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The impact of coupling digital industrialization and industrial digitization on green and low carbon development: evidence from China

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The coupling of digital industrialization and industrial digitization is crucial for advancing China's green, low-carbon development and achieving its "dual-carbon" goals. This study applies a coupling coordination model and analyzes provincial panel data from 2012 to 2021 to evaluate their effects on the green, low-carbon transition. The results show that: (1) digital coupling can significantly reduce carbon emissions intensity and promote green, low-carbon development, as evidenced by robust tests, including instrumental variables; (2) mediation analysis reveals that digital coupling enhances green, low-carbon development by improving energy efficiency and promoting technological innovation; (3) spatial spillover analysis demonstrates that coordinated digital coupling reduces emissions both within regions and in neighboring areas; and (4) heterogeneity analysis highlights the significant effects of digital coupling in central China, with industrial digitization exerting a particularly strong influence. These findings highlight the synergy between digital industrialization and industrial digitization, offering a novel perspective for understanding the green, low-carbon transition.

KEYWORDS
China, coupled coordination, digital economy, digital industrialization, green and low-carbon development, industrial digitalization

1 Introduction

To mitigate global warming and accelerate green and low-carbon governance worldwide, carbon emissions have become a focal issue for the international community, which is actively seeking pathways for green and low-carbon transformation. For example, at the 75th session of the UN General Assembly, China pledged that, in the face of carbon emissions, it would implement stronger policies to tackle carbon emissions, aiming to reach carbon peak and carbon neutrality by 2030 and 2060, respectively. These "dual-carbon" goals are essential both for combating climate change and for sustainable socioeconomic development. Despite these commitments, the transition toward green development in China still has serious obstacles on both supply and demand sides due to its heavy reliance on fossil fuels and weak awareness of green and low-carbon consumption, respectively (Zhou, 2024). Therefore, China's socioeconomic progress requires an effective reduction in carbon emissions.

With the advancement of next-generation information technologies, the digital economy has emerged as a major economic form following the agricultural and industrial economies. Grounded in digital technology, it encompasses two dimensions: digital industrialization and industrial digitalization. These two dimensions reinforce each other (Xue and Hu, 2020), thereby driving economic growth, optimization, and industrial upgrading (Yang, 2023). Promoting their coordinated integration is essential for the sustained growth of the digital economy. Digital technologies such as big data, cloud computing, and artificial intelligence play a key role in influencing carbon emissions and supporting the green, low-carbon transition. As these systems develop, their coupling raises important ecological concerns about carbon emissions. Further, Figure 1 presents the development of digital industrialization and industrial digitalization coupling coordination from 2012 to 2021. The developmental level of digital industrialization and industrial digitalization coupling coordination varies across China's provinces. The eastern region, characterized by a more developed economy and stronger technological innovation capabilities, exhibits a higher developmental level of digital industrialization and industrial digitalization coupling coordination. In contrast, the central, the north-eastern and western regions lag behind in digital industrialization and industrial digitalization coupling coordination due to their weaker innovation climate and higher dependence on traditional, resource-intensive, and labor-intensive industries. There are differences in the level of coordination of digital coupling across regions in China. Thus, analyzing the coordination between digital industrialization and industrial digitalization is crucial for addressing the challenges of digital economy development and advancing China's green and low-carbon goals.

In the current global climate governance and sustainable development agenda, "green" and "low-carbon" have increasingly become an inseparably unified whole. Both ecological modernization theory and the Environmental Kuznets Curve (in its application to the climate domain) place CO_2 emission reduction at the core of green transformation (Guo and Yu, 2024; Xu and He, 2024). Meanwhile, the global climate governance framework represented by the *Paris Agreement* and the United Nations 2030 Sustainable Development Goals (SDGs), particularly Goal 13 (Climate Action), have positioned greenhouse gas emission control and the promotion of low-carbon transition at the heart of global sustainable development. The goal set by the *Paris Agreement* to "limit global warming to well below 2 °C, preferably to 1.5 °C, compared to pre-industrial levels" (Yu et al., 2022) essentially establishes a clear carbon constraint for global economic and social development. This means that any genuine "green development" pathway must unfold within the rigid constraints of a "carbon budget" (Wu and Yu, 2023). Therefore, "low-carbon" is no longer merely an optional dimension of "green" but an indispensable prerequisite and core pillar. The low-carbon transition drives an energy system revolution, promotes fundamental adjustments in industrial structure, and leads innovation in technology and lifestyles, providing the fundamental impetus and key pathways for broader green development characterized by resource efficiency, ecological friendliness, and social inclusiveness. Against this backdrop, research focusing on core low-carbon indicators such as carbon emission intensity serves as a critical entry point and important measure for understanding the overall green transformation process. Based on this, this study incorporates the coupling between digital industrialization and industrial digitalization (i.e., "digital coupling") and green and low-carbon development (with carbon emission intensity as a proxy variable) into a unified research framework to empirically examine the impact of digital coupling on green and low-carbon development. The results indicate that digital coupling exerts a restraining effect on carbon emission intensity and contributes to China's green and low-carbon development through energy use efficiency and technological innovation. Moreover, digital coupling not only

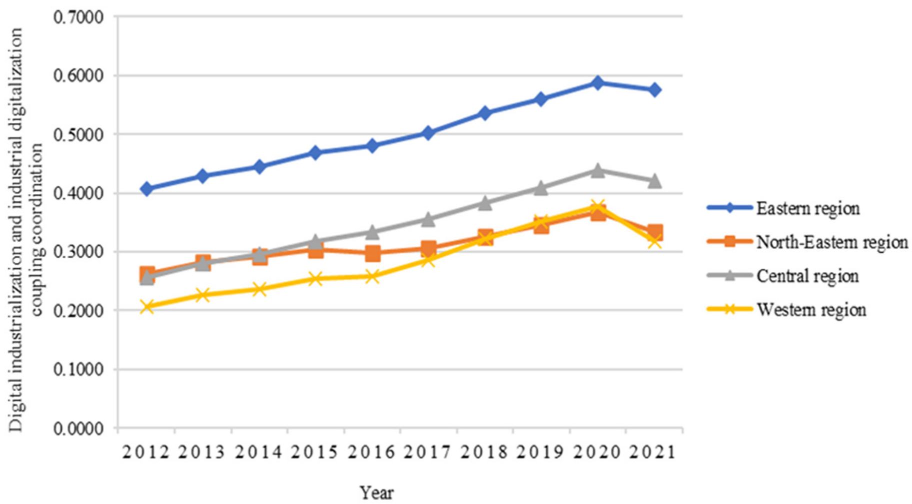

FIGURE 1
Levels of coupled coordination of digital industrialization and industrial digitization in four major regions of China, 2012–2021.

reduces carbon emission intensity within a region but also exerts a mitigating effect on carbon emissions in neighboring regions. Finally, heterogeneity analysis highlights the significant effects of digital coupling in central China, with industrial digitization exerting a particularly strong influence.

The relevant literature involves two main emerging areas of research. One area is the examination of the digital economy's impact on carbon emissions, which includes three major perspectives. The first perspective suggests that the digital economy reduces carbon emissions (Wang and Li, 2022) because energy technology advancement has increased the share of clean energy in the energy mix while reducing energy intensity (Ulucak, 2020). The second perspective, in contrast, contends that the digital economy increases carbon emissions (Avom et al., 2020), positing that low carbon is not an intrinsic attribute of the digital economy. This polluting impact is more evident in certain areas. For instance, Salahuddin and Alam (2015) analyzed the impacts of internet use in Australia from 1985 to 2012, revealing its stimulating role in electricity consumption. The third perspective views the relationship as complex and non-linear (Wang, 2023). For example, Yang and Zhao (2022), using the extended STIRPAT model and the environmental Kuznets curve, found that China's digital economy has entered a phase of low-carbon emission reduction. Similarly, Li and Wang (2022) demonstrated an inverted U-shaped relationship between the digital economy and carbon dioxide emissions.

Another area of research focuses on the coupling between digital industrialization and industrial digitalization. As the Internet becomes more widespread and the information industry develops rapidly, studies on the coupling of digital industrialization and industrial digitalization have become increasingly abundant. For instance, Zheng and Zhou (2023) use data factorization as a central pivot, finding that the coupling of digital industrialization and industrial digitalization effectively drives the intensity of economic data and digital technologies, thereby boosting economic growth. In addition, scholars have explored the spatial and temporal characteristics of this coupling. They indicate that the coupling of digital industrialization and industrial digitalization exhibits the highest degree of coordination and significant spatial correlation in eastern China (Gao and Li, 2023). Meanwhile, the central region has seen an overall upward trend in both digital economic development and coupling coordination (Yang, 2023). Similarly, the Yangtze River Economic Belt has experienced a steady increase in the level of digital industrialization and the coordination of its coupling (Liu and Yu, 2021). In addition to the aforementioned studies, several scholars have investigated the influence of various dimensions of digitization, the digital economy, and information and communication technologies (ICT) on carbon emissions. For example, Zhou et al. (2024) used a two-way fixed effects model to analyze the impact of digitization on the efficiency of the low-carbon economy, and found that digitization has a U-shaped relationship with the efficiency of the low-carbon economy, and that digitization has an important role to play in improving the efficiency of the low-carbon economy. Using China as an example, Zhou et al. (2022b) developed an I-O framework to assess the extent of the digital economy's impact on carbon emissions, and the results show that the digital economy has a growing and significant impact on carbon emissions when the combined effects of demand-driven and supply-driven emissions are considered. By constructing an information and communication technology (ICT) implied carbon analytical framework to examine the implied carbon impacts of the ICT sector, Zhou et al. (2019) found that the ICT sector is more favorable to the environment when implied carbon impacts are considered. Zhou et al. (2022a) explored the carbon emission transfer in the digital industry from an inter-regional perspective.

