang J et al., 2022). From existing literature, most scholars focus on the economic effects of digital transformation, both exploring its important impact on the economic development of countries or regions (Mićić, 2017; Pan et al., 2022; Wu and Yang, 2022) and its key role in corporate development (Bhimani, 2015; Ballestar et al., 2021; Gaglio et al., 2022; Zhang J et al., 2022). With the development of digital economy and the tightening of resource and environmental constraints, the environmental effects of digital transformation have attracted the attention of scholars. Relevant studies show that the development of regional digital economy has a positive effect on reducing energy consumption (Ren et al., 2021), improving green total factor productivity (Li and Liao, 2022; Lyu et al., 2023), promoting clean energy development (Chen, 2022), and promoting green development efficiency (Luo et al., 2022). Some scholars have studied the impact of digital transformation on energy efficiency (Zhang L et al., 2022), green technology innovation (El-Kassar and Singh, 2019; Ning et al., 2022) and environmental management (Xia et al., 2022) from the enterprise level. Their research also confirms that digital transformation can promote green development. However, the relationship between digital transformation and carbon emissions remains controversial in academia. Most scholars (Ge et al., 2022; Yu et al., 2022; Zha et al., 2022) believe that digital transformation can help reduce carbon emissions. Zhang W et al. (2022) found that the development of digital industries has squeezed out carbon-intensive industries, optimized the industrial structure, and reduced carbon emissions. Yu et al. (2022) believes that the application of digital technology has greatly improved production conditions, optimized factors other than energy input, and helped to reduce carbon emissions. However, some scholars (Salahuddin and Alam, 2015; Avom et al., 2020) believe that digital transformation will increase the demand for energy sources such as electricity, which will lead to an increase in carbon emissions.

Although scholars have conducted extensive research on the economic and environmental effects of digital transformation from a regional or corporate perspective, few studies have explored the relationship between digital transformation and environmental performance from a combined regional and industry perspective, which hinders a comprehensive understanding of the impacts of digital transformation. Therefore, this paper extends the existing research as follows: 1) This paper explores the impact of digital transformation on low-carbon development of manufacturing industry from the perspective of sub-region and sub-industry. 2) Using matching data to measure the low-carbon development level of manufacturing industry in China's provincial-level. This avoids measurement errors caused by ignoring the heterogeneity of regions or industries. 3) By combining the multi-regional input-output model with the evaluation system of digital economy development level, the measurement framework of the digital transformation of manufacturing industry in various provinces of China is constructed, which enriches the measurement research of digital transformation.

2 Theoretical analysis

Digital transformation refers to the process by which enterprises apply digital technologies such as networks, communications, and computing to transform organizational structures and business models to achieve workflow optimization, organizational efficiency improvement, and value creation (Vial, 2019). As a revolution, digital transformation may fundamentally change the structure and trading mode of production factors, which will have an important impact on production efficiency and ecological environment (Goldfarb et al., 2015; Verhoef et al., 2019).

2.1 Direct mechanism

The deep integration of digital technologies such as big data and traditional manufacturing industry can promote the low-carbon development of manufacturing industry by eliminating the information gap, achieving accurate matching of supply and demand, and adapting to the market environment (Wu et al., 2022). The acceleration of the digitization process has spawned a variety of information service platforms, which have profoundly changed the information search mode and resource allocation mode of market participants. The digital platform gradually reduces the information asymmetry in the field of resource allocation by aggregating massive resource demand information, which is conducive to the supply and demand sides to grasp each other's real needs in an instant and efficient manner, thereby improving resource utilization efficiency (Kaija et al., 2022). Producers use data mining technology to analyze consumer demand preferences, carry out targeted production activities, and form a dynamic and accurate matching mechanism between supply and demand, thereby reducing unnecessary waste in production.

Although the scale effect of digital transformation will lead to an increase in energy demand (Moyer and Hughes, 2012; Lange et al., 2020), the rapid penetration of digital technology profoundly affects the supply-demand structure and utilization efficiency of energy (Goldbach et al., 2018). The carbon reduction caused by the adjustment of energy consumption structure, the matching of energy supply-demand, and the improvement of energy efficiency is greater than the carbon increase caused by the expansion of production scale, which makes the "net" impact of digital transformation on carbon emissions show an inhibitory effect (Zhang Z et al., 2022). From the perspective of structural adjustment, the application of digital technology can strengthen the substitution role of clean energy for fossil energy, reduce the dependence of the industry on fossil energy. In addition, the application of digital technology has laid a technical foundation for the research and development and promotion of clean energy, which is conducive to changing the production mode of the industry based on fossil energy consumption. From the perspective of supply-demand matching, digital transformation is conducive to improving the coordinated and matching of energy supply side and demand side (Kaija et al., 2022). The application of digital technology makes it easy to collect and process information. Producers can use the information they have to judge the supply and demand of energy to match supply and demand (Goldbach et al., 2018). Improving energy efficiency is another effective way to achieve carbon emission reduction (Yi et al., 2022). On the one hand, the application of digital technology and data resources has spawned new technologies and formats related to energy production, helping to improve industrial energy efficiency. On the other hand, digital transformation can promote the penetration of digital technology into the enterprise's energy scheduling system, which will help realize the efficient operation of procurement, storage and management of energy, and then promote the low-carbon development of industry (Zhang et al., 2023). Based on the above analysis, this paper proposes the research hypothesis.

H1: The digital transformation has a positive effect on low-carbon development in manufacturing.

2.2 Indirect mechanism

Technological innovation is an effective way to achieve economic growth and protect the environment (Daron et al., 2012). The improvement of technology is conducive to cleaner production for enterprises, which has a positive effect on achieving carbon emission reduction (Leung et al., 2014; Xu et al., 2021). In theory, using digital technologies to improve production and management processes can have a positive impact on innovation (Nambisan et al., 2019; Ning et al., 2022). From Schumpeter's explanation of innovation (Schumpeter, 1934), the essence of innovation lies in the recombination of elements. Digitization accelerates the construction of modern information communication networks. Data, knowledge and information, as the key innovation elements, are rapidly spread and applied through communication network technology. It is more convenient for enterprises to obtain heterogeneous innovation elements and realize knowledge linkage than before. In addition, the widespread application of digital technology facilitates the flow of knowledge and information between internal and external enterprises, which is conducive to breaking down invisible barriers to innovation (Niu et al., 2023). Digital transformation not only promotes the diffusion of innovation elements, but also gives birth to more innovation elements. The application of digital technologies such as big data and cloud computing enables the storage and analysis of data, knowledge and information. The accumulation of innovative resources provides favorable conditions for low-carbon technology innovation. Based on the above analysis, this paper proposes the research hypothesis.

