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Research article

Pathways to improving carbon emission efficiency in provinces: A comparative qualitative analysis based on the technology-organization-environment framework

Qin Min [a,b], Ruifen Zhu [a,*], Leshan Peng [a]

[a] School of Software, China

[b] Management Science and Engineering Research Center, Jiangxi Normal University, Nanchang, 330022, China

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ABSTRACT

Achieving carbon peaking and carbon neutrality are important issues for global climate governance. The study of carbon emission efficiency in China's provincial regions is of practical significance for the country to achieve carbon peaking and carbon neutrality goals. Based on the framework of Technology-Organization-Environment (TOE), choosing technological progress, economic development, industrial structure, energy structure, energy prices, and carbon emission trading market as condition variables, collecting the panel data from 30 provinces in China from 2010 to 2020, the mixed study of Necessary Condition Analysis (NCA) and the fuzzy set Qualitative Comparative Analysis (fsQCA) was used to explore the complex influence mechanism of carbon emission efficiency. The findings indicate: (1) none of the single conditions are necessary for the effect of carbon emission efficiency, but technology plays an important role in supporting the improvement of carbon emission efficiency. (2) There are four recipes for the improvement of carbon emission efficiency, which are summarized into four modes: Technology-Organization dual core modes, Environment core-Organization support modes, Technology-Organization-Environment linkage modes, and Organization core-Technology support modes. Among them, the recipe of Organization core-Technology support covers the largest number of provinces, indicating that for the developed provinces, it is necessary to accelerate technological innovation, make the deep integration of economic development and technological innovation, and promote the adjustment of the industrial structure, thereby improving the carbon emission efficiency (CEE). This study contributes to carbon emission efficiency literature by providing a new theoretical perspective based on the TOE analysis framework, and development strategies for provinces to optimize the combination according to their condition endowment.

1. Introduction

China's economic development has achieved impressive accomplishments since its reform and opening up in 1978. However, the energy demand brought by the development has resulted in a rise in China's overall carbon emissions. Under the pressure of global climate deterioration and the goal of achieving low-carbon development, China has taken a number of measures to reduce carbon emissions and pledged to reach carbon peaking by 2030 and carbon neutrality by 2060 at the UN Climate Conference in 2020.

* Corresponding author.
E-mail address: 202140100850@jxnu.edu.cn (R. Zhu).

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However, China's coal-based energy structure is difficult to alter in the short term. Consequently, improving carbon emission efficiency, rather than reducing coal energy consumption, is of paramount importance to meeting the objectives of carbon peaking and carbon neutrality [1]. The research on the definition of carbon emission efficiency (CEE) by domestic and foreign scholars has experienced a shift from the single-factor indicator to the total-factor indicator. Since the single-factor indicator neither considers the contribution of other factors of production nor their related substitution [2]. CEE calculated in the full-factor framework is more compelling.

The total-factor indicator is an approach to calculating carbon efficiency by taking into account various inputs and outputs [3]. Hu and Wang [4] first introduced the total factor into the energy efficiency measurement, and since then the total factor index measurement has been widely used in the field of carbon efficiency [5–7]. Zhou et al. [8] employed the data envelopment approach (DEA) to measure carbon efficiency by considering various production factors, for example, labor, energy, and capital. However, it ignores the choice of radial and angular in the input-output problem. To address the shortcomings of DEA models, enabling inputs and outputs to vary in different proportions as well as measuring efficiency from both the input and output perspectives, Gómez-Calvet et al. [9] used a slacks-based measurement (SBM) based on non-expected output, which effectively improves the estimation accuracy and becomes the main method for CEE measurement. The DEA-Malmquist method and the three-stage SBM-undesirable model have also been used to measure CEE [10,11].

Scholars also have conducted comprehensive research on the factors influencing carbon emission efficiency [12–14]. The studies mainly concentrate on three fields: technological progress, regional differences, and government intervention. Firstly, many scholars postulate that technological progress can reduce the cost of carbon emission reduction, thus resulting in the reduction of carbon emissions and the strengthening of CEE [15–17]. He et al. [18] found that the improvement effect of renewable energy technological innovation on carbon efficiency changes with the degree of market segmentation. Xie et al. [7] found that while CO_2 emissions can be curbed through technological progress, it can also increase relative investment, negatively impacting CEE. Dong et al. [14] studied the relationship between green technological innovation and CEE in developed countries and found that green technological innovation can enhance CEE by affecting economic progress and urbanization.

Secondly, the study of carbon emission factors has obvious spatial heterogeneity. There are regional differences in the impact of economic development on CEE. Wang and Wei [19] found economically developed cities evidence of high CEE. However, another scholar argued that there are differences between economic growth and CEE in the short-term coupling effect among the provinces at different stages of economic development. Provinces with low and high economic development have positive coupling, while those with medium levels of economic development are on the contrary, thus leading to an apparent "U" shaped relation between the short-term coupling effect and real GDP per capita [20]. The impact of industrial structure upgrading on CEE also shows regional differences. Song [21] constructed the Moore index for measuring industrial structure upgrading, analyzing the impact of industrial structure upgrading on CEE, concluding that there are regional differences in the impact on CEE, with a positive impact on the east, a negative impact on the center, and an insignificant impact on the west. Sun and Huang [13] found that industrial structure inhibits the improvement of CEE by using a stochastic frontier model that combines with the translog production function. There are also significant regional disparities in the impact of changes in energy structure on CEE. Liu et al. [22] based on the K-means clustering analysis, revealed that China should be divided into five clusters in terms of CEE of each province, the characteristics of energy consumption structure, and the discrepancies among provinces. By measuring China's provincial CEE, some scholars have found that the abundance of natural resources has led to low resource prices, which has resulted in highly crude and inefficient energy consumption patterns and low CEE [23,24].

