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Has Digital Industrialization Promoted Carbon Emission Reduction in the Construction Industry?

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Abstract: Mitigating carbon emissions in the construction sector is crucial for attaining the objectives of "carbon peak" and "carbon neutrality". This research utilizes panel data from 30 Chinese provinces spanning 2011 to 2020, employing a two-way fixed-effect model and a mediation-effect model to quantitatively assess the impact of digital industrialization (DI) on carbon emissions within this industry. The findings indicate that DI notably decreases carbon emissions; however, its effectiveness is structurally imbalanced. Digital services (DI-S) have a more pronounced effect on reducing emissions than digital technologies (DI-T). Notably, DI significantly lowers indirect carbon emissions but has a minimal positive impact on direct emissions in construction. Mediation analysis shows that DI greatly enhances green innovation capabilities (GIC) and green financial services (GFS), indirectly contributing to emission reductions, evidencing a full mediation effect. This process underscores the role of DI in promoting green technological innovation and financial development, thereby supporting the sector's low-carbon transformation.

Keywords: digital industrialization; construction industry carbon emissions; two-way fixed-effect model; mediation-effect model

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Academic Editors: Antonio Caggiano and Ali Bahadori-Jahromi

Received: 23 February 2025
Revised: 25 March 2025
Accepted: 2 April 2025
Published: 3 April 2025

Citation: Liu, Y.-L.; Zhang, J.-R.; Li, H.-B. Has Digital Industrialization Promoted Carbon Emission Reduction in the Construction Industry? *Sustainability* **2025**, *17*, 3197. https://doi.org/10.3390/su17073197

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1. Introduction

In the context of global climate change, the world is witnessing a dramatic population expansion and rapid economic development, leading to an increase in greenhouse gas emissions, whose severe impacts are increasingly recognized by the public. In 2016, China was responsible for 28% of global carbon emissions, nearly twice that of the United States, positioning it as the leading global emitter [1]. Post-economic reforms, China's swift industrialization and urbanization have driven the expansion of its construction industry, a fundamental component of the national economy [2]. This industry not only provides essential infrastructure for various sectors but also stands as a significant source of greenhouse gas emissions in China due to the energy consumed in producing building materials, as well as during construction and maintenance [3]. According to the *China Building Energy Consumption Annual Report 2020*, buildings' lifecycle carbon emissions represent 51% of the nation's total, highlighting a substantial potential for reduction [4]. In the 21st century, advancements in digital technologies such as the internet, artificial intelligence, and big data have profoundly influenced all sectors [5]. The digital economy, highlighted in China's 14th Five-Year Plan and Vision 2035, plays a pivotal role in the nation's strategy to achieve carbon neutrality, focusing on the digital economy, new energy, and innovation [6]. The recognition that digitalization is an optimal tool for promoting sustainable development has grown among governments and industries.

DI, which encompasses products, services, and economic activities based on digital information and technology, is vital in providing necessary services, infrastructure, and new production factors for the digital transformation of traditional industries [7,8]. This process encompasses the deep integration and application of digital technologies across industries, thereby driving the digital transformation of traditional industries. It spans multiple domains, including hardware manufacturing, such as chips and sensors; software development, like artificial intelligence, big data, and cloud computing; information services, including digital content and the platform economy; and digital infrastructure, such as smart terminals and communication base stations. Functionally, DI provides essential technical support and service assistance for the digital transformation of traditional industries. First, it reduces the barriers and costs of digital transformation for traditional industries by delivering efficient digital infrastructure and services. Second, DI fosters novel business models and formats, such as platforms and sharing economies, injecting new vitality into traditional industries. Finally, through developing and utilizing data resources, DI promotes the refinement of production, management, and marketing processes in traditional industries, thereby enhancing overall efficiency and competitiveness. The construction industry, known for its substantial energy consumption, is a focal point for DI-driven transformation. This study differentiates between the direct and indirect carbon emissions of the industry, where direct emissions (CEC-D) predominantly arise from energy consumption in buildings, and indirect emissions (CEC-I) derive from the manufacture and processing of building materials [9,10]. These emissions constitute the majority of the lifecycle carbon emissions in construction. By analyzing the effect of DI on these emissions and fostering the industry's green transformation, the study aims to diminish the sector's carbon footprint and contribute to achieving national goals of "carbon peak" and "carbon neutrality".

For most enterprises, enhancing energy efficiency through digital elements remains the most effective strategy for sustainable development [11]. Research indicates that DI has a "spillover effect" on the real economy, particularly the construction industry [12,13]. Changes in production relationships have led to a decline in the economic share of the construction industry and other sectors with high labor productivity growth, a phenomenon known as "Baumol's disease" [14]. The pervasive adoption and network externalities of digital solutions can significantly alleviate Baumol's disease [15]. The spillover effects of DI can reduce production costs [16], enhance demand structures [17], and stimulate the high-quality development of the construction industry [18]. "The digital transformation of the construction industry" refers to a systematic reengineering of the entire lifecycle of construction projects, driven by the integration of digital technologies and service innovation. Through data integration, process optimization, and intelligent decision-making, it aims to achieve efficient resource allocation and precise control of energy consumption within the sector. As the digital transformation progresses, academic inquiry increasingly focuses on the empowering effects of digital technologies, such as the Internet of Things (IoT) and Building Information Modeling (BIM), on traditional construction practices. This research analyzes how these technologies enhance the capabilities of the construction industry [19]. Studies have demonstrated that BIM technology can optimize building energy management by predicting carbon emissions, energy consumption, and resource use at the project's early stages through accurate design and simulation [20,21]. IoT technology enables real-time monitoring of building equipment operations, facilitating precise energy scheduling [22,23]. As global efforts to reach a "carbon peak" and "carbon neutrality" intensify, the construction sector, as a major carbon emitter, faces significant pressures and challenges [24]. The integration of digital technologies throughout the construction lifecycle has been shown to improve efficiency in design, construction, and management [25] and to

reduce the costs associated with carbon emission reduction by optimizing resource use and minimizing material waste [26]. The diversity and complexity of carbon emission sources in the construction industry suggest substantial potential for further leveraging digital technologies to reduce emissions [27,28]. As a developing country, China's construction industry began its digitalization process relatively late, hindered by low technology levels and funding shortages [29,30]. Reducing the costs of digital transformation [31], along with strengthening policy guidance and financing support [32,33], will be crucial in promoting the transformation of China's construction industry toward low-carbon development. In summary, the relationship between digital transformation in the construction industry and carbon emissions involves a combination of technology-driven innovation, systemic synergy, and limitations related to scale. However, the current scalability of technological applications is hindered by regional disparities and bottlenecks in technology and capital, which require policy guidance and financial innovation to overcome cost barriers. At its core, digital transformation reduces carbon emissions in construction through two main approaches: precision intervention, such as data-driven optimization, and systematic reengineering, such as redesigning lifecycle processes. However, successfully implementing these strategies depends on lowering technological costs and fostering coordination among institutions, ultimately leading to significant breakthroughs in the industry's transition to low-carbon practices.

