Check for updates

Evaluation and promotion path of high-quality development in the Chinese construction industry under the context of carbon neutrality

Lixin Zhang[1] · Jiarui Zhang[1] (ID)

Abstract

Achieving carbon neutrality is essential for global sustainable development. In China, fostering high-quality development represents the primary strategy for enhancing energy conservation and sustaining economic growth. Despite its significance, the construction industry—a major consumer of energy and a substantial source of carbon emissions— has not been extensively studied. This research evaluates the high-quality development of construction industry (HDCI) in China and seeks to chart a course for its advancement. Initially, it constructs an evaluation index system and utilizes the composite weighting method to assess the industry's development quality across provinces from 2008 to 2020. Subsequently, it applies exploratory spatial analysis and Markov chain models to uncover the spatiotemporal patterns and evolutionary trends of HDCI. The study further examines the spatial heterogeneity of factors influencing spatiotemporal differentiation by employing a geographically and temporally weighted regression model. The findings reveal that (1) the overall index of high-quality development in the construction sector is improving, with the green energy-saving index ranking the highest among six dimensions. (2) Significant regional disparities exist, with the eastern and central regions outperforming the western and northeastern areas. (3) The focal point of high-quality development is shifting towards the southwest, indicating strong spatial correlation within HDCI. High-value provinces exhibit a more potent positive spillover effect compared to the negative impact of lower-value provinces. (4) The driving factors, including financial expenditure urbanization, energy consumption structure, and technological innovation capacity, show spatial heterogeneity. This suggests that regional industries should pursue tailored development strategies based on local characteristics. Based on these insights, the study proposes policy recommendations to foster HDCI in China, advocating for approaches that align with regional strengths and conditions.

Keywords Carbon neutrality · Construction industry · High-quality development · Evaluation system · Promotion path · GTWR model

1 Introduction

Since 1978, when China initiated its reform and opening-up policy, the construction industry (CI) has experienced a robust average annual growth rate of 12% in its gross output value. This surge has been driven by the escalating demand for infrastructure and residential buildings, paralleling the country's swift urbanization pace (CSYC, 2022). Such substantial market demand for CI development in China has been the backbone of its consistent expansion. Serving as a crucial pillar of the national economy, the CI significantly contributes to economic growth, mitigates social employment pressures, improves the quality of life for the populace, and aids in the comprehensive development of a moderately prosperous society (Gan & Lei, 2022). Despite these impressive accomplishments, the CI faces challenges related to quality and efficiency. Specifically, the industry is marked by a broad-based development strategy, low labor productivity, high energy consumption, and considerable emissions. Unplanned development, irrational innovation, and hasty advancements in technology have markedly distorted the environment (Ali et al., 2020). Such issues represent significant hurdles to China's goal of achieving carbon neutrality by 2060 and fail to align with the growing expectations of its citizens for an enhanced quality of life (Anonym, 2022).

The United Nations' Agenda 21 for Sustainable Construction in Developing Countries emphasizes that the sustainable advancement of the construction industry (CI) must harmoniously blend economic, societal, and ecological considerations (Ebolor et al., 2022). In China, the CI occupies a pivotal position within the broader economy. Yet, as a highly polluting and energy-intensive sector, it poses significant challenges to sustainable progress (Cheng et al., 2022). Domestically, the CI and its affiliated sectors are responsible for consuming approximately 40% of total energy (Chen et al., 2023). Globally, it accounts for about 30% of all greenhouse gas emissions, a figure expected to rise significantly (Friedlingstein et al., 2021; Huo et al., 2022). These figures underline the environmental cost of the industry's prosperity, marked by energy and material waste (Abdelzaher et al., 2023b). The construction industry has become a sector that needs to be prioritized for achieving sustainable development. As a major contributor to global greenhouse gas emissions, China plays a crucial role in achieving global climate governance goals and resource conservation (Abdelzaher et al., 2023a; Ali et al., 2021). Only by attaining net-zero carbon emissions worldwide by mid-century can we effectively mitigate climate change and ensure sustainable development for future generations (Bongaarts, 2019).

To promote sustainable development, the Chinese government strategically decided in 2017 to prioritize quality over speed. In 2020, China further outlined the ambitious "double carbon" goal, integrating CO2 emission reduction efforts into its national planning framework. Gradually, the country has established a comprehensive carbon peak, carbon neutral, and "1+N" policy system, tailored to its unique national context (Wang et al., 2023b). This initiative marked the beginning of China's transition from an era of rapid economic growth to a new phase focused on high-quality development. Characterized by innovation, coordination, green initiatives, openness, and sharing, this development paradigm represents an evolution and expansion of the concept of sustainable development. Serving as a key guiding principle for economic and social progress during the 14th Five-Year Plan period (2021–2025), the high-quality development model stands in stark contrast to the previous growth paradigm, which was capital and resource-intensive and often required post-pollution remediation (Wan et al., 2023). Instead, the new model emphasizes sustainability and efficiency, placing innovation and technology at its heart. It also focuses on meeting human

needs and fostering sustainable development (Jiang et al., 2021), ultimately aiming for sustained, stable, coordinated, and inclusive growth across the economic, social, environmental, and humanitarian spheres.

The construction industry plays a key role in China's energy use and carbon emissions (Yu, 2022), a fact that is closely related to the national goals of achieving carbon peaking and carbon neutrality. Promoting high-quality development in the construction industry can improve carbon efficiency and reduce emissions related to energy use and industrial processes. This is crucial for achieving the dual carbon goals and ensuring human wellbeing. Given the dual constraints of development requirements and the resources-environment nexus in the new era, transforming and upgrading the construction industry is especially urgent.

Based on this, the study seeks to facilitate the industry's shift from a traditional model prioritizing speed and scale, towards one that values quality and efficiency. It commits to a quantitative analysis of the construction industry's high-quality development, aiming for significant strides in establishing a robust development system and mechanisms, and fostering regionally coordinated growth. Building upon this, it aims to uncover the spatiotemporal disparities and evolutionary trends of high-quality development in China's construction industry, and to delve deeper into the heterogeneous effects of factors driving spatiotemporal differentiation in high-quality development across different regions.

The contribution of this research lies in creating an evaluative framework inspired by the latest development paradigms and the goal of carbon neutrality. It unveils the spatiotemporal dynamics and influencing factors of high-quality development within the sector, thus bridging an existing research void. Indeed, our findings offer a theoretical foundation for policymakers and industry leaders to craft low-carbon, sustainable strategies for the construction sector. Additionally, they enhance the empirical research corpus for the construction field and related areas globally.

The structure of this paper is as follows. Section 2 provides a literature review on the theoretical connotation and empirical studies. Section 3 introduces the research methodology and data sources. Section 4 demonstrates the spatial–temporal differences and evolutionary trends of HDCI in China, also explores and analyzes the driving factors. Section 5 summarizes the research results, provides a high-quality development path for construction industry, and points out the future research direction.

2 Literature review

As a more desirable state of progress, the exploration of HDCI merits our utmost attention. Upon reviewing and synthesizing the existing scholarly works, it becomes evident that the prevailing research predominantly revolves around three primary dimensions: the analysis of connotation, the assessment of developmental levels, and the examination of influencing factors or strategic approaches.

2.1 Connotation of high-quality development of construction industry

The report of the 19th CPC National Congress on "Establishing a sound economic system for green, low-carbon and circular development" has pointed out the direction for high-quality development in the new era. In terms of theoretical connotation, Yang et al. (2020), starting from the aspects of economic growth, believe that the HDCI is

the process of its industrial structure from extensive development to sustainable development model, and in general can meet the requirements of economic development in China at the present stage; Starting from the main contradictions in society, Gao et al. (2021a) believe that the HDCI is to achieve industrialization and greening through talent team training, technological innovation and industrial structure optimization, so as to better meet the development and change of human needs; Guan and Zhu (2021) proposed that in the development process of the construction industry, it should rely on new technologies and new energy to promote the transformation and upgrading of the industry to meet the needs of social and economic development and environmental sustainable development. Scholars have different definitions of HDCI, but they all take into account the triple bottom line, that is, the balance of economic, social and environmental performance (Kazemi et al., 2023; Selmey & Elamer, 2023).

2.2 Evaluation of the development level of construction industry

Currently, there are two perspectives for quantitatively assessing the development of CI. One is to measure the total factor productivity (Solow, 1957; Trinks et al., 2020) from the perspective of input–output to reflect the development level of the construction industry. Kapelko et al. (2014), Ma et al. (2018) calculated the production efficiency of CI in Spain and Australia respectively through the data enveloping model. Moreno et al. (2016) analyzed the technical efficiency of CI in Spain through stochastic frontier analysis (SFA) models. Additionally, Du et al. (2020), Wang et al. (2021) assessed the carbon emission efficiency and energy efficiency of CI in China, using the non-expected output super-efficiency SBM model and the game cross-efficiency DEA model respectively. Many studies have shown that TFP, as a driver of growth, is important for the development of CI, especially in developing countries such as China (Wang et al., 2020). However, the development of CI involves many aspects of sustainable development such as economy, technological innovation, social service and ecological construction. The single TFP value is not enough to fully epitomize the economic impact of CI elements, nor can it reflect the rich connotation of high-quality development.

Another is to portray the level of development of CI by constructing a multi-dimensional evaluation indicators system. For example, Sun et al. (2019) conducted an early study on the HDCI. They proposed an evaluation model based on dimensions such as scale growth, economic—social benefits, industrial structure and sustainable development, which laid the foundation for subsequent research. With the introduction of new development concept, there is a growing trend of conducting research from dimensions such as innovation, coordination, green, openness, and sharing. For example, Wang and Li (2020), Yang et al. (2020), Wu and Zhang (2021), Gao and Li (2021) built indicators systems to measure and analyze the development level of construction industry in a certain province of China from different dimensions. Most scholars try to explore the relevant indicators of high-quality development from the perspective of empirical research, but on the whole, the indicators are not unified, and the focuses are different. This shows that the academic community still needs to conduct deeper research and discussion on the evaluation system of high-quality development.

2.3 Influencing factors of construction industry development

Technological innovation is driving the Fourth Industrial Revolution (Gomaa et al., 2023; Singh et al., 2022), advanced building technologies have significantly changed the operations of the architecture, engineering and construction industry in US (Blinn & Issa, 2022). Meantime, traditional energy consumption inevitably leads to the release of a large amount of carbon emissions. Optimizing the energy consumption structure has become the key to reducing the environmental impact of the construction industry and promoting the green economy (Destek & Sinha, 2020; Feng et al., 2023), the adoption of cleaner building practices and production innovations can contribute to achieving sustainability goals (Ebolor et al., 2022). In addition, Fan et al. (2021) conducted an empirical analysis of the driving factors of CI in Northeast China, and found that the scientific research investment of local governments and enterprises can promote the structural adjustment of CI. Xiang et al. (2019) employed system dynamics to develop a theoretical model for the initiation of the dynamics mechanism of high-quality development. They identified government management, market norms, industry and enterprise development as the four key driving factors for HDCI. In fact, government support, such as fiscal expenditure, legal sounders, is crucial to the strategic performance of decision makers to introduce low carbon principles and make the built environment more sustainable (Munaro et al., 2020). These studies prove that factors such as government support and technological innovation are important drivers of low-carbon circular economy in the construction industry (Abdelzaher & Awad, 2022), and provide an important reference for a more comprehensive understanding and promotion of quality improvement in the construction industry (Hassan et al., 2023; Wuni, 2022; Zhang et al., 2023a).