H2: Digital transformation improves the low-carbon development level of manufacturing industry by promoting the mechanism of technological innovation.

3 Measurement of core variable

3.1 Low-carbon development level

The existing literature points out that the low-carbon production efficiency calculated by taking carbon emissions as undesired output, regional GDP as expected output, labor, capital and energy as production factors can not only reflect the efficiency of economic output, but also take into account the problem of carbon emissions, which can better measure the extent to which the development model meets the dual goals of economic growth and energy conservation and emission reduction (Chen and Golley, 2014).

3.1.1 Method

The traditional Data Envelopment Analysis (DEA) calculation method does not consider the slack variables, and most of them are angle and radial models. There are problems such as the incomparability of decision making units on the efficiency Frontier (Andersen and Petersen, 1993) and the same proportion of input or output changes (Tone, 2001). Therefore, this paper selects the Super-SBM model, which is improved by Tone on the basis of its non-radial and non-angle SBM model (Tone, 2002), and fully takes into account the scale reward problem, selecting the more realistic variable returns to scale (VRS). In addition, the carbon emission constraint is treated as undesirable output, and the Super-SBM model considering undesirable output is constructed. The model relaxes the constraints of the same proportion change of each factor and the effective decision-making unit efficiency value $\leqslant 1$, so that the effective decision-making unit can be comparable in time.

Specifically, assuming that there are n effective decision making units (DMU), each DMU has m input factors, and each DMU will produce r_1 expected output and r_2 undesirable output. The corresponding input factors, expected output and undesirable output are expressed as: x_{ik}, y_{qk} and b_{tk}, respectively. The calculation model of the efficiency value ρ is expressed as follows:

$$\rho = min\frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{c_i^-}{x_{ik}}}{1-\frac{1}{r_1+r_2}\left(\sum_{q=1}^{r_1}\frac{c_q^+}{y_{qk}}+\sum_{t=1}^{r_2}\frac{c_t^-}{b_{tk}}\right)}$$

$$s.t.\begin{cases}\sum\limits_{j=1,j\neq k}^{n} x_{ij}\lambda_j - c_i^- \leqslant x_{ik} & i=1,\cdots,m\\ \sum\limits_{j=1,j\neq k}^{n} y_{qj}\lambda_j + c_q^+ \geqslant y_{qk} & q=1,\cdots,r_1\\ \sum\limits_{j=1,j\neq k}^{n} b_{tj}\lambda_j - c_t^- \leqslant b_{tk} & t=1,\cdots,r_2\\ \sum\limits_{j=1,j\neq k}^{n} \lambda_j = 1,\ \lambda\geqslant 0 & j=1,\cdots,n\\ c_i^-, c_q^+, c_t^- \geqslant 0\end{cases}$$

In the formula, c_i^-, c_q^+, c_t^- are the slack vectors of input factors, expected output and undesirable output respectively; λ is the index weight, when $\sum_{j=1,j\neq k}^{n}\lambda_j = 1$ and $\lambda \geqslant 0$, it is variable returns to scale; ρ is low-carbon development level.

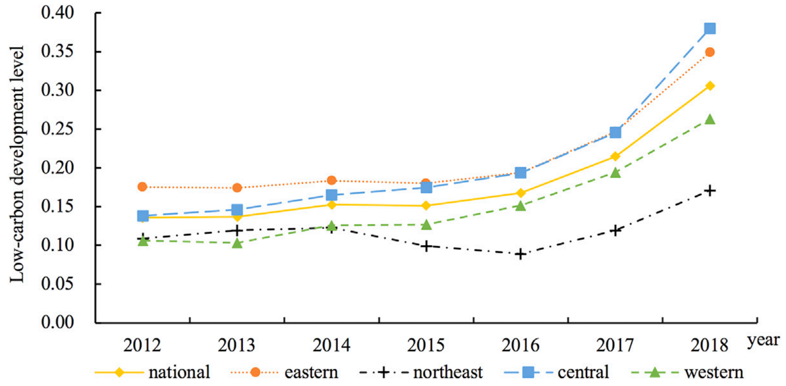

FIGURE 1
The evolution trend of the average value of low-carbon development of manufacturing industry in china and its four regions.

3.1.2 Indicators and data

This paper uses gross industrial output as the expected output index, carbon emissions as the unexpected output index; input indicators are general, including capital, labor and energy consumption. To estimate the total industrial output value data from 2012 to 2018, the industrial sales output value, the current year inventory and the previous year inventory are taken into account. Then, according to the producer price index of industrial products divided by provinces and industries in each year, the data was deflated to the comparable industrial output value based on 2012 as the base year. Capital investment is measured by the capital stock of the manufacturing industry in each province. This year's capital stock is calculated according to the perpetual inventory method. The composition of energy consumption includes 20 energy types such as coal, oil, natural gas and electricity. Because the average low calorific value of each type of energy is not the same, it can not be directly added. Therefore, the reference coefficients of various types of energy converted into standard coal provided by the "China Energy Consumption Statistical Yearbook" are used to convert units of different energy types into 10,000 tons of standard coal and add them.

The original data of expected output, capital input and labor input required for the measurement of low-carbon development level of manufacturing industry are from the "China Industrial Statistical Yearbook". The original data of unexpected output and energy consumption are from the CEADs database. The price deflator data is from the "China Price Statistical Yearbook".

