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Differentiated Improvement Path of Carbon Emission Efficiency of China's Provincial Construction Industry: A Fuzzy-Set Qualitative Comparative Analysis Approach

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Abstract: Promoting carbon reduction in the construction sector is crucial to achieving China's 'double carbon' target. However, due to the interaction of multiple factors, the carbon emission efficiency of Chinese construction industry (CEECI) varies from province to province, and the path to efficient CEECI is not uniform. This study aims to analyze the combined effects of multiple factors on CEECI and to explore the underlying logic behind the formation of efficient CEECI in the province, which measures the CEECI for 2018 and 2019 for 30 provinces, autonomous regions, and municipalities directly under the Central Government of China using the super-slack-based measure (Super-SBM), which includes non-desired outputs. From a group perspective, the qualitative comparative analysis method is applied to analyze the common mechanism of the regional economic development level, energy consumption structure, business management level, market openness, science, and technology innovation level on CEECI. The results show that the regional construction industry has three equivalent low-carbon development paths: "low energy management", "scale management", and "scale market opening". Finally, according to the differences in regional resource endowments, differentiated paths suitable for the low-carbon development of the construction industry in different regions are proposed.

Keywords: construction; CEECI; influencing factors; fuzzy set qualitative comparative analysis; upgrade path

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1. Introduction

Global warming caused by greenhouse gas emissions has become a severe threat to human survival and development, and carbon emissions have become an essential issue for significant countries worldwide. Since the 21st century, with rapid economic development, energy consumption and carbon dioxide emissions have surged [1], and China has become the world's leading energy consumer and the largest emitter of carbon dioxide. According to the World Energy Statistics Review, China's energy consumption accounted for 24.3% of the global total in 2019. Total CO_2 emissions exceeded 10 billion tons, accounting for 30.21% of global emissions. Buildings, transportation, and industry are the three main sources of CO_2 emissions that account for the highest share in China. With the number of new buildings being built each year increasing, CO_2 emissions from the construction sector are also increasing. The construction sector has become one of the high carbon emitting sectors in China, accounting for 30–40% of China's total carbon emissions [2] and 30% of China's total energy consumption [3]. It consumes more than half of the world's construction cement and steel, and the production and transportation of building materials also indirectly causes significant carbon emissions [4]. For this reason, China had set a clear goal of reaching peak carbon by 2030 and carbon neutrality by 2060 [5,6]. As a pillar of China's economic development, the construction industry faces the dual challenge of reducing carbon emissions and ensuring sustainable economic growth.

Improving the carbon emission efficiency of Chinese construction industry (CEECI) is key to promoting regional low-carbon transformation under the new economic normal and achieving China's energy-saving and emission-reduction targets. CEECI was a key indicator of regional low-carbon transition [7,8]. However, due to the large land area covered, there were significant differences in resource endowments in different regions in China, resulting in different CEECI [9,10]. An area with high CEECI does not necessarily have to have good environmental conditions such as economy and innovation. Due to regional differences, various influencing factors may affect CEECI to different degrees and in different directions in other regions [11], and thus different regional approaches to CEECI improvement need to be considered in the study. However, existing studies have mainly focused on analyzing the effects of single factors on CEECI, such as (economic, innovation, energy mix) and other factors [12–14], lacking the analysis of the combined effects between factors and ignoring the combined effects of other factors, leading to the inability to explain real cases of inefficient CEECI in areas with high innovation or high levels of economic development, contradicting the results of the study. In addition, Xie et al. [15] found that the interaction between technological progress and energy intensity also affects CEECI, but most of the existing studies use statistical regression methods to analyze the net effect of individual factors on CEECI without analyzing the combined effect of more factors, ignoring the fact that CEECI is the result of the intertwined and synergistic effects of multiple factors, and lack a systematic perspective. This is also inconsistent with reality. In order to address this issue, and with the expectation of analyzing the impact of multi-factor combination effects on CEECI from a systemic perspective, it is possible to obtain realistic pathways for low carbon development in the construction industry in regions with different resource endowments. The qualitative comparative analysis (QCA) method developed by Ragin can be used to identify the pathway to an outcome, given the interaction of antecedent and dependent variables [16]. The fuzzy set theory had wide application and strong validity in practice [17,18]. The qualitative comparative analysis method of fuzzy sets based on fuzzy set theory has advantages in analyzing the configuration conditions of regional CEECI, effectively bridging the disconnect between theory and practice.

To explore different ways to improve CEECI in regions with varying endowments of resource, this study selected provincial construction industry data for the past two years. It used the SBM super-efficiency model to measure CEECI in each area. Then, through theoretical and literature analysis, key influencing factors are derived. From a configuration perspective, the fsQCA method is applied to analyze the CEECI from 2018 to 2019 of 30 provinces, regions, municipalities directly under the central government in mainland China in five dimensions: the level of business management in the construction industry, the degree of market openness, the structure of energy consumption, scientific and technological innovation, and the economic environment, to investigate the complex causal factors leading to efficient regional CEECI, and to explore the multiple driving paths to promote the improvement of CEECI in regions with different resource endowments.

2. Literature Review

2.1. Measurement of CEECI

As the world's climate and environmental problems become increasingly severe, scholars at home and abroad focus on carbon emissions, with an increasing number of studies focusing on carbon efficiency (CEE). CEE describes the proportional relationship between carbon emissions, economic growth, and energy consumption [19]. Yamaji et al. [20] proposed using single-element indicators to estimate CEE and thus assess carbon productivity. Since then, some scholars have used various single-factor evaluation indicators to measure CEE. These indicators usually include the ratio of gross national product (GNP) to total carbon emissions and carbon emissions per unit of energy consumed per unit of the gross domestic product (GDP) [21,22]. However, the single factor indicator only considers the impact of carbon emissions on economic output, ignoring the intrinsic linkages with non-energy resources and other production inputs. Cheng et al. [9] selected inputs including capital, labor, energy consumption, and desired operating income and carbon emissions of the industry as outputs to construct a total factor index.