In summary, scholars have examined the impact of the digital economy on low-carbon development from various perspectives and analyzed the coupling and coordinated development of digital industrialization and industrial digitalization from different viewpoints, providing substantial intellectual support for related research. However, the following limitations remain: First, current studies on the digital economy and green low-carbon development predominantly focus on exploring the impact of the digital economy on carbon emissions and the spatiotemporal characteristics of the coupling between the digital economy and carbon emissions. Research on how the coupling of digital industrialization and industrial digitalization affects low-carbon development is still in its nascent stages and requires further in-depth investigation. Second, existing literature mainly studies the spatiotemporal differences in the coupling coordination levels of the two systems across regions by constructing a coupling coordination degree model for digital industrialization and industrial digitalization and classifying the states of coupling coordination. Few studies have examined the impact of digital coupling on low-carbon development by constructing econometric models.

This paper has several key contributions. First, differing from most existing literature that examines the impact of the digital economy on green and low-carbon development, this study focuses specifically on the role of synergy between the two major sub-dimensions of the digital economy—digital industrialization and industrial digitalization—in advancing low-carbon development, thereby extending research in this field. Second, by integrating the coupling of digital industrialization and industrial digitalization with green and low-carbon development within a unified research framework and based on constructing a coupling coordination degree model, this paper emphasizes analyzing the environmental effects of such coupling, particularly its influence on carbon emission intensity during the process of green and low-carbon development, thus providing empirical evidence on factors affecting carbon emission intensity. Finally, in addition to categorizing the research sample into four major regions—eastern, northeastern, central, and western China—this paper further examines heterogeneity across the two dimensions of digital industrialization and industrial digitalization. This approach aims to clarify potential differences in how the coupling of digital industrialization and industrial digitalization affects carbon emission intensity from distinct perspectives of the digital economy, thus helping to fill a gap in the existing literature. Through comprehensive and in-depth research, this paper aims to elucidate the role of digital coupling in promoting green and low-carbon development, with a view to providing theoretical foundations for achieving the "dual carbon" goals.

2 Theoretical analysis and research hypothesis

2.1 Mechanisms of the direct effect of the coupling between digital industrialization and industrial digitalization on green and low-carbon development

The digital economy can be broadly or narrowly defined. Broadly, it is regarded as a form of economic activity that centers on data elements as core resources, relies on information networks as carriers, and utilizes information and communication technologies (ICT) to enhance efficiency and optimize the macroeconomic structure (Bai et al., 2022). Narrowly, the digital economy is viewed as an industrial economy, wherein the production, consumption, and distribution of digital goods and services are separated from sectors traditionally attached to conventional economic activities and developed into an independent core industry within the national economy—namely, the digital industry (Xu and Zhang, 2020). From the dialectical perspective of these broad and narrow definitions, the coupling and synergy between digital industrialization and industrial digitalization essentially rely on data elements and digital technologies to influence low-carbon development:

On the one hand, data, as a new type of production factor, is increasingly recognized as a potential resource for promoting carbon reduction (Zhou and Ye, 2024). Data elements can optimize resource allocation, promote rational distribution and efficient utilization of resources, reduce energy consumption and pollution emissions (Market Economy Research Institute of the Development Research Center of the State Council et al., 2022), and holistically enhance green and low-carbon development. On the other hand, at the micro-enterprise level, digital technologies significantly improve production efficiency by optimizing the allocation of resource elements and the design of production processes, thereby reducing energy consumption and pollutant emissions and contributing to overall energy conservation and emission reduction goals (Chang and Xia, 2023). At the macro-governance level, the use of digital, intelligent, and green technologies enables various sectors to collect, transmit, measure, and monitor data on environmental pollutants generated during production processes. This assists governments in accurately grasping carbon emission information and achieving efficient carbon emission management (Xu and Hui, 2024). Simultaneously, digital industrialization and industrial digitalization complement and reinforce each other, progressing in synergy to provide key impetus for the socio-economic achievement of carbon reduction goals. Leveraging digital technologies, industrial digitalization transforms traditional industries to foster new industries, models, and business forms. This, in turn, accelerates digital industrialization and guides its evolution toward greater alignment with the needs of industrial digitalization (Chen et al., 2021). Consequently, the coordinated coupling of these two developmental processes can address environmental challenges and advance China's green and low-carbon transformation. Based on this analysis, the paper proposes the following research hypothesis:

Hypothesis 1: The coordinated coupling of digital industrialization and industrial digitalization accelerates the transition to green and low-carbon development.

2.2 Indirect mechanisms for coupling digital industrialization and industrial digitalization to influence green and low-carbon development

From the perspective of energy utilization efficiency, on the one hand, due to the high permeability and strong diffusivity of the digital economy, the virtuous cycle of interaction between digital industrialization and industrial digitalization accelerates the spatial flow of data elements. This not only facilitates enterprises in acquiring and forecasting data elements but also reduces energy efficiency losses caused by the misallocation of factor resources (Fang, 2023). On the other hand, as the digital economy develops in depth, the coupling of digital industrialization and industrial digitalization enhances energy utilization efficiency by achieving effective matching of supply and demand in production and operational activities, thereby reducing market dependence on energy (Cheng et al., 2023). At the same time, the improvement of energy utilization efficiency also contributes to promoting green and low-carbon development. Since energy consumption, particularly of fossil fuels, is a major driver of carbon emissions, improving the energy consumption structure and enhancing energy efficiency are two critical pathways to carbon reduction. On the one hand, digital technologies enable the analysis and optimization of energy production and consumption processes, which helps improve the energy consumption structure and ultimately suppresses carbon emissions (Jiang and Xu, 2023). On the other hand, the coordinated development of digital industrialization and industrial digitalization drives enterprises to undergo digital transformation, which aids in optimizing energy allocation, reducing energy waste, and thereby enhancing energy utilization efficiency (Wang and Li, 2022).

From the perspective of technological innovation, the digital economy, with its notable scale effects and extensive diffusion effects, has significantly driven the enhancement of technological innovation (Li, 2019). The coordinated development of digital industrialization and industrial digitalization serves as a crucial force in advancing the high-quality growth of the digital economy. Consequently, the coupled development of digitalization can also elevate the level of technological innovation. Specifically, on the one hand, the digital economy, primarily driven by the internet, cloud computing, and big data, facilitates technological innovations that are highly efficient and low in energy consumption. It effectively reduces information search costs and social transaction costs, thereby promoting the concentration of innovation resources (Xing et al., 2019). Furthermore, as the coupling of digital industrialization and industrial digitalization progresses, the landscape of innovation subjects has shifted from a scenario dominated by research institutions to one characterized by close collaboration and synergy among diverse actors, including enterprises, governments, and others. This transformation effectively fosters the efficient integration and allocation of innovation resources, thereby strengthening technological innovation capabilities (Liu et al., 2022). On the other hand, leveraging the digital economy's characteristics of sharing, permeability, and spillover effects, the coupling of digital industrialization and industrial digitalization promotes connectivity, knowledge sharing, and collaborative innovation among innovation subjects by eliminating monopolistic barriers at both administrative and market levels. This, in turn, enhances innovation efficiency (Kohli and Melville, 2019). Moreover, the improvement in innovation efficiency contributes to reducing energy consumption and increasing the utilization efficiency of fossil fuels, thereby lowering carbon emissions. Based on this, the following research hypothesis is proposed:

Hypothesis 2a: The coupling of digital industrialization and industrial digitalization can drive China's green and low-carbon development through enhanced energy efficiency.

Hypothesis 2b: The coupling of digital industrialization and industrial digitalization can drive China's green and low-carbon development through technological innovation.