Based on the current state of research, existing literature provides valuable insights into high-quality development. However, the connotation and evaluation of high-quality development of the construction industry still need to be further explored. In terms of content, existing research has laid a solid foundation for constructing an evaluation index system for high-quality development in the construction industry. However, as can be seen from the literature, most scholars have the following limitations when studying the high-quality development of the construction industry: (1) Most studies are targeted at a specific province or city, with less comparative analysis at the regional level and between provinces, not considering the spatial dependency and interaction between regions. Ignoring spatial effects may lead to distortions in research results. (2) Most research methods adopt principal component analysis, factor analysis, TOPSIS method, etc., lacking in studies on the identification of the spatial–temporal differentiation, evolutionary trends, and influencing factors of the high-quality development level of the construction industry.

Therefore, this study uses data from 30 provinces in China from 2008 to 2020 to analyze the spatial heterogeneity characteristics of HDCI and its driving factors. The present situation of regional differentiation is revealed and the path of promoting high-quality development of construction industry is proposed. Compared with previous studies, the innovations are as follows: (1) In contrast to previous evaluations focusing on total factor productivity or other indexes, this study assess the comprehensive level of HDCI by integrating six dimensions of scale growth, innovation-driven approaches, openness & coordination, green & energy conservation, comprehensive benefits and livelihood sharing. (2) The study introduces a weight allocation method which combines G1 method, entropy method and coefficient of variation method. The internal

statistical law and expert authority value between the index data are considered comprehensively, which can effectively overcome the dependence of single weighting. (3) This study uses exploratory spatial data analysis method and Markov chain model to reveal the spatio-temporal differentiation and evolution characteristics of HDCI, and the spatial heterogeneity of driving factors was explored by GTWR model. The spatial effect and spatiotemporal non-stationarity are fully considered, which makes the research system more rigorous and robust.

3 Data and methods

3.1 Research framework

We propose a framework for studying the spatio-temporal evolution of HDCI and its driving factors (Fig. 1). First, provincial panel data are collected to construct an evaluation indicators system integrating the new development concept, and quantitatively measure the level of HDCI in 30 provinces nationwide from 2008 to 2020 based on the combination of assignments. Second, the spatio-temporal differentiation and evolutionary trend characteristics are analyzed through the exploratory spatial data analysis and Markov chain. Geographically and temporally weighted regression model are used to identify the spatial heterogeneity of driving factors. Finally, the paper puts forward relevant policy suggestions and path to promote the low-carbon and high-quality development of construction industry.
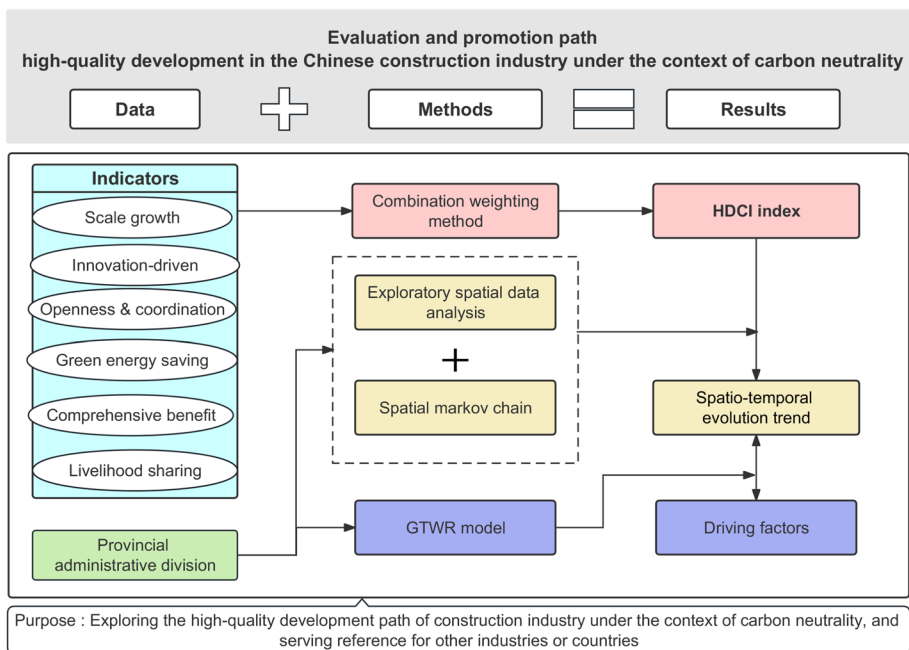

Fig. 1 Research framework

3.2 Evaluation system

3.2.1 The connotation of high-quality development of construction industry

High-quality development is a pivotal decision undertaken by the Chinese government, taking into account both the international and domestic political and economic landscapes. In the context of the construction sector, the "dual carbon" target poses a significant challenge to the industry's growth, thereby heightening the sector's eagerness and commitment to accelerating emission reduction efforts. Unlike developed nations, China's ambition for achieving "double carbon" aims to effectively mitigate emissions while ensuring sustainable socio-economic progress. This endeavor facilitates the transition from a "high-growth" paradigm to a "high-quality" one.

The HDCI is no longer solely gauged by its velocity or aggregate magnitude, nor does it hinge on excessive resource allocation to attain swift expansion on a vast scale. Rather, it underscores the efficiency and efficacy of the output relative to the level of input invested (Yang et al., 2020). Therefore, the concept of HDCI should encompass various aspects such as scale growth, energy conservation and emission reduction, sharing, and sustainability. In this study, HDCI is defined as the pragmatic evolution of the extensive development paradigm. It entails striking a harmonious balance between quality enhancement and quantity expansion through technological progress, efficiency optimization, and dynamic adaptations. Moreover, it strives to fulfill the sustainable development demands of the economy, environment, and resources across the entire spectrum of construction and utilization processes.

3.2.2 Indicators

Drawing upon the development concept of "innovation, coordination, green, openness, and sharing", we conducted an extensive review of literature published in reputable journals and magazines on platforms such as Web of Science, Science Direct, and CNKI in recent years. Aiming at the theme of "sustainability", the main indicators and factors of CI are analyzed in word frequency. Furthermore, according to the "14th Five-Year Construction Industry Development Plan" issued by the Ministry of Housing and Urban–Rural Development and the opinions of various regions on promoting HDCI, the principles of availability, scientificity and comparability of indicators selection are followed. With reference to previous literature (Abdelzaher, 2023; Gao et al., 2021b; Zhang et al., 2022), this research constructs an evaluation indicator system for the HDCI, which is based on industrial scale, driven by innovation and open coordination, guided by green energy saving, and targeted at comprehensive benefits and people's livelihood sharing, as shown in Table 1. The weighting of these indicators is determined using the combined weighting methodology detailed in Sect. 3.4.1.

3.3 Data sources

Based on the reliability and availability of data, we design and select the index system. The construction industry data of 30 provinces (Tibet, Hong Kong, Macao and Taiwan were not included in the study due to the large amount of missing data) from 2008 to 2020 are collected for the study. The indicators data are mainly from the

Table 1 Evaluation indicator system of HDCI

System	Dimension	Indicators	Attributes	Weights
High Quality Development of CI	Scale growth	Growth rate of total output value/%	+	0.0308
		Proportion of total output value in GDP/%	+	0.0230
		Number of employees in enterprises/n	+	0.0266
		Signed the contract amount/trillion yuan	+	0.0580
		New housing construction area this year/hectare	+	0.0657
	Innovation-driven	R&D intensity/%	+	0.0524
		Proportion of senior title personnel in survey and design units/%	+	0.0235
		Labor productivity/(yuan/person)	+	0.0258
		Technical equipment rate/(yuan/person)	+	0.0454
		Power equipment rate/(kW/person)	+	0.0319
	Openness & coordination	Proportion of output value of private enterprises/%	+	0.0292
		Proportion of output value completed outside the province/%	+	0.0351
		Proportion of output value of local construction enterprises/%	+	0.0118
		Proportion of general contracting enterprises above the first level/%	+	0.0358
		Proportion of first-level professional contracting enterprises/%	+	0.0313

Table 1 (continued)

| System	Dimension	Indicators	Attributes	Weights
	Green & energy saving	Steel consumption per billion output output value/t	−	0.0259
		Wood consumption per billion output output value/m^3	−	0.0205
		Green coverage rate of built district/%	+	0.0375
		Carbon emissions per billion output value/t	−	0.0450
		City daily sewage treatment capacity/10000m^3	+	0.0501
	Comprehensive benefit	Total output value/billion yuan	+	0.0597
		Housing completion rate/%	+	0.0158
		Output value profit tax rate/%	+	0.0235
		Asset-liability ratio/%	−	0.0130
		Total profit / billion yuan	+	0.0508
	Livelihood sharing	Per capita urban road area/m^2	+	0.0188
		Urban per capita housing construction area/m^2	+	0.0138
		Average wages/yuan	+	0.0281
		Proportion of completed area of commercial and service buildings/%	+	0.0364
		Percentage of completed area of buildings for science, education, medical and recreation/%	+	0.0348
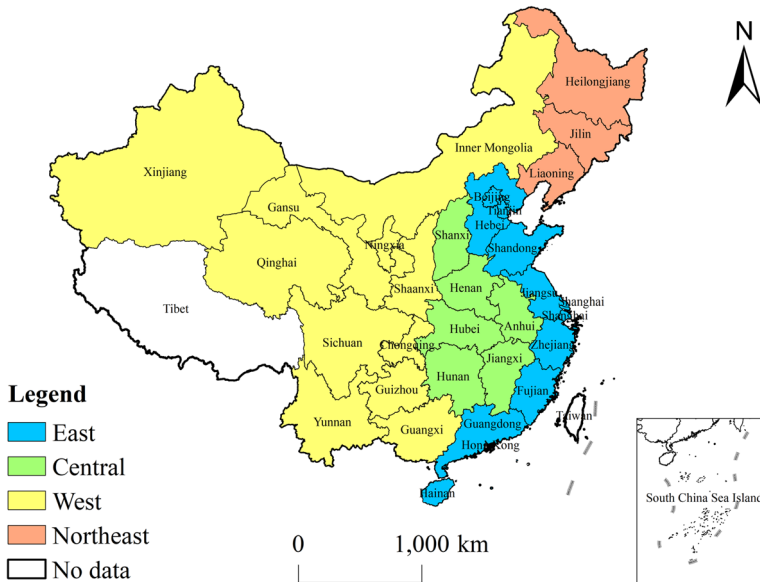
Fig. 2 China's four major regions and provincial administrative divisions

China Construction Industry Statistical Yearbook (2009–2021) and China Yearbook (2009–2021) of the National Bureau of Statistics of China, as well as statistical year-books and statistical bulletins of national economic and social development issued by various provinces. For very few missing data, linear interpolation method is used to complete. The data on the boundaries of China's provincial administrative divisions (version 2022) were taken from the Resource and Environmental Science Data Registration and Publication System (Xu, 2023). According to the standards of the National Bureau of Statistics, the country's 30 provinces are divided into four regions: eastern, central, western and northeastern regions (Fig. 2).

3.4 Methods

3.4.1 Combination weighting evaluation

(1) G1 method

The G1 method, also referred to as the sequential relation method, is a subjective weighting method designed to enhance the Analytic Hierarchy Process (AHP) originally proposed by scholar Guo Yajun. This method effectively addresses the challenges associated with ensuring consistency after constructing the judgment matrix in AHP. Additionally, it mitigates the drawbacks of AHP related to extensive calculations and numerous comparison elements (Guo & Wang, 2006). The G1 method stands out as a straightforward approach to weight assignment that obviates the need for consistency testing, making it particularly well-suited for evaluating intricate index factors in complex evaluation scenarios (Ye et al., 2023). Specific steps are as follows:

(1) Determine sequential relationships. Through expert opinions and relevant literature research, the importance of *m* evaluation indicators is determined and ranked, and the importance is recorded as follows in descending order: $j_1, j_2, \ldots, j_m$.