Research on CEECI in China and abroad have focused on the measurement and influencing factors of CEECI. The question of how to accurately measure the CEECI of a region or industry is the focus of attention in current research. In input–output efficiency analysis, some scholars have used stochastic frontier analysis (SFA) to quantify differences in the efficiency of decision-making units (DMUs). These are based on economic theory, and more accurate results are obtained by applying the methodological models [23–25]. Du Q et al. [26] used the SFA model to measure CEECI, carbon abatement potential, and abatement costs for different regions of China. However, the SFA model needs to be set up in a function-specific format, and the assumptions required are stringent. When the model is not set up accurately, the measured results will likely have significant deviations. The DEA method calculates efficiency by using linear programming to construct production boundaries and assesses efficiency in terms of inputs and outputs without the need to set patterns of production for input and output factors [15]. Furthermore, it can objectively calculate the weight of each indicator based on the input and output data, thus avoiding estimation bias due to incorrectly set or subjective parameter models. This approach is recognized by most scholars and is widely used in energy efficiency [27,28], corporate performance [29,30], and CEE in the thermal power industry [31]. Zhang et al. [32] used a three-stage DEA model to reflect the CEECI in China (2006–2017) from the perspective of non-management factors.

Compared to other DEA-based approaches, the super-efficient SBM model has the advantage of treating carbon emissions as undesired outputs and radial and non-radial in the production process, thus providing more comprehensive and realistic efficiency assessment results [33]. Du et al. [34] used the (Super-SBM) method and data from 2005–2016 to estimate CEECI for 30 provinces and explored the spatial distribution characteristics of CEECI.

2.2. CEECI Influencing Factors

Regarding awareness of the factors influencing CEECI, scholars generally agree that CEECI is controlled by a variety of factors. Zhang et al. [32] used the Tobit model to analyze the internal influencing factors of CEECI, and found that GDP, industrialization level, degree of market openness, technological innovation, and energy mix had a significant effect on CEECI. Niu et al. [35] explored the impact of external drivers such as level of economic development, openness, level of science, and technological innovation on emissions efficiency using stochastic frontier models. Zeng et al. [12] adopted the Tobit model to analyze the factors influencing CEECI, and the study showed that industrial structure, external economic development, and the level of science and technology showed a positive correlation on the impact of CEECI. Still, the energy intensity would show a negative correlation. Zhou et al. [13] used a GVAR model to study the internal drivers of CEECI and found that technological progress and a rational energy mix had a positive impact on CEECI improvement. Xie et al. [15] used country panel quantile regressions to analyze the effects of technological progress on CEECI in different countries and showed that technological progress could significantly increase CEECI, while technological progress interacting with the energy intensity also affects CEECI. Ma et al. [36] used a spatial econometric model to analyze the drivers of CEECI, indicating that economic growth and energy mix have a significant driving effect on efficiency. In addition, some scholars have also studied the impact of CEECI from a single factor, technological innovation. Wen et al. [7], Li et al. [10] and Zhang [37], have shown that technological advancement and technological innovation could increase CEECI. Feng et al. [38] used a spatial econometric model to study the impact of green technology innovation on CEECI and found that green technology innovation had a significant enhancing effect on CEECI. He et al. [14] used the Tobit fixed-effect model and the panel threshold model to study the impact of renewable energy technology innovation on CEECI and found that renewable energy technology innovation can increase CEECI.

Differences in the factors influencing CEECI between regions have also raised concerns among some academics. Some scholars believe that research on the factors influencing carbon emissions in individual areas is more relevant and that the research results can contribute to reducing carbon emissions in each area. Shi and Bai [39] argued that the level of technology, technical efficiency, and scale efficiency have an enhancing effect on CEECI in Henan Province. Liu and Zhu, 2019 [40], suggested that economic development has led to a steady increase in carbon emissions from the construction sector in Hunan Province and a steady increase in CEECI. Wang and Ma [41] found that the structure of energy consumption was the main driver of CEECI in Jiangsu Province. Due to the interaction between neighboring areas, these influences can not only impact the CEECI in the area, but they can also have a different impact on adjacent areas. Liu and Hu [42] studied the factors influencing the CEECI of the Yangtze River Economic Zone and showed that the scale of economic development and the level of science and technology innovation have a positive impact on the region's CEECI but negatively affect neighboring areas, while the level of energy consumption increases the CEECI of the region as well as neighboring areas. Through the analysis of the above literature, this study has sorted out that the influencing factors of CEECI mainly include the level of regional economic development, energy consumption structure, business management level, market openness, science and technology innovation level, which provide reference for the selection of condition variables.

2.3. Literature Comment

This study answers the question of which combination of factors can improve the regional CEECI, namely the combined effects of the construction industry's business management capabilities, market openness and energy consumption structure, and external environmental conditions on the CEECI. We then identified three gaps in the existing research that need to be addressed.

Firstly, efficiency is a significant issue of research in economics and management. The improvement of socio-economic efficiency depends to a large extent on the growth of business efficiency. Most of the current studies on the factors influencing CEECI have examined the impact of external factors on CEECI, such as the level of economic development [35], the degree of market openness [32], the level of science and technological innovation [15], and less focus on the level of management of the firm's operations. Therefore, the study of CEECI should also focus on the role of business management capabilities of firms in the construction industry.

Secondly, CEECI enhancement is a multi-factor interactive process with complex driving mechanisms and multiple cointegrations between factors, often due to interconnectedness, which makes it possible for the unique effects of individual variables to be masked or substituted by related variables. At the same time, traditional regression methods only analyze meaningful interactions for up to three variables [43]. The results of an efficient CEECI formation are an organic set of different business management capabilities, market openness, energy consumption structures, and external environmental conditions. Regression methods cannot deal with such causal complexity.

Thirdly, few existing studies have explored the reasons for the formation of efficient CEECI. However, this has important practical implications for how governments and construction companies allocate factors to pursue high environmental performance.

To sum up, this paper, based on the research related to histories, combined with the analysis of the literature mentioned above review, chose the regional construction industry management level, market openness, energy consumption structure, scientific and technological innovation, and economic environment as the condition variables, with efficient CEECI as an outcome variable. The aim was to investigate the grouping effect of condition variables on CEECI and construct a research framework for the CEECI enhancement pathway, as shown in Figure 1.