While existing research extensively examines the role of digital technologies in advancing high-quality development and reducing carbon emissions in the construction industry (CEC), much of this literature focuses predominantly on the digital transformation processes within the sector. Specifically, they examine how digitalization optimizes carbon emissions within the construction sector, with fewer studies addressing the specific impacts and mechanisms of DI on reducing carbon emissions. This gap hinders current research from fully explaining how the development of the digital economy facilitates energy savings and emission reductions in the construction industry. The mediation-effect model, which analyzes how an explanatory variable influences an explained variable through a mediating variable, is suitable for exploring phenomena with complex, indirect mechanisms [34]. This study analyzes panel data from 30 Chinese provinces from 2011 to 2020, employing both the two-way fixed-effect model and the mediation-effect model to comprehensively evaluate how DI influences CEC through mediating variables, thereby revealing the underlying mechanisms that facilitate emission reductions via DI. This analysis aims to offer theoretical support for policy formulation and implementation.

Besides the introduction, the paper is structured into four sections. Section 2 constructs a framework to explore the potential connections between DI, GIC, GFS, and CEC. Section 3 details the employed models, the criteria for variable selection, and the origins of the data used. In Section 4, the impact of DI on carbon emissions is dissected, with a particular focus on the mediating roles of GIC and GFS, utilizing both aforementioned models. Section 5 reflects on the interrelationships and causal dynamics between DI and carbon emissions in the construction sector, underscoring the relevance of this study to strategies for carbon emission reduction.

2. Conceptual Framework and Research Hypotheses

The conceptual framework depicted in Figure 1 outlines the potential impact pathways through which DI affects CEC via green innovation capabilities (GIC) and green financial services (GFS).

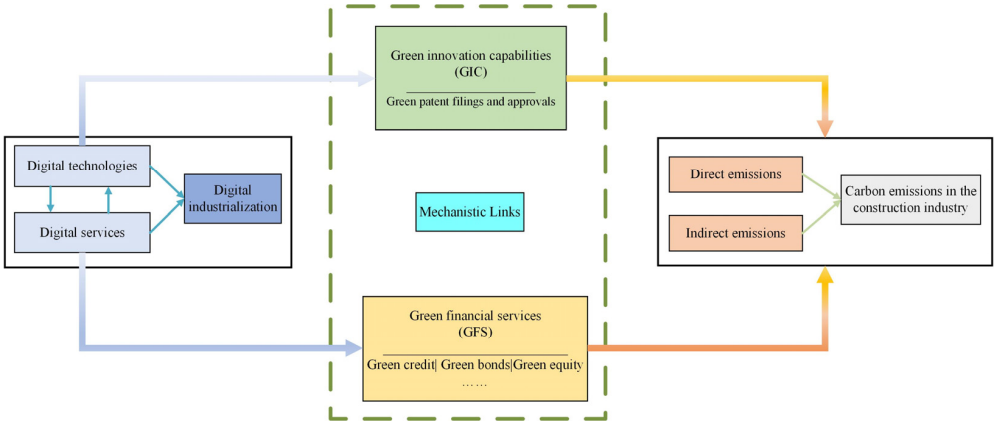


Figure 1. Conceptual framework for the potential pathways.

DI-T and DI-S together constitute the core features of DI.

DI entails the integration of digital technologies, services, and solutions to transform traditional industries. It encompasses all economic activities reliant on digital elements [7]. Based on differences in functional attributes and pathways of influence, this study categorizes DI into two complementary dimensions: digital services (DI-S) and digital technologies (DI-T). DI-S activities derived from digital elements reduce resource waste in the construction industry and optimize carbon footprint management in upstream supply chains by integrating supply chain and financial resources. DI-T provides technical support and minimizes energy and material consumption throughout buildings' lifecycle through optimized construction processes and energy-efficient designs. These two dimensions offer distinct digital driving forces for low-carbon transformation in the construction industry through respective technological and service empowerment pathways. Therefore, based on the above analysis, this study puts forward the following hypothesis:

Hypothesis 1. *DI has a significant negative impact on CEC.*

The development of DI promotes the advancement of GIC and GFS through the widespread adoption of DI-T and DI-S.

GIC is defined as the capacity for technological innovation aimed at supporting low-carbon, environmentally friendly, and sustainable development [35]. This research predominantly showcases capabilities through the development, research, and implementation of green technologies, products, and processes, as evidenced by metrics such as green patent applications and authorizations [36]. The advancement of DI has facilitated the widespread adoption of cutting-edge DI-T and services in traditional sectors, enhancing the R&D process for green technologies. Utilizing capabilities like information sharing, data integration, and real-time interaction [37], DI empowers firms to address challenges in energy efficiency and environmental impacts effectively [38], promoting the development and market adaptation of green technologies [39]. The term "GFS" refers to financial tools and services that support low-carbon, environmentally friendly, and sustainable development [40], encompassing various forms such as green credit, green bonds, and carbon trading [41,42]. DI introduces tools like blockchain and big data analysis, which provide precise data and decision-making support to financial institutions [43,44]. This technological support boosts the awareness and confidence of financial institutions in green projects, driving the innovation of green financial products and services [45] and drawing more investment into projects aimed at energy conservation, emission reduction, and sustainable development. The robust integration of digital elements and the cost-effectiveness of digital platforms facilitate the efficient pooling of financial resources, providing tailored

financial solutions for the greening and low-carbon transformation of the real economy and supporting the implementation and application of green technologies [46]. Based on the above analysis, this study puts forward the following hypothesis:

Hypothesis 2. *DI has a significant positive impact on GIC and GFS.*

Enhanced GIC and the evolution of GFS play critical roles in reducing carbon emissions within the construction industry.

The enhancement of green innovation capacity introduces efficient energy technologies, environmentally friendly building materials, and intelligent management systems to the construction sector [47,48], reducing the reliance on fossil fuels and thereby optimizing the carbon emissions throughout the entire lifecycle of buildings [49]. Green finance lowers the cost of financing for companies by providing financial support and incentives for low-carbon building projects, encourages the use of environmentally friendly materials and energy-saving technologies [50–52], and supports the construction industry in implementing more sustainable construction and maintenance practices across the building lifecycle, thus facilitating the industry's shift toward greener and decarbonized practices [53]. Based on the above analysis, this study puts forward the following hypothesis:

Hypothesis 3. *DI can indirectly suppress CEC by enhancing GIC and GFS.*

CEC includes direct emissions from energy use during construction activities and indirect emissions from the manufacture and processing of building materials [9,10]. Achieving carbon emission reduction targets in this sector requires a holistic approach, encompassing energy mix optimization, reduced energy consumption during construction phases, and the adoption of eco-friendly building materials to minimize waste [54]. Given the cross-sectoral nature of carbon emission reduction in construction [55], it is reliant on the synergistic progress of green technology and financial backing for environmental protection [48,50,51]. DI not only enhances GIC but also supports the development of GFS, offering an indirect route to address the technological and financial challenges in reducing carbon emissions within the construction industry.

3. Materials and Methods

3.1. Model

3.1.1. Calculation Model of CEC

The complexity of CEC stems from its lifecycle, which encompasses multiple stages such as building material production, construction, and operational maintenance. This complexity also poses challenges for carbon emission accounting in the sector. This study categorizes construction industry carbon emissions into direct and indirect emissions based on their sources. In this study, CEC-D refers to CO_2 generated from directly consuming energy sources such as diesel, gasoline, and raw coal during construction activities. CEC-I refers to CO_2 produced during the manufacturing and processing of key building materials such as steel and cement for construction, covering upstream carbon emission sources in the construction supply chain. This classification method helps to identify hidden sources of emissions while simplifying the accounting process.