(2) Quantify the relative importance degree between two adjacent indicators:

$$r_k = \frac{j_{k-1}}{j_k}, k = 2, 3, \ldots, m \tag{1}$$

In the formula, the assignment and meaning of r_k are as follows: 1.8, indicators j_{k-1} is extremely important than j_k; 1.6, strongly important; 1.4, obviously important; 1.2, slightly important; 1.0, equally important.

(3) Calculate the weight of indicator *j*:

$$R_j = \left(1 + \sum_{k=2}^{m} \prod_{j=k}^{m} r_j \right)^{-1} \tag{2}$$

(2) Entropy weight-coefficient of variation method

Entropy is a measure of uncertainty. When the values of evaluation objects differ greatly on an indicator, the entropy value is small, indicating that the effective information provided by the indicator is large, and the weight of the indicator should also be large (Zare Banadkouki, 2023). Entropy weight is an objective weighting method that reflects the relative importance of indicators by calculating the information entropy weight. Coefficient of variation refers to the ratio of mean and standard deviation, which can effectively reflect the difference of each indicator value. In this paper, the average of the weights of the entropy weight method and the coefficient of variation method is set as the objective weight of the indicator. The steps are:

(1) Standardized data. In order to eliminate the influence of dimensions and attributes of indicators on the evaluation results, the original data is standardized. The formula is:

$$L_{ij} = \begin{cases} \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} + 0.0001, & positive\ attributes \\ \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} + 0.0001, & negative\ attributes \end{cases} \tag{3}$$

where L_{ij} is the dimensionless value of indicator; x_{ij} is the original indicator value; $max(x_j)$ and $min(x_j)$ are the maximum and minimum values of the *j* TH indicator, respectively and the value of 0 after standardizing is replaced by 0.0001.

(2) Calculate entropy weight:

Calculate the proportion of indicators

$$P_{ij} = \frac{L_{ij}}{\sum_{i=1}^{n} L_{ij}} \tag{4}$$

where *n* is the number of samples, and $0 \le P_{ij} \le 1$.

Calculate the entropy of the *j*th indicator

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} P_{ij} \ln P_{ij}, e_j \geq 0 \tag{5}$$

Define weights:

$$W_j = \frac{1 - e_j}{\sum_{j=1}^{m} 1 - e_j} \tag{6}$$

(3) Calculate the weight of the coefficient of variation:

Calculate the coefficient of variation of indicators

$$v_j = \frac{\sigma_j}{\bar{x}_j} \tag{7}$$

where σ_j and $\bar{x}_j$ are the standard deviation and mean of the jTH indicator, respectively。

Define weights:

$$W_j = \frac{v_j}{\sum_{j=1}^{m} v_j} \tag{8}$$

The average of the weights obtained by entropy weight method and coefficient of variation method is the objective weight of indicator.

(3) Combination of subjective and objective

The determination of the comprehensive weight of indicators involves a judicious blend of subjectivity and objectivity. This approach not only takes into account the subjective expertise of professionals regarding the significance of various indicators but also considers the inherent relationships between the original data of these indicators and their internal statistical patterns. By doing so, it effectively mitigates potential biases that may arise from relying solely on either subjective or objective weighting, thereby enhancing the scientific rigor and rationality of the research methodology. Leveraging the principle of minimum discriminative information (Sun et al., 2022) as a foundation, the calculation of optimal comprehensive weights ensures a balanced consideration of both subjective and objective factors, preventing any undue favoritism towards either aspect. The initial construction of the optimal decision model is as follows:

$$\begin{cases} \min(F) = \sum_{j=1}^{m} \left(F_j \ln \frac{F_j}{R_j} + F_j \ln \frac{F_j}{W_j} \right) \\ s.t. \sum_{j=1}^{m} F_j = 1, F_j \geq 0 \end{cases} \tag{9}$$

The model is solved to obtain the comprehensive weight (F_j^*), and Eq. (11) is then used to calculate the construction industry quality development index for province i in year t.

$$F_j^* = \frac{\sqrt{R_j W_j}}{\sum_{j=1}^{m} \sqrt{R_j W_j}} \tag{10}$$

$$D_{it} = \sum_{j=1}^{m} L_{ijt} F_j^*$$ (11)

Here R_j and W_j represent the subjective and objective weights of the indicator, respectively, while L_{ijt} denotes the standardized value of the data. The comprehensive weights of indicators are shown in Table 1.

3.4.2 Exploratory spatial data analysis

(1) Spatial autocorrelation.

Moran's index is an important indicator for observing spatial correlation and heterogeneity (Dong et al., 2023). The global Moran's index is shown in Eq. (12), w_{ij} is the spatial weight matrix, S^2 is the sample variance, and x_i and x_j are the HDCI values in the neighboring regions. The Moran'sI takes the range of $[-1,1]$, and the closer to 1 indicates that the spatial positive correlation of the level of high-quality development of the construction industry between the regions is stronger.

$$Moran'sI = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(x_i - \overline{X} \right) \left(x_j - \overline{X} \right)}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}$$ (12)

where $\overline{X} = \frac{1}{n} \sum_{j=1}^{n} X_i$, $S^2 = \frac{1}{n} \sum_{i=1}^{n} \left(x_i - \overline{X} \right)^2$.

(2) Standard deviation ellipse.

The standard deviation ellipse can be used to show the distribution direction of a geographic element to reveal the overall characteristics of its spatial distribution. The model mainly includes parameters such as the center of gravity coordinates, half-axis length, and azimuth Angle, etc. The specific calculation process can be referred to Li et al. (2023a), and the center of gravity migration distance of the ellipse is calculated according to the following formula (Liu et al., 2021):

$$S_{(t+1)-t} = R \times \sqrt{\left(Y_{(t+1)} - Y_t \right)^2 + \left(X_{(t+1)} - X_t \right)^2}$$ (13)

where (X_t, Y_t) and $(X_{(t+1)}, Y_{(t+1)})$ represent the center of gravity coordinates of the ellipse between years; R is a constant of 111.11 km.

3.4.3 Markov chain

This study uses Markov chain to reveal the transfer direction and probability of the HDCI. The $n \times n$ order probability transfer matrix is constructed, and the element P_{ij} in the matrix represents the probability that the province with the development level of class i in period

t will jump to class j in period $t + 1$. The probability is calculated using the following formula:

$$P_{ij} = \frac{n_{ij}}{n_i} \tag{14}$$

where n_{ij} is the number of provinces whose HDCI has shifted from grade i to grade j during the study period; n_i indicates the total number of provinces at grade i.

The spatial markov chain introduces the condition of "spatial lag", and the spatially weighted average of the attribute values in the neighboring areas of the observed provinces is used as the spatial lag value to analyze the trend of state transfer of samples under the effect of spatial factors (Wang et al., 2023c). The formula for calculating the spatial lag value is:

$$Lag_a = \sum_{b=1}^{n} Y_b W_{ab} \tag{15}$$

where Y_b is the development level of province b, and the spatial weight matrix W_{ab} is determined by the adjacency principle (1 if two regions are neighboring and 0 if they are not).

3.4.4 Geographically and temporally weighted regression model

The Geographically Weighted Regression model (GWR) focuses on spatial effects at a particular point in time, but its accuracy can be easily affected by limitations in the number of sample data (Wang et al., 2023a). The Geographically and Temporally Weighted Regression model (GTWR) builds upon the GWR model by introducing a temporal dimension and considering both spatial and temporal non-stationarity. This allows for a reduction in parameter estimation biases and model errors, enabling a more comprehensive analysis of complex spatio-temporal data (Fotheringham et al., 2015). The GTWR model is:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i \tag{16}$$

where Y_i is the HDCI index in region i, X_{ik} is the influence factor k, (u_i, v_i, t_i) is the coordinates of the center of the region, $\beta_k(u_i, v_i, t_i)$ is the influence coefficient, $\beta_0(u_i, v_i, t_i)$ is the constant, and ε_i is the residual. This study utilizes ArcGIS software, along with the GTWR model plug-in developed by Huang et al. (2010), to analyze the driving factors behind the spatio-temporal evolution of high-quality development in the regional construction industry.

4 Results and discussion

4.1 Trends in the development index of each dimension

The HDCI indices for each dimension across 30 provinces in China from 2008 to 2020 were computed using the combination weighting method. As seen in Fig. 3a, the development indices of all dimensions exhibit an overall upward trajectory. Notably, the green energy saving index stands out as the highest, highlighting the effective implementation of
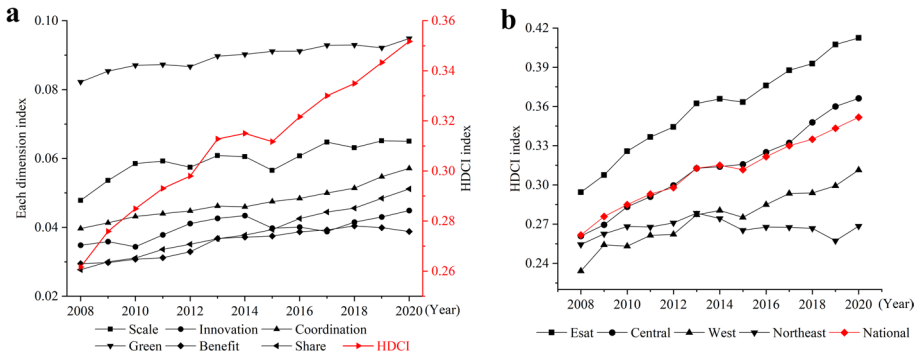
Fig. 3 Temporal trend of index of each dimension (**a**) and HDCI in four regions (**b**)

carbon reduction and environmental protection measures in China's construction industry, aligned with the carbon neutrality goal. However, there are notable fluctuations in the innovation-driven and scale growth indices. Furthermore, the scale growth and comprehensive benefit indices for 2019–2020 show a downward trend due to the impact of the epidemic. This underscores the challenges faced by the construction industry, including limited innovation capacity, low efficiency, and inadequate modernization.

The indices of green energy conservation, open coordination, and people's livelihood sharing have exhibited a consistent upward trajectory. Notably, the most significant increase was observed in people's livelihood sharing, which surged by over 84.78%. This was followed by open coordination and scale growth, which recorded increases of 44.10% and 35.85%, respectively. These findings underscore that China's construction industry is firmly aligned with meeting people's needs, resulting in remarkable improvements in the level of livelihood sharing. As the market mechanism continues to evolve, the importance of open coordination in driving the industry's growth will only intensify. Therefore, construction enterprises must prioritize investing in innovation resources, focus on modernizing the construction industry chain, and strive to enhance the quality and efficiency of construction production in the coming years.