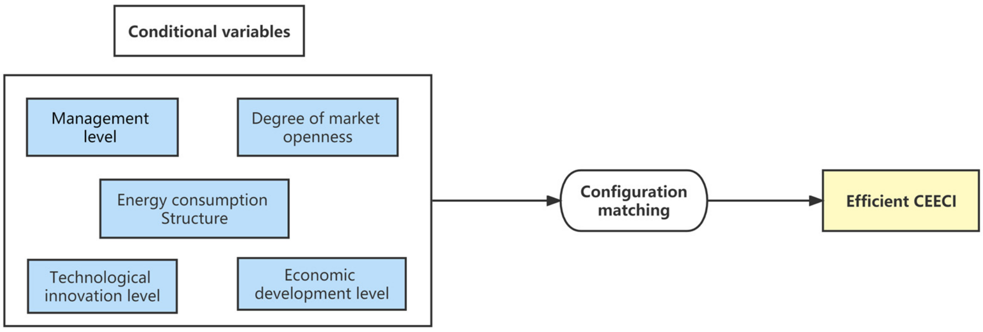

Figure 1. Research framework.

3. Research Design

3.1. CEECI Measurement Model

The DEA method is a non-parametric efficiency evaluation method that uses a mathematical planning model to calculate the efficiency scores of many decision-making units (DMUs). It was first proposed by Charnes et al. [44], and can be defined as the distance from each decision unit to the production frontier. In contrast, the combination of the optimal performance of all decision units is the distance. When using this method, the calculation tends to include undesirable outputs as inputs, which can result in the original economic significance of the undesirable outcomes being missing. As a result, the DEA model is inadequate in dealing with the problem of undesirable outcomes. To this shortcoming, a slack-based efficiency measure (SBM) was first proposed by Tone [45]. At the same time, the SBM model was modified by Tone [46] to avoid the influence of pollutant emissions on the results, taking into account the large number of pollutants caused during the production process. The SBM model was subsequently extended by Zhou et al. [47], who argued that some decision units (DMUs) could be excluded by adding some undesirable outputs to be processed through the model and allowing valid DMU values to be greater than or equal to 1 for better comparison. Because the model excludes the decision unit being evaluated from the set, the resultant efficiency value obtained will be greater than 1. The super-SBM model will be widely used later. In addition, the method avoids radial and directional bias because it has non-radial and non-directional measurements. In this paper, based on previous studies, the Super-SBM model was used to set variable scales and non-directionality. Carbon emissions are used as non-desired outputs to measure the CEECI for 30 provinces in Mainland China in 2018 and 2019 to obtain a more accurate environmental impact index. The specific model can be expressed as Formulas (1) and (2).

$$\rho = min\frac{1+\frac{1}{n}\sum_{i=1}^{n}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{q}\sum_{r=1}^{q}\frac{s_r^+}{y_{rk}}} \quad (1)$$

$$s.t.\begin{cases} \sum\limits_{j=1,j\neq k}^{m} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ \sum\limits_{j=1,j\neq k}^{m} y_{rj}\lambda_j + s_i^+ \leq y_{rk} \\ \lambda, s_i^-, s_i^+ \geq 0 \\ i = 1,2,\cdots,n; r = 1,2,\cdots,q; j = 1,2,\cdots,m(j\neq k) \end{cases} \quad (2)$$

In the Formulas (1) and (2): a production system with n decision-making units (DMUs) was constructed and each of them includes four factors as inputs, desirable outputs, and undesirable outputs. Input indicators include capital, labor, energy, and machines; desired outputs include GDP; undesired outputs include carbon emissions. ρ indicates the CEECI value to be calculated, n and q mean the total number of input and output indicators, respectively, i.e., n = 4 and q = 2. x_{ik} means input i of the kth decision unit. y_{rk} means the rth output of the kth decision unit. s_i^-, s_r^+ means the amount of slack in inputs, and outputs, respectively. λ means the weight vector.

If and only if $\rho \geq 1$, the DMU is considered effective. Otherwise, the DMU is in an inefficient state and needs to be further improved in terms of inputs, outputs, etc.

3.2. Qualitative Comparative Analysis

Qualitative Comparative Analysis (QCA), introduced by American sociologist Charles C. Ragin in 1987 [16], combines the strengths of case studies and variables research to conduct qualitative and quantitative cross-case studies aimed at solving causally complex social problems. Compared to traditional statistical methods, such as regression analysis and cluster analysis, the QCA approach is less susceptible to the negative effects of autocorrelation and multicollinearity and examines 'group effects' rather than 'net effects', revealing complex and multiple causal factors. Considering that our regional CEECI results in a combination of conditional variables, i.e., there is a so-called "different path", QCA is more suitable for solving such path problems. There are three QCA methods: (CsQCA), (FsQCA), and (MvQCA). Fuzzy set qualitative comparative analysis is suitable for dealing with problems where the research variables are continuous and can take values between 0 and 1 when the variables are set, which is more in line with the actual situation of this study. Therefore, this paper adopts the fsQCA approach to study the complex causal factors of efficient CEECI in each province from a histological perspective and explore the driving paths of efficient CEECI that are suitable for different regional characteristics.

The QCA comprises three basic ingredients: the outcome(s), conditions, and configurations. The outcome is the focus of a study. Exploring how the outcome would arise is what QCA aims to address. In this study, the outcome is the CEECI. Conditions are identical to factors, which are potential reasons that may lead to a certain result (outcome). A configuration is a specific combination of factors (conditions) that produces a given outcome of interest. To enable the systematic comparative analysis of complex cases, these cases must be transformed into configurations. Boolean algebra is used in QCA. An uppercase letter represents the (1) value for a binary variable, while a lowercase letter represents the (0) value for a binary variable. A dash symbol (–) represents the do not care value for a given binary variable. Logical AND is represented by an asterisk (*). An arrow symbol ($\rightarrow$) is used to express the (usually causal) link between a set of conditions on the one hand and the outcome the authors are trying to explain on the other hand [48].

Based on Boolean algebra, this paper introduces a detailed research process. First, the collected data should be dichotomized through the threshold to obtain the dichotomous data table, which uses 0 and 1 to represent the data. According to this table, QCA software is used to obtain the truth table of each result variable. A truth table is a table of configurations (There are three normal configuration types: configuration with result (1) and configuration with result (0). In addition, there are two configuration types: configuration with result [–] or logical remainder). Then, contradictory configurations (the same combination of conditions with different outcomes) may emerge and should be resolved. Once they are solved, a Boolean minimization procedure is next. This procedure is a reduction of a long, complex expression into a shorter, more parsimonious expression. For instance, by Boolean minimization, the expression Q * B * I + Q * B * i $\rightarrow$ O can be shortened to Q * B $\rightarrow$ O. The simpler the Boolean expression is, the more configurations it contains and the more information it describes. The Boolean minimization procedure is also performed by QCA. Finally, the unobserved logical remainder generated because the number of cases is less than the configured number (the second power of the number of conditions) is included to help generate a formula for a given result (called the minimization formula), which indicates the attribute of the combination of conditions to the result. For each result, QCA can generate a minimum formula to help later analysis. Figure 2 shows a concise program.