This study calculates CEC-D using an energy-based method that estimates emissions based on fuel consumption. This approach references the net calorific value (NCV) and carbon content (CC) of various fuels from the research conducted by Shan et al. [56] and

the oxidation rate (O) data from the "2006 IPCC Guidelines for National Greenhouse Gas Inventories (2019 Refinement)" [57]. The formula used is as follows:

$$\text{CEC-D} = \sum_{i=1}^{17} E_i \times NCV_i \times CC_i \times O_i \times f \quad (1)$$

In Equation (1), CEC-D represents the direct carbon emissions in the construction industry; E_i is the consumption of fuels i (pre-conversion physical quantity); NCV_i is the net calorific value of fuels i; CC_i is the carbon content of energy i; O_i represents the oxidation rate of fuels i; f is the ratio of the mass of carbon dioxide to the mass of carbon, valued at 44/12. The net calorific values, carbon contents, and oxidation rates of various fuels are detailed in Table 1.

Table 1. Net calorific value, carbon content, and oxidation rate coefficients for various types of fuels.

Fuels	NCV_i	CC_i	O_i
	(PJ/10^4 tons, $10^8 m^3$)	(tons C/TJ)	(%)
Raw coal	0.21	26.32	0.98
Cleaned coal	0.26	26.32	0.98
Other washed coal	0.15	26.32	0.98
Briquette	0.18	26.32	0.98
Coke	0.28	31.38	0.98
Coke oven gas	1.61	21.49	0.99
Other gas	0.83	21.49	0.99
Other coking products	0.28	27.45	0.98
Crude oil	0.43	20.08	0.99
Gasoline	0.44	18.90	0.99
Kerosene	0.44	19.60	0.99
Diesel oil	0.43	20.20	0.99
Fuel oil	0.43	21.10	0.99
Other petroleum products	0.51	17.20	0.99
LPG	0.47	20.00	0.99
Refinery gas	0.43	20.20	0.99
Nature gas	3.89	15.32	0.99

This study calculates CEC-I by employing the sectoral greenhouse gas emission structures researched by Ji et al. [58] and the calculation methods developed by Ma [59]. Five principal building materials in the construction industry—steel, wood, cement, glass, and aluminum—are considered. The carbon dioxide emissions produced during the manufacturing and processing of these materials are categorized as CEC-I. Notably, as inherently recyclable materials, steel and aluminum have their emissions calculated using the recycling coefficient method, yielding more realistic and precise emission estimates. The formula is as follows:

$$\text{CEC-I} = \sum_{j=1}^{5} M_j \times V_j \times (1 - K_j) \quad (2)$$

In Equation (2), CEC-I signifies the indirect carbon emissions in the construction industry; M_j denotes the consumption of material j; V_j represents the carbon emission coefficient of material j; K_j represents the recycling utilization coefficient of material j. The carbon emission coefficients and recycling utilization coefficients of various materials are itemized in Table 2.

Table 2. Carbon emission and recycling utilization coefficients of various materials.

Materials	Carbon Emission Coefficients	Recycling Utilization Coefficients	References
Steel	1.789 (kg/kg)	0.8	[60]
Wood	−842.8 (kg/m^3)	\	[61]
Cement	0.822 (kg/kg)	\	[62]
Glass	0.966 (kg/kg)	\	[63]
Aluminum	2.6 (kg/kg)	0.85	[64]

Notes: The photosynthesis of trees reduces carbon dioxide in the air, so the carbon emission coefficient of wood is negative in carbon emission accounting. The unit of measurement for the glass in the raw data is the box, which was converted to a weight of 50 kg per box.

In Equation (3), CEC comprises both CEC-D and CEC-I:

$$\text{CEC} = \text{CEC-D} + \text{CEC-I} = \sum_{i=1}^{17} E_i \times NCV_i \times CC_i \times O_i \times f + \sum_{j=1}^{5} M_j \times V_j \times \left(1 - K_j\right) \quad (3)$$

3.1.2. Two-Way Fixed-Effect Regression Model

To assess the impact of DI on CEC, with CEC as the explained variable and DI as the explanatory variable, a two-way fixed-effect (TWFE) model incorporating individual (provincial) and temporal (yearly) effects is employed. Unobservable provincial and temporal characteristics in the panel data may confound the relationship between DI and CEC. By incorporating provincial and time-fixed effects, the model mitigates omitted variable bias caused by inherent provincial differences such as energy structures, policy traditions, and global temporal shocks such as macroeconomic fluctuations.

The model is expressed as follows:

$$CEC_{it} = \alpha_0 + \alpha_1 DI_{it} + \sum_{k=2}^{8} \alpha_k Control_{it} + \omega_i + \gamma_t + \varepsilon_{it} \quad (4)$$

In Equation (4), CEC_{it} is the explained variable, representing the carbon emissions from the construction industry in province i in year t. DI_{it} is the explanatory variable, representing the level of DI in province i in year t. α_0 is the constant term, and α_1 represents the impact of DI on promoting carbon emission reduction in the construction industry. $Control_{it}$ includes the control variables. ω_i denotes the provincial fixed effects. γ_t represents the time-fixed effects. ε_{it} represents the random error term.

Subsequent analyses further validate the superiority of the TWFE model over Ordinary Least Squares (OLS) and Random Effect (RE) models through BP-LM and Hausman tests. Additionally, the instrumental variable (IV) method is introduced to address endogeneity issues, ensuring the robustness of the estimation results. This approach enables the precise identification of the net effect of DI on carbon emissions in the construction industry.

3.1.3. Mediation-Effect Model

The mediation-effect model analyzes how one variable influences another through mediators. It is beneficial for exploring complex phenomena that operate indirectly through these mediating variables [34]. This study constructs a mediation-effect model to examine the transmission pathways of GIC and GFS and reveal the mechanism through which DI affects CEC. Using the three-step method proposed by Wen and Ye [65], the model first verifies the total effect of DI on CEC, then analyzes its impact on the mediating variables

(GIC and GFS), and finally examines the changes in effects after incorporating the mediating variables. Building on Equation (1), the mediation-effect model is constructed as follows:

$$MED_{it} = \beta_0 + \beta_1 DI_{it} + \sum_{k=2}^{8} \beta_k Control_{it} + \omega_i + \gamma_t + \varepsilon_{it} \quad (5)$$

$$CEC_{it} = \delta_0 + \delta_1 DI_{it} + \sum_{k=2}^{3} \delta_k MED_{it} + \sum_{k=4}^{10} \delta_k Control_{it} + \omega_i + \gamma_t + \varepsilon_{it} \quad (6)$$

In Equation (5), MED_{it} represents the mediating variable. β_0 is the constant term, and β_1 represents the impact of DI on the mediating variable.

In Equation (6), δ_0 is the constant term. δ_1 quantifies the influence of DI on carbon emission reduction in the construction industry, considering the mediating variable. δ_k (k = 2, 3) measure the impact of GIC and GFS on reducing CEC, respectively.