4.2 Spatial and temporal pattern of HDCI

The HDCI index in China exhibits a prominent upward trend, as illustrated in Fig. 3, rising from 0.262 in 2008 to 0.352 in 2020, with an average annual growth rate of 2.86%. However, there exist pronounced disparities in both the level and growth rate of HDCI across different regions. In 2008, the HDCI index of the four major regions followed the pattern: Eastern > National > Central > Northeast > Western, with only the eastern region exceeding the national average and the western region lagging behind. By 2020, the regional hierarchy had shifted to: Eastern > Central > National > Western > Northeast. Notably, in recent years, the central region has marginally surpassed the national average, while both the western and northeastern regions have persistently maintained an average annual HDCI index that falls below the national mark. In terms of growth rates, the average annual increases in the eastern, central, western, and northeastern regions were 3.34%, 3.35%, 2.74%, and 0.49%, respectively. Evidently, the central and eastern regions have demonstrated robust
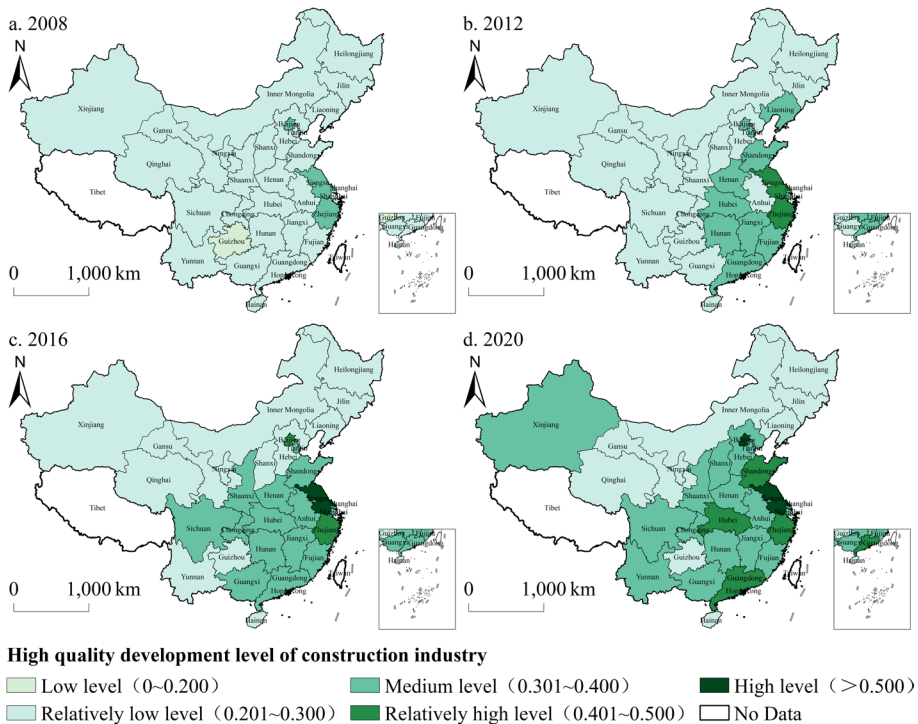
High quality development level of construction industry

☐ Low level（0~0.200）	☐ Medium level（0.301~0.400）	☐ High level（＞0.500）
☐ Relatively low level（0.201~0.300）	☐ Relatively high level（0.401~0.500）	☐ No Data

Fig. 4 Distribution of high-quality development of China's provincial CI

development momentum, whereas the western region has witnessed a comparatively slower development, and the northeast has displayed slightly weaker growth.

To discern the spatial and temporal patterns of HDCI, 30 provinces were categorized into five distinct levels. Utilizing ArcGIS, we visualized the spatial patterns for the years 2008, 2012, 2016, and 2020, as depicted in Fig. 4. The medium-level region has gradually extended from east to west, with a growing number of provinces attaining higher levels. Simultaneously, inter-regional disparities have become increasingly apparent. In 2008, only Beijing, Jiangsu, and Zhejiang provinces had reached the medium level, while most other provinces lingered at the primary level. Notably, Guizhou exhibited the lowest HDCI with a score of 0.191. By 2012, remarkable progress in CI development was evident in the eastern and central provinces. Jiangsu and Zhejiang had elevated to higher levels, while nine provinces, including Tianjin, Hubei, Shanghai, Guangdong, Shandong, and Liaoning, had transitioned from the primary to the medium level. However, the western region saw minimal changes during this time frame. By 2016, Jiangsu had emerged as the sole province to achieve a relatively high level, while Zhejiang and Beijing maintained their high-level status. Several western provinces, including Sichuan, Shaanxi, Chongqing, and Guangxi, had progressed from the primary to the medium level. Conversely, Liaoning had regressed to the primary level. As of 2020, all provinces, except Qinghai, Gansu, Ningxia, Guizhou, Hainan, and the northeastern provinces, had attained HDCI levels of medium or above. Jiangsu led the pack with the highest HDCI score of 0.587.
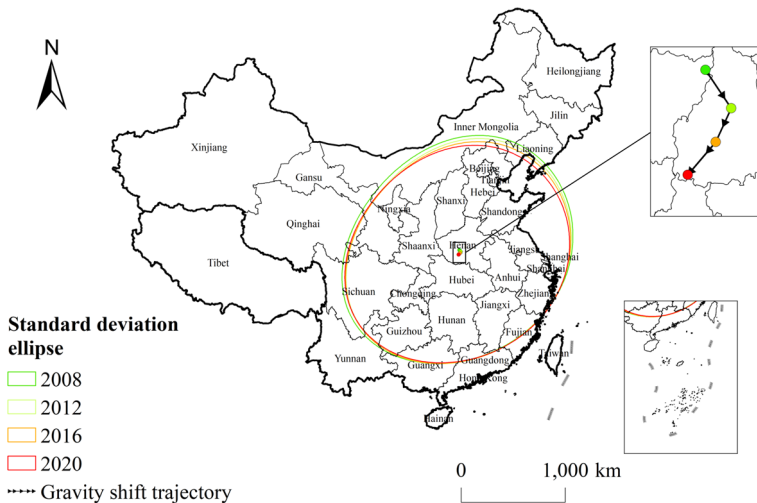
Fig. 5 Standard deviation ellipse and gravity center migration

It is evident that the HDCI exhibits a spatial pattern characterized by high values in the east and low values in the west. This pattern can be attributed to several reasons, including the steady intensification of industrialization, the progression of information technology, and the expansion of secondary and tertiary industries. The eastern region, favored by advantageous coastal transportation and robust economic growth, possesses a pioneering edge in terms of an advanced and innovative industrial structure (Yang et al., 2023). This allows construction companies to swiftly harness cutting-edge technologies and embrace green production practices, enabling the rational allocation of resources and driving green economic progress (Han et al., 2023). As a result, this region is at the forefront of transitioning to high-quality development. In contrast, the western region faces challenges in its construction industry development due to a scattered population and a relatively underdeveloped industrial foundation (Lang & Ding, 2023). The Northeast, historically an industrial base, has a heavy reliance on traditional industries such as manufacturing and mining. This reliance has resulted in less focus and investment in the modernization and innovation within the construction sector compared to more economically diversified regions (Chen & Zhang, 2021; Zou & Zhang, 2023). This region struggles with significant brain drain, sluggish growth in strategic emerging industries, and difficulties in elevating its HDCI, resulting in a prolonged lag behind the national average.

4.3 Center of gravity migration and discrete trend of HDCI

Between 2008 and 2020, the center of gravity for HDCI in China underwent a noticeable shift. Initially located in Henan Province, its coordinates fluctuated from (112.81° E, 33.53° N) to (112.70° E, 33.15° N) during this timeframe. When referencing Fig. 5, it becomes apparent that from 2008 to 2012, there was a slight tendency for the center of gravity to migrate southeastward, progressing at a rate of 5.01 km per year. However, in 2012, the direction of this shift altered, moving southwestward. From 2012 to 2016, the migration speed was 4.01 km per year, which then accelerated to 4.73 km per year from 2016 to 2020. This indicates that the speed of the center of gravity's movement has been

Table 2 Global Moran'sI of HDCI

Years	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Moran'sI	0.367	0.367	0.383	0.384	0.389	0.341	0.358	0.379	0.353	0.371	0.366	0.377	0.284
z-Score	3.368	3.368	3.495	3.525	3.582	3.183	3.317	3.457	3.247	3.402	3.340	3.390	2.647
p-Value	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.004

increasing, and interestingly, the displacement in the north–south direction is more significant than that in the east–west direction.

Changes in Spatial Distribution Pattern: The standard deviation ellipse of HDCI has significantly contracted, decreasing by nearly 300,000 km^2, from 3,646,700 km^2 in 2008 to 3,386,800 km^2 in 2020. This substantial reduction occurred over a twelve-year period. The ellipse has exhibited a shift towards the southeast, followed by a movement towards the southwest, accompanied by an increasing change in azimuth. Both the long and short semi-axes of the ellipse have undergone a decrease, with the long semi-axis reducing from 1255.32 to 1203.75 km and the short semi-axis decreasing from 924.75 to 895.64 km between 2008 and 2020. This trend of diminishing size is particularly evident in the northeast region, leading to a convergence of provinces towards the south, while the northeast gradually becomes more peripheral.

The economic scale of Southwest China may be small, but currently, the region boasts a relatively large-scale industrialization and urbanization infrastructure development (Gao et al., 2020; Shi et al., 2021). Conversely, Northeast China still has a significant proportion of its economy rooted in the secondary industry, leading to regional imbalances in economic growth and ultimately impeding green and low-carbon development efficiency. Provinces like Yunnan and Chongqing, situated in the southwest, stand out with their high forest coverage rates, conferring significant natural advantages. Aligned with the national push for achieving "double carbon" objectives, the integration of these green resources with sustainable industries has been pivotal in driving the high-quality progress of the construction sector (Li et al., 2023b; Xue et al., 2023).

4.4 State transfer trend of HDCI

4.4.1 Global autocorrelation

Table 2 presents the global Moran'sI values for HDCI spanning from 2008 to 2020. The findings reveal that throughout the entire study period, all Moran'sI values are positive, accompanied by a *P*-value less than 0.01, thus successfully satisfying the significance test at a 99% confidence level. This provides compelling evidence of a robust spatial positive correlation, indicating that the regional HDCI exhibits distinct spatial clustering patterns. More specifically, from 2008 to 2019, the Moran'sI values exhibited a slight upward trajectory, fluctuating within a narrow range of 0.34–0.38. This trend underscores a gradual strengthening of spatial correlation in HDCI and a narrowing of regional disparities. However, by 2020, there was a notable decline in Moran's I. This sudden shift may be attributed to the impact of the COVID-19 pandemic, which appears to have diminished the spatial clustering effect observed previously.

Table 3 Transition probability matrix

Spatial lag	t/t + 1	L	ML	MH	H	n_i
No lag	L	0.726	0.274	0.000	0.000	95
	ML	0.108	0.624	0.269	0.000	93
	MH	0.011	0.044	0.778	0.167	90
	H	0.000	0.000	0.037	0.963	82
L	L	0.766	0.234	0.000	0.000	47
	ML	0.182	0.636	0.182	0.000	22
	MH	0.000	0.000	0.000	0.000	0
	H	0.000	0.000	0.000	0.000	0
ML	L	0.718	0.282	0.000	0.000	39
	ML	0.158	0.605	0.237	0.000	38
	MH	0.048	0.095	0.810	0.048	21
	H	0.000	0.000	0.000	1.000	4
MH	L	0.556	0.444	0.000	0.000	9
	ML	0.000	0.571	0.429	0.000	21
	MH	0.000	0.029	0.735	0.235	34
	H	0.000	0.000	0.025	0.975	40
H	L	0.000	0.000	0.000	0.000	0
	ML	0.000	0.750	0.250	0.000	12
	MH	0.000	0.029	0.800	0.171	35
	H	0.000	0.000	0.053	0.947	38

4.4.2 The state transition characteristics of HDCI

The index was categorized into four grades: low (L), medium low (ML), medium high (MH), and high (H), based on quartile. A Markov state transition probability matrix (Table 3) was constructed to thoroughly analyze the evolving pattern of HDCI. Disregarding spatial lag, the evolution exhibits the following notable characteristics: Firstly, there is a propensity towards ascending to a superior grade. Specifically, provinces initially classified as low, medium–low, and high grades possess probabilities of 0.274, 0.269, and 0.167, respectively, for ascending to higher grades. Secondly, achieving a leap-forward transfer is challenging. The HDCI demonstrates a gradual progression, with zero probability of a direct leap from a low level to a medium–high or high grade. Lastly, the diagonal value signifies the likelihood of the grade remaining unchanged, and it exceeds the non-diagonal value, indicating that CI maintains stability in its original state throughout the high-quality development process.