2.3 Spatial spillover mechanisms of the coupling of digital industrialization and industrial digitalization affecting green and low-carbon development

The "core-periphery" theory in New Economic Geography posits that the cross-regional flow of production factors strengthens the spatial interconnectedness of economic activities, leading to agglomeration or diffusion effects in economic activities across space (Wang and Tao, 2023). Building on the characteristics of the digital economy—high permeability, strong diffusivity, and instant transmission—the coupled interaction between digital industrialization and industrial digitalization further reinforces spatial interconnections and spillover effects among regions. Digital industrialization continuously supplies cutting-edge technologies and data elements, while industrial digitalization provides abundant application scenarios and transformation demands. Their coordinated development accelerates the flow of production factors (Xiao and Zeng, 2023) and facilitates resource sharing, thereby deepening the interactive linkages among regions. Specifically, on the one hand, as the coupling of digital industrialization and industrial digitalization deepens, technology spills over to surrounding areas. Such technological spillovers can break down information barriers, foster emerging industries, improve energy efficiency, and reduce energy consumption resulting from the interregional flow of production factors (Yang and Zhao, 2022), thereby promoting low-carbon development. On the other hand, leveraging the scale effects and positive externalities of the digital economy, the coupled development of digitalization helps overcome geographical constraints on information circulation, enables cross-regional information exchange, and enhances the spillover and absorptive capacities of neighboring regions in terms of capital, knowledge, and technical talent (Cai and He, 2024). Simultaneously, the application of "data elements ×" and "artificial intelligence +" initiatives helps establish new highlands for the coordinated development of the digital economy driven by technological innovation. By fully leveraging demonstration effects, these initiatives promote the cross-regional flow of high-quality production factors such as talent, equipment, and resources (Kong, 2024), enhance cooperation and exchanges in green and low-carbon development between local and neighboring regions, and drive carbon emission reductions in surrounding areas. Therefore, the coupled development of digital industrialization and industrial digitalization not only advances local low-carbon transformation but also generates significant spatial spillover effects on the green and low-carbon development of neighboring regions. According to this analysis, the research introduces the subsequent research hypothesis:

Hypothesis 3: The coupling of digital industrialization and industrial digitalization generates a spatial spillover effect on green and low-carbon development in adjacent regions.

Based on hypotheses 1–3, this article proposes a theoretical framework as shown in Figure 2.

3 Methodology

3.1 Modeling

3.1.1 Coupled coordination degree model

Given the complex interrelationship between the digital industrialization system and the industrial digitization system—particularly in terms of their relevance, coordinated development, and mutual constraints (Liu and Yu, 2021)—this paper proposes a coupling degree assessment model to evaluate the interaction between these two systems.

$$C = 2\left[\frac{U_1 \times U_2}{(U_1 + U_2)}^{2}\right]^{\frac{1}{2}} \tag{1}$$

where C represents the coupling degree, while U_1 and U_2 denote the comprehensive scores of the two systems: digital industrialization and industrial digitization, respectively. However, both systems may have high scores while indicating a low level of coupling. To consider this limitation, Equation 2 measures the degree of coupling coordination.

$$T = \alpha U_1 + \beta U_2 \tag{2}$$

where T represents the comprehensive coordination index of the two subsystems, and α and β are the weights of digital industrialization and industrial digitization, respectively. Given the comparable importance of these two subsystems, we set $\alpha = \beta = 0.5$.

$$D = \sqrt{C \times T} \tag{3}$$

where D denotes the degree of coupling coordination, as a higher value indicates a stronger level of coupling coordination.

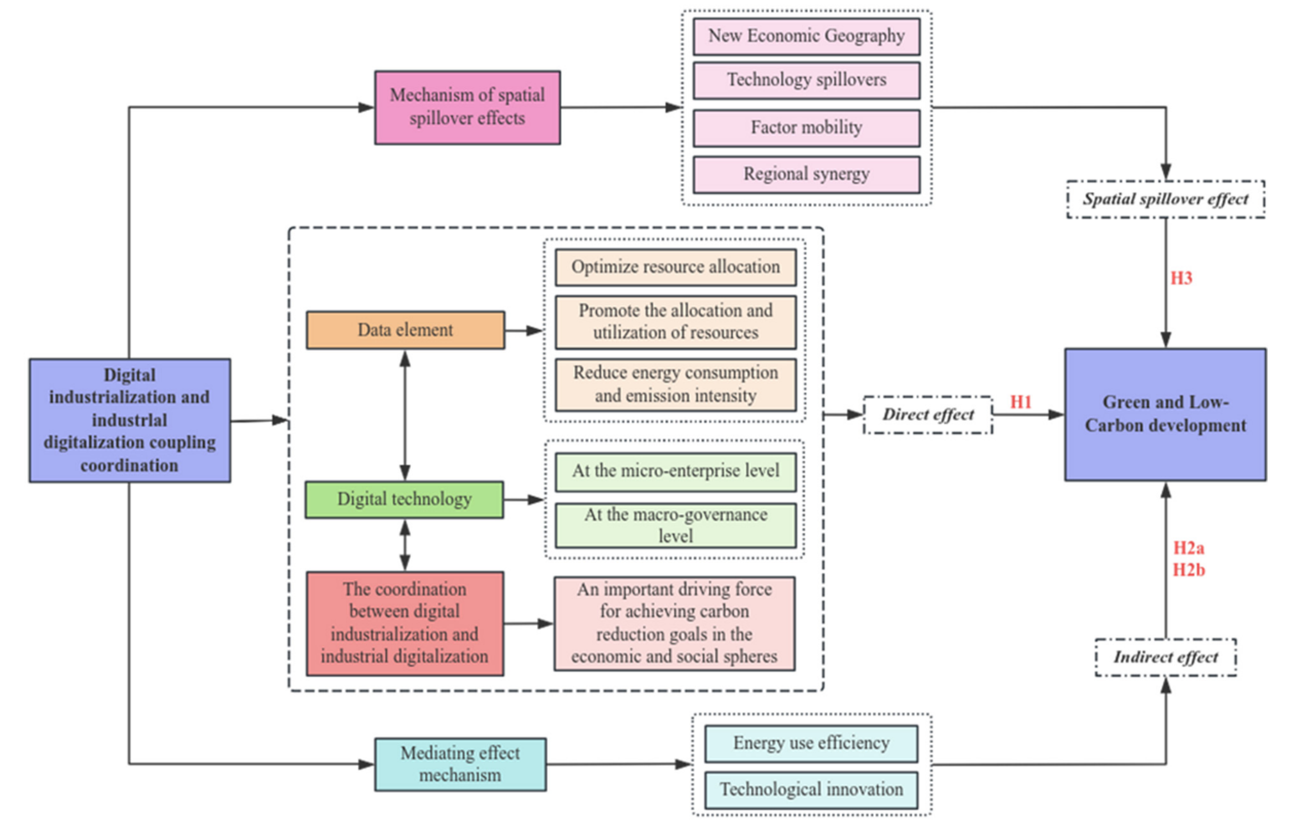

FIGURE 2
The influencing mechanism of digital industrialization and industrial digitalization coupling coordination on carbon emission reduction.

3.1.2 Benchmark model

Based on the presented theoretical analysis, this paper investigates the direct impact of the coupling between digital industrialization and industrial digitization on low-carbon development. To achieve this, it constructs Equation 4 which is a two-way fixed effects benchmark regression model (Zhang and Shen, 2025).

$$\ln \text{Car}_{it} = \alpha_0 + \alpha_1 \text{Coupling}_{it} + \alpha_2 \sum \ln\text{Control}_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{4}$$

where Car_{it} denotes carbon emission intensity, Coupling_{it} signifies the degree of coordination between digital industrialization and industrial digitization coupling, α_0 is the intercept term, and α_1 represents the influence of the coupling between digital industrialization and industrial digitization on carbon emission intensity. If $\alpha_1 > 0$, the digital coupling reduces carbon emissions; otherwise, it implies no such benefit. Control_{it} includes a series of control variables, i denotes province, t shows year, μ_i indicates an individual fixed effect, ν_t signifies a time fixed effect, and ε_{it} reflects a random error term.

3.1.3 Mediation effects model

Equation 4 reflects the direct effect of the coupling between digital industrialization and industrial digitization on low-carbon development. To explore the transmission mechanism of this coupling on low-carbon development, this paper follows Jiang (2022) to introduce two mediating variables: energy use efficiency and technological innovation. These mediating variables are theoretically linked to the explanatory variables. Therefore, the research builds Equation 5 to analyze the mediating effect:

$$\ln M_{it} = \beta_0 + \beta_1 \text{Coupling}_{it} + \beta_2 \sum \ln\text{Control}_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{5}$$

where M_{it} represents the mediating variable, which includes energy use efficiency (En_eff) and technological innovation (Innovation). The interpretation of the other variables follows the same logic as in Equation 4.