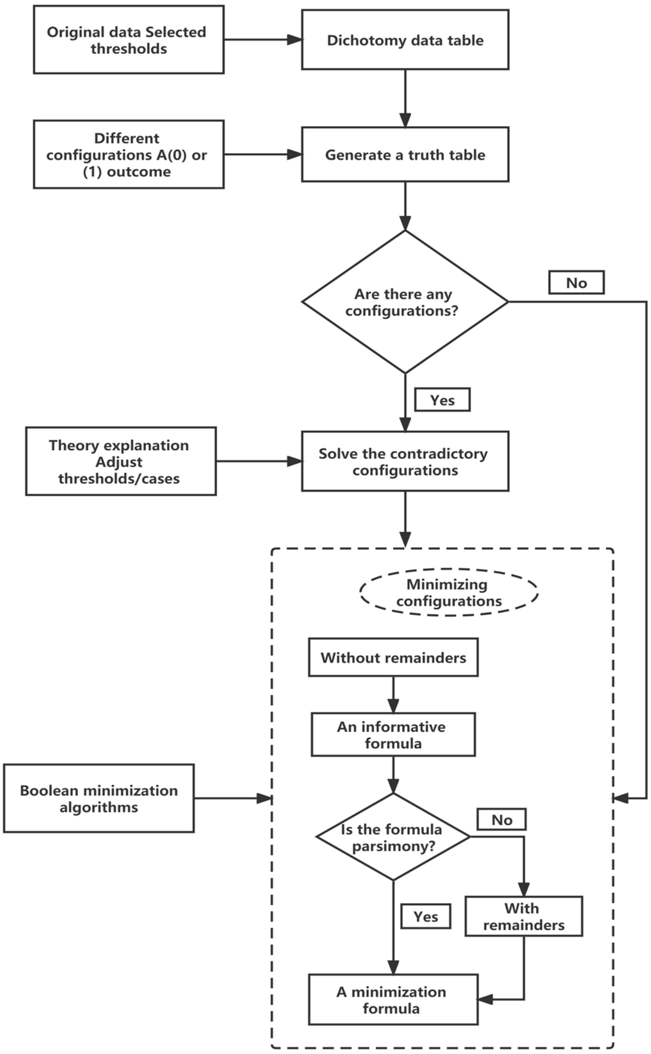

Figure 2. Qualitative comparative analysis procedure.

3.3. Variable Selection

This study is based on the construction industry in 30 provinces (excluding Tibet, Hong Kong, Macau, and Taiwan) across China in 2018 and 2019. Data are obtained from China Statistical Yearbook, China Construction Statistical Yearbook, China Energy Statistical Yearbook, and China Science and Technology Statistical Yearbook.

The explanatory variable is CEECI; Yu and Zhang [19] suggested that the CEECI describes the proportional relationship between carbon emissions, economic growth, and energy consumption. Based on the input–output perspective and based on previous scholars' research related to CEECI, CEECI should take complete account of economic benefits and environmental damages under the requirements of human-centered, green, and efficient high-quality development. This paper argues that CEECI, in the context of high-quality product, is the proportional relationship between the inputs in the production process of the construction industry and the outputs of economic benefits and environmental damages. Referring to the CEECI evaluation indicator adopted by Du et al. [34], the indicator includes both energy input and carbon emissions, where carbon emissions from the construction sector are measured using carbon emissions from building material consumption plus carbon emissions from energy consumption. The input–output indicators are described in Table 1.

Table 1. The input–output index of the CEECI.

Type	Index	Meaning
Input	Capital	Fixed assets of construction enterprises
	Labor	Number of employees in the construction industry
	Energy	Standard coal equivalent of energy consumption in the construction industry
	Machines	Total power of mechanical equipment
Output	GDP	Construction industry GDP
	Carbon emission	Construction industry carbon emissions

The conditional variables are the main factors affecting CEECI. In this paper, based on the above research framework and drawing on relevant literature, the dependent variables are explained, and the following indicators of measurement are selected:

Management level. To achieve long-term development, modern enterprises must break through the traditional management concepts and methods [49], and constantly innovate management methods and means for enterprise management, thus improving their market competitiveness. For the construction industry, a higher control level inevitably contributes to a higher CEECI. This paper draws on the research of existing scholars to measure the level of control in the construction industry using profit per capita in the construction industry.

Degree of market openness. The higher the degree of market openness, the faster the pace of the "importation" of the construction industry. Private enterprises play an exemplary role by relying on their advanced management concepts and models, as well as their highly skilled personnel, thus improving CEECI. However, the increased openness of the market may also intensify unhealthy competition in the market, forcing the construction market to be constantly segmented, raising costs and reducing efficiency. Zhang et al. [32] and Niu et al. [35] found that the degree of market openness can significantly affect CEECI. This paper uses the ratio of the total output value of non-state construction enterprises in a region to the total output value of the construction industry in that region, as constructed by Yong-an, D to measure the degree of market openness [50].

Energy consumption structure. The high proportion of conventional energy used in the construction sector is mainly reflected in the demand for fossil fuels such as oil, which brings about large carbon emissions and thus reduces its efficiency in reducing emissions, thus affecting the quality of the regional construction industry. Zhang et al. [32], Zhou et al. [13], Xie et al. [15], Ma et al. [36], and other scholars found that the energy consumption structure has a significant impact on CEECI, and this paper adopts the share of electrical energy in the energy consumption of the construction industry constructed by Zeng et al. [12] and other scholars to measure the structure of energy consumption.

Science and technology innovation. Quality, efficiency, and dynamic change are the inevitable path to achieving high-quality development. For the construction industry, science and technological innovation are the fundamental driving force behind its high-quality development and an essential means of enhancing its productivity and the competitiveness of its corporate products. Wen et al. [7], Li et al. [10], Zhang [37], and other scholars have demonstrated that science and technology innovation has a substantial impact on CEECI, and this paper chooses R&D expenditure intensity to measure the strength of science and technology innovation.