3.1.3 Results and analysis

This paper uses Matlab 2020b software to calculate the low-carbon development level of 17 manufacturing industries in 30 provinces of China from 2012 to 2018, and analyzes its evolution characteristics from the national level, regional level and industry level. As shown in Figure 1, from 2012 to 2018, the low-carbon development level of manufacturing industry in China and its regions showed an upward trend. According to the changing characteristics of low-carbon development level of manufacturing industry, the research interval can be divided into two stages. During the first stage from 2012 to 2015, the low-carbon development level of the manufacturing industry increased at a relatively low rate, and the growth trend was not obvious. The second stage is from 2016 to 2018. During this period, the low-carbon development level of China's manufacturing industry showed a rapid upward trend, and the increase was obvious. The reason for this change trend may be that 2012–2015 is the early stage of China's low-carbon transformation and development. Because the economic development model has a certain path dependence effect, the effect of low-carbon development in the short term is not significant. In addition, China's digital transformation during this period is still in its infancy, and the digital economy and the real economy have not achieved deep integration, which makes the low-carbon development level of manufacturing industry grow more slowly. With the deepening of the concept of low-carbon development and the deep integration of digital economy and real economy, the low-carbon transformation kinetic energy accumulated in the early stage has been released, and the low-carbon development level of manufacturing industry has been rapidly improved.

From the perspective of regional differences, the low-carbon development level of manufacturing industry in the eastern and central regions is relatively close, which is higher than the national average; the level of low-carbon development in the western region has greatly improved, but there is still a big gap with the eastern and central regions. The low-carbon development level of manufacturing in northeast is not only lower than the eastern and central regions, but also gradually lags behind the western region, and the gap with other regions gradually widened. This regional difference is highly correlated with China's economic development, industrial layout and spatial distribution of resources.

Further, analyze the changes in the level of low-carbon development of China's manufacturing industry from an industry perspective. Table 1 lists the calculation results for 2012, 2015, and 2018. On the whole, the low-carbon development level of each manufacturing industry is on the rise. From the perspective of industry differences, food and tobacco, communications electronic equipment and electrical machinery and equipment in the three industries of low-carbon development level in each year ranked high, and Paper printing cultural education sports, metal smelting and non-metallic products low-carbon development level ranked low. It can be found that industries with high levels of low-carbon development are mostly low-energy-consuming industries. These industries for energy dependence is not strong, low-carbon development action less resistance. Most of the industries with low low-carbon development levels belong to traditional manufacturing industries with high energy consumption and high pollution. Such

TABLE 1 Measurement results of low-carbon development level of manufacturing industry.

Industry code	Abbreviation	2012	Rank	2015	Rank	2018	Rank
6	Food and tobacco	0.1960	3	0.2585	1	0.4549	1
7	Textile industry	0.0906	13	0.1121	12	0.3311	8
8	Manufacture of leather, fur, feather and related products	0.1040	11	0.1417	8	0.3237	9
9	Processing of timber and furniture	0.1215	9	0.1672	5	0.4353	2
10	Paper printing cultural education sports	0.0700	17	0.0953	17	0.1872	16
11	Petroleum processing	0.2913	1	0.1080	14	0.2093	14
12	Chemical products	0.1242	8	0.1381	10	0.2372	12
13	Non-metallic products	0.0861	15	0.1031	15	0.2091	15
14	Metal smelting	0.1572	6	0.0967	16	0.1866	17
15	Metal products	0.1269	7	0.1566	6	0.2766	10
16	General purpose machinery	0.1020	12	0.1238	11	0.2229	13
17	Special purpose machinery	0.1158	10	0.1386	9	0.2433	11
18	Transportation equipment	0.1596	4	0.2205	3	0.3694	6
19	Electrical machinery and equipment	0.2332	2	0.2094	4	0.3964	4
20	Communication electronic equipment	0.1581	5	0.2484	2	0.3985	3
21	Instrumentation	0.0843	16	0.1449	7	0.3851	5
22	Other manufactured goods	0.0880	14	0.1095	13	0.3379	7

industries have high demand for energy and many have overcapacity problems, so the level of low-carbon development is low. This industry difference shows that the traditional high-pollution and high-energy-consuming manufacturing industry is still the key industry of China's low-carbon reform, and improving the low-carbon development level of such industries plays a key role in achieving the "dual-carbon goals" and promoting the high-quality development of the manufacturing industry.

3.2 Digital transformation

From the literature on digital economy measurement, most studies measure the level of digital economy development at the national and regional levels or the degree of digital transformation at the enterprise level. Scholars usually use input-output tables or macroeconomic indicators to measure the level of digital economic development including national, provincial and urban dimensions (Balcerzak and Pietrzak, 2017; Liu et al., 2022; Zhang C et al., 2022). Or use text analysis to measure the degree of digital transformation at the enterprise level (Feng et al., 2022), and a small number of studies have measured the degree of digital transformation at the industry level. These studies can reflect the development of digital economy or digital transformation in China to some extent. However, measuring the degree of digital transformation from the regional level or the industry level alone will lead to deviations in the measurement of digital transformation. Out of self-interest motivation, enterprises exaggerate the disclosure of digital related words, which will lead to distortion of digital measurement at the enterprise level. In view of this, this paper constructs a new measurement model of digital transformation degree.

3.2.1 Measurement model and data

The degree of digital transformation of manufacturing in different regions depends not only on the intensity of industry digital input, but also on the development of regional digital economy. Therefore, drawing on the research ideas of Arnold et al. (Arnold et al., 2016), using China's multi-regional input-output model, combined with the measurement system of digital economy development level of each province, this paper constructs a framework for measuring the digital transformation degree of manufacturing industry in different provinces in China. The benchmark calculation formula is:

$$\boldsymbol{digital_{ijt} = Idigital_{ijt} \times Rdigital_{it}}$$

In the formula, $digital_{ijt}$ represents the degree of digital transformation of i province and j industry in the t year; $Idigital_{ijt}$ represents the digital input intensity of i province and j industry in the t year; $Rdigital_{it}$ represents the level of digital economy development in province i in year t.

This paper uses input-output method to measure the digital input intensity of manufacturing industry. Industry digital input intensity is the proportion of industry digital intermediate input in total input. Among them, the digital intermediate input part includes direct digital intermediate input and complete digital intermediate input. In the case of only considering direct digital intermediate input, the calculation expression of digital input intensity is:

$$\boldsymbol{Idigital_{cj}^{direct} = Z_{cj} \big/ X_j}$$

TABLE 2 Measurement system of digital economy development level.