3.1.4 Spatial Durbin model

Using the represented theoretical analysis, this paper investigates the spatial spillover effects of the coupling between digital industrialization and industrial digitization on low-carbon development. To examine this theoretical relationship, the study follows Miu et al. (2022) to employ the spatial Durbin model with two-way fixed effects. This model is selected based on the results of a series of tests, including the LM test, Wald test, LR test, and Hausman test. Equation 6 represents the specific model.

$$\begin{aligned}\ln \mathrm{Car}_{it} &= \rho W \ln \mathrm{Car}_{it} + \eta_1 \mathrm{Coupling}_{it} + \eta_2 W \mathrm{Coupling}_{it} + \\ &\eta_3 \sum W \ln \mathrm{Control}_{it} + \eta_4 \sum \ln \mathrm{Control}_{it} + \mu_i + \nu_t + \varepsilon_{it}\end{aligned} \tag{6}$$

where ρ represents the spatial autoregressive coefficient, W denotes the spatial weight matrix, and η_2 and η_3 signify the coefficients of the spatial interaction terms of the core explanatory variables and control variables, respectively. The interpretation of the other variables follows the same logic as in Equation 4. Furthermore, the research checks the robustness of the empirical results, using two types of weight matrices—the neighborhood matrix and the spatial distance matrix—for regression analysis.

3.2 Definition of variables

3.2.1 Dependent variable

Carbon emission intensity (Car). Reducing carbon emissions is a critical pathway and core objective for achieving green and low-carbon development. Generally, the level of carbon emissions significantly influences the implementation of national green and low-carbon development strategies and the achievement of carbon reduction targets (Zhang et al., 2017). In academia, indicators such as carbon emissions (Yang and Wang, 2025), carbon emission intensity (Li et al., 2025), and green total factor productivity (Zou et al., 2024) are commonly used to measure the level of green and low-carbon development. In 2024, the General Office of the State Council issued the *Work Plan for Accelerating the Development of a Dual-Control System for Carbon Emissions*, emphasizing the establishment of a new mechanism for a comprehensive transition from dual control of energy consumption to dual control of carbon emissions. It called for accelerating the development of a dual-control system for both total carbon emissions and carbon intensity, actively and steadily advancing carbon peaking and carbon neutrality, and speeding up the green transformation of development patterns (Zhang et al., 2025). Meanwhile, Yang and Zhao (2022) and Liu and Li (2025), in their studies on the influencing factors of green and low-carbon development, used carbon emission intensity as the dependent variable to measure the level of green and low-carbon development. In the policy discourse and statistical monitoring systems of China and many other countries worldwide, "green and low-carbon development" often appears as an integrated concept, with its quantitative assessment core frequently including key low-carbon indicators such as carbon emission intensity. Supported by relevant policies and literature, it is evident that carbon emission intensity serves as a crucial indicator for assessing the green and low-carbon development level of a country, region, industry, or enterprise. It effectively reveals the decoupling characteristics between carbon emissions and economic growth in the process of ecological civilization development (Jiang and Long, 2026), reflecting the concept of "reducing emissions in the course of development." Compared to simple aggregate indicators, carbon emission intensity better reflects the quality of green and low-carbon development. In accordance with the principles of scientific rigor and reasonableness, this paper adopts carbon emission intensity to measure the level of green and low-carbon development, aiming to provide insights for China's green and low-carbon development. A lower carbon emission intensity indicates a higher level of green and low-carbon development. A decline in carbon emission intensity typically signifies that the region has achieved certain progress in promoting low-carbon development. Based on the above analysis, carbon emission intensity is calculated using the following formula:

Since fossil fuels are the primary source of carbon emissions, this paper calculates CO_2 emissions for each province based on seven major fossil energy sources, including coal. Equation 7 conducts this calculation, according to Du (2010) and Zhu et al. (2018).

$$\mathrm{EC} = \sum_{i=1}^{7} E_i \times \mathrm{CF}_i \times \mathrm{CC}_i \times \mathrm{COF}_i \times 3.67 + Q \times M_0 \tag{7}$$

where EC represents carbon dioxide emissions, i denotes the consumption of seven types of fossil energy: coal, coke, diesel, paraffin, gasoline, fuel oil, and natural gas,Ei,CFi,CCi, and COFi signify the consumption, calorific value, carbon content, and oxidation factor, respectively, for different types of fossil energy, 3.67 is the ratio of the molecular weight of carbon dioxide to that of carbon, Q indicates the total amount of cement production, and $M0$ shows the carbon emission factor in the cement production process.

Carbon emission intensity refers to the amount of carbon dioxide emissions generated per unit of economic activity. Therefore, the carbon emission intensity of each province is expressed as the natural logarithm of the ratio of its total carbon dioxide emissions to its GDP. Meanwhile, recognizing the limitations of carbon emission intensity in failing to encompass other dimensions of low-carbon development, such as carbon sinks and non-CO_2 greenhouse gases, this study will further incorporate per capita carbon emissions and a comprehensive low-carbon development index as dependent variables in future re-examinations. This approach aims to mitigate potential biases in measuring green and low-carbon development based solely on carbon emission intensity.

3.2.2 Independent variable

Coupling degree of digital industrialization and industrial digitalization (Coupling). The coupling and coordination between digital industrialization and industrial digitalization serve as the core engine driving the high-quality development of the digital economy, reflecting the deep integration of digital technologies with traditional industries. Digital industrialization and industrial digitalization mutually reinforce and develop in synergy, jointly injecting strong momentum into high-quality economic development. Specifically, digital industrialization provides technological support and innovation impetus for industrial digitalization, while industrial digitalization offers extensive application scenarios and market demand for digital

TABLE 1 Comprehensive evaluation index system for digital industrialization.

Target index	Secondary indexes	Three-level indexes	Weights
Digital industrialization	Industrial foundation	The length of long-distance fiber optic cable per unit area	0.0895
		Mobile phone penetration rate	0.0193
		The density of Internet broadband access ports to reflect the digital infrastructure	0.1218
	Industrial entity	The number of enterprises in the electronic information manufacturing industry	0.1416
		The number of legal entities in the information transmission, computer services, and software industries	0.0854
	Industrial scale	The revenue of the electronic information manufacturing industry	0.1435
		The total amount of telecommunications services per capita	0.0746
		The software business revenue	0.1356
	Innovation capacity	The number of patents filed and granted per 10,000 people	0.1057
		The employment rate in the information transmission, software, and IT services industries per 10,000 people	0.0830

industrialization, thereby stimulating further innovation and upgrading of digital industrialization. In line with the connotations of digital industrialization and industrial digitalization, and drawing on the research of Yang (2023) and Liu and Yu (2021), this paper constructs comprehensive evaluation indicator systems for digital industrialization and industrial digitalization, respectively. The entropy value method is an objective approach for measuring the indicators. This approach is superior to subjective assignment methods which potentially produce inaccurate and non-objective weight assignments due to human bias. Based on this, drawing on the research of Xie (2022), this paper adopts the entropy method to assign weights to each indicator of digital industrialization and industrial digitalization, ultimately obtaining the weight of each indicator. Building on this, according to Equation 1 through 3, the coupling degree of digital industrialization and industrial digitalization, as well as their comprehensive coordination index, are sequentially calculated. Finally, the coupling coordination degree between digital industrialization and industrial digitalization is derived using the coupling coordination degree model. This approach systematically assesses the development level of digital coupling.

The comprehensive evaluation index system for digital industrialization is presented in Table 1. The core of digital industrialization lies in transforming digital technologies directly into economic products and services, thereby forming new industrial forms. Drawing on the research of Gao and Li (2023), this paper establishes four secondary indexes: industrial foundation, industrial entity, industrial scale, and innovation capability. Among these, the industrial foundation is represented by the length of long-distance fiber optic cable per unit area, mobile phone penetration rate, and density of internet broadband access ports, reflecting the foundational digital industries. The industrial entity primarily encompass the number of enterprises in electronic information manufacturing industry and the number of legal entities in the information transmission, computer services, and software industries, indicating the reserve strength for digital technology development. The industrial scale mainly includes revenue of the electronic information manufacturing industry, total amount of telecommunications services per capita, and software business revenue, reflecting the contribution to economic growth. Innovation capability is measured by the number of patents filed and granted per 10,000 people and the number of employees in information transmission, software, and information technology services per 10,000 people, reflecting the development level of the digital economy.

The comprehensive evaluation index system for industrial digitalization is presented in Table 2. Industrial digitalization refers to the comprehensive transformation and empowerment of traditional industries through the application of digital technologies. Following the approach of Tang and Xu (2023), this paper constructs three secondary indexes: digital transformation scale, industrial digitalization input, and the effect of industrial digital application and transformation. Among these, digital transformation scale includes three tertiary indicators: the proportion of enterprises engaged in e-commerce transactions, the depth of digital finance usage, and the full-time equivalent (FTE) of R&D personnel in large-scale industrial enterprises. Industrial digitalization input comprises two three-level indexes: the number of computers owned by enterprises per 100 employees and the ratio of R&D expenditure in large-scale industrial enterprises to GDP. The effect of industrial digital application and transformation are measured by two three-level indexes: the number of websites per 100 enterprises and energy consumption per 10,000 yuan of regional GDP.