Economic environment. The higher the level of economic development, the higher the level of urbanization, and therefore the more robust the market demand for the construction industry tends to be, with demand escalating and thus driving the development of the construction industry. In addition, an increase in economic growth can provide good financial support for carbon emission reduction in the construction industry, such as upgrading the investment in construction facilities and technology upgrades to promote CEECI. Zeng et al. [12], Zhang et al. [32], Niu et al. [35], Ma et al. [36], and other scholars have shown that the regional economic environment has an impact on the productivity of the construction industry, which is represented by GDP per capita in this paper.

For the 30 samples in this paper, the choice of five condition variables is more in line with the QCA method to avoid the problem of limited diversity due to too many variables resulting in more groupings than the number of observed cases. The condition variables are described in Table 2.

Table 2. Model variables and their descriptions.

Condition Variable	Describe
(ML) Management level	Profit per capital in the construction industry
(DM) Degree of market openness	The proportion of output value of non-state/state-owned construction enterprises
(ECS) Energy consumption structure	The proportion of electric energy in energy consumption of the construction industry
(TIL) Technological Innovation level	R&D input intensity
(EDL) Economic Development Level	GDP per capital

4. Results

4.1. Conditional Variable Results

The regional construction data were collated and calculated in accordance with the conditional variable calculation requirements to produce the conditional variable data required for this study for 2018–2019, as shown in Table 3.

Table 3. Conditions variables by province (municipality, autonomous region).

DMU	ML		DM		ECS		TI		EL	
Year	2019	2018	2019	2018	2019	2018	2019	2018	2019	2018
East										
Beijing	38,612	24,627	0.75	0.76	0.259	0.242	6.31	6.17	6580	6202
Tianjin	10,169	8918	0.81	0.79	0.076	0.067	3.28	2.62	3516	3355
Hebei	14,838	12,531	0.82	0.83	0.051	0.052	1.61	1.39	12,458	11,665
Guangdong	16,321	17,835	0.81	0.81	0.183	0.134	2.88	2.78	21,801	20,528
Hainan	19,327	20,378	0.82	0.80	0.340	0.299	0.56	0.56	1177	1112
Shanghai	19,179	18,445	0.70	0.71	0.326	0.320	4.00	4.16	9649	9103
Jiangsu	13,490	13,125	0.95	0.96	0.246	0.228	2.79	2.70	21,618	20,375
Zhejiang	7462	7379	0.98	0.99	0.298	0.249	2.68	2.57	14,997	14,042
Fujian	7942	9275	0.93	0.93	0.195	0.187	1.78	1.80	8918	8288
Shandong	11,953	12,238	0.86	0.86	0.115	0.101	2.10	2.15	21,283	20,174
Central										
Shaanxi	8859	8814	0.86	0.86	0.211	0.205	1.12	1.05	4600	4331
Anhui	11,690	12,164	0.85	0.83	0.224	0.211	2.03	2.16	6980	6493
Jiangxi	11,418	12,611	0.90	0.90	0.342	0.315	1.55	1.41	5155	4773
Henan	18,739	18,803	0.90	0.89	0.152	0.179	1.46	1.40	11,976	11,193
Hubei	26,762	32,754	0.79	0.79	0.131	0.128	2.09	2.09	10,582	9844
Hunan	11,016	12,114	0.81	0.80	0.107	0.098	1.98	1.81	8452	7855
Northeast										
Liaoning	9336	10,782	0.87	0.86	0.115	0.115	2.04	1.82	8001	7584
Jilin	18,998	18,500	0.92	0.92	0.032	0.028	1.27	0.76	4206	4083
Heilongjiang	11,199	5707	0.78	0.74	0.240	0.254	1.08	0.83	5154	4946
West										
Inner Mongolia	12,051	13,137	0.82	0.86	0.031	0.030	0.86	0.75	2808	2669
Guangxi	7190	7323	0.70	0.69	0.357	0.478	0.79	0.71	5151	4860
Chongqing	12,838	14,166	0.91	0.91	0.265	0.254	1.99	2.01	3467	3261
Sichuan	9604	11,327	0.89	0.85	0.125	0.114	1.87	1.81	9718	9040
Guizhou	11,623	13,499	0.74	0.71	0.326	0.329	0.86	0.82	3093	2856
Yunnan	14,043	15,646	0.87	0.86	0.334	0.290	0.95	1.05	4860	4495
Shaanxi	10,971	13,724	0.80	0.79	0.245	0.224	2.27	2.18	4998	4715
Gansu	13,094	10,212	0.70	0.70	0.189	0.170	1.26	1.18	1972	1857
Qinghai	6801	10,908	0.52	0.49	0.136	0.127	0.69	0.60	686	645
Ningxia	7425	7475	0.73	0.71	0.082	0.076	1.45	1.23	825	775
Xinjiang	7262	8025	0.88	0.87	0.155	0.146	0.47	0.53	3195	3009

4.2. Regional CEECI Calculations

The MAXDEA software was used to set up non-desired outputs as carbon emissions by setting up super-efficiency, non-direction, and variable return to scale. MaxDEA is a professional data envelope analysis software. There is no limit to the number of data cells, as it can run very large DEA models and can quickly and accurately apply the built-in super-SBM model to calculate CEECI. The CEECI for the 30 provinces, municipalities, and autonomous regions for 2018 and 2019 was calculated year-by-year, with specific data for each section shown in Table 4. As can be seen from Table 4, the overall average CEECI of the participating areas is 0.66, with a low intermediate CEECI and more room for development. By region, the CEECI is higher in the East and Central areas, with an average CEECI above 1.07. In comparison, the CEECI is lower in the Northeast and West regions, with an average CEECI below 0.47. In recent years, the east and central areas had higher economic, market, and technological advantages, with CEECI being significantly higher than the national average. However, the vast majority of provinces in the west and northeast regions are unable to provide good support for the development of the construction industry due to their insufficient level of economic growth and scientific and technological innovation, and the low level of market openness and business management in the construction industry, as well as rather traditional energy consumption, resulting in the overall construction industry in the west and northeast regions being in a rough development stage and showing a relatively sluggish development situation.

Table 4. The CEECI from 2018 to 2019.