First grade indexes	Second index	Measurement index	Unit	Attribute
Digital industrialization	Computer communications and other electronic equipment manufacturing	Main business income	CNY100 million	+
		Number of employees	10,000	+
	Telecommunications broadcast television and satellite transmission services	Total telecommunications business *per capita*	CNY 10,000	+
		Long-distance optical cable line length	10,000 km	+
		Mobile phone penetration rate	%	+
	Internet and related services	Internet penetration rate	%	+
		Number of Internet broadband access ports	Unit	+
		Number of websites *per capita*	Unit	+
	Software and information technology services	Per capita software business income	CNY 10,000	+
		Information technology service income *per capita*	CNY 10,000	+
Industrial digitalization	Digital application	The proportion of enterprises with e-commerce transactions	%	+
		E-commerce sales	CNY100 million	+
		Per capita express business volume	Piece	+
		Number of websites per 100 enterprises	Unit	+
		Digital inclusive financial index	—	+
Digital economy development environment	Innovation environment	R&D expenditure intensity	%	+
		Number of patent applications	10,000 piece	+
	Market circumstances	Whether to issue policies in support of the 'digital economy'	—	+
		Marketization index	—	+

where $Idigital_{cj}^{direct}$ represents the direct digital input intensity of industry j; Z_{cj} represents the intermediate input of digital industry c to industry j; X_j represents the total input of industry j. The calculation expression of complete digital input intensity is:

$$Idigital_{cj}^{complete} = Idigital_{cj}^{direct} + \sum_{k=1}^{n} Idigital_{ck}^{direct} Idigital_{kj}^{direct} + \sum_{s=1}^{n}\sum_{k=1}^{n} Idigital_{cs}^{direct} Idigital_{sk}^{direct} Idigital_{kj}^{direct} + \cdots$$

Where $Idigital_{cj}^{complete}$ represents the full digital input intensity of industry j; the first item on the right side of the equal sign is the direct digital input intensity, and the subsequent items are the forward indirect digital input intensity, that is, the n+1th item is the nth indirect digital input intensity, which adds up to the complete digital input intensity. Considering that complete digital intermediate input can accurately measure the real situation of industry digitization, this paper uses the digital input intensity under the measurement of complete digital intermediate input to calculate the degree of industry digital transformation, and uses the degree of digital transformation obtained under the measurement of direct digital intermediate input as a substitution variable for subsequent robustness tests.

The data of digital input intensity are derived from China's multi-regional input-output table in 2012, 2015, and 2017 released by CEADs database. China's multi-regional input-output table contains 31 provinces and 42 economic sectors. Some sectors related to the digital economy only have some digital content, so this paper constructs the digital industry stripping coefficient to separate the digital content part. The digital industry stripping coefficient is the proportion of digital output in the total output of the industry containing digital content. The formula is expressed as:

$$\delta_{it} = X_{it}^{d} \big/ X_{it}$$

Among them, δ_{it} is the digital industry divestiture coefficient of industry i in year t, X_{it}^{d} is the digital output part of industry i in year t, and X_{it} is the total output of industry i in year t. Constrained by data constraints, this paper uses industry operating income to characterize total output to determine the digital industry stripping coefficient. Considering the change of digital output and total output in the time dimension, this paper determines the stripping coefficient of digital industry in different years. Since the China multi-regional input-output table is not continuous, this paper uses the digital industry divestiture coefficient to obtain digital intermediate input data for consecutive years from 2012 to 2018.

According to the definition of the core industries of the digital economy in the "Statistical Classification of Digital Economy and Its Core Industries (2021)", this paper constructs a measurement system for the development level of digital economy from three dimensions: digital industrialization, industrial digitization and digital economic development environment (Zhang J et al., 2022; Lyu et al., 2023), as shown in Table 2. The marketization index data in the sample are derived from the "China Provincial Marketization Index Report

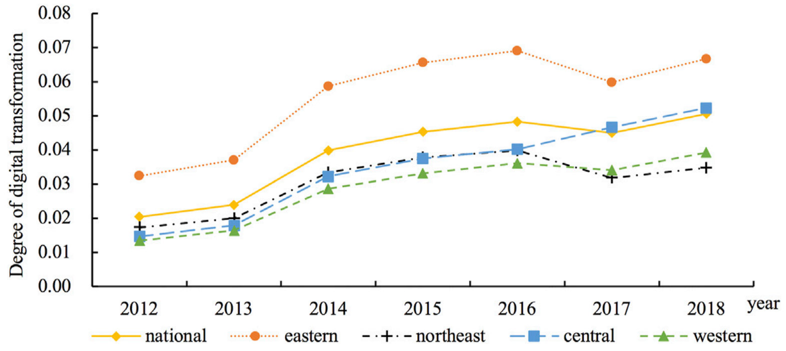

FIGURE 2
Evolution trend of average degree of digital transformation of manufacturing industry in china and four regions.

(2021)", the Digital Inclusive Finance Index is derived from the "Peking University Digital Inclusive Finance Index (2011–2020)", and other data are derived from the "China Statistical Yearbook", "China Information Yearbook" and the CSMAR digital economy database. In order to avoid the subjectivity of the evaluation results and fully reflect the original information of the data, the entropy method is used to measure the level of digital economy development at the provincial level.

3.2.2 Results and analysis

According to the measurement model constructed above, the degree of digital transformation of manufacturing industry in China's provinces from 2012 to 2018 is measured. Figure 2 shows the changes in the degree of digital transformation of manufacturing industry in the whole country and its four major regions. Overall, from 2012 to 2018, the degree of digital transformation of manufacturing in various regions of the country is on the rise. In terms of time nodes, 2012–2015 is a period of rapid growth of digital transformation of manufacturing industry in various regions. This period is a period of rapid integration of digital technology and real economy. The demand for digital input in manufacturing industry is strong, and the degree of digital transformation shows rapid growth. From 2016 to 2018, it was a stage of fluctuating growth. During this period, the growth rate of digital transformation of manufacturing industry slowed down, and it decreased slightly in 2017. The reason for this trend may be that the scale dividend in the early stage of digital transformation of manufacturing industry gradually disappeared, the transformation entered a mature stage of development, and the demand for digital input was relatively stable.

From the perspective of regional differences, the eastern region has the highest degree of digital transformation of manufacturing industry, which has remained above the national average. The degree of digital transformation of manufacturing industry in the central, western and northeastern regions is similar and lower than the national average. It is worth noting that the digital transformation gap between the eastern and central regions and the western and northeastern regions has been expanding year by year, which to some extent reflects the "digital divide" phenomenon caused by unbalanced regional development in the digital era.