3.2. Variable Selection

3.2.1. Explained Variable

In this research, carbon emissions from the construction industry serve as the explained variable. These emissions comprehensively include all emissions related to construction activities, such as the production of building materials, transportation, the construction process itself, operational phases of buildings, demolition, and the transportation of waste. As shown in Table 3, carbon emissions from the construction industry comprise both direct emissions from the energy consumption of construction activities and indirect emissions from the consumption of building materials [24]. Specifically, direct CEC refers to the carbon dioxide produced by the direct consumption of energy sources such as diesel, gasoline, and raw coal, while indirect emissions are generated during the production and processing of the five principal building materials, such as cement and steel [9,10]. The total carbon emissions from the construction industry thus encompass both these direct and indirect sources.

Table 3. Structure of CEC.

Explained Variable	Primary Indicators
CEC	Direct carbon emissions in the construction industry (CEC-D) (10^4 tons)
	Indirect carbon emissions in the construction industry (CEC-I) (10^4 tons)

3.2.2. Explanatory Variable

The explanatory variable under study is DI. To evaluate DI's impact on the construction industry's carbon emissions effectively, this study utilizes criteria from the Classification of China's Digital Economy and its Core Industries (2021), ratified by the National Bureau of Statistics (NBS) in its 10th executive meeting on 14 May 2021 [66]. DI encompasses the application of DI-T, products, services, infrastructure, and digital solutions across various sectors [7], signifying all economic activities that depend on digital components [8]. As shown in Table 4, two primary indicators were selected to characterize DI: DI-S and DI-T. Six secondary indicators represent DI-S: per capita telecommunications service volume, mobile phone penetration rate, proportion of internet users to the resident population, mobile phone base station density, e-commerce transaction volume, and proportion of enterprises engaged in e-commerce transactions. DI-T is quantitatively assessed using four secondary indicators: revenue from the electronic information manufacturing industry, the number of enterprises in this sector, revenue generated from software services, and

employment figures in the information transmission, software, and information technology services sector. The entropy method is utilized to derive a comprehensive evaluation of DI from these indicators.

Table 4. Indicator system for DI.

Explanatory Variable	Primary Indicators	Secondary Indicators
DI	DI-S	Per capita telecommunications service volume (Yuan/person) Mobile phone penetration rate (Units/100 people) The proportion of internet users to the resident population (%) Mobile phone base station density (Units/km^2) E-commerce transaction volume (100 million Yuan) The Proportion of enterprises engaged in e-commerce transactions (%)
	DI-T	Revenue from the electronic information manufacturing industry (10^4 yuan) Number of enterprises in electronic information manufacturing industry (Units) Revenue generated from software services (10^4 yuan) Employment figures in the information transmission, software, and information technology services sector (10^4 people)

3.2.3. Mediating Variables

To examine the pathway through which DI promotes carbon emission reductions in the construction industry, as summarized in Table 5, this study selects two mediating variables: GIC and GFS.

Table 5. Indicator system for mediating variables.

Mediating Variables	Primary Indicators	Secondary Indicators
GIC	Green patent applications	Number of green invention patent applications (Units) Number of green utility model patent applications (Units) Number of green patent applications (Units)
	Green patent authorizations	Number of green invention patent authorizations (Units) Number of green utility model patent authorizations (Units) Number of green patent authorizations (Units)
GFS	Green credit	The Ratio of environmental protection project credits to total credits (%)
	Green investment	Investment ratio in environmental pollution control to GDP (%)
	Green insurance	Share of environmental pollution liability insurance income relative to total premium income (%)
	Green bonds	The proportion of green bond issuances to total bond issuances (%)
	Green support	Fiscal environmental protection expenditure's proportion to the general budgetary expenditure (%)
	Green funds	Market value ratio of green funds to total funds (%)
	Green equity	The proportion of transactions in carbon trading, energy rights trading, and emission rights trading within the total equity market (%)

Drawing from Song et al.'s research [67] on green innovation capacity and their construction of an indicator system, green innovation capacity in this study is represented by two primary indicators: green patent applications and green patent authorizations. For green patent applications, the indicators include the number of green invention patent applications, the number of green utility model patent applications, and the aggregate number of green patent applications. In the context of green patent authorizations, the breakdown includes the number of green invention patent authorizations, the number of green utility model patent authorizations, and the total number of green patent authorizations. The entropy value method is employed to conduct a thorough assessment of GIC using this intermediary variable index system.

Synthesizing the construction of a green financial indicator system by Wang et al. [68], Liu, and He [69], the GFS in this study are structured around seven primary indicators, each with corresponding secondary indicators. GFS is evaluated through several indicators: green credit, represented by the ratio of environmental protection project credits to total credits within the province; green investment, measured by the investment ratio in environmental pollution control to GDP; green insurance, quantified by the share of environmental pollution liability insurance income relative to total premium income; green bonds, indicated by the proportion of green bond issuances to total bond issuances; green support, defined as the fiscal environmental protection expenditure's proportion to the general budgetary expenditure; green funds, measured by the market value ratio of green funds to total funds; and green equity, which includes the proportion of transactions in carbon trading, energy rights trading, and emission rights trading within the total equity market. Utilizing the entropy value method with this indicator system, a comprehensive evaluation of GFS is conducted.

3.2.4. Control Variables

To comprehensively analyze the impact of DI on carbon emission reduction in the construction industry, it is essential to select control variables that may influence carbon emissions. Economic development and urbanization levels, which reflect regional prosperity, have been shown to significantly affect the construction industry's growth [70] and, consequently, its carbon emissions [71]. Industrial economic output and the level of industrialization form the backbone of the modern construction industry and significantly influence both the development of the industry and its carbon emission efficiency [72]. Governmental efforts in environmental protection and technological advancement reflect the degree of policy intervention in these areas, affecting the level of environmental protection technology in construction projects [73,74]. Additionally, investment intensity in the real estate industry indicates the sector's prosperity and has a considerable impact on the construction industry's carbon emissions [75]. The control variables described above are detailed in Table 6.

Table 6. Control variables.

Control Variables	Description of Variables
Economic development levels (EDL)	GDP per capita (10^4 yuan/person)
Industrial economic output (IEO)	Industrial added value (100 million yuan)
Governmental efforts in environmental protection (GEP)	Local fiscal environmental protection expenditure (100 million yuan)
Governmental efforts in technological advancement (GTA)	Local fiscal science and technology expenditure (100 million yuan)
Investment intensity in the real estate industry (IRE)	Investment completed by real estate development enterprises (100 million yuan)
Urbanization levels (URB)	Share of urban population in total population (%)
Industrialization levels (IND)	Share of industrial added value in GDP (%)

3.3. Research Region and Data Sources

The statistical data for the DI-related indicators in this study cover the period from 2011 to 2020. Due to limitations in data completeness and availability, data from regions including Hong Kong, Macau, Taiwan, and Tibet were excluded. Statistical data encompassing 30 provinces (including autonomous regions and municipalities directly under the central government) were employed, yielding 300 balanced provincial-level panel observations. Descriptive statistics for key variables are detailed in Table 7.

Table 7. Descriptive statistics for key variables.