Provinces	2019	2018	Provinces	2019	2018
	East		Hunan	0.36	0.37
Beijing	1.42	1.42		Northeast	
Tianjin	0.36	0.37	Liaoning	0.28	0.27
Hebei	0.22	0.21	Jilin	0.26	0.25
Guangdong	1.01	0.51	Heilongjiang	0.31	0.33
Hainan	3.21	3.05		West	
Shanghai	1.20	1.11	Inner Mongolia	0.23	0.20
Jiangsu	1.28	1.26	Guangxi	1.15	1.14
Zhejiang	1.05	1.05	Chongqing	1.03	1.00
Fujian	1.03	1.00	Sichuan	1.00	0.49
Shandong	0.37	0.31	Guizhou	0.52	0.41
	Central		Yunnan	0.42	0.35
Shaanxi	0.35	0.31	Shaanxi	0.36	0.34
Anhui	0.36	0.36	Gansu	0.27	0.27
Jiangxi	0.53	0.50	Qinghai	0.34	0.33
Henan	0.34	0.29	Ningxia	0.35	0.36
Hubei	1.00	0.59	Xinjiang	0.30	0.35

The intra-regional comparison reveals that there are also significant differences in provincial CEECI levels within each region. For example, the mean value of Beijing in the eastern area (1.42) is significantly higher than the mean values of Hebei and Tianjin (0.22, 0.37), the mean value of Hubei in the central area (0.8) is considerably higher than the mean value of Shanxi (0.33), the mean value of Guangxi in the western area (1.14) is quiet higher than the mean value of Qinghai (0.33), while the mean values of the three provinces in the northeast region were not considerably different. It can be seen that areas with similar economic development within an area can have vastly different CEECI, thus showing that a single factor, such as the level of economic growth, is not the only condition that determines CEECI. Most of the provinces with lower efficiency have a lower level of economic growth and a lower capacity for technological innovation. Still, there are exceptions, such as Hubei, which relies on the advantages of a clean construction energy consumption structure to form a green production model and combine a higher level of business management and market openness, which can promote technological integration and innovation in the regional construction industry. On the other hand, an open market environment is conducive to injecting high-quality capital and technology, thus accelerating the enhancement of CEECI and ultimately driving high-quality development in the construction industry. Conversely, the provinces with high efficiency do not have good economic, innovation, and other environmental conditions, and there are also provinces with a better regional development base but low efficiency. For example, Shandong province has a high level of economic development and scientific and technological innovation, and a high level of business management in the construction industry, but its CEECI is not high. In terms of condition variables, the construction industry in Shandong province has a more traditional energy consumption structure and a higher degree of market openness, which on the one hand ignores green production, and on the other hand the higher degree of market may have caused vicious competition among construction enterprises, and Tianjin has a high level of economic development and scientific and technological innovation, but the construction industry has a low level of business management, which leads to waste of resources in the production process and a high degree of market openness, resulting in vicious competition among regional construction enterprises. The two regions are more economically developed, but the quality development of the local construction industry has been hindered by the unreasonable allocation of resources.

On the whole, regional economic development will bring a vast market to the construction industry in each province. Scientific and technological innovation can promote technological innovation and technological upgrading in the construction industry in each area, prompting quality change, efficiency change, and power change in the construction industry, enhancing the competitiveness of construction enterprises. The opening up of the construction market will be able to bring good technology and talents to the construction industry in each province, but if the regional construction industry cannot make reasonable use of its conditions, make up for its shortcomings, and form a positive interaction between resource conditions, it will result in redundant resources and fierce competition, which is counterproductive. Therefore, regions must fully understand their needs, optimize the allocation of resources, and find a suitable path for their development, which is the key to the efficient development of the regional construction industry. To this end, the fsQCA method was used to explore how multiple factors jointly influence CEECI and to explore differentiated driving paths for efficient regional CEECI development, which is of high research and practical value in promoting high-quality products in the construction industry.

4.3. Calibration of Variables in the fsQCA Method

The fsQCA method first requires the identification of fuzzy sets, where each antecedent condition (i.e., the five conditional variables in this paper) and outcome (CEECI) is considered as a set, respectively. Each case is transformed into the corresponding fuzzy set affiliation in the group, and the variable calibration is the assignment in the set affiliation to each patient. Referring to Fiss [51] for a more calibrated approach, this study set the fully affiliated, crossover, and fully unaffiliated anchor points for the explanatory variable CEECI and the five conditional variables to the 95% quantile, 50% quantile, and 5% quantile of the sample data, respectively, with the anchor points set as shown in Table 5, after which each variable was then converted to a pooled affiliation between 0 and 1. The calibration rules for non-high efficiency are the opposite of high efficiency, i.e., the calibration results in a non-set of high efficiency. After the anchor points have been set, all variables are calibrated using the calibration functions in the fsQCA 3.0 software.

Table 5. Anchor setting reference points.

Year	2019						2018					
Full affiliation point	22,715	0.95	0.32	3.54	20,285	1.30	23,416	0.94	0.34	3.68	21,467	1.31
Maximum blurring point	12,385	0.83	0.18	1.61	4903	0.66	11,657	0.82	0.19	1.70	5155	0.62
Completely unaffiliated points	7348	0.69	0.04	0.58	927	0.29	7222	0.70	0.04	0.62	984	0.27

4.4. Univariate Necessity Analysis before fsQCA Analysis

The values of each provincial CEECI and the five antecedent condition variables obtained from the above calculations were combined and analyzed year-by-year using the fsQCA method. The individual conditional variables were examined for necessity before the group analysis, a consistency test was performed, and if the consistency score was above 0.9 [52], the conditional variable is considered necessary for the outcome variable. Using the fsQCA 3.0 software, the results of CEECI were used to verify the necessity of individual condition variables, and the results of the test are shown in Table 6, with "~" indicating a non-set. The results show that the consistency level of all the condition variables is below 0.9 and does not constitute a necessary condition for the outcome variable. It is once again confirmed that CEECI is not determined by a single factor but is the result of multiple factors interacting and acting synergistically, with complex cause–effect relationships, and further configuration analysis is needed to identify the differentiated driving paths of regionally efficient CEECI.

Table 6. Necessary condition testing.