Finally, government intervention has played an important role in improving carbon emission efficiency. The government adjusts energy prices through subsidies to different provincial energy policies, and energy prices are key to energy efficiency [25]. Li et al. [26] explored the transmission relationship between energy prices and carbon emissions combining the GWR model, quantile regression, and scenario analysis, and found energy prices can promote or suppress carbon intensity through economic development, industrial structure, and so on. Meanwhile, the Chinese government pays attention to changes in CEE and sets the carbon emission trade exchange (CETE). Zhang et al. [27] comprehensively evaluated the seven carbon emissions trading pilots since 2013, finding that the carbon trading market has been effective in reducing total carbon emissions and improving CEE.

In summary, scholars at home and abroad have laid an important theoretical and methodological foundation for the study of CEE and its factors in China. However, there are still some contradictions between the conclusions on the influencing factors: due to the variation of technical level, resource endowment, and policy support among different provinces, the same measures will have disparate effects on carbon emission efficiency in different provinces. In addition, there are gaps in the existing literature: Most of the literature is based on a multiple regression approach that assumes symmetric relationships between variables. Therefore, studies on asymmetric relationships between variables are lacking; Besides, most of the existing studies explore the impact of individual factors on CEE, but ignore the impact of the combination of multiple factors on CEE. Therefore, integrating multiple factors influencing CEE and systematically exploring the impact of the combination of multiple factors on CEE is a new perspective of the study on CEE.

To complement the gaps in related research, we draw on the Technology-Organization-Environment (TOE) framework to identify the key factors that influence the carbon efficiency of provinces [28], and employ a fuzzy-set qualitative comparative analysis (fsQCA) [29] and a necessary comparative analysis (NCA) [30] to explain the complex causality of provincial carbon emission efficiency. We find no single factor is necessary or sufficient to explain high carbon emission efficiency, but technological innovation has supported the achievement of high carbon efficiency. Meanwhile, the results identify four distinct combinations of the factors to account for the outcome. The possible contributions of this paper are as follows: First, based on the TOE framework, we try to figure out the impact of factors combined on carbon emission efficiency from the perspective of configuration to explore combinations of factors to achieve high carbon efficiency. Second, four types of achieving high carbon emission efficiency are derived, which provide development strategies for provinces to optimize the combination according to their condition endowment.

2. Research methodology

2.1. Conceptual model

Existing studies and governance practices point out that CEE is influenced by three aspects: technological progress, regional differences, and government intervention. However, it is challenging to directly enhance CEE by altering individual factors as changes to one factor affect the other, which validates the asymmetric relationship between carbon efficiency and various factors and illustrates the complex causality of carbon efficiency. However, there are few analytical frameworks in the available literature to identify the key factors of CEE.

Technology-Organization-Environment analysis framework was proposed by Tornatzky and Fleischer [28], which is widely regarded as a synthesis analytical framework based on technology application contexts. Specifically, the adoption and implementation of technological innovation are influenced by three dimensions: technology, organization, and environment. TOE analytical is initially applied to information system management [12,31,32]. Over time, researchers have conducted solid empirical research based on the TOE framework and have continued to enrich the model with differentiated research objects and technology application contexts [33–35]. Meanwhile, it is practical to explore the path of CEE improvement from three dimensions: technology (technological progress), organization (regional differences), and environment (government intervention), therefore, we find it theoretically and practically feasible to use the TOE framework to select the factors of CEE.

Although the TOE analysis framework has an important role in identifying factors and explaining complex causality [36], it is difficult to explain how the simultaneous effects of the three dimensions affect technology adoption. Practical experience in the governance of complex organizations shows that analysis of the combination of multiple conditions (configuration) can help researchers further clarify the complex mechanisms of each condition in influencing organizational outcomes [37]. From a configuration perspective, multiple influencing conditions are interrelated and will collectively shape the organization's results by matching each other's interactions [38]. Therefore, the combination of the fsQCA and the TOE analysis framework can not only deepen the findings of the TOE analysis framework but also explore how the combination of conditions (configuration) affects the results [39].

As shown in Table 1, we collected 128 highly cited papers and hot papers in Web of Science in the past three years (the keywords are "CEE" and "impact"), and summarized the high-frequency influencing factors among them from three dimensions of technology, organization and environment based on TOE framework.

First, **the technology dimension**, the conditional variable of technological progress is selected. In the process of innovation implementation, technology and organization interact, and the characteristics of the technology itself will influence a series of behaviors such as the adoption and application of the technology by the organization [40]. Existing studies show that emission reduction impacts brought by technological advancement are related to the economic development of the region, showing a threshold effect [41]. Otherwise, the improvement of technological progress makes the economic growth pattern gradually reduce the reliance on coal energy, which will reduce the rate of growth of total carbon emission, and thus improve the CEE [18]. Therefore, it is of great importance to investigate the impact of technological progress on CEE.

Second, **the organizational dimension,** economic development, industrial structure, and energy structure are selected as condition variables. In the process of innovation implementation, technological innovation will affect and even change the organization's structure, and the change of the organization's structure will also affect the direction of technology [42]. Economic development has different effects on CEE in different periods of economic development [20]. Provinces with high levels of economic development have higher demands on the living environment, which will drive the advancement of low-carbon technologies and implement low-carbon development, thus improving carbon efficiency, while cities with low economic development do the opposite. However, the economic development level of different provinces is not the same, and the joint influence of other conditions needs to be considered. Meanwhile, industrial structure upgrading is effective in improving CEE [43]. Industrial structure upgrading reduces the share of secondary industry, limits energy consumption at a low technological level, and reduces the production and use of products leading to high energy consumption and high emissions, which will effectively decrease carbon emissions and thus improve CEE. However, the reduction of the proportion of secondary industry is likely to result in a decline in economic development level. Excessive energy consumption and

Table 1
Frequency of partial influencing factors.