3.2.3 Mediating variables

Energy use efficiency (En_eff). Energy use efficiency is a key strategy for reducing carbon emissions through the coupling of digital industrialization and industrial digitization. According to Zhang J. et al. (2022), this paper defines energy use efficiency as the natural logarithm of the ratio of GDP to total energy consumption.

Technological innovation (Innovation). The level of technological innovation directly reflects progress in green development. Based on Zhu et al. (2019), this research uses the perpetual inventory method to calculate the stock of patent capital in each province to measure the level of technological innovation.

TABLE 2 Comprehensive evaluation index system for industrial digitalization.

Target index	Secondary indexes	Three-level indexes	Weights
Industrial digitalization	Digital transformation scale	The proportion of enterprises engaged in e-commerce	0.1049
		The depth of digital financial usage	0.084
		The full-time equivalent (FTE) of R&D personnel in large-scale industrial enterprises	0.4651
	Industrial digital input	The number of computers owned by enterprises per 100 employees	0.1309
		The ratio of R&D expenditure in Large-scale industrial enterprises to GDP	0.1384
	The effect of industrial digital application and transformation	The number of websites per 100 enterprises	0.0351
		The energy consumption per 10,000 yuan of regional GDP	0.0416

3.2.4 Control variables

To control for the influence of other potential factors on carbon emission intensity, this paper refers to relevant existing literature (Wang and Li, 2022; Ren et al., 2024; Gao et al., 2023; Yang et al., 2020; Lee et al., 2023; Wang et al., 2024) to select the subsequent control variables: Population density (Pop), calculated as the ratio of a region's total population to its administrative area; Industrial structure upgrade (Update), expressed as the ratio of tertiary industry output to secondary industry output; Degree of government intervention (Gov), represented by the ratio of local government public budget expenditures to regional GDP; Foreign direct investment (FDI), measured as the ratio of FDI to regional GDP; Energy structure (ES), represented by the proportion of regional to national electricity consumption; Environmental regulation (Er), measured by the ratio of completed investment in industrial pollution control to industrial value-added; Economic development level (Pgdp), indicated by GDP per capita; and Degree of openness (Open), assessed as the proportion of total imports and exports to regional GDP.

3.3 Data sources and descriptive statistics

Given the availability and completeness of data, this study uses panel data from 30 provinces of China within 2012–2021. It excludes Tibet, due to substantial data gaps, Hong Kong, Macao, and Taiwan. In order to ensure statistical consistency and the significance of the test results, this paper selects the data from 2012-2021 as the research sample. The data are primarily sourced from the *China Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Urban Statistical Yearbook*, *China Electronic Information Industry Statistical Yearbook*, Digital Finance Research Center at Peking University, as well as provincial (municipal) statistical yearbooks and official statistics from previous years. To resolve the issue of data unavailability, the research interpolates some missing data. In addition, the research transforms the variables into natural logarithm form to mitigate the effects of heteroskedasticity and non-stationarity in macro-level data on empirical results. Table 3 represents the descriptive statistics for the main variables.

4 Empirical analysis

Building on the model construction and variable definitions outlined earlier, this section conducts empirical analyses to test the proposed hypotheses. The methodology follows a structured approach (illustrated in Figure 3): First, a baseline regression analysis is performed using a two-way fixed-effects model, supplemented by robustness tests to validate the results. Next, a mediation effects analysis examines the transmission mechanisms through which energy use efficiency and technological innovation link digital coupling to carbon emission intensity. Subsequently, the spatial Durbin model (SDM) is employed to assess the spatial spillover effects of digital coupling on carbon emission intensity. Finally, the study explores regional heterogeneity and variations across digital economy dimensions.

It should be noted that this paper uses carbon emission intensity as the dependent variable, while interpreting the empirical results by describing it as green and low-carbon development. This approach is based on the profound systemic connection between the two. Carbon emission intensity is not an isolated indicator; its reduction fundamentally relies on three key drivers: technological progress, optimization of the energy structure, and upgrading of the industrial structure (Zhang X. et al., 2022). These drivers not only suppress carbon dioxide emissions but also significantly reduce the generation and discharge of other pollutants—such as sulfur dioxide, nitrogen oxides, and industrial wastewater—by decreasing dependence on fossil fuels and promoting production models that enable efficient resource utilization (Ding, 2022; Zhang X. et al., 2022; Feng et al., 2025). Therefore, a decline in carbon emission intensity effectively reflects the overall transition of the economic system toward resource conservation and environmental friendliness. This indicator translates the macro objective of "green and low-carbon development" into a quantifiable, comparable, and systematically representative core observable variable, thereby providing a solid empirical basis for understanding green and low-carbon development in its broader sense. For these reasons, this paper explicitly employs carbon emission intensity as a proxy variable for green and low-carbon development in the empirical analysis and directly interprets it as such in the results, offering critical low-carbon dimension support for the broader green and low-carbon transition.

TABLE 3 Results of descriptive statistics of variables.

Variable	Symbol	Mean	SD	Max	Min
Carbon emission intensity	*Car*	2.074	1.731	10.450	0.192
Degree of coordination of digital industrialization and industrial digitalization coupling	*Coupling*	0.372	0.138	0.864	0.163
Energy use efficiency	*En_eff*	1.737	0.904	5.778	0.434
Technological innovation	*Innovation*	9.705	1.365	12.400	5.697
Population density	*Pop*	475.100	707.900	3,926.000	7.905
Industrial structure upgrade	*Update*	1.283	0.711	5.297	0.549
Degree of government intervention	*Gov*	0.251	0.103	0.643	0.107
Foreign direct investment	*FDI*	0.018	0.014	0.080	0.000
Energy structure	*ES*	0.033	0.023	0.095	0.004
Environmental regulation	*Er*	0.003	0.004	0.031	0.000
Economic development level	*Pgdp*	12,770.000	8,145.000	48,075.000	5,423.000
Degree of openness	*Open*	0.259	0.277	1.441	0.008

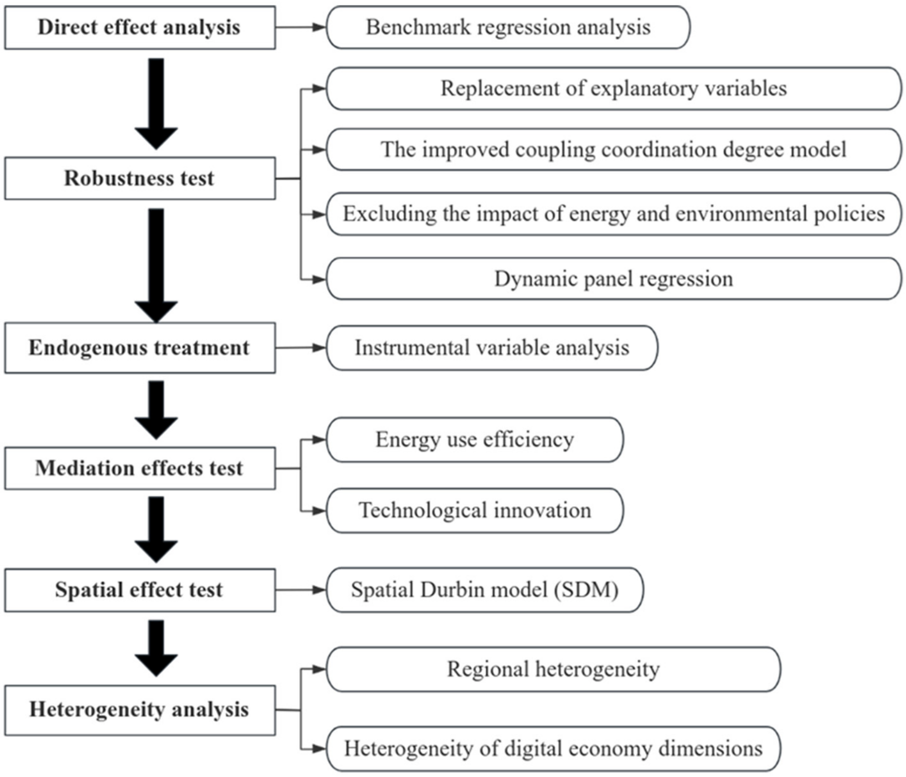

FIGURE 3
Flowchart of empirical analysis.

4.1 Baseline regression results

To account for macroeconomic volatility and eliminate the influence of time-invariant individual differences, Equation 4 employs a two-way fixed-effects model for regression analysis. Table 4 represents the baseline regression results, illustrating the impact of the coupling between digital industrialization and industrial digitalization on carbon emission intensity.

Columns (1) and (2) provide the results without and with control variables, respectively. Based on the results, the estimated coefficients of Coupling are −2.045 and −1.494, respectively, without and with the control variables. These coefficients are negative and statistically significant at 1% level. Taking the example of the column with the control variables added, this suggests that an increase of 1 unit in Coupling development can decrease carbon emissions by 1.494 units. Furthermore, the absolute value of the Coupling coefficient decreased upon the inclusion

TABLE 4 Benchmark regression results.