Conditional Variable	2019		2018	
	Consistency	Coverage	Consistency	Coverage
EDL	0.5809	0.8943	0.5676	0.8304
~EDL	0.6298	0.3666	0.6626	0.3826
ECS	0.8082	0.6624	0.8124	0.6687
~ECS	0.4049	0.3528	0.4557	0.3796
ML	0.5556	0.7090	0.5950	0.6843
~ML	0.6606	0.4170	0.6804	0.4401
DM	0.6361	0.4991	0.6691	0.5344
~DM	0.5627	0.5148	0.6361	0.5467
TIL	0.6156	0.7078	0.6063	0.7247
~TIL	0.6109	0.4078	0.6804	0.4309

4.5. Efficient CEECI Pathway Analysis

This section explores the multiple concurrent causalities of CEECI using fsQCA 3.0 software. The consistency threshold for configuration analysis was set at 0.8, and the frequency threshold was set at 1 about the study by Fiss [51]. The data were then normalized and analyzed to obtain complex, parsimonious, and intermediate solutions. The intermediate solution was considered to reflect the results of the study best, and the condition variables that appeared in both the medium and parsimonious solutions were core conditions. In contrast, those that appeared only in the middle solution were marginal conditions. As can be seen from Table 7, four conditional configurations for six histories led to the emergence of efficient CEECI expectation results in both 2018 and 2019. The consistency of individual designs for all histories was more significant than the minimum criterion of 0.75, indicating that the various histories can be considered as sufficient combinations of conditions to achieve efficient CEECI and that the results of the histories analysis are valid. The consistency of the broad configurations in 2018 and 2019 were 0.9167 and 0.9233, with coverage of 0.6200 and 0.5510, respectively, and with high overall coverage explaining approximately 62% and 55% of the reasons for increased efficiency, respectively.

Table 7. High-efficiency configuration of regional CEECI.

Conditional Variable	2019 Configuration 1	2	3	2018 Configuration 1	2	3
EDL	⊗	●	●	⊗	●	●
ECS	●	•	•	●	•	•
ML	●	●	⊗	●	●	⊗
DM	⊗	⊗	●	⊗	⊗	●
TIL	⊗	•	•	⊗	•	-
Consistency	0.8556	0.9792	0.9674	0.8756	0.9673	0.9294
Coverage	0.2478	0.3339	0.3283	0.3003	0.3333	0.3285
Unique coverage	0.0663	0.135	0.1508	0.1176	0.1667	0.1457
Consistency		0.9233			0.9167	
Solution coverage		0.5510			0.6200	

Note: "●" indicates Core condition exist, "•" indicates Edge conditions exists, "⊗" indicates missing Edge condition, "-" indicates that the presence or absence of this condition does not affect the results.

The highly efficient CEECI groupings for 2018 and 2019 show a very high degree of consistency, demonstrating the robustness of the research results. Based on the conditional variables and the differences between the 2018 and 2019 groupings, the efficient CEECI drive paths can be summarized as "low energy management", "scale management", and "scale market opening", and the specific analysis is as follows.

Low energy consumption management type. 2018–2019 Histogram 1, "management level x energy consumption structure" is the core condition, and the level of economic development, market openness, and technological innovation are the missing marginal conditions. This shows that good management and a clean energy consumption structure are the core of efficient CEECI in the region, compensating for the lack of other states for efficient CEECI. This path shows that a higher level of business management positively contributes to the development of the construction industry along the lines of standardization, modernization and scaling, and significantly improves the regional CEECI by raising the level of business management of enterprises. At the same time, combining a higher level of business management and a cleaner energy consumption structure can better play a role in carbon emission reduction.

Scale management type. Grouping 2 for 2018–2019, with "level of economic development x level of management" as a core condition, energy consumption structure and level of technological innovation as marginal conditions, and degree of market openness as a marginal missing condition, the cases that fit this grouping include Beijing, Shanghai, and Guangdong. This path shows that sound business management skills can efficiently translate into a giant construction market due to higher levels of economic development, thus contributing to the efficient development of the construction industry and enhancing CEECI. It is also necessary to strengthen investment in science and technology innovation and optimize the energy consumption structure. The path suggests that on the basis of good primary conditions in regions with a high economic environment and business management level, the construction industry development model should be fundamentally changed by improving scientific and technological innovation capabilities, promoting quality, efficiency and dynamic changes in the construction industry, promoting innovation spillover and innovation absorption by avoiding vicious competition among construction enterprises in the area, making the region's construction enterprises as a whole take a high technology development route, preventing an imbalance between innovation inputs, and this will enable the construction enterprises in the region to follow a high technology development route as a whole, avoiding an imbalance between innovation input and output, thus obtaining more innovation benefits and stimulating construction enterprises to innovate continuously, ultimately promoting the high-quality development of the construction industry in the region.

Open market type at scale. For 2018–2019 Cluster 3, "level of economic development x degree of market openness" is the core condition, and energy consumption structure and level of technological innovation are the marginal conditions. The level of management is the marginal missing condition, and cases that fit this cluster include Zhejiang Province, Jiangsu Province, and Fujian Province. This path shows that in areas where the regional economy is more developed and has a larger construction market, but where construction enterprises themselves have insufficient management capacity, opening up the construction market can increase competition among construction enterprises, allowing enterprises with advanced management models, highly skilled personnel, and other advantages to develop and play an moral role, which in turn generates technological spillover to construction enterprises in the region through the human capital flow effect, the good effect, the competitive effect, and the correlation effect. Following that, by matching the higher regional science and technology innovation capacity, conversely, it can provide a constant supply of innovative talents and advanced technologies for the region's enterprises, fundamentally changing the construction industry's development model, promoting quality, efficiency, and dynamic changes in the construction industry, and ultimately contributing to the enhancement of CEECI in the region.

5. Discussion

5.1. Discussion

This study presents the following two conclusions by analyzing data on the construction industry in 30 provinces across China (excluding Tibet, Hong Kong, Macau, and Taiwan) in 2018 and 2019. Firstly, the overall CEECI in China is low and there is more room for development, and the situation is not the same in different regions. Secondly, it is also found that there are three different paths to effectively motivate different regions in China to improve CEECI, and that efficient CEECI is characterized by "different paths to the same destination".