Classification	Influencing Factors	Factor frequency
Technology	Technological progress	23 %
Organization	Economic Development	13 %
	Industrial Structure	17 %
	Energy Structure	27 %
	Economic Opening Rate	8 %
	Urbanization Rate	9 %
Environment	Energy Prices	2 %
	Carbon Emission Trading Market	3 %

In this paper, six factors are selected as conditional variables under different dimensions by combining a low-carbon development strategy and China's national conditions, based on the following selection.

coal-based energy structure directly lead to higher CO_2 emissions in China than in other countries. The use of clean energy and the development of renewable energy can effectually decrease carbon emissions and improve CEE. However, China's coal-based energy consumption structure cannot be changed in the short term, and this high carbon emission and high pollution energy consumption pattern hinders the improvement of CEE. The empirical results show that both the level of economic development and the industrial structure have an important influence on the decarbonization of the energy structure, which is to some extent endogenous to the economic system and the industrial structure [12,44]. The three factors are interdependent and jointly influence the improvement of CEE.

Third, **the environmental dimension**, energy prices, and the carbon emissions trading pilot are selected as condition variables. The macro-environment can affect the effectiveness of an organization's application of new technologies. Although there are fewer studies on energy prices, market-oriented reform of energy prices will be an important policy direction for low-carbon development [45]. Government governance practices show that the government makes provincial energy prices fluctuate by adjusting energy policy subsidies in different provinces, which in turn forces local governments to improve carbon efficiency. In addition, the carbon emission trading market influences the CEE of enterprises through incentive and constraint mechanisms. In the process of building a national carbon emission trading market, the carbon emission trading market has a significant impact on CEE by providing a way to trade carbon emission rights with low-carbon technologies, which pushes enterprises to achieve technological progress or buy/sell carbon emission rights, thus achieving the optimal allocation of market resource [46]. The combination of energy prices and the carbon trading market can effectively improve CEE. The implementation of a carbon trading market and raising energy prices can both force organizations to develop clean energy and also ensure the organization's energy supply by lowering energy prices.

In summary, technological innovation based on the development of green energy sources, and government intervention will accelerate the cleanliness of coal energy and the low-carbonization of the energy structure to achieve high CEE. However, excessive carbon emissions have brought a series of ecological and environmental problems, which have seriously hindered the improvement of people's quality of life and the low-carbon development of the economy and society, which are closely related to the rough economic development model, weak green production technology and the lack of government policy support. The improvement of CEE requires not only the upgrading of industrial structure but also the synergistic effect of green technological innovation and government policy support. Therefore, based on the TOE analytical framework, this paper selects six conditional variables, including technological progress, economic development, industrial structure, energy structure, energy price, and carbon emission trading market to explore the impact of factors under the three dimensions on enhancing CEE. The results are presented in Fig. 1.

2.2. Method of mixing NCA and fsQCA

Qualitative Comparative Analysis (QCA) is a data analysis tool that explores complex causal relationships, which can explore the causal relationships between outcomes and conditions from a configuration perspective, revisiting existing research and contradictory findings [47]. Unlike other qualitative comparative analyses, fsQCA can handle the problems of degree change or partial membership, that is, cases have an affiliation score between 0 (nonmembership) and 1 (full membership) [48]. Although the fsQCA method can determine whether the antecedent condition is necessary for the outcome, it cannot determine the degree of necessity of different conditions for the outcome. Dul [30] proposed NCA (Necessary Condition Analysis) that can quantify the extent to which conditions

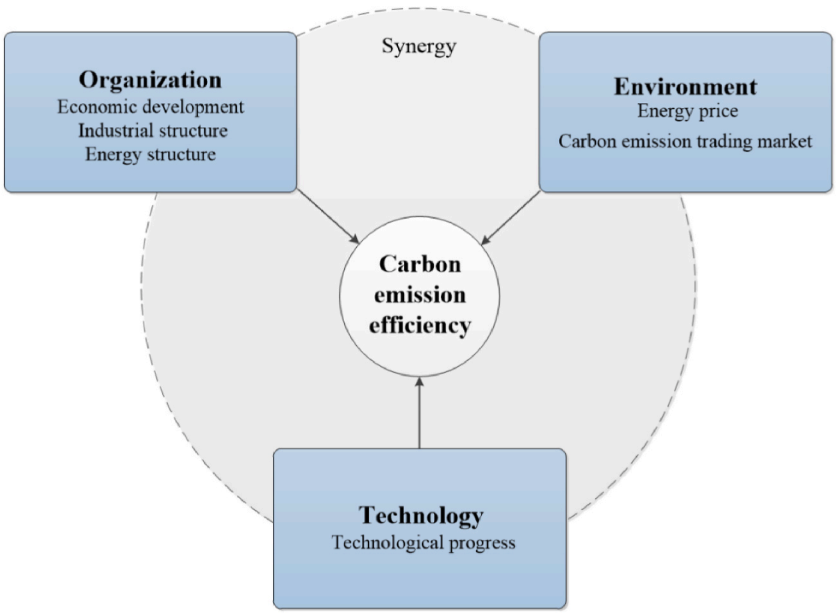

Fig. 1. TOE Analytical framework.

are necessary for the outcome, which complements the necessity analysis of fsQCA. Especially in fsQCA, the change of condition is not a qualitative "yes" or "no", but a change of affiliation, which makes the combination of fsQCA and NCA methods more meaningful.

In this paper, we first use NCA to investigate the degree to which individual conditions are necessary for high carbon efficiency. Then, we use the fsQCA to explore the complex causal relationship of CEE.