The Moran index highlights a substantial spatial correlation in the HDCI. By employing the spatial Markov chain approach, we delve deeper into the characteristics of HDCI grade transfers, accounting for spatial relationships. A comparison of data in Table 3 reveals the following insights:

Firstly, spatial spillover occurs during the high-quality development process of CI. The average peripheral level exerts an influence on the transfer probability of the observed areas. For instance, when spatial factors are disregarded, the probability of provinces transitioning from the L grade to the ML grade stands at 0.274. However,

Table 4 Regression coefficient of driving factors

Factors	2008	2010	2012	2014	2016	2018	2020	Average
Financial expenditure	0.0145	0.0180	0.0236	0.0274	0.0278	0.0246	0.0196	0.0222
Urbanization process	0.0274	0.0269	0.0249	0.0232	0.0226	0.0244	0.0289	0.0255
Energy consumption structure	0.0012	0.0014	0.0015	0.0018	0.0022	0.0030	0.0035	0.0021
Technological innovation	0.0237	0.0265	0.0295	0.0323	0.0355	0.0397	0.0442	0.0330

when considering the spatial lag condition, this transfer probability fluctuates between 0.234, 0.282, and 0.444.

Secondly, the development levels of neighboring regions exert varying impacts on the observed regions. In the traditional Markov transfer probability matrix, the transfer probability from the ML grade to the MH grade in the observed region is 0.269. However, this probability decreases to 0.182 when the average grade of neighboring provinces is L. Conversely, when the average grade of neighboring provinces is MH, the transfer probability increases to 0.429. This suggests that the positive spillover effect of high-value provinces outweighs the negative spillover effect of low-value provinces.

Lastly, the absence of provinces in the neighboring grade H and the observation area L indicates that provinces at a lower level are not adjacent to those at a higher level. The spatial spillover of high-value provinces necessitates a "ladder" state, where ML and MH provinces play a pivotal role. This indirectly suggests that the HDCI has evolved into a club convergence phenomenon characterized by overall divergence and local convergence in space.

4.5 Analysis of driving factors for HDCI

4.5.1 Selection of driving factors and analysis of model credibility

Taking into account the requirements for high-quality development of CI and the current economic and social context, and building on existing research (Ali et al., 2019a; Liu et al., 2023; Xu et al., 2022), this paper selects financial support (measured by the proportion of fiscal expenditure on science and technology, energy conservation, and environmental protection), urbanization process (quantified by the proportion of urban population), technological innovation capability (represented by the number of authorized patents), and energy consumption structure (reflected in the proportion of electricity and natural gas in CI energy consumption) as potential influencing factors for the high-quality development of the construction industry.

To mitigate the impact of magnitude and errors resulting from multiple covariance and heteroskedasticity, the proxy data for the selected factors were log-transformed before performing correlation analysis using SPSS software. The results revealed that the variance inflation factor (VIF) for each variable was less than 2, indicating the absence of significant multicollinearity. Furthermore, the non-smoothness test yielded goodness-of-fit values R^2 of 0.635, 0.750, and 0.811 for the Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and Geographically and Temporally Weighted Regression (GTWR) models, respectively. Correspondingly, the AIC values were -743.033, -799.987, and -817.391, respectively. These results suggest that the GTWR model offers the highest
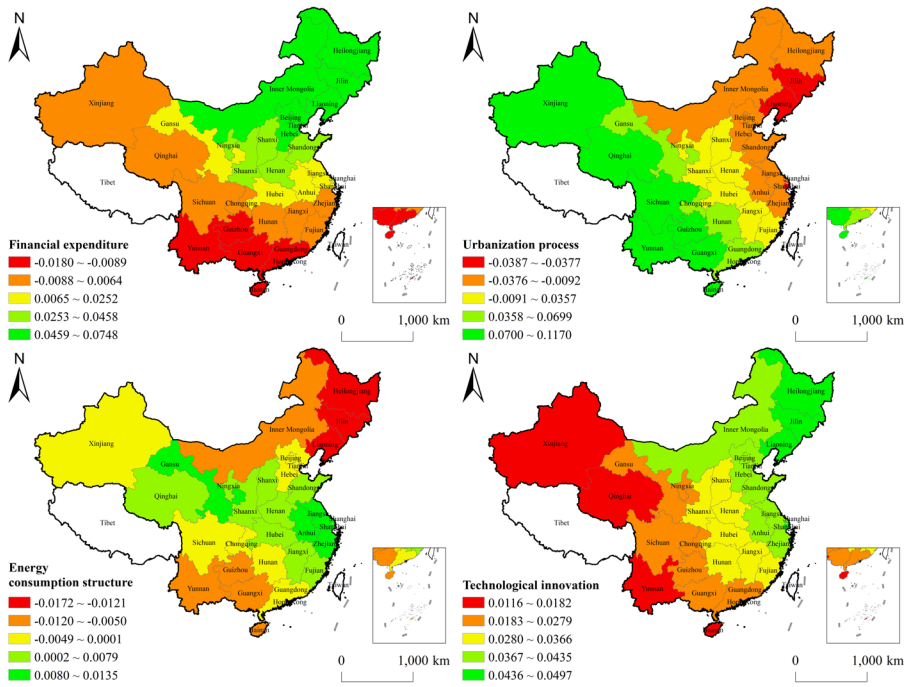
Fig. 6 GTWR regression coefficient distribution

credibility in analyzing the spatio-temporal heterogeneity of factors influencing the high-quality development of the construction industry.

4.5.2 Result analysis

From the perspective of the global coefficients of influencing factors (Table 4), the parameter estimation results of the four explanatory variables vary, indicating that there are spatio-temporal differences in the impact of each explanatory variable on the development level of the construction industry. The order of influence from greatest to least is: technological innovation capability > urbanization process > financial support > energy consumption structure. Using ArcGIS software and the natural break method, the coefficients of each variable were visualized (Fig. 6) to further examine the spatial heterogeneity of their influencing effects.

(1) The overall regression coefficient for financial expenditure is positive, indicating a promotional effect of fiscal support on the high-quality development of the construction industry. The spatial distribution of this coefficient exhibits a pattern of "high in the north and low in the south" when considering the influence of fiscal support on HDCI. Specifically, regions such as Beijing-Tianjin-Hebei and Northeast China have coefficients ranging from 0.0459 to 0.0748, indicating significant improvement in HDCI due to fiscal expenditure. The government can continue to guide financial investments in science and technology, energy conservation, and environmental protection to foster

green and intelligent development in the CI (Lan et al., 2023; Yue et al., 2024). Conversely, in regions like South China, Xinjiang, Qinghai, and others, although financial expenditure on science and technology and environmental protection accounts for a considerable proportion, its supporting effect on HDCI is not as significant. This suggests a weaker collaboration between these expenditures and CI development in these regions, necessitating further enhancement of fiscal expenditures' guiding role in promoting green and low-carbon construction industry development.

(2) The positive overall regression coefficient for the urbanization process indicates that the concentration of population in cities and towns remains beneficial for the HDCI. Spatially, the impact of urbanization on CI development exhibits a gradient decrease from west to east, resulting in distinct regions of promotion and inhibition. The promotional regions, primarily located in central and western provinces, are characterized by weak industrialization foundations and relatively low urbanization levels (Lang & Ding, 2023). The spatial agglomeration of urban population elements can effectively reduce pollutant and carbon emission intensities (Clark, 2013), fostering urban green development. Additionally, population urbanization enhances labor knowledge and skills, promoting the formation and accumulation of human capital (Amer et al., 2022). This provides fundamental conditions for the innovation and promotion of environmental protection technology, ultimately contributing to the enhancement of green total factor productivity in the construction industry. Conversely, the inhibition zone comprises the northeast and the majority of eastern coastal provinces. In these regions, the increase in urban population has an adverse effect on the HDCI. The urbanization process in the eastern and northeastern regions is at a mid to late stage (Liu et al., 2022). Excessive population influx not only leads to a decline in the marginal benefit of human capital but also gives rise to urban issues such as land resource scarcity, housing supply–demand imbalances, and environmental pollution (Ali et al., 2019b; Cheng & Yu, 2023; Yao et al., 2020). These factors have a negative impact on the sustainable development of the construction industry.

(3) The overall regression coefficient for the energy consumption structure exhibits a positive and upward trend, indicating its progressively increasing beneficial impact on the HDCI. Spatial heterogeneity is evident in the coefficients, with higher values concentrated primarily in the eastern and central provinces, and lower values observed in the northeast. Notably, the Northeast region has historically served as a major base for heavy industrial development in China (Zhang et al., 2021). However, the region's lack of industrial modernization has resulted in a narrow energy consumption structure heavily reliant on coal and oil energy sources (Liao et al., 2020; Nie et al., 2019). This dependence has hindered industrialization progress and is detrimental to the HDCI. In contrast, provinces such as Jiangsu and Zhejiang in the east have been pioneers in adopting comprehensive new energy devices and equipment during production and operation stages. This has enabled the utilization of clean energy and electrification transformation, allowing these provinces to fully harness the environmental benefits associated with the optimized energy structure (Abbas et al., 2024; Yin & Hu, 2023). Consequently, these provinces are leading the way in realizing the benefits of sustainable energy consumption patterns and driving forward green development in China.

(4) Science and technology innovation have the most significant impact on the HDCI, emphasizing its pivotal role in elevating productivity and competitiveness of enterprise products. Nationwide, the regression coefficient demonstrates a positive correlation, with a spatial distribution pattern exhibiting higher values in the east and lower values in the west. Given the advanced economic development in the eastern and central

regions, augmented investment in scientific research can foster the development and implementation of novel energy and technology (Asghar et al., 2024; Lamnatou et al., 2022). Technological innovation can propel the green and low-carbon transformation of traditional industries, foster the growth of emerging industries, and cultivate fresh momentum for high-quality development (Jiakui et al., 2023; Zou, 2024). It reinforces the resilience of the industrial chain and supply chain internally, promotes the deep integration of digitization and greening externally, and offers comprehensive support for the achievement of the "double carbon" goal (Zhang et al., 2023b). However, for the western region, which has a weaker economic and social foundation and a scarcity of emerging industries, the time-lag effect of scientific research investment (Gao & Suo, 2018) results in relatively smaller outputs of scientific and technological achievements and a lower conversion rate. This limits the impact on high-quality development in the regional construction industry. Therefore, to effectively promote the modernization of the construction industry in the short term, western provinces should consider alternative strategies, such as actively seeking cooperation and introducing innovative processes.

5 Conclusion and policy implications

5.1 Conclusion

Since the reform and opening up in 1978, China's construction industry has rapidly expanded in scale, with a continuous increase in industry output value. However, the development of the industry has been accompanied by excessive resource consumption, low production efficiency, and environmental degradation. In light of this, a deep understanding of the quality of development in the construction industry across Chinese provinces is crucial for guiding carbon neutrality and sustainable industry development. Based on data from 30 provinces in China from 2008 to 2020, a high-quality development evaluation system for the construction industry was established. Using a combination of composite weighting, exploratory spatial data analysis, Markov chains, and GTWR models, the study explores the spatiotemporal differentiation patterns, evolutionary trends, and influencing factors of high-quality development in the construction industry. The main conclusions are as follows:

(1) The high-quality development index of the construction industry shows an upward trend. Notably, the green energy-saving index emerges as the highest, underscoring a strong commitment to sustainability. In contrast, the comprehensive benefit index remains the lowest, highlighting areas in need of further improvement. The indices related to openness, coordination, and sharing the fruits of development with the people have made steady progress. Meanwhile, those for innovation-driven development and scale expansion have seen significant fluctuations. In the future, more resources should be invested in innovation, and attention should be paid to improving the modernization level of the construction industry chain and promoting the improvement of quality and efficiency of the construction industry production.