This study has three points of contribution. Firstly, this study constructs a CEECI evaluation index system based on the input–output perspective, evaluates CEECI in 30 provinces across China, clarifies the CEECI situation in different regions, and finds that CEECI is not the same in different resource endowment regions, which provides fundamental help to improve China's CEECI and facilitates the targeted low-carbon transformation of the construction industry in different regions of China.

Secondly, by combing through a large amount of literature, this study finds that the main internal and external factors affecting China's regional CEECI are the level of regional economic development [32,35,36], energy consumption structure [12,36,41], business management level [39], degree of openness to the outside world [32,35], and the level of science and technology innovation [7,10,37]. At the same time, considering the influence of a combination of factors on CEECI, this study applies the group theory to conduct a comprehensive analysis of the influencing factors of CEECI from a system perspective.

Finally, this study introduces the fsQCA method into the study of CEECI enhancement paths in China, providing a method to explain regional differences in CEECI, and then analyses the realistic paths to enhance regional CEECI with the help of histories, clarifying that efficient CEECI is the result of a combination of multiple factors, and finding that three realistic paths can achieve efficient CEECI, which can provide concrete references for the achievement of carbon reduction targets in the construction industry in regions with different environmental conditions.

5.2. Managerial Implication

This paper brings a new understanding of efficient CEECI development models in the provinces and, based on the above findings, can give two insights to promote quality development in the regional construction industry.

1. The high-quality development of the regional construction industry should focus on a balanced development among the driving factors. Research has shown that efficient CEECI comes from the synergistic linkage of multiple elements within and outside the organization. When the external environment, such as economic development conditions and the ability to innovate in science and technology, is insufficient, you can take the initiative to improve the level of business management and open up the construction market to obtain advanced management concepts and technology, thus enhancing CEECI. When the external environment conditions are better, the organization should internally improve the enterprise development mode, enhance the enterprise management level, and scientific and technological innovation ability, take the intelligent, informatization, and industrialization development road, avoid low-level rough competition, and enhance the core competitiveness of the enterprise.
2. Each region should take into account local conditions and choose the best solution according to the internal and external environmental conditions of the construction industry in each area. The study found three linked paths to achieve differentiated and efficient CEECI. This means that the government should choose the appropriate development path in light of the province's construction industry development and external environmental conditions, rather than blindly imitating the development paths of advanced regions. First of all, for areas with an average level of economic growth, a small construction market, and insufficient management level of construction enterprises, such as Jilin, Ningxia, Qinghai, and Inner Mongolia, which can follow the "low energy consumption management" path and reveal that the government should strengthen the promotion of such regions to take the lead in optimizing the energy consumption structure to reduce carbon emissions in the construction industry. Enterprises should continue to learn advanced management concepts and technologies to drive the improvement of their management level in the construction industry. Secondly, regions with substantial construction markets, but with average economic development and inadequate management of their construction enterprises, such as Hubei, Shandong, Anhui, Henan, Sichuan, Shaanxi, and other regions, can follow the "open market on a large scale" path and build internal strength as soon as possible in the next phase, relying on enterprise management to change to a highly efficient and high-quality development approach, strengthening economic construction while opening up the construction market, depending on the need to attract private enterprises to bring advanced management concepts and technologies, while enhancing investment in science and technology innovation, thus promoting the region to improve CEECI. Finally, for a high level of economic development, such as Tianjin, Jiangsu Province, and Zhejiang Province, one should follow the "scale management" path, and in the future, should strengthen their management capabilities, strengthen investment in science and technological innovation, avoid the vicious competition brought about by the high degree of market opening, take the route of synergistic development of construction industrialization and intelligent construction, enhance the competitiveness of enterprises by strengthening the endogenous power of efficient CEECI development, and thus promote the high-quality development of the construction industry.

6. Conclusions

In recent years, under the requirement of high-quality national development, a series of low-carbon development policies for the construction industry has guided and promoted the continuous low-carbon transformation of the national construction industry. Still, there are significant differences in CEECI among provinces. This paper measures the CEECI using the Super-SBM model with a sample of 30 provincial-level construction industries in China. By sorting out and analyzing the main influencing factors affecting the regional CEECI, the fsQCA method was applied to dissect the multiple concurrent causal relationships between the level of business management, openness, energy consumption structure, technological innovation, and economic environment as antecedent conditions affecting the CEECI. The findings of the study are as follows.

1. China's CEECI is low, and there is more room for development. By region, China's east and central regions are driven by high CEECI due to sound economic and innovative environment conditions, high levels of construction business management, and market openness, while the opposite is true for the northeast and western regions, but a comparison of the provinces shows that Shandong and Tianjin have good economic and innovation environment conditions but have not developed efficient CEECI, while Guangxi has a lack of economy and innovation environment development levels but has developed efficient CEECI, suggesting that driving CEECI is the result of a combination of factors.
2. The results of the qualitative comparative analysis of fuzzy sets show that there are three different paths to effectively motivate China's regions to improve CEECI, namely "low energy management", "scale management", and "scale market opening" as the three differentiated driving paths for efficient CEECI. The different paths show that efficient CEECI is characterized by "different paths", suggesting that a multi-factor approach is more suitable for driving efficient CEECI than the pursuit of single-factor extremes. Therefore, the optimal development path should be chosen in light of the development status of the regional construction industry and the state of internal and external conditions.

This study also has shortcomings. Firstly, the provincial sample of the construction industry selected for this study is currently small and lacks guiding recommendations for construction enterprises. In the future, samples should be obtained from construction enterprises for research to guide them in carbon reduction.

Secondly, forced by the availability of data, the measurement of the condition and outcome variables in this study is rather one-sided. The measurement of CEECI as an outcome variable, for which data relating to energy consumption are available in the input–output indicators, lacks rigor, and future attention should be paid to the latest CEECI measurement methods so that accurate measurements of CEECI can be made.

Thirdly, the selection of conditional variables lacks comprehensiveness. In this study, the five factors selected as conditional variables, namely the level of regional economic development, energy consumption structure, business management level, degree of openness to the outside world, and level of scientific and technological innovation, are influencing factors obtained by combing existing literature studies, without considering whether there are other influencing factors involved in the group effect on CEECI. Future research should be carried out in the construction industry to identify the main influencing factors and then carry out research.

Finally, as the latest available official data were updated to 2019, the study was conducted in 2019 for China's provincial areas, resulting in slightly outdated findings, which should be updated when the latest data are released so as to obtain the latest findings.

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