2.3. Super-efficiency SBM model

(1) A super-efficiency SBM model considering the undesirable output

The super-efficient SBM model can identify the efficiency differences among effective decision units, and then by comparing and ranking the effective decision units, the practical applicability of the model is improved. Based on the input-output perspective, this paper uses MATLAB software to measure the CEE of Chinese provinces by using a super-efficiency SBM model considering undesirable output. The model is constructed as follows:

$$\min \rho = \frac{\frac{1}{m}\sum_{i=1}^{m}(\overline{x}/x_{ik})}{\frac{1}{r_1+r_2}\left(\sum_{S=1}^{r_1}\overline{y^d}/y^d_{sk}+\sum_{q=1}^{r_2}\overline{y^u}/y^u_{qk}\right)}$$

$$\begin{cases} \overline{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j; \overline{y^d} \leq \sum_{j=1,\neq k}^{n} y^d_{Sj}\lambda_j \\ \overline{y^d} \geq \sum_{j=1,\neq k}^{n} y^d_{qj}\lambda_j; \overline{x} \geq x_k \\ \overline{y^d} \leq y^d_k; \overline{y^u} \geq y^u_k; \\ i = 1,2,\cdots,m; j = 1,2,\cdots,n; \\ s = 1,2,\cdots,r_1; q = 1,2,\cdots,r_2; \\ \lambda_j \geq 0; \end{cases} \tag{A}$$

Suppose there are n Decision-Making Units (DMUs), DMUs are responsible for converting inputs into outputs, each DMU consists of input m, desired output r_1 and non-desired output r_2; x; y^d; y^u are the elements in the corresponding input matrix, desired output matrix, and non-desired output matrix, and ρ are the CEE values.

(2) Variable selection and data in super-efficiency SBM-DEA model

The super-efficient SBM model, taking into account undesirable output, is utilized to evaluate the inter-provincial CEE of China in 2020 in this research. Considering the availability of data, the data of 30 provinces (municipalities and autonomous regions) in China in 2020 were selected for the study. Based on the input-output perspective, outputs are categorized into desired and non-desired outputs, which we define here as first-grade indicators, which are further refined and split into second-grade indicators, with GDP as the desired output, and CO2 emissions as the non-desired output. CEE arises from the collective influence of input factors, such as capital, labor, and energy. Capital stock, labor level, and energy consumption are selected as input variables. The capital stock is measured by reference to the perpetual inventory method using the year 2000 as the base period [49]. The labor level is the year-end employment in each province. Energy consumption is total energy consumption by region. GDP data is obtained by deflating nominal GDP for each year using 2000 prices as the base period to obtain real GDP. CO_2 emissions are the total carbon emissions of each region.

Table 2
Composition of input-output indicators.

Indicator Type	First Grade Indicators	Second Grade Indicators.	Definition	Unit
Input Indicators		Capital stock	Calculated for each region using 2000 as the base period based on the perpetual inventory method	Billion yuan
		Labor level	Number of employees by region	Ten thousand people
		Energy consumption	Total energy consumption by region	Ten thousand tons of standard coal
Output Indicators	Desired output	GDP	Real GDP by region with 2000 as the base period	Billion yuan
	Non-desired outputs	**CO_2** emissions	Total Carbon Emissions by Region	Ten thousand tons

The data required for each variable comes from the regional statistical yearbooks, and the total carbon emission data comes from China Emission Accounts and Datasets (CEDA). Specific indicators are listed in Table 2.

2.4. Data selection

According to the availability of data, we selected 30 provinces (municipalities and autonomous regions) as the study subjects. The data on conditions including technological progress, economic development level, industrial structure, energy structure, and energy prices are all from the *China Energy Statistical Yearbook* [50] and *China Statistical Yearbook* [51] from 2000 to 2020. We identified Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, Fujian, and Sichuan as the developing provinces for the carbon emissions trading market [52–54].

2.5. Measurement and calibration

2.5.1. Outcome variable

When measuring the capital stock, we found that some of the data were missing. Concerning the literature on the method of supplementing missing data, we supplement and predict the data and finally measured the CEE [49]. The measurement results of CEE for each province in 2020 are obtained as shown in Table 3.

2.5.2. Conditional variables

All indicators of influencing factors are listed in Table 4.

2.5.3. Calibration

In this paper, with reference to existing studies and actual data, we use the direct calibration method to transform the data into affiliation [48]. We set the affiliation of the maximum fuzzy points (the intermediate point between full affiliation and full disaffiliation) for the six conditional and outcome variables to 0.5, the affiliation of the fully affiliated points to 0.95, and the affiliation of the fully unaffiliated points to 0.05. The maximum fuzzy points for each variable were chosen in Table 5 [55]. The calibration of each variable is shown in Table 6.

3. Findings

In this paper, we use fsQCA3.0 (2016) software and R software to analyze the necessity and sufficiency of CEE, naming the configuration for high CEE with reference to the configuration theorizing process [56]. For the analysis of necessity, we set the consistency threshold to 0.9. For analysis of sufficiency, we set the consistency threshold to 0.8, the Proportional Reduction in Inconsistency (PRI) consistency threshold to 0.7, and the case frequency to 1 [57]. (PRI consistency is used to avoid simultaneous subset relations of configurations in both the outcome and the absence of the outcome (i.e., negation)).

3.1. Analysis of necessity

We use the fsQCA method to determine if a single condition is necessary for the result. The results are shown in Table 7.

The results show that there are no necessary conditions for high CEE and two necessary conditions for non-high CEE (consistency>0.9), The results of the fsQCA analysis cannot conclude the degree of necessity of a single condition on the outcome.

To explore whether the improvement of CEE has to meet the bottleneck level of a certain variable, we use the NCA for necessity analysis. In this paper, except for the data of the "carbon emission trading market" which are dichotomous, the other data are

Table 3
Carbon emission efficiency by province in 2020.