Variable	(1)	(2)
	lnCar	*lnCar*
Coupling	−2.045***	−1.494***
	(−6.01)	(−3.88)
lnPop		−0.538
		(−1.55)
lnUpdate		−0.281***
		(−3.91)
lnGov		0.277***
		(2.65)
lnFDI		−0.005
		(−0.38)
lnES		0.524***
		(5.13)
lnEr		0.014
		(1.24)
lnPgdp		−0.206
		(−1.46)
lnOpen		−0.016
		(−0.55)
Constant	1.366***	8.365***
	(−13.57)	(3.70)
Observations	300	300
Number of groups	30	30
Adj-R^2	0.831	0.789
Province fixed	Yes	Yes
Year fixed	Yes	Yes

* indicate significance at the 1% significance level, and the values in parentheses represent t-statistics.

of control variables, which aligns with the study's hypothesis. The observed decline in carbon emission intensity is in line with this paper's expectations. Regarding the control variables, the estimated coefficients for industrial structure upgrading, government intervention, and energy structure are statistically significant at the 1% level, suggesting a strong influence on carbon emission intensity. Notably, industrial structure upgrading exhibits a negative coefficient, implying that optimizing industrial structure contributes to lowering carbon emission intensity. Conversely, government intervention and energy structure show positive coefficients, indicating adverse effects on low-carbon development. In contrast, variables such as population density, foreign direct investment, environmental regulation, economic development level, and openness to external trade do not exhibit statistically significant effects on carbon emission intensity. In addition, the baseline regression model without control variables has a higher Adj-R^2 than the model with control variables, which may be due to the fact that the complexity of the model increases with the addition of control variables, and thus the Adj-R^2 becomes smaller.

The above results suggest that the development of digital industrialization and industrial digitalization coupling coordination optimizes the industrial structure, reduces the costs associated with green technologies, and minimizes the consumption of non-renewable energy. Therefore, digital industrialization and industrial digitalization coupling coordination considerably reduces carbon emission intensity and supports China's green and low-carbon development, validating Hypothesis 1.

4.2 Robustness test

4.2.1 Replacement of explanatory variables

Given that the carbon emission data derived from fossil energy consumption calculations may deviate from the actual emissions in each province, such discrepancies could bias the results of the baseline regression. To address this issue, this study adds the natural logarithm of the ratio of carbon emissions to GDP for each province, reported by the China Carbon Accounting Database (CEADs) in the model. Table 5 represents the results of this robustness check. According to Column (1), the coefficient of Coupling remains negative and statistically significant at 1% level, confirming the robustness of the results.

4.2.2 The improved coupling coordination degree model

Based on Shen et al. (2018), this study objectively estimates the relative importance and contribution of digital industrialization and industrial digitalization. It assigns greater weight to the relatively underdeveloped system of the two. Accordingly, the weighted model re-calculates the coupling coordination degree of digital industrialization and industrial digitalization. Table 5 provides the re-estimated results. Column (2) shows that the coefficient of Coupling remains negative and statistically significant at 1% level, confirming the robustness of the findings.

4.2.3 Excluding the impact of energy and environmental policies

To account for potential interference from energy and environmental policy implementation on the benchmark regression results, this study re-estimates the model excluding provinces involved in low-carbon pilot programs and carbon emissions trading market pilots (Yang et al., 2023). As shown in Column (3) of Table 5, the coefficient of Coupling remains negative and statistically significant at 1% level, confirming the robustness of the estimations.

4.2.4 Dynamic panel regression

To ensure the accuracy and reliability of the results, this study re-estimates the model using the system GMM approach.

TABLE 5 Robustness test results.

Variable	(1) Replacement of explanatory variables	(2) The improved coupling coordination degree model	(3) Excluding the impact of energy and environmental policies	(4) Dynamic panel regression
L.lnCar				0.156*
				(1.83)
Coupling	−1.113***	−1.371***	−2.025***	−3.093**
	(−4.20)	(−3.54)	(−4.00)	(−2.20)
Control variable	Yes	Yes	Yes	Yes
Constant	2.029	8.942***	7.607***	−41.574
	(0.19)	(3.99)	(2.96)	(−0.80)
Province fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
AR (1) test p-value				0.033
AR (2) test p-value				0.124
Hansen test p-value				0.294
Observations	300	300	240	299
Number of groups	30	30	24	30
R^2	0.904	0.829	0.792	

*, **, *** significant at 10%, 5%, and 1%, respectively, the value in parentheses represents t-statistics.

As presented in Column (4) of Table 5, the statistics of AR (1) and AR (2) are statistically significant and insignificant at 10% level, respectively, which accepts the first-order autocorrelation of the error term while rejecting the second-order autocorrelation in the system GMM model. Additionally, the *P*-value of Hansen's test falls between 0.1 and 0.25, confirming the validity of the selected instrumental variables. Furthermore, the lagged one-period carbon emission intensity (L.Cg) is significant at 10% level, and the coefficient of digital coupling (Coupling) remains significantly negative, reaffirming the robustness of the benchmark regression results.

4.3 Endogenous treatment

While robustness tests can mitigate potential endogeneity issues in the study to some extent, the policy constraints oriented toward the "dual carbon" goals compel advances in green and low-carbon technologies during the promotion of low-carbon development. Such green-biased technological progress may in turn create a demonstration effect on the development of the digital economy (Yang and Zhao, 2022). That is to say, low-carbon development may also affect the coupled development level of digital industrialization and industrial digitization, which could introduce potential reverse causality into model estimation, thereby leading to endogeneity problems. In view of this, following the approach of Huang et al. (2019), this study adopts the volume of postal and telecommunications services in each region in 1984 as an instrumental variable for endogeneity testing. On the one hand, generally speaking, the historical scale of postal and telecommunications services and the penetration rate of fixed-line telephones influence the current construction of information infrastructure and the development of the internet. Given that network infrastructure and the internet are key drivers of digital economic development (Fan et al., 2023), this indicates that the selected historical postal and telecommunications volume as an instrumental variable satisfies the relevance requirement. On the other hand, the impact of factors such as the number of post offices in 1984 on contemporary digital economic development diminishes over time with declining usage frequency and does not directly affect current regional carbon emission intensity, which suggests that the selected historical postal and telecommunications volume meets the exclusivity requirement. However, as the data for the selected instrumental variable are cross-sectional and cannot satisfy the requirement for temporal heterogeneity, this study further draws on the method of Zhao et al. (2020), constructing an interaction term (Tel) by multiplying the number of post offices per million people in 1984 by the previous year's national internet user count, and uses it as the instrumental variable for the coupling of digital industrialization and industrial digitization. To ensure the robustness of the results, the digital coupling variable is winsorized at the 10% level.

The regression results of the instrumental variable approach are presented in Table 6. The first-stage regression results indicate that the instrumental variable (Tel) has a statistically significant positive effect on the endogenous variable (Coupling) at the 1% level. This suggests that the development of digital coupling increases with the rise in the product of the number of post offices per million people in 1984 and the national internet user count of the previous year, which satisfies the relevance

TABLE 6 Endogeneity test results.

Variable	(1)	(2)
	2SLS	
	First-stage regression	Second-stage regression
Coupling		−4.628*
		(−2.76)
Tel	0.001***	
	(0.00)	
Kleibergen-Paap rk LM statistic		3.169
		[0.075]
Kleibergen-Paap rk Wald F statistic		23.070
		{16.38}
Control variable	Yes	Yes
Province fixed	Yes	Yes
Year fixed	Yes	Yes
Observations	300	300
Number of groups	30	30

*, *** significant at 10% and 1%, respectively; () values are robust standard errors; [] values are p-values; and {} values are critical values at the 10% level of the Stock-Yogo weak identification test.

condition required for a valid instrumental variable. Based on the second-stage regression results, indicate the Kleibergen-Paap rk LM statistic rejects the null hypothesis of under-identification at 10% level, confirming the reliability of the instrumental variable. Similarly, the Kleibergen-Paap rk Wald F statistic of the weak identification test substantially exceeds the critical threshold of the Stock-Yogo test at the 10% significance level, demonstrating that the instrumental variable is robustly identified. Moreover, after mitigating endogeneity concerns to a certain extent, the estimated coefficient of digital coupling on carbon emission intensity remains significantly negative, indicating that the research conclusion—that digital coupling significantly promotes regional green and low-carbon development—holds true. Specifically, the coefficient estimate obtained using the instrumental variable is lower than that from the benchmark regression, suggesting that the carbon reduction effect of the coupling between digital industrialization and industrial digitization may have been underestimated, which further validates the findings of the benchmark regression.