(2) In regional terms, the central and eastern areas of China display strong development momentum, in stark contrast to the western and northeastern regions, where the average annual HDCI falls below the national average. Looking at the situation from an

inter-provincial angle, there's a clear eastward expansion of provinces at a medium development level, accompanied by an increase in the number of provinces at higher and high levels of development. There is still much room for improvement in the high-quality development of the construction industry on the whole, with prominent regional imbalances.

(3) The spatial epicenter of high-quality development in China's construction industry is shifting towards the southwest. HDCI shows pronounced spatial correlation, with the Markov probability transfer matrix indicating that the positive spillover effects from high-value provinces surpass the negative impacts from low-value provinces. How to break the regional barriers and give full play to the positive spillover effects among regions and provinces is the key to the development of China's construction industry to a higher level.

(4) Analysis using the GTWR model sheds light on the driving factors of high-quality development in the construction industry. Crucially, financial support, the urbanization process, the structure of energy consumption, and the capacity for scientific and technological innovation stand out as pivotal. Nevertheless, the impact of these factors varies across different areas, mirroring the distinct challenges and opportunities that diverse regions encounter.

In the context of carbon neutrality, conducting research on the evaluation and enhancement pathways for high-quality development in the construction industry holds significant theoretical and practical implications. By exploring the essence, regional differences, and pathways of high-quality development in the construction sector, we can deepen our understanding of the concept of high-quality development within this industry, offering theoretical insights and benchmarks for the development of other sectors. Furthermore, the pursuit of high-quality development in construction intersects with multiple disciplines, such as architecture, engineering, economics, and management. Engaging in such multifaceted research encourages interdisciplinary collaboration, leading to the development of holistic research methodologies and theoretical frameworks. In practical terms, a comprehensive assessment of the construction industry's overall performance can reveal its strengths and weaknesses, aiding in the formulation of targeted improvement suggestions. This, in turn, supports the industry's broader goals of embracing green, low-carbon, and transformative objectives.

5.2 Policy implications

In conclusion, the findings of this paper will drive the low-carbon transition in the construction industry and promote sustainable development. As the constraints on scaling growth, adopting innovation-driven strategies, enhancing overall efficiency, and implementing green energy-saving practices intensify, there's a pressing need to accelerate the adoption of an innovation-driven approach to industrial development. This involves seizing the opportunities presented by the latest technological advancements, bolstering talent protection policies, prioritizing research and development investments across all stages, fast-tracking the integration of digital construction technologies, and aspiring to cultivate a digital economy that bolsters the high-quality development of infrastructure. Furthermore, it's critical to elevate design standards and regulations for green buildings, reinforce

mechanisms for low-carbon and environmental oversight, and improve the enforcement and penalties associated with polluting and energy-intensive operations. Introducing financial support measures, such as tax incentives and exemptions, is also vital to foster green technological innovations within construction firms. By actively venturing into green building markets—including ultra-low-energy buildings, energy efficiency retrofits for existing structures, and modular construction—the construction industry can achieve stable growth in scale, efficiency, and sustainability.

In Eastern regions, such as Jiangsu and Beijing, high-quality development in the construction industry has set a benchmark. To sustain their leading positions, these regions need to amplify their focus on independent innovation and cultivate networks for regional cooperation and support. Such initiatives will encourage the sharing of industrial resources, technologies, and expertise in construction, generating beneficial spatial spillover effects. Centrally positioned provinces like Hubei and Henan are uniquely placed to foster partnerships with their developed neighbors, including forefront construction enterprises. Embracing technology-intensive and eco-friendly projects will not only optimize the allocation of innovation resources but also ensure their effective conversion into real-world benefits. Moreover, as pivotal regional connectors, areas such as Sichuan and Chongqing are positioned to facilitate and propel development across the east–west divide, fostering a pattern of development that is both synergistic and complementary. Exploiting the "One Belt, One Road" initiative, it's crucial to forge extensive networks for the construction sector, weaving geographically remote provinces such as Heilongjiang, Xinjiang, and Yunnan into a cohesive spatial development framework. This approach will enhance the interconnectedness of these regions and safeguard the continuity and stability of high-quality development within the construction industry.

Considering the spatial variations in financial support, urbanization progress, energy consumption structure, and scientific and technological innovation capabilities, it is advisable to implement policies tailored to the specific needs of each region. For areas like Beijing, Tianjin, Hebei, and Northeast China, effectively utilizing government financial resources to guide and enhance investments in science, technology, energy efficiency, and environmental protection can significantly improve the construction industry's technical expertise and competitiveness. This approach will direct its development towards more green, intelligent, and sustainable practices. In contrast, regions that are currently behind in scientific and technological innovation, such as Xinjiang, Qinghai, and Yunnan, should focus on leveraging urban planning and infrastructure demands to bolster the construction of green infrastructure and enhance the provision of ecological services, thereby accelerating urbanization. These areas are encouraged to adopt policies, investments, and initiatives that integrate new energy sources, advanced equipment, and innovative construction methods. Such measures will facilitate the broad adoption of technological innovations in the construction sector, leading to greater mechanization and modernization. While the influence of energy consumption structure on the HDCI is less pronounced in the northeast and southwest, the promotion of renewable energy sources and the initiation of building electrification projects remain crucial. These efforts should be supported by strong systems and a strict adherence to the rule of law. Moreover, improving the use of clean coal and focusing on the high-quality refinement and deep processing of coal are vital steps. Allocating resources strategically to these areas will not only have a greener impact but also stimulate industrial transformation and upgrading through technological innovation, ultimately enhancing the construction industry's quality and efficiency.

5.3 Study limitations

The empirical findings of this study can guide other countries or regions seeking coordinated development in the construction industry, focusing on economic benefits, environmental protection, and social welfare, to formulate effective intervention measures for sustainable development. However, there are limitations that merit further investigation. Firstly, the selection of evaluation indicators is hindered by data availability, thus restricting the inclusion of crucial factors. Future studies should consider indicators that better capture the development quality of the construction industry, such as green building area, BIM, and the utilization of digital technology. Secondly, while this study computes the index of six dimensions of high-quality development in the construction industry, it lacks a granular analysis of each dimension's progress across all provinces. Thirdly, the study only delves into the spatial heterogeneity of four driving factors, such as financial support. Future research should adopt more appropriate methods or models to identify factors with stronger explanatory power. Furthermore, this paper focuses exclusively on 30 provinces in mainland China. Incorporating developed countries into the comparative analysis would offer a more comprehensive perspective, highlighting conventional features and offering more precise guidance for promoting high-quality development in the construction industry, particularly in the context of carbon neutrality.

Appendix 1 High-quality development index of construction industry in each province

Region	Provices	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
East	Beijing	0.339	0.362	0.370	0.374	0.376	0.411	0.412	0.417	0.448	0.458	0.469	0.517	0.537
	Tianjin	0.274	0.304	0.313	0.325	0.349	0.339	0.336	0.346	0.349	0.328	0.318	0.332	0.324
	Hebei	0.263	0.267	0.278	0.286	0.292	0.301	0.305	0.280	0.288	0.306	0.335	0.331	0.327
	Shanghai	0.280	0.291	0.298	0.300	0.306	0.322	0.329	0.328	0.333	0.352	0.365	0.386	0.382
	Jiangsu	0.365	0.377	0.402	0.418	0.448	0.487	0.501	0.494	0.512	0.534	0.563	0.572	0.587
	Zhejiang	0.347	0.367	0.403	0.427	0.441	0.462	0.478	0.474	0.481	0.506	0.449	0.451	0.449
	Fujian	0.259	0.275	0.295	0.313	0.314	0.320	0.328	0.328	0.336	0.349	0.365	0.384	0.384
	Shandong	0.266	0.279	0.298	0.314	0.307	0.347	0.353	0.342	0.361	0.376	0.371	0.396	0.413
	Guang-dong	0.275	0.293	0.313	0.326	0.317	0.351	0.348	0.354	0.365	0.385	0.413	0.427	0.440
	Hainan	0.276	0.259	0.288	0.283	0.293	0.283	0.269	0.270	0.288	0.283	0.280	0.279	0.281
Central	Shanxi	0.227	0.240	0.251	0.253	0.254	0.259	0.255	0.244	0.264	0.268	0.274	0.287	0.304
	Anhui	0.264	0.271	0.289	0.295	0.292	0.310	0.313	0.312	0.310	0.316	0.332	0.331	0.339
	Jiangxi	0.260	0.264	0.273	0.277	0.302	0.310	0.317	0.316	0.325	0.334	0.333	0.343	0.344
	Henan	0.267	0.275	0.285	0.295	0.301	0.318	0.299	0.321	0.335	0.340	0.361	0.376	0.377
	Hubei	0.273	0.284	0.306	0.321	0.338	0.352	0.363	0.367	0.376	0.389	0.423	0.439	0.437
	Hunan	0.275	0.281	0.294	0.304	0.310	0.327	0.336	0.333	0.340	0.345	0.364	0.384	0.397

Region	Provices	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
West	Inner Mongolia	0.218	0.243	0.234	0.266	0.259	0.262	0.252	0.238	0.247	0.242	0.220	0.248	0.258
	Guangxi	0.236	0.255	0.274	0.275	0.276	0.273	0.282	0.297	0.305	0.317	0.311	0.332	0.328
	Chongqing	0.248	0.263	0.271	0.283	0.284	0.299	0.343	0.314	0.320	0.328	0.329	0.345	0.352
	Sichuan	0.255	0.271	0.264	0.286	0.270	0.308	0.314	0.321	0.330	0.343	0.369	0.368	0.385
	Guizhou	0.191	0.203	0.203	0.235	0.223	0.248	0.237	0.239	0.238	0.266	0.279	0.288	0.299
	Yunnan	0.220	0.244	0.248	0.255	0.272	0.299	0.264	0.277	0.293	0.302	0.316	0.310	0.313
	Shaanxi	0.269	0.292	0.296	0.287	0.296	0.311	0.331	0.326	0.328	0.333	0.339	0.341	0.355
	Gansu	0.235	0.256	0.256	0.240	0.266	0.265	0.261	0.263	0.265	0.265	0.259	0.261	0.264
	Qinghai	0.220	0.249	0.234	0.253	0.240	0.251	0.272	0.249	0.271	0.275	0.268	0.265	0.288
	Ningxia	0.240	0.250	0.248	0.246	0.249	0.264	0.258	0.237	0.268	0.277	0.270	0.254	0.270
	Xinjiang	0.245	0.270	0.258	0.250	0.250	0.267	0.272	0.265	0.268	0.281	0.273	0.280	0.313
Northeast	Liaoning	0.251	0.268	0.290	0.299	0.306	0.324	0.304	0.279	0.269	0.281	0.293	0.295	0.296
	Jilin	0.255	0.252	0.255	0.260	0.250	0.247	0.256	0.255	0.262	0.261	0.261	0.244	0.273
	Heilongjiang	0.257	0.268	0.260	0.244	0.257	0.265	0.263	0.262	0.272	0.261	0.246	0.233	0.236

Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval and Consent to participate Not applicable.

Consent to publish Not applicable.