Region	CEE	Region	CEE
Beijing	1.2011	Henan	0.4575
Tianjin	0.5348	Hubei	0.4304
Hebei	0.2716	Hunan	0.5177
Shanxi	0.2648	Guangdong	1.1721
Inner Mongolia	0.318	Guangxi	0.3363
Liaoning	0.3981	Hainan	1
Jilin	0.3488	Chongqing	0.6812
Heilongjiang	0.4427	Sichuan	0.5073
Shanghai	1.1241	Guizhou	0.3024
Jiangsu	1.0653	Yunnan	0.3455
Zhejiang	0.7247	Shaanxi	0.3376
Anhui	0.4667	Gansu	0.4217
Fujian	0.6483	Qinghai	1
Jiangxi	0.515	Ningxia	0.3526
Shandong	0.5145	Xinjiang	0.2266

Table 4
Indicators of influencing factors.

Indicator Properties	Indicator Name	Indicators Explanation
Outcome Variable	Carbon Emission Efficiency	Using DEA to measure carbon efficiency by considering various factors of production such as labor, energy, and capital
Conditional Variables	Technological Progress	Internal Expenditure on R&D Activities by Region as a Share of GDP by Region
	Economic Development	GDP per capita
	Industry Structure	Share of secondary industry in GDP
	Energy Structure	Share of coal consumption in total energy consumption
	Energy Prices	Raw materials, fuel, and power purchase price index with 2000 as the base period
	Whether to carry out carbon emissions trading market	Take the pilot of the carbon emission trading market by 2020

Table 5
The basis for anchor point selection.

Variables	The basis for anchor point selection
Technological progress	The province with the smallest R&D investment intensity (Sichuan Province) among provinces with R&D investment expenditures of more than $100 billion
Economic development	The World Bank's (2020) standard for high-income GDP per capita in developing countries, with $12,000 per capita.
Industrial structure	The national ratio of secondary GDP to total GDP
Energy structure	Median
Energy prices	Median
Carbon emission efficiency	Median

Table 6
Calibration of each condition and result.

Variables	anchor point			
		full affiliation	maximum fuzzy point	zero affiliation
outcome variable	Carbon Emission Efficiency	1.2011	0.4667	0.2266
Conditional Variables	Technological Progress	0.0644	0.0217	0.0045
	Economic Development	164,889	84,000	35,995
	Industry Structure	0.463	0.378	0.1583
	Energy Structure	2.461	0.777	0.025
	Energy Prices	2.2	1.715	1.38
	Carbon Emissions Trading Market	1		0

Table 7
Analysis of necessity for the presence and negation.

Causal Conditions	Outcome variable	
	carbon emission efficiency	~ Carbon emission efficiency
T	0.697	0.466
~T	0.729	0.925
E	0.606	0.323
~E	0.712	0.968
I	0.723	0.734
~I	0.676	0.632
ES	0.563	0.819
~ES	0.879	0.587
EP	0.547	0.799
~EP	0.849	0.562
CETM	0.400	0.144
~CETM	0.599	0.856

Note: T = technological progress; E = economic development: I = industrial structure; ES = energy structure; EP = energy price; CETM = carbon emission trading market; ~ = low/medium; Number in Table 7 = consistency in each condition.

continuous. Therefore, we use the NCA approach to analyze the degree of necessity of the five condition variables. The effect size is shown in Table 8, and the bottleneck level is shown in Table 9.

Table 8 documents the effect sizes derived from CR and CE methods for individual conditional variables. There are two requirements that need to be met if the condition is necessary for the outcome: ①the effect size d is not less than 0.1. ②the effect size d is significant ($p < 0.01$). The results found that the size effect of T is more than 0.1 and significant ($P < 0.01$), which can be considered as a necessary condition for the outcome. The effect size of E is greater than 0.1, but the effect size is insignificant, and the other condition can't satisfy any requirements. Therefore, they are not necessary for the outcome.

The bottleneck effect means the minimum level (percentage) that a single condition must reach when the outcome variable reaches a certain level (percentage) of the maximum observed range. Table 9 shows a bottleneck effect of T and E on the outcome (CEE). Because of the insignificant effect size of E, the bottleneck effect is valid only for T. The results in Table 9 show that to achieve a 50 % maximum CEE level, the level of T needs to be at least 5.5 % of the maximum. Combining the necessity analysis of fsQCA and NCA, we find that individual conditions cannot be necessary for the outcome, but technological progress has a bottleneck effect on CEE, which plays an important role in supporting the improvement of CEE. Besides, low/medium technological progress and low/medium economic development are necessary for low/medium carbon efficiency.

3.2. Analysis of sufficiency for high carbon emission efficiency

The findings of the fsQCA for high CEE are presented in Table 10. Configurations in the solution will explain the same outcome at a specific amount.

In this paper, the core and peripheral conditions of the configuration are determined by the results of the parsimonious and intermediate solutions from fsQCA 3.0 software. For high carbon emission sufficiency, solutions 1–4 offer configurations in which the condition may be present or absent, depending on the composition of the samples. Specifically:

Solution 1: **Technical-Organizational dual core type**, a configuration with high technological progress, a low/medium industrial structure, and a low/medium energy structure as core conditions, as well as a low/medium level of economic development, high energy prices and carbon emission trading pilot as the peripheral conditions achieve high CEE. Provinces matching this type have a low/medium GDP per capita, an industrial structure accounting for a low/medium proportion of manufacturing industry, and an energy structure accounting for a low/medium proportion of coal energy as organizational features, high R&D investment funding as technology features, high energy prices and becoming a carbon trading pilot as environment features. The type indicates that provinces with a low proportion of coal energy consumption and a low proportion of manufacturing industry both have a unique clean energy endowment and do not rely on the rugged development that comes with a large number of heavy industrial enterprises, which is uniquely advantageous for improving the carbon emissions efficiency. When the provinces invest enough R&D to develop green energy and the central government launches a carbon trading pilot to regulate enterprise carbon emissions, the province's carbon emissions efficiency will be improved. The prototypical province is Sichuan Province, which has injected over 100 billion Yuan into R&D and heavily funded Renewable Energy development, photovoltaic power generation, power battery, and other industries in order to capitalize on its resource endowment. Sichuan has devoted considerable effort to leveraging its resource endowment, with clean energy consumption comprising 53 % of the total, ultimately resulting in an energy structure dominated by clean energy consumption [58]. The configuration 1 is presented in Fig. 2.