4.4 Mediation effects test

Building on the previous theoretical analysis, the coupling of digital industrialization and industrial digitalization (Coupling) may influence low-carbon development through two mechanisms: energy use efficiency (En_eff) and technological innovation (Innovation). To examine the existence of these pathways, Equation 5 performs a mediation effect test. Table 7 presents the estimated impacts of digital coupling on the mediating variables. Based on the estimations, digital coupling reduces carbon emission intensity.

TABLE 7 Results of the mediation effect test.

Variable	(1)	(2)
	lnEn_eff	lnInnovation
Coupling	0.973***	26.350***
	(3.80)	(8.74)
Constant	−1.609	11.599
	(−1.07)	(0.66)
Control variable	Yes	Yes
Observations	300	300
Number of groups	30	30
Adj-R^2	0.896	0.991
Province fixed	Yes	Yes
Year fixed	Yes	Yes

* indicate significance at the 1% significance level, and the values in parentheses represent t-statistics.

Specifically, Column (1) presents the results of the mediation effect test for energy use efficiency (En_eff). The analysis shows that the digital coupling (Coupling) coefficient is positive and statistically significant at 1% level, indicating that digital coupling improves energy efficiency. This effect arises from synergies between digital industrialization and industrial digitization, which enhance supply chains and enable real-time monitoring of production processes. In this way, digital coupling optimizes resource allocation and process management, thereby reducing carbon emission intensity. Thus, the results support the proposed mechanism, confirming Hypothesis 2a.

Column (2) presents the results of the mediation effect test for technological innovation (Innovation). The analysis shows that digital coupling (Coupling) has a positive impact on technological innovation, which is statistically significant at 1% level. This effect results from the coordinated development of digital industrialization and industrial digitization, which fosters cross-industry collaboration and resource allocation efficiency. By optimizing the use of human, material, and financial resources, enterprises can focus more on research and innovation in key technologies. Thus, increased technological innovation reduces carbon emission intensity, supporting Hypothesis 2b.

4.5 Spatial effect test

4.5.1 Spatial weight matrix

The spatial weight matrix serves as both a representation of the spatial influence patterns between regions and a prerequisite and foundation for spatial econometric analysis. To investigate the spatial spillover effects of the coupling between digital industrialization and industrial digitalization on green and low-carbon development, this paper introduces both a neighborhood matrix and a spatial distance matrix for analysis. Specifically, the neighborhood matrix emphasizes direct neighboring relationships between regions, focusing on the influences among directly

TABLE 8 Results of spatial autocorrelation test for numerical coupling coherence and carbon emission intensity, 2012-2021.

Year	*Coupling* Moran's I	*Car* Moran's I
2012	0.287***	0.411***
2013	0.261***	0.400***
2014	0.282***	0.415***
2015	0.306***	0.420***
2016	0.322***	0.416***
2017	0.325***	0.408***
2018	0.285***	0.414***
2019	0.284***	0.419***
2020	0.288***	0.432***
2021	0.322***	0.417***

*indicate significance at the 1% significance level.

adjacent areas through a binary representation. This facilitates the analysis of interaction effects arising from geographical proximity. The spatial distance matrix primarily reflects the distance relationships between different geographical units, revealing that influences may still exist between regions even over longer distances. Based on this, considering that both digital coupling and green and low-carbon development may be influenced by geographical proximity and distance, the neighborhood matrix is selected to capture the spatial association arising from "whether regions are adjacent," while the spatial distance matrix further captures the "distance-decay effect." Therefore, this paper employs both the neighborhood matrix and the spatial distance matrix as spatial weight matrices to enhance the robustness of the model estimation results.

4.5.2 Spatial autocorrelation test

The coupled interaction between digital industrialization and industrial digitalization can strengthen spatial interconnections and spillover effects among regions. Specifically, as digital coupling deepens, technology spillovers can break down information barriers and reduce energy consumption resulting from the cross-regional flow of production factors (Yang and Zhao, 2022), thereby promoting low-carbon development. Furthermore, leveraging the scale effects and positive externalities of the digital economy, digital coupling development helps overcome geographical constraints on information circulation, facilitates cross-regional information exchange, and enhances the spillover and absorptive capacities of neighboring regions in terms of capital, knowledge, and technical talent (Cai and He, 2024), thereby driving carbon reduction in surrounding areas. Based on this, there exists a practical logic of spatial correlation between digital coupling and green and low-carbon development. In the following section, spatial correlation analysis will be conducted to further clarify the spatial association between the two.

Spatial autocorrelation analysis serves as a prerequisite for applying spatial econometric models. Before testing the spatial measurement, this paper employs Moran's I index method to examine the spatial autocorrelation of carbon emission intensity and the coupling coordination degree between digital industrialization and industrial digitalization. Table 8 presents the results. The test outcomes reveal a positive correlation between carbon emission intensity and the coupling coordination degree of digital industrialization and industrial digitalization, which is statistically significant at 1% level. This result is based on the neighborhood matrix and global Moran's I index between 2012 and 2021, which confirms a positive spatial autocorrelation and spatial agglomeration. In other words, the results highlight that carbon emission intensity and coupling of digital industrialization and industrial digitalization display a positive spatial correlation, with a tendency for spatial clustering. Furthermore, the global Moran's I index for carbon emission intensity is higher than that for digital coupling. This indicates that carbon emission intensity exhibits stronger spatial positive correlation, with its geographical distribution displaying more pronounced high-high and low-low clustering characteristics. In contrast, the spatial agglomeration degree of digital coupling is relatively weaker, suggesting its distribution may be more balanced or dispersed.

4.5.3 Spatial econometric model selection

Under both the neighborhood matrix and the spatial distance matrix, the LM test results are statistically significant at the 1% level, indicating that the variables in this study exhibit spatial distribution characteristics and are suitable for spatial econometric modeling. The LR test and Wald test results both pass the significance test at the 1% level, rejecting the null hypothesis that the Spatial Durbin Model (SDM) can be simplified to either the Spatial Lag Model (SAR) or the Spatial Error Model (SEM), thereby confirming that the Spatial Durbin Model (SDM) is more appropriate for this research. The Hausman test statistics are 17.83 and 201.35, respectively, both significantly rejecting the null hypothesis and thus supporting the selection of the fixed-effects model. Furthermore, to ensure the accuracy of model estimation, this study employs a Spatial Durbin Model with two-way fixed effects for the analysis.

4.5.4 Analysis of spatial Dubein model results

For deeply analyzing the spatial effects of digital industrialization and industrial digitalization coupling on low-carbon development, this paper uses Equation 6 to decompose the total effect of digital coupling on carbon emission intensity into direct and indirect effects. The direct effect refers to the impact of digital coupling in a given region on its own low-carbon development. The indirect effect denotes the influence of a region's digital coupling on the low-carbon development of neighboring areas. The total effect represents the average impact of digital coupling on the overall low-carbon development of the region. Table 9 presents the results. They indicate that the coefficients of the spatial interaction term ($W \times$Coupling) for digital industrialization and industrial digitalization coupling are negative and significant under both spatial weight matrices. This confirms a considerable

TABLE 9 Results of the test for spatial spillover effects.

Variable	(1) Neighborhood matrix	(2) Spatial distance matrix
Coupling	−1.082***	−0.856**
	(−2.94)	(−2.49)
W×Coupling	−1.189**	−1.807*
	(−2.06)	(−1.95)
ρ	0.331***	0.192*
	(4.08)	(1.83)
Direct effect	−1.215***	−0.915***
	(−3.23)	(−2.63)
Indirect effect	−2.239**	−2.412**
	(−2.55)	(−2.04)
Aggregate effect	−3.453***	−3.327***
	(−3.53)	(−2.79)
Sigma2_e	0.007***	0.007***
	(12.06)	(12.19)
Control variable	Yes	Yes
Observations	300	300
Number of groups	30	30
R^2	0.820	0.527
Province fixed	Yes	Yes
Year fixed	Yes	Yes

*, **, *** significant at 10%, 5%, and 1%, respectively, the value in parentheses represents t-statistics.

and negative externality in the effect of digital coupling on carbon emission intensity: an increase in the degree of digital coupling coordination reduces the carbon emission intensity in neighboring regions. Furthermore, the spatial autoregressive coefficient ρ for carbon emission intensity is significantly negative at the 1% significance level, while at the 10% significance level, it is positive. This indicates that carbon emission intensity exhibits a significant spatial spillover effect, whereby an increase in carbon emission intensity in neighboring regions corresponds to a higher carbon emission burden in the region under study.