Category	Variables	Sample Size	Mean	Standard Error	Min	Max
Explained Variable	CEC	300	8.297	1.146	5.438	11.464
Explanatory Variable	DI	300	0.109	0.12	0.006	0.935
Mediating Variables	GIC	300	0.101	0.137	0	0.78
	GFS	300	0.469	0.156	0.203	0.923
Control Variables	EDL	300	1.598	0.421	0.479	2.645
	IEO	300	8.66	1.00	6.03	10.58
	GEP	300	4.817	0.625	3.055	6.617
	GTA	300	4.3	1.044	1.324	7.064
	IRE	300	7.797	0.871	4.975	9.759
	URB	300	0.59	0.122	0.369	0.893
	IND	300	0.322	0.083	0.101	0.556

The data used in this study are categorized into four main parts:

(1) Explanatory variables (DI): These indicators were derived from the "China Statistical Yearbook [76]", " China Statistical Yearbook of the Tertiary Industry [77]", and the "Yearbook of China Information Industry [78]".

(2) Dependent variable (construction industry carbon emissions): This variable incorporates data on various types of energy consumption from the "China Energy Statistical Yearbook [79]" and information on consumption of different building materials from the "China Statistical Yearbook on Construction [80]". The coefficients for carbon

emissions and recycling rates for these materials were determined through a comprehensive review of relevant literature [60–64].

(3) Mediating variables (GIC and GFS): Data on GIC were obtained from the China National Research Data Services Platform (CNRDS), while information on GFS was gathered from the "China Statistical Yearbook of Science and Technology [81]", "Almanac of China's Finance and Banking [82]", and "China Third Industry Statistical Yearbook".

(4) Other variable data: These data were sourced from the "China Statistical Yearbook", "China Industry Statistical Yearbook [83]", and "China Statistical Yearbook on Construction".

To ensure uniform data dimensions, variables related to quantities and amounts in the other variables section were logarithmically transformed (for indicators measured in currency, the GDP deflator was first used for adjustment). Ratio variables retained their original form. For missing data, supplementary information was obtained from other sources, or interpolation methods were employed where appropriate for data imputation.

4. Results

4.1. Temporal Evolutionary Pattern of DI and CEC

4.1.1. Temporal Evolution of DI and CEC

Figure 2 displays the trend of China's DI and carbon emissions from the construction industry from 2011 to 2020 using a line graph. The graph shows that while the overall level of China's DI was initially modest, it exhibited continuous growth, averaging an annual increase of approximately 18%. The growth rate accelerated from 2016 to 2020 after a slower period from 2011 to 2016. Concurrently, carbon emissions from China's construction industry demonstrated a fluctuating decline, averaging an annual decrease of about 2%. Notably, carbon emissions declined significantly from 2012 to 2015 and rebounded slightly from 2015 to 2019. Based on these observations, this paper suggests that enhancing DI levels may be a significant factor in reducing carbon emissions from the construction industry.

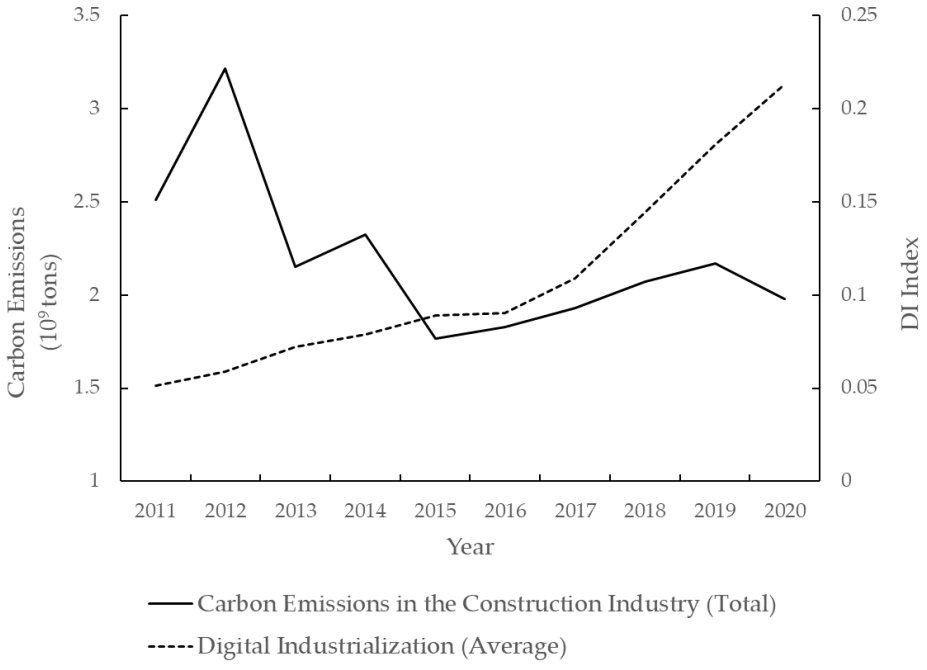


Figure 2. Trends of CEC and DI in China.

4.1.2. Spatial Distribution Characteristics of DI and Carbon Emission in the Construction Industry

This study examines the spatial distribution characteristics of DI and carbon emissions from the construction industry on a provincial scale in China, visualized using ArcGIS 10.7 software (Figures 3 and 4). As shown in Figure 3, from 2011 to 2020, the level of DI in China continuously improved, with the spatial pattern expanding progressively from the southeastern coast to the northwestern inland. The development of DI was spatially unbalanced, with southeastern coastal provinces consistently leading, central provinces catching up with the eastern region, and northeastern and northwestern provinces lagging. By 2020, this spatial imbalance had lessened, as evidenced by the expansion of high-value regions and contraction of low-value regions, indicating nationwide diffusion and gradient enhancement of DI. Figure 4 reveals that the spatial pattern of carbon emissions from China's construction industry from 2011 to 2020 exhibited clear regional differences and dynamic changes. Carbon emissions were predominantly concentrated in the eastern coastal and central core provinces, while emissions in the western and northeastern provinces were relatively low. Over the decade, carbon emissions generally declined, with significant reductions in high-emission areas and fluctuating emissions in some central provinces. Comparing the spatial characteristics of DI and construction carbon emissions at the provincial scale in China reveals a notable trend: provinces with higher levels of DI experienced significant reductions in construction carbon emissions, demonstrating a negative spatial correlation between the development of DI and the level of construction carbon emissions.