Solution 2: **Environmental core-Organizational** support **type**, a configuration with low/medium energy prices, carbon emission trading pilot as core conditions, as well as low/medium technological progress, a high industrial structure, and a low/medium energy structure as peripheral conditions, achieves high CEE. Provinces matching this type have an industrial structure accounting for a high proportion of manufacturing industry, an energy structure accounting for a low/medium proportion of coal energy as organizational features, low/medium R&D investment funding as technology features, low/medium energy prices and becoming a carbon trading pilot as environment features. The type indicates that provinces with a low proportion of coal energy consumption and a high proportion of manufacturing industry, even with some clean energy endowment, find it difficult to achieve high CEE without high R&D investment funding to support. In this case, the regulation of the external environment becomes extremely important. By establishing a carbon emissions trading market to limit corporate carbon emissions while maintaining low energy prices to ensure energy supply, the government can increase the use of clean energy to improve CEE as well as maintain industrial capacity.

A typical province is Fujian, which has a high industrial share of 46.3 % (highest in 2020). Despite having a clean energy

Table 8
Result of the NCA method.

Conditions	Method	Accuracy	Ceiling zone	Scope	Effect size d	P value
T	CR	93.3 %	0.148	0.811	0.183	0.000*
	CE	100 %	0.047	0.81	0.058	0.102
E	CR	93.3 %	0.094	0.81	0.116	0.013
	CE	100 %	0.053	0.81	0.066	0.011
I	CR	100 %	0.000	0.81	0.000	1
	CE	100 %	0.000	0.81	0.000	1
ES	CR	100 %	0.000	0.81	0.000	1
	CE	100 %	0.000	0.81	0.000	1
EP	CR	100 %	0.000	0.81	0.000	1
	CE	100 %	0.000	0.81	0.000	1

Note: T = technological progress; E = economic development: I = industrial structure; ES = energy structure; EP = energy price; CETM = carbon emission trading market; CE = ceiling regression; CR = ceiling envelopment.

Table 9
Bottleneck level table of NCA method based on CR method.

CEE	T	E	I	ES	EP
0	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN
20	NN	NN	NN	NN	NN
30	NN	NN	NN	NN	NN
40	NN	NN	NN	NN	NN
50	5.5	NN	NN	NN	NN
60	17.9	6.7	NN	NN	NN
70	30.2	17.7	NN	NN	NN
80	42.5	28.6	NN	NN	NN
90	54.8	39.5	NN	NN	NN
100	67.2	50.4	NN	NN	NN

Note: NN = not necessary; CEE = carbon emission efficiency; Number in Table 9 = X percent of the maximum value of the condition or outcome.

Table 10
Configuration to achieve high carbon emission efficiency.

Condition	H1	H2	H3	H4
T	●	⊗	●	●
E	⊗		●	●
I	⊗	●		●
ES	⊗	⊗	⊗	⊗
EP	●	⊗	⊗	⊗
CETM	●	●	●	
Consistency	1	0.972	0.978	0.993
Raw Coverage	0.112	0.195	0.274	0.415
Unique Coverage	0.007	0.025	0.108	0.242
Overall Solution Consistency	0.975			
Overall Solution Coverage	0.567			

Note: H1-4 = four configurations to improve carbon efficiency; Raw Coverage measures the proportion of memberships in the outcome explained by each term of the solution; Unique Coverage measures the proportion of memberships in the outcome explained solely by each individual solution term (memberships that are not covered by other solution terms); Black circle (●) represents 'presence of conditions'; Circle with cross (⊗) represents 'absence of conditions'; Blank space represents 'do not care' conditions. Moreover, large and small circles show core and peripheral conditions.

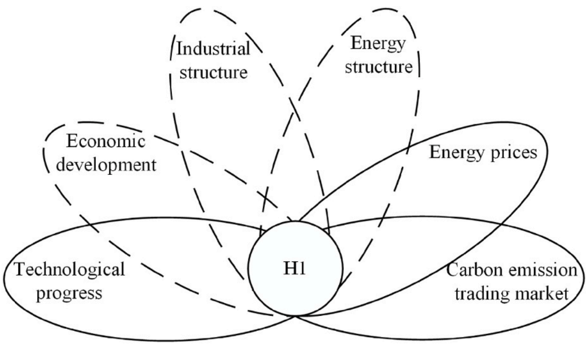

Fig. 2. Configuration 1 for high CEE. Note: The normal ellipse represents the presence of conditions; the dotted ellipse represents the absence of conditions and no ellipse represents do not care conditions.

endowment, Fujian's primary energy self-sufficiency rate is initially low (30 %). To address this, the government has implemented a carbon emissions trading market, incentivizing companies to develop and use clean energy sources (hydro, nuclear, wind) while keeping energy prices low, ultimately leading to efficient clean energy utilization. By 2020, Fujian Province will have established hydropower plants in the Minjiang and Jiulong rivers, put nine nuclear power units into operation, and accessed nearly 5 million kilowatts of offshore wind power, thus fully exploiting its hydropower, nuclear power, and wind power resources [59]. The configuration 2 is presented in Fig. 3.