The results of the spatial effect decomposition show that the estimated coefficients for the direct, indirect, and total effects of digital coupling under both spatial weight matrices are negative and statistically significant at 1% level. This indicates that the coordination of digital coupling has a significant spatial spillover effect on carbon emission intensity, effectively reducing the carbon emission intensity in both the region and its neighboring regions. In the process of coupling digital industrialization and industrial digitalization, "early-mover" regions can not only provide reference for "neighboring" areas through their pioneering experiences and exemplary practices, but also directly promote industrial transformation in adjacent regions through regional industrial division and transfer, thereby generating significant spatial spillover effects (Wu and Deng, 2023). Meanwhile, through technology spillover effects, neighboring regions can learn from the successful practices of advanced areas in low-carbon technology application, industrial upgrading, and green innovation, thereby effectively driving their own green and low-carbon development. This demonstrates that digital coupling can not only enhance the local level of green and low-carbon development but also exert a positive influence on neighboring regions through its demonstration effect. Additionally, the regression results from the spatial measurement test are consistent under both spatial weight matrices, suggesting that the spatial Durbin model of digital coupling on carbon emission intensity is robust, thereby supporting Hypothesis 3.

4.6 Heterogeneity analysis

4.6.1 Regional heterogeneity

Considering the potential regional differences in the development of digital industrialization and industrial digitalization coupling, this paper further examines their impact on the regional heterogeneity of low-carbon development. It subdivides the research sample into four major regions: the East, Northeast, Central, and West. Table 10 shows the results of the regional heterogeneity analysis. The coefficient of digital coupling (Coupling) is positive and significant at the 5% level in the eastern region, while the coefficients are negative and significant at 1% level in the northeastern, central, and western regions. This indicates that the carbon emission reduction effect in the eastern region is not significant, whereas the northeastern, central, and western regions show a significant reduction in carbon emission intensity. One explanation for this discrepancy is that in the eastern region, the economic structure is predominantly centered on service and high-tech industries, coupled with mature digital infrastructure. This results in inherently lower energy consumption per unit of output and carbon emission intensity. Consequently, the further emission reduction potential brought by digital coupling exhibits diminishing marginal returns. Additionally, the eastern region's economy is relatively developed, with a complex industrial structure and an overall advanced technological level. The expansion of economic scale to some extent exacerbates carbon emissions, leading to a non-significant carbon reduction effect. In contrast, the northeast, central, and western regions have a higher proportion of heavy and chemical industries as well as resource-dependent sectors, accompanied by lower energy efficiency. Here, digital coupling facilitates the greening and intelligent transformation of existing industries, directly optimizing production processes and achieving substantial marginal benefits in carbon reduction, thereby effectively lowering carbon emission intensity.

4.6.2 Heterogeneity of digital economy dimensions

To investigate the relationship between low-carbon development and the coupled coordination of digital industrialization and industrial digitalization, this paper examines the impact of "digital industrialization" and "industrial

TABLE 10 Results of heterogeneity test.

Variable	(1)				(2)	
	Regional				Digital economy dimensions	
	Eastern region	North-Eastern region	Central region	Western region	Digital industrialization	Industrial digitalization
Coupling	0.479**	−5.255***	−9.766***	−2.515***	−0.699***	−0.905***
	(2.02)	(−3.44)	(−3.40)	(−3.19)	(−3.24)	(−3.53)
Constant	4.975**	5.095	8.693	1.521	8.858***	8.493***
	(2.12)	(0.54)	(0.51)	(0.45)	(3.86)	(3.70)
Observations	100	30	60	110	300	300
Number of groups	10	3	6	11	30	30
R^2	0.985	0.986	0.875	0.896	0.828	0.829
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes

, * significant at 5% and 1%, respectively; the values in parentheses represent t-statistics.

digitalization" on carbon emission intensity from both dimensions. Table 10 represents the results of the analysis. Column (2) shows that the estimated coefficients for both digital industrialization and industrial digitalization are negative and significant at 1% level, affirming that both factors reduce carbon emission intensity. However, the carbon emission reduction effect of industrial digitalization is more pronounced than that of digital industrialization. This discrepancy may be explained by the fact that the regional economic structure determines the potential for emission reduction. In regions with a concentration of traditional high-energy-consuming industries, industrial digitalization can directly optimize production processes and energy structures through digital technologies such as the Industrial Internet, delivering significant direct emission reduction effects. Additionally, industrial digitalization integrates the efficiency of infrastructure such as 5G and the Internet of Things into core processes such as R&D and production, enabling precise management and coordinated optimization across the entire value chain. This facilitates energy conservation and carbon reduction on a broader scale. In contrast, while digital industrialization possesses technological and infrastructural advantages, its operations—including data computation, transmission, and storage—inherently involve a certain level of electricity consumption. As a result, its effect on reducing carbon emission intensity is less pronounced than that of industrial digitalization.

5 Conclusions and policy implications

From a theoretical perspective, this paper argues that the coupling of digital industrialization and industrial digitalization both directly and indirectly promotes low-carbon development. The indirect impact has two main mechanisms: energy use efficiency and technological innovation. Additionally, the coupling of digital industrialization and industrial digitization has spatial spillover effects on the green and low-carbon development of neighboring regions. The study uses panel data including 30 Chinese provinces between 2012 and 2021, constructs an index system for digital coupling, and employs the entropy method to measure its development. Based on this, the paper empirically examines the impact of digital coupling on carbon emission intensity. The model estimations provide the following conclusions. First, digital coupling significantly reduces carbon emission intensity, becoming a key driver of China's green and low-carbon development, particularly in the context of the "dual-carbon" goal. This result remains robust after various robustness tests, including the instrumental variable approach. Second, energy efficiency and technological innovation serve as mediators in the relationship between digital coupling and green low-carbon development. Third, both digital coupling and carbon emission intensity exhibit spatial autocorrelation, with a significant spatial spillover effect of digital coupling coordination on carbon emission intensity, thereby promoting low-carbon development both locally and in neighboring regions. Fourth, the heterogeneity analysis reveals that digital coupling has a more pronounced reduction effect on carbon emission in the northeast, central, and western regions compared to the eastern region. Finally, while both digital industrialization and industrial digitalization reduce carbon emission intensity, the carbon emission reduction effect of industrial digitalization is stronger than that of digital industrialization.

Based on the conclusions drawn, this paper offers the following policy implications:

First, focus on promoting the coordinated development of digital industrialization and industrial digitalization to fully unlock their potential in advancing green and low-carbon development. Specifically, it is essential to facilitate the deep integration of digital technologies with traditional industries. By introducing advanced technologies such as artificial intelligence and big data, production efficiency and resource utilization can be improved, thereby reducing energy consumption and carbon emissions. Simultaneously, governments should establish an innovation-driven policy framework to incentivize corporate investment in research and development in both green and digital technologies. Additionally, leveraging digital media to raise public awareness and engagement with green and low-carbon concepts will help foster a supportive social environment, contributing to the achievement of the dual carbon goals.

Second, emphasize the critical role of energy efficiency and technological innovation in promoting green and low-carbon development. By promoting energy-saving technologies, optimizing industrial processes, and improving energy management systems, overall societal energy demand can be systematically reduced, driving energy conservation and emission reductions. Governments can utilize advanced technologies such as big data and artificial intelligence to optimize production processes and energy management, thereby enhancing energy efficiency and promoting green and low-carbon development. At the same time, technological innovation—through increased investment in green technology R&D, promotion of cross-sector collaboration, and technology sharing—can accelerate the application and widespread adoption of low-carbon technologies. This will effectively lower the costs of key technologies such as clean energy and energy conservation, ultimately leading to scaled emission reduction effects across industries and regions.

Third, promote resource sharing among regions to strengthen the spatial spillover effects of the coupling between digital industrialization and industrial digitalization on green and low-carbon development. Digital coupling not only enhances the low-carbon development level of a local region but also generates positive spillover effects on neighboring areas. Therefore, it is crucial to deepen the understanding of the spatial correlation characteristics of carbon emission intensity, actively explore the establishment of regional carbon sink trading mechanisms, and improve horizontal carbon compensation mechanisms. This will enable different regions to leverage their comparative advantages and collectively improve the overall level of green and low-carbon development.

Fourth, implement context-specific policies to create a favorable environment for the coordinated development of digital industrialization and industrial digitalization. Given the significant regional and dimensional heterogeneity in the impact of digital coupling on green and low-carbon development, each region should formulate and implement differentiated development strategies based on its comparative advantages. For instance, the Northeast, Central, and Western regions should seize the carbon reduction opportunities presented by digital coupling, with industrial digitalization as the core focus, vigorously promoting the green and intelligent transformation of traditional industries. The Eastern region, on the other hand, should concentrate on enhancing the quality and efficiency of digital industrialization while strengthening technological dissemination and regional coordination. At the national level, policies should appropriately prioritize industrial digitalization, which exhibits greater emission reduction effects, and establish incentive mechanisms to reduce the transition costs for enterprises. Meanwhile, enterprises should leverage data-driven approaches to achieve refined, intelligent management of production and operations, as well as green and low-carbon transformation, thereby enhancing their capacity for sustainable and low-carbon development.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: https://www.stats.gov.cn/sj/ndsj/.

Author contributions

JH: Writing – review & editing, Funding acquisition, Supervision. LN: Conceptualization, Software, Formal analysis, Data curation, Methodology, Writing – original draft. RJ: Investigation, Validation, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work 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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