Table 3 shows the average degree of digital transformation at the two-digit industry level in 2012, 2015, and 2018. On the whole, from 2012 to 2018, the degree of digital transformation in China's manufacturing industries is on the rise. From the perspective of industry differences, communication electronic equipment, instrumentation and electrical machinery and equipment are the industries with the highest degree of digital transformation, which are mostly high-end manufacturing industries with low energy consumption and obvious technical characteristics. Petroleum processing, metal smelting, food and tobacco are industries with low degree of digital transformation. Most of these industries are traditional manufacturing industries. The traditional production mode is relatively solid, the pace of digital transformation is relatively slow, and the degree of transformation is low. This industry difference shows that it is urgent to promote the digital transformation of traditional manufacturing industry.

4 Empirical design

4.1 Empirical model

This paper uses high-dimensional panel data at the provincial and industry levels in China from 2012 to 2018 to empirically study the impact of digital transformation on low-carbon development of manufacturing. The high-dimensional fixed effect model is constructed as follows:

$$\boldsymbol{Lcp_{ijt} = \alpha_0 + \alpha_1 Digital_{ijt} + \beta Control_{ijt} + \mu_i + \mu_j + \mu_t + \varepsilon_{ijt}}$$

Among them, Lcp_{ijt} is the level of low-carbon development, $Digital_{ijt}$ is the degree of digital transformation, and $Control_{ijt}$ represents the collection of control variables; μ_i、 μ_j and μ_t are province effect, industry effect and time fixed effect respectively; ε_{ijt} is random error term; subscripts i, j and t represent province, industry, and year, respectively. The model mainly focuses on the symbol, size and significance level of the coefficient α_1.

4.2 Variables

The explanatory variable is the level of low-carbon development in manufacturing (Lcp). The core explanatory variable is the degree of digital transformation in manufacturing ($Digital$). The mechanism variable is the level of technological innovation ($Innov$), which is measured by the proportion of industry patents in national patents.

TABLE 3 Measurement results of digital transformation degree of manufacturing industry.

Industry code	Abbreviation	2012	Rank	2015	Rank	2018	Rank
6	Food and tobacco	0.0086	17	0.0197	17	0.0230	16
7	Textile industry	0.0090	16	0.0215	16	0.0269	14
8	Manufacture of leather, fur, feather and related products	0.0132	9	0.0262	13	0.0330	9
9	Processing of timber and furniture	0.0105	13	0.0239	15	0.0301	12
10	Paper printing cultural education sports	0.0120	12	0.0304	11	0.0318	11
11	Petroleum processing	0.0102	15	0.0250	14	0.0205	17
12	Chemical products	0.0134	8	0.0333	9	0.0340	8
13	Non-metallic products	0.0130	10	0.0344	8	0.0327	10
14	Metal smelting	0.0103	14	0.0301	12	0.0230	15
15	Metal products	0.0129	11	0.0327	10	0.0296	13
16	General purpose machinery	0.0199	4	0.0479	4	0.0469	5
17	Special purpose machinery	0.0182	6	0.0435	5	0.0471	4
18	Transportation equipment	0.0169	7	0.0380	7	0.0409	6
19	Electrical machinery and equipment	0.0234	3	0.0553	3	0.0607	3
20	Communication electronic equipment	0.0932	1	0.1761	1	0.2394	1
21	Instrumentation	0.0431	2	0.0926	2	0.1021	2
22	Other manufactured goods	0.0184	5	0.0390	6	0.0380	7

According to the existing research conclusions, this paper selects the following control variables: Energy consumption structure (Es). The energy consumption structure is measured using the proportion of coal energy consumption in the manufacturing industry's total energy consumption. Production factor structure (Fe). Capital and labor are the two most basic production factors in production activities. Therefore, the ratio of capital stock to labor force is used to measure production factor structure. R&D investment intensity ($Lnrd$). R&D investment intensity is represented by the logarithm of internal expenditure of research and experimental development funds of industrial enterprises above designated size. It is generally believed that green technology innovation is the basis for achieving low-carbon production, and R&D investment, as an important source of green technology innovation, should have a positive impact on achieving low-carbon development. Environmental regulation intensity ($Ereg$). The environmental regulation intensity index was constructed by using the industrial wastewater discharge compliance rate, industrial sulfur dioxide removal rate, industrial smoke (powder) dust removal rate and solid waste comprehensive utilization rate. Level of openness ($Lnfdi$). The opening level is measured by the logarithmic form of the total amount of foreign capital actually utilized. Government intervention (Gov). Considering that local fiscal expenditure is an important index to reflect‘s participation in economic activities, this paper uses the ratio of fiscal expenditure deducting education expenditure to regional GDP as the proxy variable of government intervention (Li and Lin, 2017).

TABLE 4 Descriptive statistics of main variables.

Variables	Obs	Mean	Std.Dev.	Min	Max
Lcp	3570	0.181	0.205	0.001	5.742
$Digtial$	3570	0.039	0.049	0.001	0.537
Es	3570	0.220	0.221	0.000	0.992
Fe	3570	0.020	0.082	0.000	1.861
$Lnrd$	3570	5.087	1.331	1.872	7.653
$Ereg$	3570	0.510	0.534	0.000	2.585
$Lnfdi$	3570	5.366	1.944	−2.345	7.722
Gov	3570	0.224	0.103	0.096	0.672

4.3 Data sources

The sample period of this paper is 2012–2018, and 17 two-digit manufacturing industries in 30 provinces in China are selected for the study. The control variable data comes from "China Statistical Yearbook", "China Industrial Statistical Yearbook", "China Economic Census Yearbook", "China Science and Technology Statistical Yearbook", provincial statistical yearbooks and CEADs database. Variable data are provided in the Supplementary Table S1. The descriptive statistics of the main variables are shown in Table 4.

TABLE 5 Results of benchmark regression and further analysis[a].