References

Abbas, R., Abdelzaher, M. A., Shehata, N., & Tantawy, M. A. (2024). Production, characterization and performance of green geopolymer modified with industrial by-products. *Scintific Reports*. https://doi.org/10.1038/s41598-024-55494-8

Abdelzaher, M. A. (2023). Sustainable development goals for industry, innovation, and infrastructure: Demolition waste incorporated with nanoplastic waste enhanced the physicomechanical properties of white cement paste composites. *Applied Nanoscience, 13*(8), 5521–5536. https://doi.org/10.1007/s13204-023-02766-w

Abdelzaher, M. A., & Awad, M. M. (2022). Sustainable development goals for the circular economy and the water-food nexus: Full implementation of new drip irrigation technologies in Upper Egypt. *Sustainability*. https://doi.org/10.3390/su142113883

Abdelzaher, M. A., Farahat, E. M., Abdel-Ghafar, H. M., & Balboul, B. A. A. (2023a). Environmental policy to develop a conceptual design for the water–energy–food nexus: A case study in wadi-dara on the red sea coast, Egypt. *Water*. https://doi.org/10.3390/w15040780

Abdelzaher, M. A., Hamouda, A. S., & El-Kattan, I. M. (2023b). A comprehensive study on the fire resistance properties of ultra-fine ceramic waste-filled high alkaline white cement paste composites for progressing towards sustainability. *Scientific Reports, 13*(1), 22097. https://doi.org/10.1038/s41598-023-49229-4

Ali, S., Xu, H., & Ahmad, N. (2021). Reviewing the strategies for climate change and sustainability after the US defiance of the Paris Agreement: An AHP–GMCR-based conflict resolution approach. *Environment, Development and Sustainability, 23*(8), 11881–11912. https://doi.org/10.1007/s10668-020-01147-5

Ali, S., Xu, H., Ahmed, W., & Ahmad, N. (2020). Metro design and heritage sustainability: Conflict analysis using attitude based on options in the graph model. *Environment, Development and Sustainability, 22*(4), 3839–3860. https://doi.org/10.1007/s10668-019-00365-w

Ali, S., Xu, H., Al-amin, A. Q., & Ahmad, N. (2019a). Energy sources choice and environmental sustainability disputes: An evolutional graph model approach. *Quality & Quantity, 53*(2), 561–581. https://doi.org/10.1007/s11135-018-0775-9

Ali, S., Xu, H., Xu, P., & Ahmed, W. (2019b). Evolutional attitude based on option prioritization for conflict analysis of urban transport planning in Pakistan. *Journal of Systems Science and Systems Engineering, 28*(3), 356–381. https://doi.org/10.1007/s11518-019-5413-0

Amer, E. A. A. A., Meyad, E. M. A., Gao, Y., & Niu, X. (2022). Exploring the link between natural resources, urbanization, human capital, and ecological footprint: A case of GCC countries. *Ecological Indicators, 144*, 109556. https://doi.org/10.1016/j.ecolind.2022.109556

Anonym. (2022). '14th Five-Year ' Construction Industry Development Plan. *Engineering Cost Management, 184*(02), 4–10. https://doi.org/10.3969/j.issn.1008-2166.2022.02.002

Asghar, M., Ali, S., Hanif, M., & Ullah, S. (2024). Energy transition in newly industrialized countries: A policy paradigm in the perspective of technological innovation and urbanization. *Sustainable Futures, 7*, 100163. https://doi.org/10.1016/j.sftr.2024.100163

Blinn, N., & Issa, R. R. (2022). Integration strategies for advanced construction technologies in the US AECO industry. *Journal of Information Technology in Construction*. https://doi.org/10.36680/j.itcon.2022.006

Bongaarts, J. (2019). Intergovernmental panel on climate change special report on global warming of 1.5°C Switzerland: IPCC, 2018. *Population and Development Review, 45*(1), 251–252. https://doi.org/10.1111/padr.12234

Chen, L., Zhao, Y., Xie, R., & Su, B. (2023). Embodied energy intensity of global high energy consumption industries: A case study of the construction industry. *Energy, 277*, 127628. https://doi.org/10.1016/j.energy.2023.127628

Chen, Y., & Zhang, D. (2021). Multiscale assessment of the coupling coordination between innovation and economic development in resource-based cities: A case study of Northeast China. *Journal of Cleaner Production, 318*, 128597. https://doi.org/10.1016/j.jclepro.2021.128597

Cheng, B., Lu, K., Li, J., & Chen, H. (2022). Comprehensive assessment of embodied environmental impacts of buildings using normalized environmental impact factors. *Journal of Cleaner Production, 334*, 130083. https://doi.org/10.1016/j.jclepro.2021.130083

Cheng, K., & Yu, J. (2023). Resource spatial misallocation of cities in China: Characteristic measurement and spatio-temporal evolution. *Scientia Geographica Sinica, 43*(04), 617–628. https://doi.org/10.13249/j.cnki.sgs.2023.04.005

Clark, T. A. (2013). Metropolitan density, energy efficiency and carbon emissions: Multi-attribute tradeoffs and their policy implications. *Energy Policy, 53*, 413–428. https://doi.org/10.1016/j.enpol.2012.11.006

CSYC. (2022). The total output value of construction industry in each region over the years. In *China statistical yearbook on construction* (Vol. 978-7-5230-0002-1, pp. 4). BeiJing. https://doi.org/10.43269/y.cnki.yzlpl.2023.000004

Destek, M. A., & Sinha, A. (2020). Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. *Journal of Cleaner Production, 242*, 118537. https://doi.org/10.1016/j.jclepro.2019.118537

Dong, Y.-H., Peng, F.-L., Li, H., & Men, Y.-Q. (2023). Spatial autocorrelation and spatial heterogeneity of underground parking space development in Chinese megacities based on multisource open data. *Applied Geography, 153*, 102897. https://doi.org/10.1016/j.apgeog.2023.102897

Du, Q., Wu, J., Cai, C., & Li, Y. (2020). Carbon mitigation by the construction industry in China: A perspective of efficiency and costs. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-020-10412-z

Ebolor, A., Agarwal, N., & Brem, A. (2022). Sustainable development in the construction industry: The role of frugal innovation. *Journal of Cleaner Production, 380*, 134922. https://doi.org/10.1016/j.jclepro.2022.134922

Fan, X., Zhang, Y., & Wang, X. (2021). Research on the impact of scientific and technological progress on the development of construction industry in Northeast China from the perspective of industrial chain. *Journal of Industrial Technological Economics, 40*(05), 138–145. https://doi.org/10.3969/j.issn.1004-910X.2021.05.017

Feng, X., Jin, R., Chiu, Y.-H., & Zhang, L. (2023). The government-production nexus of energy efficiency in China's construction industry: Regional difference and factor analysis. *Environmental Science and Pollution Research, 30*(48), 106227–106241. https://doi.org/10.1007/s11356-023-29470-0

Fotheringham, A. S., Crespo, R., & Yao, J. (2015). Geographical and temporal weighted regression (GTWR). *Geographical Analysis, 47*(4), 431–452. https://doi.org/10.1111/gean.12071

Friedlingstein, P., Jones, M., Osullivan, M., & Zeng, J. (2021). Global carbon budget. Earth System Science. https://doi.org/10.5194/essd-14-1917-2022

Gan, X., & Lei, Z. (2022). Research on the effectiveness of China 's fiscal and taxation policies to promote the transformation of industrial structure. *Taxation Research, 7*, 142–145. https://doi.org/10.19376/j.cnki.cn11-1011/f.2022.07.018

Gao, H., & Li, X. (2021). Research on high-quality development evaluation of construction industry based on matter-element extension model. *Construction Economy, 42*(11), 85–89. https://doi.org/10.14181/j.cnki.1002-851x.202111085

Gao, H., Li, X., & Gao, X. (2021a). Research on evaluation index system of high-quality development of construction industry. *Journal of Engineering Management, 35*(01), 1–6. https://doi.org/10.13991/j.cnki.jem.2021.01.001

Gao, H., Li, X., & Gao, X. (2021b). Research on evaluation index system of high-quality development of construction industry. *Journal of Engineering Management, 35*(1), 1–6. https://doi.org/10.13991/j.cnki.jem.2021.01.001

Gao, J., & Suo, W. (2018). Study on multi-phases time-lag effect between inputs and outputs of S&T resource for scientific research institutes. *Management Review, 30*(8), 69–78. https://doi.org/10.14120/j.cnki.cn11-5057/f.2018.08.006

Gao, Y., Zhang, Y., & Yang, M. (2020). 20 years of China's western development: A comparison of the northwest regions and southwest regions. *Regional Economic Review, 47*(05), 36–51. https://doi.org/10.14017/j.cnki.2095-5766.2020.0087

Gomaa, M., Schade, S., Bao, D. W., & Xie, Y. M. (2023). Automation in rammed earth construction for industry 4.0: Precedent work, current progress and future prospect. *Journal of Cleaner Production, 398*, 136569. https://doi.org/10.1016/j.jclepro.2023.136569

Guan, D., & Zhu, J. (2021). Evaluation of high-quality development of construction industry in Jiangsu Province based on DPSIR-PCA model. *Journal of Engineering Management, 35*(02), 6–10. https://doi.org/10.13991/j.cnki.jem.2021.02.002

Guo, Y., & Wang, X. (2006). Analyzing consistency of comparison matrix based on G1 method. *Chinese Journal of Management Science, 14*(3), 6. https://doi.org/10.3321/j.issn:1003-207X.2006.03.012

Han, X., Fu, L., Lv, C., & Peng, J. (2023). Measurement and spatio-temporal heterogeneity analysis of the coupling coordinated development among the digital economy, technological innovation and ecological environment. *Ecological Indicators, 151*, 110325. https://doi.org/10.1016/j.ecolind.2023.110325

Hassan, M. S., Ali, Y., Petrillo, A., & De Felice, F. (2023). Risk assessment of circular economy practices in construction industry of Pakistan. *Science of the Total Environment, 868*, 161418. https://doi.org/10.1016/j.scitotenv.2023.161418

Huang, B., Wu, B., & Barry, M. (2010). Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *International Journal of Geographical Information Science, 24*(3–4), 383–401. https://doi.org/10.1080/13658810802672469

Huo, T., Ma, Y., Xu, L., & Feng, W. (2022). Carbon emissions in China's urban residential building sector through 2060: A dynamic scenario simulation. *Energy, 254*, 124395. https://doi.org/10.1016/j.energy.2022.124395

Jiakui, C., Abbas, J., Najam, H., & Liu, J. (2023). Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China. *Journal of Cleaner Production, 382*, 135131. https://doi.org/10.1016/j.jclepro.2022.135131

Jiang, L., Zuo, Q., Ma, J., & Zhang, Z. (2021). Evaluation and prediction of the level of high-quality development: A case study of the Yellow River Basin. *China. Ecological Indicators*. https://doi.org/10.1016/j.ecolind.2021.107994

Kapelko, M., Lansink, A. G. J. M. O., & Stefanou, S. E. (2014). Assessing dynamic inefficiency of the Spanish construction sector pre- and post-financial crisis. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2014.01.047

Kazemi, M. Z., Elamer, A. A., Theodosopoulos, G., & Khatib, S. F. A. (2023). Reinvigorating research on sustainability reporting in the construction industry: A systematic review and future research agenda. *Journal of Business Research, 167*, 114145. https://doi.org/10.1016/j.jbusres.2023.114145

Lamnatou, C., Chemisana, D., & Cristofari, C. (2022). Smart grids and smart technologies in relation to photovoltaics, storage systems, buildings and the environment. *Renewable Energy, 185*, 1376–1391. https://doi.org/10.1016/j.renene.2021.11.019

Lan, J., Wei, Y., Guo, J., & Li, Q. (2023). The effect of green finance on industrial pollution emissions: Evidence from China. *Resources Policy, 80*, 103156. https://doi.org/10.1016/j.resourpol.2022.103156

Lang, X., & Ding, S. (2023). Study on the regional differences, dynamic evolution and influencing factors of industrial eco-efficiency in the western region. *Modernization of Management, 43*(1), 157–163. https://doi.org/10.19634/j.cnki.11-1403/c.2023.01.019