Solution 3: **Technology-Organization-Environment linkage type,** a configuration with a high level of economic development, low/medium energy prices, and carbon emission trading pilot as core conditions, high technological progress, and a low/medium energy structure as peripheral conditions achieve high CEE. Provinces matching this type have a high GDP per capita, an energy structure accounting for a low/medium proportion of coal energy as organizational features, high R&D investment funding as

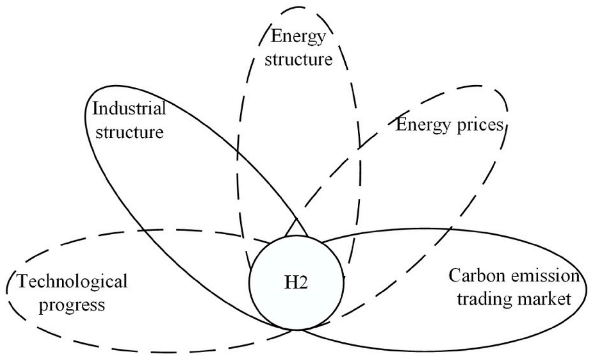

Fig. 3. Configuration 2 for high CEE
Note: The normal ellipse represents the presence of conditions; the dotted ellipse represents the absence of conditions and no ellipse represents do not care conditions.

technology features, low/medium energy prices, and becoming a carbon trading pilot as environment features. The type indicates that provinces with a high GDP per capita, high R&D investment funding, and a low proportion of manufacturing industry, will not rely on rugged economic development and have enough R&D funding to develop and utilize clean energy. In this case, if it is still necessary for the government to keep energy prices low to ensure energy supply and to develop a carbon emissions trading market to limit corporate carbon emissions, it means that the provinces have their own internal energy shortage and need to be supplied from outside provinces.

A typical municipality is Shanghai. Shanghai's per capita income and R&D investment funds are among the highest in the country, but its own energy is relatively scarce and it is a typical energy-importing city. During the 13th Five-Year Plan ***(FYP)***, major power grid projects such as the Huainan-Nanjing-Shanghai 1000 kV ultra-high voltage AC channel were completed and put into operation one after another. Additionally, Shanghai's new energy sources are all clean energy, total coal consumption has dropped by about 6 %, and the proportion of natural gas in primary energy consumption has risen to about 12 % [60]. The configuration 3 is presented in Fig. 4.

Solution 4: **Organizational core-Technology** support **type**, a configuration with a high level of economic development as a core condition, a high technological progress, a high industrial structure, a low/medium energy structure, and low/medium energy prices as peripheral conditions achieve high carbon emission sufficiency. Provinces matching this type have a high GDP per capita, an industrial structure accounting for a high proportion of manufacturing industry and an energy structure accounting for a low/medium proportion of coal energy as organizational features, and high R&D investment funding as technology features, low/medium energy prices as an environment feature. The type indicates that the provinces with enough R&D investment funding, a high GDP per capita, a high proportion of manufacturing industry, and coal energy consumption no longer rely on a rough economic development mode but exploit and use clean energy and deepen clean coal energy technology to decrease carbon emissions. This kind of province can meet its own industrial capacity needs by developing clean energy and higher energy efficiency, even if not become the carbon trading pilot. Meanwhile, the low need for external energy has kept energy prices low.

A typical province is Zhejiang, which is the first national clean energy demonstration province in China. In 2020, Zhejiang Province will rank sixth in the country in terms of GDP per capita and fourth in terms of R&D expenditure. During the 13th Five-Year Plan ***(FYP)*** period, Zhejiang Province had a diversified energy structure, with external thermal power and other sources accounting for 10.1 % of the province's total primary energy consumption. The province's large coal-fired units and local coal-fired cogeneration units have been transformed in the cleanliness of coal energy, so its energy efficiency is at the forefront of the country [61]. The configuration 4 is presented in Fig. 5.

3.3. Analysis of sufficiency for low/medium carbon emission efficiency

We also explored the configurations that lead to low/medium CEE. The results in Table 11 show an overall solution coverage of 0.87 for low/medium CEE meaning that these four solutions cover a majority of outcomes.

Comparing the solutions between high and low/medium CEE, we can find that the configurations achieving high CEE are not inverse conditions of their negative configuration. There are four solutions leading to low/medium carbon emissions. In detail, solution 1 indicates that the provinces matching the configuration with a high proportion of coal energy consumption, a low/medium GDP per capita, a high proportion of manufacturing industry and not being a carbon trading market cause low/medium CEE. Solution 2 indicates that the provinces matching the configuration cause low/medium CEE with a combination of low/medium R&D investment funding, a low/medium GDP per capita, energy prices, and becoming a carbon trading pilot. Solution 3 indicates that the provinces matching the configuration cause low/medium CEE with a combination of a low/medium GDP per capita, a high proportion of coal energy consumption, low/medium energy prices and not being a carbon trading market causing low/medium CEE. Solution 4 indicates that the provinces matching the configuration cause low/medium CEE with a combination of large R&D investment funding, a low/medium GDP per capita, a low/medium proportion of coal energy consumption, high energy prices, and a carbon emission trading market.

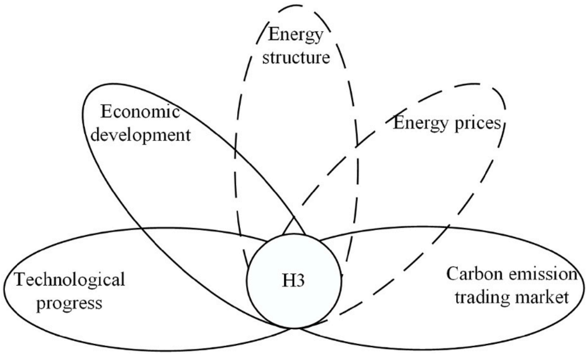

Fig. 4. Configuration 3 for high CEE
Note: The normal ellipse represents the presence of conditions; the dotted ellipse represents the absence of conditions and no ellipse represents do not care conditions.