Variables	(1)	(2)	(3)	(4)	(5)
Digital	0.2382**	0.3084***			
	(2.2640)	(2.9262)			
Digital_id			0.4001*** (3.2560)		
Digital_di				0.2067*** (2.6033)	
Digital_de					0.2079** (2.2106)
Es		−0.0626***	−0.0629***	−0.0618***	−0.0617***
		(−3.4748)	(−3.4922)	(−3.4336)	(−3.4219)
Fe		0.1891***	0.1907***	0.1860***	0.1868***
		(4.9833)	(5.0271)	(4.9105)	(4.9174)
Lnrd		0.0685***	0.0686***	0.0693***	0.0678***
		(3.3168)	(3.3217)	(3.3535)	(3.2784)
Ereg		−0.0538***	−0.0536***	−0.0533***	−0.0545***
		(−2.8338)	(−2.8289)	(−2.8085)	(−2.8710)
Lnfdi		−0.0033	−0.0031	−0.0035	−0.0033
		(−1.0209)	(−0.9605)	(−1.0796)	(−1.0009)
Gov		−0.5435***	−0.5460***	−0.5401***	−0.5517***
		(-3.0520)	(-3.0676)	(-3.0308)	(-3.0976)
Constant	0.1715***	−0.0027	−0.0040	−0.0055	0.0063
	(34.0161)	(−0.0238)	(−0.0356)	(−0.0487)	(0.0558)
Province effect	*YES*	*YES*	*YES*	*YES*	*YES*
Industry effect	*YES*	*YES*	*YES*	*YES*	*YES*
Year effect	*YES*	*YES*	*YES*	*YES*	*YES*
$Adj.R^2$	0.2819	0.2954	0.2958	0.2950	0.2946
Obs	3570	3570	3570	3570	3570

[a]The ***, **, and * in the table represent the significant levels of 1%, 5%, and 10%, respectively. The t statistic is in parentheses. The following table has the same meaning.

5 Empirical results and analysis

5.1 Benchmark regression results

Considering that industry differences, regional differences and time factors may have an impact on the estimation results, this paper uses high-dimensional fixed effects model for parameter estimation. The benchmark regression results are shown in Table 5. Among them, column 1) is the estimation result without control variables, and the estimation coefficient of the core explanatory variable is significantly positive at the 5% level. Column 2) is the estimated result of adding control variables. The estimated coefficient of digital transformation is still significantly positive and can reject the null hypothesis at the 1% level. The above results show that digital transformation can significantly promote the low-carbon development level of manufacturing industry. H1 of this paper is verified. Digital transformation can strengthen the synergy between the upstream and downstream of the industrial chain and reduce unnecessary losses in the production process, which has a positive impact on promoting low-carbon development.

The control variable symbol is consistent with expectations. The impact coefficient of energy consumption structure on low-carbon development was significantly negative at the level of 1%, indicating that the excessive proportion of coal energy consumption was not conducive to the improvement of low-carbon development level of the manufacturing industry. The structure of production factors has a significant role in promoting the low-carbon development of manufacturing industry. The regression coefficient of R&D investment is positive, indicating that increasing R&D investment in manufacturing can help its low-carbon development. The impact of government intervention on low-carbon development is negative, which may be because excessive government intervention in the market harms the level playing field. The regression coefficient of environmental regulation is positive, indicating that environmental regulation can promote the low-carbon development of manufacturing industry. The regression coefficient of openness is negative, but the result is not significant, indicating that foreign investment has not effectively promoted the low-carbon development level of manufacturing industry.

TABLE 6 Results of stability test.

Variables	(1)	(2)	(3)	(4)	(5)
	Lcp_sbm	*Lcp*	*Lcp_cp*	*Lcp_ct*	*Lcp*
Digital	0.2632***		0.7034***	−0.8312***	0.3084***
	(3.1872)		(5.2535)	(−4.2942)	(2.9262)
$Digital^{direct}$		0.5154***			
		(2.6856)			
Control variables	*YES*	*YES*	*YES*	*YES*	*YES*
Province effect	*YES*	*YES*	*YES*	*YES*	*YES*
Industry effect	*YES*	*YES*	*YES*	*YES*	*YES*
Year effect	*YES*	*YES*	*YES*	*YES*	*YES*
$Adj.R^2$	0.3952	0.2951	0.1892	0.0921	0.2954
Obs	3570	3570	3570	3570	3570

5.2 Further analysis

Exploring the impact of sub-indicators of digital transformation on the low-carbon development of manufacturing industry is of great significance for optimizing the digital transformation strategy to give full play to its low-carbon effect. This paper divides the development level of regional digital economy into three dimensions: digital industrialization ($Digital\_id$), industrial digitization ($Digital\_di$) and digital development environment ($Digital\_de$), and constructs sub-indicators of digital transformation based on this. The sub-indicators of digital transformation were used as the explanatory variables for regression, and the results were shown in columns (3)–(5) in Table 5. It can be found that all sub-indicators of digital transformation have a significant positive impact on the low-carbon development of the manufacturing industry, but their impact is different. Among them, the effect of digital industrialization on the low-carbon development of manufacturing industry is the most obvious. The promoting effect of industrial digitalization and digital development environment on low-carbon development of manufacturing industry is weaker than that of digital industrialization. As the foundation of the development of the digital economy, digital industrialization plays a supporting role in the digital transformation of the manufacturing industry. At the current stage, digital industrialization is developing faster and the most mature, so its positive effect on promoting the low-carbon development of manufacturing industry is strong. Industrial digitalization also plays a positive role in promoting the low-carbon development of the manufacturing industry, but due to cost and technology constraints, the process of industrial digitalization lags behind digital industrialization. The digital development environment mainly affects the low-carbon development of the manufacturing industry by promoting digital transformation, so its impact effect is weaker than that of digital industrialization. Further analysis shows that in order to give full play to the role of digital transformation in the low-carbon development of the manufacturing industry, it is necessary to accelerate the process of digital industrialization and industrial digitization, and the importance of the digital development environment cannot be ignored.

5.3 Robustness test

5.3.1 Replace the key variable measurement method

First, the SBM model is used to recalculate the low-carbon development level of manufacturing industry. Second, the measurement method of replacing the core explanatory variables. The degree of digital transformation ($Digital^{direct}$) measured by the direct digital intermediate input method is used as the core explanatory variable. The estimation results after replacing the main variables are shown in columns (1)–(2) of Table 6.