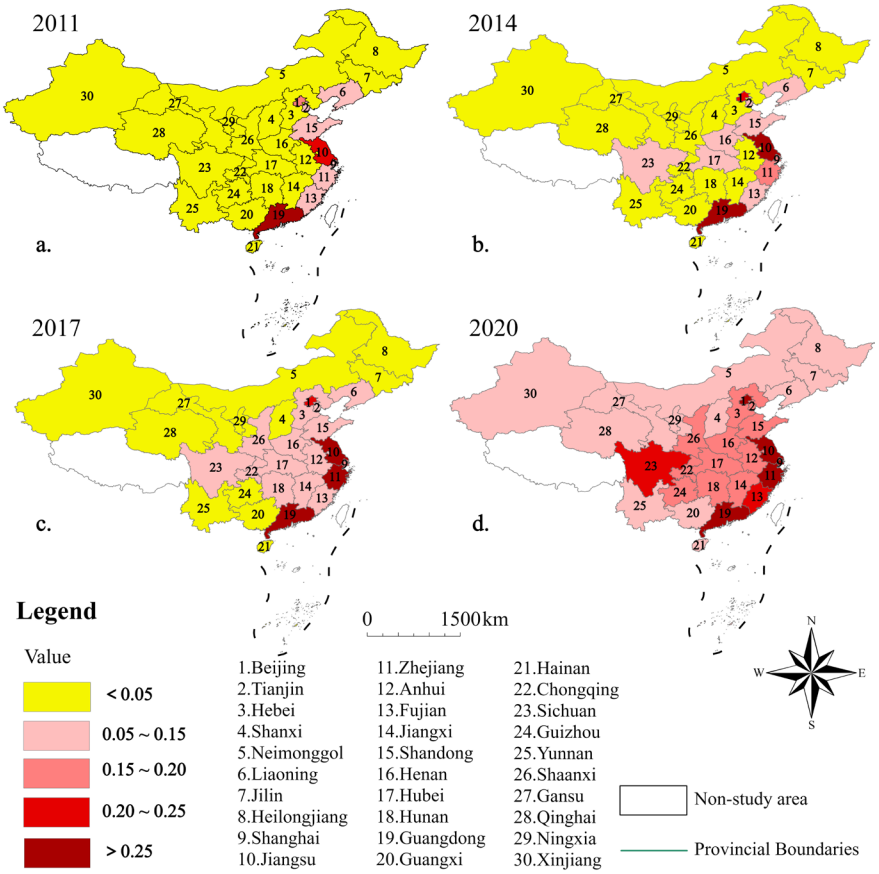


Figure 3. Spatial–temporal evolution pattern of DI in China.

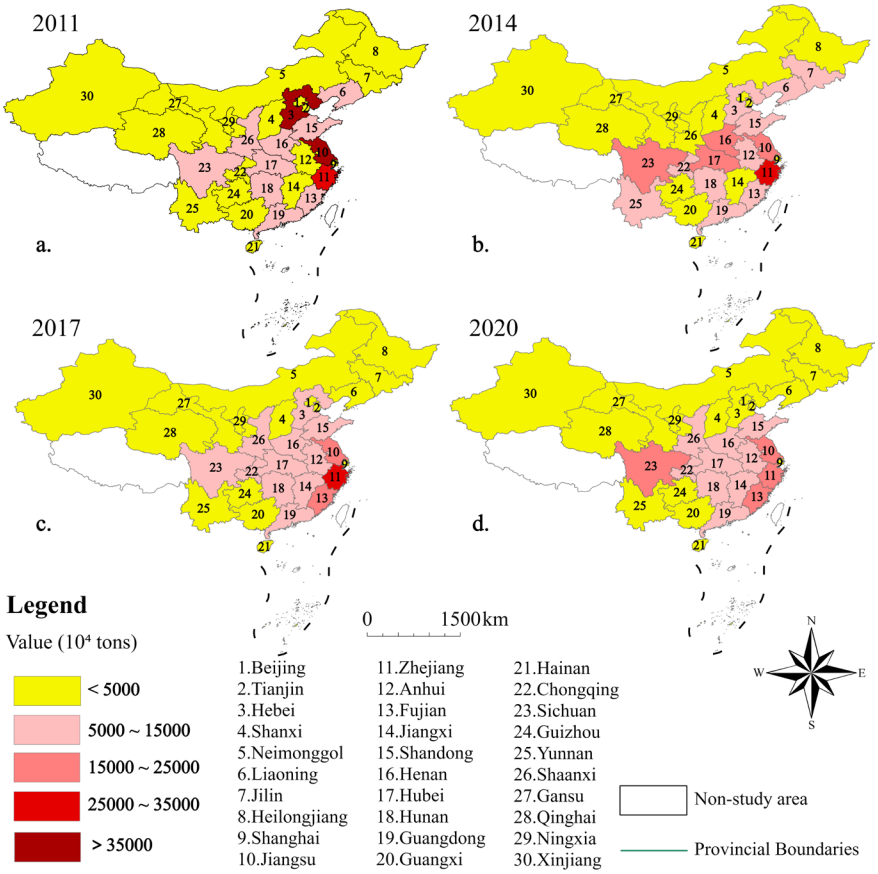


Figure 4. Spatial–temporal evolution of CEC in China.

4.2. The Mechanism of DI Promoting Carbon Emission Reduction in the Construction Industry

4.2.1. Baseline Regression

This study initially compared the results of the Ordinary Least Squares (OLS), Random Effects (RE), Fixed Effects (FE), and two-way fixed-effect (TWFE) models to validate the appropriateness of the chosen model. The results are shown in Table 8.

The BP-LM test was conducted to compare the OLS model with the RE model, indicating that at a significance level of $p < 0.001$, the OLS model failed to effectively control for inter-group random effects, leading to its rejection. The Hausman test, contrasting the RE model with the FE model and indicating a significant $p < 0.001$, highlighted endogeneity concerns within the RE model, leading to its rejection. Subsequently, a TWFE model was developed, integrating fixed effects at the provincial level and time effects to manage cross-provincial heterogeneity and negate unobserved standard shocks and systematic biases across the temporal axis. This adjustment significantly enhanced the robustness and explanatory capacity of the estimation results. The regression outcomes of the TWFE model aligned with those of the FE model in terms of significance and the direction of effects, confirming the appropriateness of the model selection for this analysis.

Further assessments based on the baseline regression outcomes from the TWFE model examined the influence of DI on CEC. The model estimated that DI's impact on reducing CEC was significant, with a coefficient of −1.570 at the 5% significance level, indicating that DI effectively reduces carbon emissions in this sector. Thus, Hypothesis 1 is verified.

Table 8. Baseline regression results under different models.

Variables	CEC			
	OLS	**RE**	**FE**	**TWFE**
	(1)	**(2)**	**(3)**	**(4)**
DI	−1.986 ***	−1.056 **	−1.738 ***	−1.570 **
	(0.411)	(0.517)	(0.583)	(0.778)
EDL	1.047 ***	0.534	−2.902 ***	−1.851 **
	(0.238)	(0.363)	(0.656)	(0.746)
IEO	0.314 **	0.637 ***	3.022 ***	2.619 ***
	(0.129)	(0.188)	(0.495)	(0.513)
GEP	0.005	−0.217 **	−0.121	0.019
	(0.091)	(0.105)	(0.112)	(0.129)
GTA	0.154 *	0.201 *	0.292 **	0.229 *
	(0.088)	(0.119)	(0.134)	(0.138)
IRE	0.597 ***	0.420 ***	0.292 **	0.307 **
	(0.092)	(0.126)	(0.137)	(0.143)
URB	−3.687 ***	−4.114 ***	−6.277 ***	−3.661 *
	(0.817)	(1.112)	(1.344)	(1.918)
IND	2.976 ***	−0.410	−11.466 ***	−9.623 ***
	(0.780)	(1.178)	(2.152)	(2.286)
Constant term	−0.001	−1.241	−8.604 ***	−9.048 ***
	(0.585)	(0.927)	(2.606)	(2.681)
BP-LM Test	Chi-squared = 151.86, $p < 0.001$			
Hausman Test	Chi-squared = 46.68, $p < 0.001$			
N	300.000	300.000	300.000	300.000
R^2	0.791		0.269	0.315
Provincial fixed	NO	NO	YES	YES
Time fixed	NO	NO	NO	YES

Notes: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with the values in ( ) indicating the standard errors.