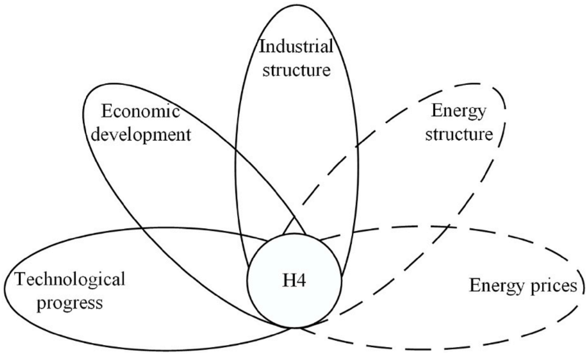

Fig. 5. Configuration 4 for high CEE
Note: The normal ellipse represents the presence of conditions; the dotted ellipse represents the absence of conditions and no ellipse represents do not care conditions.

Table 11
Configuration to achieve non-high carbon emission efficiency.

Conditions	S1	S2	S3	S4
T		⊗		●
E	⊗	⊗	⊗	⊗
I	●			●
ES	●		●	⊗
EP		●	⊗	●
CETM	⊗	⊗	⊗	●
Consistency	0.927	0.920	0.922	1
Raw Coverage	0.585	0.672	0.405	0.112
Unique Coverage	0.013	0.144	0.021	0.112
Overall Solution Consistency	0.901			
Overall Solution Coverage	0.873			

Note: S1-4 = four configurations to lead to low/medium carbon efficiency; Black circle (●) represents 'presence of conditions'; Circle with cross (⊗) represents 'absence of conditions'; Blank space represents 'do not care' conditions. Moreover, large and small circles show core and peripheral conditions.

4. Discussion

Based on the TOE framework, this paper selects six conditional variables, including technological progress, economic development, the industrial structure, the energy structure, the energy price, and the carbon emission trading market.

Firstly, the findings show that the level of technological progress, economic development, industrial structure, energy structure, energy price, and carbon emission trading market can't constitute the necessary conditions for the betterment of CEE alone. However, technological progress has a bottleneck effect on the improvement of CEE, which plays an important supporting role.

Secondly, depending on the different core factors, the improvement of CEE shows four different paths: technology-organization dual core, environment core-organization support, technology-organization-environment linkage, and organization core-technology support. The realization of each path needs the cooperation of many factors, and the cooperation mechanism of the factors in different paths is different.

Thirdly, both provinces and central government can gain insight into what affects the efficiency of carbon emissions and how their combination (configuration) improves CEE from the four different paths. Provinces should investigate the actual local situation, focusing on the optimization of the combination of the factors. The central government should adjust the policy according to the specific situation of different provinces. In details:

The **Technical-Organizational dual core type** reflects the solution for certain provinces that have a unique clean energy endowment and do not rely on the rugged development that comes with a large number of heavy industrial enterprises. These provinces should invest enough R&D to develop green energy, and the central government should launch a carbon trading pilot to regulate enterprise carbon emissions so that the province's carbon emissions efficiency will be improved.

The **Environmental core-Organizational** support **type** reflects the solution for certain provinces that have green energy endowments and a high industrial share. The central government should carry out a carbon emission trading market to limit the total carbon emission of enterprises and force them to use green energy, while appropriately lowering energy prices to avoid the risk of insufficient energy supply and reduced capacity in the process of optimizing the energy structure of provinces, so that the province's carbon emissions efficiency will be improved.

The **Technology-Organization-Environment linkage type** reflects the solution for certain provinces that have developed economies and sufficient research funding but lack internal energy sources. The central government should implement a carbon emissions trading market to force enterprises to develop supporting facilities for clean energy supply and form an energy structure dominated by clean energy, while appropriately lowering energy prices to avoid the risk of insufficient energy supply from external inputs in the process of optimizing the energy structure of provinces, so that the province's carbon emissions efficiency will be improved.

The **Organizational core-Technology** support **type** reflects the solution for certain provinces that have a high GDP per capita, a high proportion of manufacturing industry, and coal energy consumption. These provinces should invest enough R&D funding, and develop clean energy and higher energy efficiency to meet their own industrial capacity needs so that the province's carbon emissions efficiency will be improved.

Finally, the results indicate that low economic development and low technological progress are necessary conditions for low CEE. Provinces with low CEE imply low economic development and technological progress. In addition, all four pathways leading to low CEE include low economic development levels, indicating that organizational features of insufficient economic development will lead to low CEE.

5. Conclusion

The contribution of this study is concluded in the following two points. First, this paper uses the method of mixing NCA and fsQCA to explore the asymmetric causality of CEE, which explains the inconsistency of previous findings and comes into new theories. Meanwhile, it extends research in the area of carbon emissions. Secondly, previous studies lack a more comprehensive theoretical framework for identifying the key factors for organizations to improve CEE. Combining the previous study and governance practice, the study tries to extend the TOE framework to the field of carbon emissions efficiency. In addition, the study can be further detailed, such as distinguishing research objects according to the city level or combining the significant characteristics of the region itself. Despite the limitations, this study is still meaningful and provides a theoretical basis and practical case for future research.

Data availability

Data will be made available on request

CRediT authorship contribution statement

Qin Min: Writing – review & editing, Supervision, Funding acquisition, Formal analysis, Conceptualization. **Ruifen Zhu:** Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Data curation. **Leshan Peng:** Investigation, Resources, Validation, Visualization, Writing – Original Draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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