5.3.2 Replace the measurement indicators of low-carbon development level

The connotation of low-carbon development of manufacturing industry is rich, and excessive reliance on single indicators will inevitably make the research conclusion one-sided. Therefore, drawing on the measurement of low-carbon development level in existing literature, single-factor low-carbon production efficiency (i.e., output per unit of carbon emissions) and carbon emission intensity are used as indicators of low-carbon development level of manufacturing industry to re-estimate the benchmark model (Kaya and Yokobori, 1997). The results are shown in columns (3)–(4) of Table 6.

5.3.3 Processing extreme values

OLS estimation method is susceptible to extreme values. If there are extreme values in the data set, it will cause the regression curve to shift in the direction of extreme values, making the estimated results deviate from the real situation. Therefore, the bilateral extreme values of all variables are indented according to the 5% and 95% quantiles, respectively, and the parameters are re-estimated. The estimation results are shown in column (5) of Table 6.

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TABLE 7 Results of endogenous treatment.

Variables	IV-2SLS				SYS-GMM
	(1)	(2)	(3)	(4)	(5)
L1.Lcp[a]					0.7511***
					(11.8342)
Digital	0.2611**	0.3840**	0.4557*	0.3474**	0.2112***
	(2.0060)	(2.1287)	(1.8962)	(2.4371)	(3.2498)
Control variables	*YES*	*YES*	*YES*	*YES*	*YES*
Province effect	*YES*	*YES*	*YES*	*YES*	*YES*
Industry effect	*YES*	*YES*	*YES*	*YES*	*YES*
Year effect	*YES*	*YES*	*YES*	*YES*	*YES*
Anderson test	2392.0370***	1358.9540***	874.6510***	1951.0610***	—
Cragg-Donald test	11000 {16.38}[b]	2844.4530 {16.38}	1489.089 {16.38}	4231.2750 {16.38}	—
AR (1) test	—	—	—	—	0.029
AR (2) test	—	—	—	—	0.361
Hansen test	—	—	—	—	0.115
$Adj.R^2$	0.0184	0.0173	0.0132	0.0202	—
Obs	3060	2550	2040	3570	3060

[a] *L1.* represents one period lagged variable.
[b] The critical value of the Stock-Yogo test at the 10% level is within {}.

The above robustness test results show that the positive impact of digital transformation on low-carbon development is still significant, indicating that the core conclusions of this paper are robust.

5.4 Endogenous treatment

Effectively controlling endogeneity is key to accurately identifying the causal relationship between digital transformation and low-carbon development. First of all, this paper attempts to use digital transformation lag phase I, lag phase II and lag phase III as the instrumental variables of the current digital transformation. China's industrial digital transformation often has the characteristics of top-down and step-by-step, so the current digital process is rooted in the previous accumulation. At the same time, the current low-carbon development level will not interfere with the previous digital process. This satisfies the exogeneity and relevance criteria for instrumental variable selection. Columns (1)–(3) in Table 7 show the estimation results of two-stage least squares (2SLS). Anderson test and Cragg-Donald test show that the model does not have the problem of unidentifiable and weak instrumental variables, indicating that the instrumental variables are effective. The regression coefficients of digital transformation are significantly positive, indicating that digital transformation can still effectively promote the low-carbon development of manufacturing industry after dealing with potential endogenous problems.

In addition, the instrumental variable construction method proposed by Lewbel has been widely used in existing research (Lewbel, 1997). Miruna (2022) used this idea to construct the instrumental variables of Industry 4.0. Wang Q et al. (2022) used this method to construct instrumental variables of the degree of digitization at the provincial level in China. The above research verifies the effectiveness of this instrumental variable construction method. Therefore, this paper refers to Lewbel's idea, using the digital transformation variable and the corresponding industry digital transformation mean difference of three power as the instrumental variable of digital transformation (Lewbel_IV). The 2SLS estimation results are shown in column (4) of Table 7. The Anderson test and the Cragg-Donald test show that the instrumental variables are valid. The estimated coefficients of the core explanatory variables are in good agreement with the benchmark regression results, which again shows that the digital transformation of the manufacturing industry has a promoting effect on low-carbon development.

Further, this paper uses the generalized moment estimation method (GMM) to alleviate the endogenous bias caused by problems such as two-way causality and missing variables. Considering that the difference generalized moment estimation method (DIF-GMM) still has the problem of weak instrumental variables, and the two-step estimation is more effective than the one-step estimation, this paper uses the two-step system generalized moment estimation method (SYS-GMM) to deal with endogeneity. The estimation results of the two-step SYS-GMM are shown in column (5) of Table 7. Among them, the Arellano-Bond test and the Hansen test show that the instrumental variables are valid and that the model does not have over-identification problems and satisfies the two-step SYS-GMM usage conditions (Arellano and Bover, 1995; Blundell and Bond, 1998). From the estimation results, the coefficient of the core explanatory variable is significantly positive at the 5% level.

TABLE 8 Results of heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)
	Developed regions	Underdeveloped regions	High-energy-consuming industry	Medium-low-energy-consuming industry
Digital	0.2827*	0.3298**	0.5272	0.2747**
	(1.6688)	(2.1533)	(1.1357)	(2.2727)
Control variables	*YES*	*YES*	*YES*	*YES*
Province effect	*YES*	*YES*	*YES*	*YES*
Industry effect Year effect	*YES* *YES*	*YES* *YES*	*YES* *YES*	*YES* *YES*
$Adj.R^2$	0.2815	0.3408	0.4893	0.2880
Obs	1564	2006	1050	2520

The two-step SYS-GMM regression results are basically consistent with the benchmark regression results, which verifies the robustness of the basic conclusions of this paper.

5.5 Heterogeneity analysis

5.5.1 Heterogeneity of regional economic development level

Heterogeneity analysis based on regional economic development level. In order to explore the impact of digital transformation on the low-carbon development of manufacturing industry in different economic development levels. In this paper, the average *per capita* GDP of each region is used as the standard, and the whole sample is divided into developed regions and underdeveloped regions and makes regression respectively. From the regression results in Table 8, digital transformation has a significant positive impact on the low-carbon development of the manufacturing industry, whether in developed regions or underdeveloped regions, but the magnitude of the impact is different. The impact of digital transformation in underdeveloped areas on the low-carbon development of manufacturing industry is higher than that in developed areas. This may be due to the fact that the manufacturing industry in developed regions is in a higher stage of development, the low-carbon production level itself is high, and the role of digital empowerment in its low-carbon development is relatively limited, while the low-carbon production capacity in underdeveloped regions is relatively weak, with greater room for improvement, and the effect of digital empowerment is higher than that in developed regions.