4.2.2. Structural Effects Analysis

This study's evaluation system for DI includes two dimensions: DI-S and DI-T. The carbon emission indicators encompass both direct and indirect CEC. Based on these indicators, the study explores the structural effects of DI on carbon emissions. Model (1) in Table 9 presents the baseline regression results, while Models (2) and (3) analyze the impact of DI-S and DI-T, respectively, on carbon emissions. Models (4) and (5) assess the effects of DI on direct and indirect carbon emissions, respectively. The findings indicate that DI-S significantly reduces carbon emissions, whereas DI-T has a non-significant negative impact. Additionally, DI shows a non-significant positive impact on direct carbon emissions and a significant negative impact on indirect carbon emissions.

Table 9. Results of the structural effects test.

Variables	CEC	CEC	CEC	CEC-D	CEC-I
	(1)	(2)	(3)	(4)	(5)
DI	−1.570 ** (0.778)			0.187 (0.345)	−1.571 * (0.840)
DI-S		−1.429 ** (0.611)			
DI-T			−1.115 (0.827)		
Constant term	−9.048 *** (2.681)	−9.562 *** (2.678)	−8.417 *** (2.662)	2.426 ** (1.188)	−10.370 *** (2.896)
N	300.000	300.000	300.000	300.000	300.000
R^2	0.315	0.318	0.309	0.399	0.322
Control variables	YES	YES	YES	YES	YES
Provincial fixed	YES	YES	YES	YES	YES
Time fixed	YES	YES	YES	YES	YES

Notes: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with the values in ( ) indicating the standard errors.

4.2.3. Mediation Effects Analysis

Regression analysis based on the mediated-effect model, with the results displayed in Table 10, examines the influence of DI on GIC and GFS and their subsequent effects on CEC. Model (1) outlines the baseline regression results, Model (2) details the impact of DI on GIC, and Model (3) assesses the combined effects of DI and GIC on carbon emissions. Models (4) and (5) follow a similar structure for GFS. The results demonstrate that DI significantly boosts both GIC and GFS. Therefore, Hypothesis 2 is valid. In Models (4) and (5), while the direct impact of DI on carbon emissions becomes non-significant, both GIC and GFS significantly decrease carbon emissions, suggesting a complete mediation effect of DI on carbon emissions through GIC and GFS as mediating variables. Therefore, Hypothesis 3 is established.

Table 10. Results of the mediation-effect test.

Variables	CEC	GIC	CEC	GFS	CEC
	(1)	(2)	(3)	(4)	(5)
DI	−1.570 ** (0.778)	1.104 *** (0.077)	−0.067 (1.040)	0.316 *** (0.100)	−1.178 (0.785)
GIC			−1.362 ** (0.631)		
GFS					−1.239 ** (0.484)
Constant term	−9.048 *** (2.681)	0.055 (0.265)	−8.973 *** (2.662)	0.881 ** (0.345)	−7.957 *** (2.686)

Table 10. *Cont.*

Variables	CEC	GIC	CEC	GFS	CEC
	(1)	(2)	(3)	(4)	(5)
N	300.000	300.000	300.000	300.000	300.000
R^2	0.315	0.790	0.327	0.915	0.332
Control variables	YES	YES	YES	YES	YES
Provincial fixed	YES	YES	YES	YES	YES
Time fixed	YES	YES	YES	YES	YES

Notes: ***, and ** represent significance levels of 1%, and 5%, respectively, with the values in ( ) indicating the standard errors.

4.2.4. Robustness Test

Given the potential presence of outliers in panel data—such as abnormal fluctuations in DI levels or extreme values in CEC across certain provinces/years—this paper employs two methods to verify the robustness of the results: applying 1% winsorization to the variables and shortening the research period. Initially, all variables underwent 1% winsorization to remove extreme outliers, with the regression results presented in Table 11, Model (2). Subsequently, data from the periods 2013–2020 and 2011–2018 were extracted and subjected to regression analysis separately, with the results displayed in Table 11, Models (3)–(4). According to the regression outcomes shown in Table 11, the core explanatory variable's estimated coefficient in Model (2) is positively significant at the 5% level, demonstrating an increase in effect size compared to the baseline regression without altering its significance, which aligns with expectations after removing extreme outliers, thus confirming that these outliers do not drive the observed relationships. As shown in Models (3)–(4) of Table 11, the regression results for the 2013–2020 and 2011–2018 subsamples demonstrate statistically significant coefficients at the 5% and 10% levels, respectively, with consistent effect directions, confirming the robustness of our findings. This design explicitly tests the sensitivity of conclusions to policy environments and external shocks. The 2013–2020 subsample covers the late phase of China's 12th Five-Year Plan through the 13th Five-Year Plan period when the government vigorously implemented the "Internet Plus" strategy and carbon emission trading pilots. This interval validates the resulting robustness during intensive policy intervention. The 2011–2018 subsample excludes abnormal disruptions to the construction industry from the COVID-19 outbreak in late 2019, such as construction halts and supply chain breakdowns. The test results of both models are statistically significant, with effect directions consistent with the baseline model, demonstrating that the suppressive effect of DI on CEC remains robust against disturbances from period-specific policies or economic fluctuations.

To address potential endogeneity issues with DI as an explanatory variable, this study introduces the instrumental variable (IV) method for re-evaluation. In alignment with established practices in the literature [84,85], this study employs DI lagged by one period as an instrumental variable, using the two-stage least squares method for analysis. Diagnostic tests for this instrumental variable regression confirm robust model identification and the validity of the instrumental variables. Notably, the Kleibergen–Paap rk LM statistic is significantly high at 10.376 with a *p*-value of 0.0013, indicating no under-identification issues. Furthermore, the strength of the instrumental variables is substantiated by a Kleibergen–Paap rk Wald F statistic of 1191.313, which substantially surpasses the Stock–Yogo weak identification test threshold of 16.38 at the 10% level, thereby ruling out any weak identification concerns. The regression results presented in Table 11, Model (5), confirm that DI's impact on carbon emissions remains significantly negative at the 10%

level. These tests collectively affirm the rationale behind selecting DI lagged by one period as an instrumental variable.

The robustness of this study's findings across varying time periods and model specifications demonstrates that DI constitutes a sustainable pathway for promoting carbon emission reductions in the construction industry, rather than being a product of short-term fluctuations or data noise.

Table 11. Results of the robustness test.

Variables	CEC				
	Baseline Regression	**1% Winsorization**	**2013–2020**	**2011–2018**	**IV**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DI	−1.570 ** (0.778)	−2.406 ** (1.035)	−1.331 ** (0.670)	−2.366 * (1.399)	
L.DI					−1.358 * (0.752)
Constant term	−9.048 *** (2.681)	−7.326 *** (2.343)	−6.268 ** (2.286)	−12.663 *** (3.790)	−8.099 *** (2.421)
K-P rk LM					10.376 [0.001]
K-P Wald F					1191.313 {16.38}
N	300.000	300.000	240.000	240.000	270.000
R^2	0.315	0.322	0.383	0.279	0.353
Control variables	YES	YES	YES	YES	YES
Provincial fixed	YES	YES	YES	YES	YES
Time fixed	YES	YES	YES	YES	YES

Notes: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, with the values in ( ) indicating the standard errors; The value in [ ] represents *p*-values, and the value in { } represents the critical values at the 10% level of the Stock–Yogo weak identification test.