Li, L., Li, J., Wang, X., & Sun, S. (2023a). Spatio-temporal evolution and gravity center change of carbon emissions in the Guangdong-Hong Kong-Macao greater bay area and the influencing factors. *Heliyon, 9*(6), e16596. https://doi.org/10.1016/j.heliyon.2023.e16596

Li, X., Liu, X., Huang, Y., & Li, J. (2023b). Theoretical framework for assessing construction enterprise green innovation efficiency and influencing factors: Evidence from China. *Environmental Technology & Innovation, 32*, 103293. https://doi.org/10.1016/j.eti.2023.103293

Liao, S., Wu, Y., Wong, S. W., & Shen, L. (2020). Provincial perspective analysis on the coordination between urbanization growth and resource environment carrying capacity (RECC) in China. *Science of the Total Environment, 730*, 138964. https://doi.org/10.1016/j.scitotenv.2020.138964

Liu, H., Chen, Z., & Qiao, L. (2023). Evaluation and path analysis of high-quality development of China's construction industry: A comparative analysis based on provincial samples. *Science and Management, 43*(02), 25-31+65. https://doi.org/10.3969/j.issn.1003-8256.2023.02.004

Liu, M., Wang, B., & Zhong, J. (2021). Regional differences and spatial pattern of population-economy-food in Qinghai Province in the past 30 years. *Northwest Population Journal, 42*(06), 113–124. https://doi.org/10.15884/j.cnki.issn.1007-0672.2021.06.010

Liu, Y., Yang, R., & Lin, Y. (2022). Pattern evolution and optimal paths of county urbanization in China. *Acta Geographica Sinica, 77*(12), 2937–2953. https://doi.org/10.11821/dlxb202212001

Ma, L., Hosseini, M. R., Jiang, W., & Martek, I. (2018). Energy productivity convergence within the Australian construction industry: A panel data study. *Energy Economics, 72*, 313–320. https://doi.org/10.1016/j.eneco.2018.04.030

Moreno, D. J., Justo Huertas, D., & Virginia, J. (2016). Assessment of the efficiency of the Spanish construction industry using parametric methods: Case study. *Journal of Construction Engineering & Management*. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001149

Munaro, M. R., Tavares, S. F., & Bragança, L. (2020). Towards circular and more sustainable buildings: A systematic literature review on the circular economy in the built environment. *Journal of Cleaner Production, 260*, 121134. https://doi.org/10.1016/j.jclepro.2020.121134

Nie, Y., Li, Q., Wang, E., & Zhang, T. (2019). Study on the nonlinear relations between economic growth and carbon dioxide emissions in the Eastern, Central and Western regions of China. *Journal of Cleaner Production, 219*, 713–722. https://doi.org/10.1016/j.jclepro.2019.01.164

Selmey, M. G., & Elamer, A. A. (2023). Economic policy uncertainty, renewable energy and environmental degradation: Evidence from Egypt. *Environmental Science and Pollution Research, 30*(20), 58603–58617. https://doi.org/10.1007/s11356-023-26426-2

Shi, Y., Zhai, G., Lu, Y., & Liu, H. (2021). Measurement and dynamic analysis of the coordination level of urbanization scale and quality in China. *Areal Research and Development, 40*(06), 12–18. https://doi.org/10.3969/j.issn.1003-2363.2021.06.003

Singh, A., Kumar, V., Verma, P., & Kandasamy, J. (2022). Identification and severity assessment of challenges in the adoption of industry 4.0 in Indian construction industry. *Asia Pacific Management Review, 1*, 1. https://doi.org/10.1016/j.apmrv.2022.10.007

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics, 39*(3), 312–320. https://doi.org/10.2307/1926047

Sun, J., Zheng, M., & Fu, J. (2019). Connotation and policy suggestions of high quality development of construction industry in new era. *Construction Economy, 40*(05), 5–9. https://doi.org/10.14181/j.cnki.1002-851x.201905005

Sun, Y., Zhao, Y., Li, A., & Zhang, M. (2022). Laboratory safety management evaluation method based on combination weighting method and cloud model-Taking the national engineering laboratory of high-speed railway system test as an example. *Experimental Technology and Management, 39*(06), 204–209. https://doi.org/10.16709/j.cnki.sjg.2022.06.035

Trinks, A., Mulder, M., & Scholtens, B. (2020). An efficiency perspective on carbon emissions and financial performance. *Ecological Economics, 175*, 106632. https://doi.org/10.1016/j.ecolecon.2020.106632

Wan, J., Wang, Z., Ma, C., & Su, Y. (2023). Spatial-temporal differentiation pattern and influencing factors of high-quality development in counties: A case of Sichuan, China. *Ecological Indicators, 148*, 110132. https://doi.org/10.1016/j.ecolind.2023.110132

Wang, L., & Li, H. (2020). Measurement and path choice of high quality development level of construction industry: A case study of shaanxi province. *Construction Economy, 41*(9), 24–28. https://doi.org/10.14181/j.cnki.1002-851x.202009024

Wang, L., Song, X., & Song, X. (2021). Research on the measurement and spatial-temporal difference analysis of energy efficiency in China's construction industry based on a game cross-efficiency model. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2020.123918

Wang, S., Teng, T., & Bao, H. (2023a). Spatial-temporal evolution characteristics and driving factors of urban tourism efficiency in the Yellow River Basin. *Journal of Statistics and Information, 38*(05), 105–117. https://doi.org/10.3969/j.issn.1007-3116.2023.05.009

Wang, X., An, Y., Tang, H., & Liu, H. (2023b). Research on the implementation path of industrial field under the strategic goal of " dual carbon ". *Applied Chemical Industry*. https://doi.org/10.16581/j.cnki.issn1671-3206.20230821.011

Wang, Y., Chen, F., Wei, F., & Yang, M. (2023c). Spatial and temporal characteristics and evolutionary prediction of urban health development efficiency in China: Based on super-efficiency SBM model and spatial Markov chain model. *Ecological Indicators, 147*, 109985. https://doi.org/10.1016/j.ecolind.2023.109985

Wang, Y., Ye, G., Zhang, Y., & Mu, P. (2020). Is the Chinese construction industry moving towards a knowledge- and technology-intensive industry? *Journal of Cleaner Production, 259*, 120964. https://doi.org/10.1016/j.jclepro.2020.120964

Wu, X., & Zhang, L. (2021). Research on comprehensive evaluation of high-quality development of construction industry-a case study of Jiangsu Province. *Construction Economy, 42*(12), 20–26. https://doi.org/10.14181/j.cnki.1002-851x.202112020

Wuni, I. Y. (2022). Mapping the barriers to circular economy adoption in the construction industry: A systematic review, Pareto analysis, and mitigation strategy map. *Building and Environment, 223*, 109453. https://doi.org/10.1016/j.buildenv.2022.109453

Xiang, Y., Zheng, M., & Dai, T. (2019). Research on the dynamic factors and influencing mechanism of high-quality development of China 's construction industry. *Construction Economy, 40*(12), 15–20. https://doi.org/10.14181/j.cnki.1002-851x.201912015

Xu, S., Ma, C., Zhang, S., & Yuan, B. (2022). Measurement and influencing factors of eco-economic efficiency of China 's construction industry. *Environmental Pollution & Control, 44*(06), 833–840. https://doi.org/10.15985/j.cnki.1001-3865.2022.06.024

Xu, X. (2023). China 's multi-year provincial administrative division boundary data. *Resource and Environmental Science Data Registration and Publishing System*. https://doi.org/10.12078/2023010103

Xue, S., Na, J., Wang, L., & Wang, S. (2023). The outlook of green building development in china during the "fourteenth five-year plan" period. *International Journal of Environmental Research and Public Health*. https://doi.org/10.3390/IJERPH20065122

Yang, C., Xiong, H., & Li, M. (2020). Research on the evaluation of high-quality development of construction industry in Hubei Province. *Construction Economy, 41*(12), 15–20. https://doi.org/10.14181/j.cnki.1002-851x.202012015

Yang, G., Yang, Y., & Gui, Q. (2023). Analysis of the spatial and temporal evolution characteristics of the coupling and coordination between scientific and technological innovation efficiency and economic development level. *Statistics & Decision, 39*(11), 112–116. https://doi.org/10.13546/j.cnki.tjyjc.2023.11.019

Yao, C., Cao, Z., & Han, Y. (2020). Industrial agglomeration, population urbanization, land urbanization and environmental pollution. *Areal Research and Development, 39*(05), 145–149. https://doi.org/10.3969/j.issn.1003-2363.2020.05.026

Ye, F., Sun, J., Wang, Y., & Nedjah, N. (2023). A novel method for the performance evaluation of institutionalized collaborative innovation using an improved G1-CRITIC comprehensive evaluation model. *Journal of Innovation & Knowledge, 8*(1), 100289. https://doi.org/10.1016/j.jik.2022.100289

Yin, X., & Hu, J. (2023). evaluation and spatial-temporal evolutionary characteristics on energy industrial green development of China's provinces. *Journal of Statistics and Information, 38*(07), 75–86.

Yu, B. (2022). The impact of the internet on industrial green productivity: Evidence from China. *Technological Forecasting and Social Change, 177*, 121527. https://doi.org/10.1016/j.techfore.2022.121527

Yue, H., Zhou, Z., & Liu, H. (2024). How does green finance influence industrial green total factor productivity? Empirical research from China. *Energy Reports, 11*, 914–924. https://doi.org/10.1016/j.egyr.2023.12.056

Zare Banadkouki, M. R. (2023). Selection of strategies to improve energy efficiency in industry: A hybrid approach using entropy weight method and fuzzy TOPSIS. *Energy, 279*, 128070. https://doi.org/10.1016/j.energy.2023.128070

Zhang, K., Lu, Y., & Lu, H. (2022). Countermeasures for high-quality development of green buildings in China under the background of double carbon goal. *Construction Economy, 43*(3), 14–20. https://doi.org/10.14181/j.cnki.1002-851x.202203014

Zhang, R., Tang, Y., Zhang, Y., & Wang, Z. (2023a). Collaborative relationship discovery in green building technology innovation: Evidence from patents in China's construction industry. *Journal of Cleaner Production, 391*, 136041. https://doi.org/10.1016/j.jclepro.2023.136041

Zhang, S., Wang, X., Xu, J., & Chen, Q. (2023b). Green manufacturing for achieving carbon neutrality goal requires innovative technologies: A bibliometric analysis from 1991 to 2022. *Journal of Environmental Sciences*. https://doi.org/10.1016/j.jes.2023.08.016

Zhang, Y., Zhao, F., Zhang, J., & Wang, Z. (2021). Fluctuation in the transformation of economic development and the coupling mechanism with the environmental quality of resource-based cities: A case study of Northeast China. *Resources Policy, 72*, 102128. https://doi.org/10.1016/j.resourpol.2021.102128

Zou, J., & Zhang, W. (2023). Study on the idea of coordinated regional development for the revitalization of northeast china in the new era. *Northeast Asia Economic Research, 7*(03), 63–74. https://doi.org/10.19643/j.cnki.naer.2023.03.005

Zou, T. (2024). Technological innovation promotes industrial upgrading: An analytical framework. *Structural Change and Economic Dynamics, 70*, 150–167. https://doi.org/10.1016/j.strueco.2024.01.012

Authors and Affiliations

Lixin Zhang[1] · Jiarui Zhang[1]

✉ Jiarui Zhang
challengerzjr@163.com

Lixin Zhang
zlx@qtech.edu.cn

1 School of Management Engineering, Qingdao University of Technology, Huangdao District, Jialingjiang East Road No. 777, Qingdao 266520, China