5.5.2 Heterogeneity of industrial energy consumption level

Heterogeneity analysis based on industry energy consumption types. There are great differences in energy consumption among different manufacturing industries. Therefore, according to the "2010 National Economic and Social Development Statistical Report", this paper divides 17 manufacturing industries into high-energy-consuming industry groups and medium-low-energy-consuming industries groups for heterogeneity analysis. From the results of Table 8, it can be found that digital transformation has a positive impact on low-carbon development in both high-energy-consuming industries and medium-low-energy-consuming industries, but the regression results of high-energy-consuming industries are not significant. There may be two reasons: First, the degree of digital transformation of high-energy-consuming industries is relatively low, and the energy-saving effect, technological innovation effect and resource allocation optimization effect of digital transformation have not yet been formed. Second, high-energy-consuming industries are often traditional manufacturing sectors, many factors restricting green development, may lead to the promotion of digital transformation is offset.

TABLE 9 Results of mechanism test.

Variables	(1)	(2)
	Innov	***Lcp***
Digital	0.021***	0.2845***
	(7.7192)	(2.6775)
Innov	—	1.112* (1.74)
Control variables	*YES*	*YES*
Province effect	*YES*	*YES*
Industry effect Year effect	*YES* *YES*	*YES* *YES*
$Adj.R^2$	0.9924	0.2960
Obs	3570	3570

5.6 Mechanism test

According to theoretical analysis, digital transformation promotes low-carbon development of manufacturing industry through technological innovation effect. This paper constructs a mediation model to test this mechanism. The model is constructed as follows:

$$Innov_{ijt} = \rho_0 + \rho_1 Digital_{ijt} + \delta Control_{ijt} + \mu_i + \mu_j + \mu_t + \varepsilon_{ijt}$$
$$Lcp_{ijt} = \alpha_0 + \alpha_1 Digital_{ijt} + \beta Control_{ijt} + \mu_i + \mu_j + \mu_t + \varepsilon_{ijt}$$
$$Lcp_{ijt} = \sigma_0 + \sigma_1 Digital_{ijt} + \gamma Control_{ijt} + \mu_i + \mu_j + \mu_t + \varepsilon_{ijt}$$

Among them, $Innov_{ijt}$ represents the mechanism variable, and the other variables mean the same as the benchmark model. The mechanism test is divided into three steps: First, the core explanatory variables and mechanism variables are regressed, and the regression coefficient represents the impact of digital transformation on technological innovation. Secondly, we will return to digital transformation and low-carbon development. Finally, digital transformation and technological innovation are included in the regression equation to verify whether the digital economy has an impact on low-carbon development through technological innovation.

The mechanism test results are shown in Table 9, where column 1 shows that digital transformation has a significant role in promoting technological innovation and passes the 1% significance test. Column 2 shows that both digital transformation and technological innovation have significantly promoted low-carbon development and passed the 10% significance test. The above results show that digital transformation promotes low-carbon development of manufacturing industry through technological innovation effect. H2 of this paper is verified. Low-carbon development is closely related to technological innovation. Digital transformation can promote low-carbon technology innovation by diffusing innovation elements, which in turn can promote low-carbon development.

6 Conclusion

Using the matching data of China Industrial Economy Database, CEADs Database and China's multi-regional input-output table, this paper constructs a measurement framework for the low-carbon development level and digital transformation degree of 17 manufacturing industries in 30 provinces in China, and conducts an empirical study on the relationship between digital transformation and low-carbon development from the perspective of sub-regions and sub-industries. The results show that:

(1) The low-carbon development level of China's manufacturing industry is increasing year by year, but the development gap between regions and industries is large. At the regional level, the development level of the eastern and central regions is higher, and the development level of the western and northeastern regions is lower. At the industry level, the development level of medium-low-energy-consuming industries is higher, while that of high-energy-consuming industries is lower.
(2) The degree of digital transformation of China's manufacturing industry is on the rise, but there is an imbalance between regions and industries. At the regional level, the eastern region has a higher degree of transformation, while the central, western and northeastern regions have lagged behind. At the industry level, the high-end manufacturing industry has a higher degree of transformation, while the traditional manufacturing industry has a lower degree of transformation.
(3) The digital transformation of the manufacturing industry has a significant role in promoting its low-carbon development, and this conclusion still holds after the robustness tests such as changing the measurement method of variables, replacing core variables, dealing with extreme values and considering endogeneity.
(4) For sub-indicators, digital industrialization, industrial digitization and digital development environment can significantly promote the low-carbon development of manufacturing industry. Among them, the impact of digital industrialization is the most obvious.
(5) The impact of digital transformation of manufacturing on its low-carbon development is heterogeneous across regions and industries. The low-carbon effect of digital transformation in underdeveloped areas is higher than that in developed areas. The low-carbon effect of digital transformation in medium-low-energy-consuming industries is obvious, but the low-carbon effect of digital transformation in high-energy-consuming industries has not appeared.
(6) The mechanism test results show that technological innovation is an important channel for digital transformation to promote the low-carbon development of the manufacturing industry.

The policy orientation of the research conclusion is clear. The government should actively affirm the environmental performance of digital transformation and create a good external environment for the digital transformation of manufacturing industry. On the one hand, the government should continue to increase investment in digital infrastructure to provide support for the digital transformation of the manufacturing industry. On the other hand, the government should actively promote cooperation between enterprises and universities, scientific research institutions and other institutions, establish a technology exchange platform, open up digital technology application channels, and accelerate the application of digital technology. In addition, the differences in digital transformation in different regions and industries should be taken seriously to avoid further widening the gap. By formulating differentiated support policies, providing policy support for backward areas can narrow the development gap. At the same time, the construction of big data platform can provide more adequate data resource services for traditional manufacturing enterprises, which is conducive to the digital transformation of enterprises.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

YL: Conceptualization, methodology, resources, validation. LZ: Data curation, Software, writing-original draft preparation, visualization. DW: Writing-reviewing and editing, supervision.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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