5. Discussion and Conclusions

5.1. The Impact of DI on CEC

This study rigorously analyzes the structural effects and mechanisms through which DI influences carbon emission reduction in the construction industry, using panel data from 30 provinces in China from 2011 to 2020. As illustrated in Table 8, regression outcomes from the OLS, RE, FE, and TWFE models consistently show a significant negative impact of DI on carbon emissions. Specifically, in the TWFE model, after adjusting for provincial and temporal effects, DI's influence on carbon emissions is quantified at −1.570, significant at the 5% level, validating the substantial role of DI in mitigating carbon emissions in this sector.

Further analysis explores the impacts of the two primary components of DI—DI-S and DI-T—on carbon emissions, differentiating between their effects on direct and indirect emissions. According to Table 9, the impacts of DI-S and DI-T on carbon emissions are quantified at −1.429 and −1.115, respectively, with the impact of DI-S being significant at the 5% level. This suggests that DI-S, which directly enhances operational management and information sharing within the construction industry and facilitates the investment of green technology and capital [86,87], is more crucial in reducing carbon emissions than DI-T. This finding

contradicts the intuition that "technology-driven emission reduction" should dominate. DI-S can rapidly reduce transaction costs, facilitating resource integration and low-carbon decision-making in the construction industry while accelerating green technology diffusion. In contrast, DI-T requires alignment with construction-specific technical standards and industry norms and complementary technical training and equipment upgrades to drive CEC reduction effectively. Therefore, governments should prioritize support for developing digital service platforms in construction to enhance the role of DI-S in resource allocation. Simultaneously, they should strengthen tax incentives and technology subsidies for DI-T applications, using policy tools to shorten technology adoption cycles. Also presented in Table 9, the estimated impact of DI on indirect carbon emissions is −1.571, which is significant at the 10% level. In contrast, its effect on direct carbon emissions is insignificant and slightly positive. This indicates that the predominant negative impact of DI on carbon emissions primarily concerns the reduction in indirect emissions, which are sourced mainly from the production and manufacturing of building materials. Indirect carbon emissions account for a much larger share of CEC than direct carbon emissions. This result aligns with the conclusions drawn from the life cycle theory and process analysis cited by Zhang and Wang [88]. In contrast, direct emissions, which arise from various energy consumption by the construction sector, are more affected by regional energy consumption patterns and economic conditions [9,10]. The production of building materials involves multiple industries and supply chains, offering more significant potential and feasibility for emission reductions through innovations in environmental technology, the optimization of resource allocation, and enhanced supply chain management compared to the reduction in direct emissions [24].

5.2. The Mechanism of DI on CEC: The Mediating Role of GIC and GFS

Mediation analysis examines the roles of GIC and GFS as mediators in the relationship between DI and CEC. As detailed in Models (2) and (4) of Table 10, the findings show that DI's estimated coefficients on GIC and GFS are 1.104 and 0.316, respectively, both significant at the 1% level, demonstrating that DI significantly enhances GIC and GFS. However, when these mediators are introduced in Models (3) and (5), DI's direct impact on carbon emissions becomes non-significant, with GIC and GFS' coefficients on carbon emissions at −1.362 and −1.239, respectively, both significant at the 5% level. This indicates that GIC and GFS fully mediate DI's effect on reducing CEC. In essence, DI indirectly reduces carbon emissions by enhancing GIC and GFS. The advancement of DI, marked by the proliferation of DI-T and services, has been shown to optimize enterprise technology R&D processes, enhance cross-enterprise and cross-industry collaboration [37], and facilitate the sharing and market transformation of green patented technologies [38,39]. The widespread adoption of DI-S also expands financing channels for green projects, reduces transaction costs, and increases the transparency and traceability of green investments, thereby advancing the maturity of the green financial market [44,45]. The enhancements in GIC provide a technical foundation for energy conservation and emission reduction across the construction industry and related sectors [89]. Concurrently, the expansion of green finance provides essential financial support for adopting low-carbon technologies and promoting green building practices [46]. DI must leverage a synergistic "technology-capital" pathway to promote the reduction in CEC. GIC and GFS thus act as both a 'bridge' and a 'catalyst' in DI's role in reducing CEC.

5.3. Impact on Carbon Emission Reduction in the Construction Industry

1. The findings underscore that DI significantly curtails carbon emissions in the construction sector, suggesting that construction enterprises should leverage the rapid development of the digital economy to advance the digitalization of carbon emission

management in this industry. For example, construction enterprises can adopt Building Information Modeling (BIM) to optimize project planning and resource allocation, thereby reducing material waste during construction. Building material manufacturers may utilize Internet of Things (IoT) sensors to monitor and optimize production processes, minimizing carbon emissions derived from fossil energy consumption.

2. DI-S has a more pronounced role in reducing carbon emissions. The impact of DI-T on carbon emissions is less marked, likely due to the underutilized potential of DI-T in the construction processes [27,28,90]. The government should continue to guide the advanced DI-T in carbon emission management to unlock its carbon reduction potential gradually. The government should continue to promote the deep integration of emerging DI-T in carbon emission management within the construction industry, unlocking their potential for reducing emissions. Construction enterprises can collaborate with digital service providers to develop customized solutions, such as AI-based carbon emission monitoring systems. Building material manufacturers can leverage blockchain technology to monitor energy consumption and carbon emissions during production, thus enhancing carbon footprint management in the construction industry.
3. This study concludes that bolstering the digital infrastructure and enhancing DI-T and service platforms are imperative. The government should create special funds to support the research and development of green technologies, promoting the adoption of green patented technologies in construction. Simultaneously, the government should utilize financial instruments like green loans and bonds to support the low-carbon transition in the construction industry. Strengthening the digital oversight of green financial services to minimize financial risks is also essential [91]. For construction enterprises, this means actively pursuing green financing and innovating sustainable materials and construction technologies to tackle challenges related to carbon emission management. Additionally, they should enhance digital skills training for industry professionals and actively implement AI systems to improve efficiency in managing carbon emissions and optimizing resources throughout all stages of operation.

Author Contributions: Conceptualization, Y.-L.L. and J.-R.Z.; methodology, Y.-L.L.; software, J.-R.Z.; formal analysis, Y.-L.L.; resources, J.-R.Z. and H.-B.L.; writing—original draft preparation, Y.-L.L. and J.-R.Z.; writing—review and editing, J.-R.Z. and H.-B.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research is funded by the National Natural Science Foundation of China, grant number 41871179.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DI	Digital industrialization
DI-S	Digital services
DI-T	Digital technologies
CEC	Carbon emissions in the construction industry
CEC-D	Direct carbon emissions in the construction industry
CEC-I	Indirect carbon emissions in the construction industry
GIC	Green innovation capabilities
GFS	Green financial services
EDL	Economic development levels
IEO	Industrial economic output
GEP	Governmental efforts in environmental protection
GTA	Governmental efforts in technological advancement
IRE	Investment intensity in the real estate industry
URB	Urbanization levels
IND	Industrialization levels

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