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Original Research

Achieving Low-Carbon Goals: Analysis of the Configuration Path for Manufacturing Enterprises to Reduce Carbon Emissions Intensity

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Abstract

Enterprise carbon emissions intensity (CEI) is an important measure of corporate environmental responsibility management. Existing studies exploring the net effects of single factors are insufficient to fully reveal the complex causal relationships behind them. Taking the top 40 listed manufacturing enterprises in China as examples, this study adopted the technological, organizational, and environmental (TOE) framework and selected green technology innovation, digital transformation, dual carbon leadership, financial redundancy, environmental regulatory pressure, and public environmental concern as the key antecedents influencing CEI. This study employs necessary condition analysis (NCA) and fuzzy set qualitative comparative analysis (fsQCA) methods to identify the configuration path of CEI in manufacturing enterprises and uses machine learning to rank the importance of antecedent variables. The findings reveal that no single factor alone is necessary or sufficient for determining the CEI. This study identified five different configurational pathways associated with a low CEI and three different pathways with a higher CEI. Machine learning shows that green technology innovation is the most important antecedent factor affecting CEI. These insights provide valuable guidance for manufacturing companies that adopt practices that facilitate low-carbon transformations.

Keywords: carbon emissions intensity, TOE framework, necessary condition analysis, fsQCA, green technology innovation

Introduction

As global concerns about climate change intensify, carbon emissions have become a key factor affecting the ecological balance of Earth. Industrialization has accelerated global carbon emissions, exacerbating climate warming and increasing the frequency of extreme weather events [1, 2]. The manufacturing industry, a major contributor to carbon emissions in the industrial sector, is particularly notable in China, a world manufacturing powerhouse, where carbon emissions account for approximately 80% of the national total [3].

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Among the numerous manufacturing enterprises, listed companies stand out due to their large scale of operations and broad industry influence, making their carbon footprint particularly prominent. Since the signing of the Paris Agreement, many globally listed companies have committed to reducing their emissions to levels consistent with the agreement's temperature targets [4, 5], which has led to increased societal attention to the carbon emission intensity (CEI) of listed companies. In China, since 2021, Caijing magazines have published annual carbon emissions data from the top 100 listed companies. According to the latest data from 2023, the total carbon emissions of 100 companies will amount to 5.046 billion tons, accounting for 44% of the national total. Among these industries, emissions from power, cement, coal, and steel amounted to 4.141 billion tons, accounting for 36.08% of the country's total emissions. These findings clearly underscore that promoting carbon reduction in the manufacturing sector of listed companies in China is crucial for achieving national carbon neutrality goals [6]. Therefore, investigating the key factors influencing the CEI of manufacturing enterprises and finding effective pathways to reduce their CEI have become urgent management issues for the low-carbon transformation and development of manufacturing enterprises.

Recent research has underscored the pivotal role of various factors influencing enterprise CEI, including institutional pressure [7], enterprise digital transformation [8-10], digital technologies [11], corporate social responsibility [12], senior management carbon awareness [13], and government policies [14]. However, there is no consensus on the impact of these factors on enterprises' carbon emissions. While some studies have indicated that digital transformation can decrease enterprise carbon emissions [15, 16], others have proposed a U-shaped relationship between enterprise carbon emissions and digital transformation [8, 9]. This divergence underscores the complexity of the factors that influence carbon emissions in manufacturing enterprises. Existing theories and practices suggest that enterprise carbon emissions should consider the interplay of multiple factors encompassing the organization, technology, and environment [17, 18]. Pathways to reduce carbon emissions may entail intricate causal relationships that are dependent on combinations of multiple factors operating synergistically [18, 19]. Essentially, the CEI of manufacturing enterprises is shaped by various interplaying factors [20], necessitating further comprehensive research to unveil their intricate relationships. This study addressed two fundamental questions: (1) What are the primary drivers of CEI in manufacturing enterprises? (2) Which configurational pathways lead to high and low CEI in manufacturing enterprises amidst the combined influence of multiple factors?

To address the research questions, this study collected and organized samples from the Caijing magazine's ranking of the top 100 listed companies' CEI in China from 2021 to 2022, which only includes manufacturing enterprises. Based on the technological, organizational, and environmental (TOE) framework, this study employed necessary condition analysis (NCA), fuzzy-set qualitative comparative analysis (fsQCA), and machine learning methods to explore the complex causal relationships and importance of variables affecting the CEI of manufacturing enterprises. Our study contributes to the literature on CEI in manufacturing enterprises. First, unlike most previous studies that emphasize the independent roles of factors such as digital transformation and green technology innovation in the CEI of manufacturing enterprises, our study explores the synergistic effects of multiple combined factors from technological, organizational, and environmental dimensions based on the TOE theoretical framework. Second, we used the NCA and fsQCA methods to identify the configurational pathways of the CEI in manufacturing enterprises, delve into the causal complexity and interlinking relationships between the CEI and its influencing factors, and reveal the complementary or substitutive effects of various antecedents. Furthermore, machine learning was used to identify the importance of these factors. Our research results can guide manufacturing enterprises in reducing their CEI.

Material and Methods

Theoretical Basis

The TOE framework posited that technological innovation within enterprises resulted from the interaction of three dimensions: technology, organization, and environment [21]. Specifically, the technology element primarily referred to the actual and potential technological capabilities acquired through technology adoption, which revealed aspects such as technology availability, usefulness, and compatibility [22]. The organizational element referred to characteristics of organizational structure that aligned with technology, including factors such as organizational size, financial support, and top management support [23]. The environmental element referred to the pressures from the external environment regarding technology adoption, including institutional pressures, competitive intensity, and policy instruments [23, 24].

The literature indicates that manufacturing enterprises have characteristics such as high costs, long cycles, and high uncertainty [25]. When engaging in carbon emission reduction activities, they often face multiple constraints regarding resources, capabilities, and the environment owing to inadequate financial support, lack of technical strategic knowledge, insufficient low-carbon competitiveness, and inadequate transformation awareness [26, 27]. Carbon emission reduction is a complex process that involves technological change, organizational behavior, and external environmental factors [17]. This suggests that the carbon emission reduction activities of manufacturing enterprises are not only influenced by the internal resources, capabilities, and technologies of the enterprises but also constrained by external environmental factors. We chose the TOE framework as the theoretical foundation because it comprehensively considers technology characteristics, internal organizational factors, and external environmental factors. Additionally, Wang et al. (2024) [18] utilized the TOE framework to study carbon emission reduction performance using a mixed method that combined supply chain modeling, regression analysis, and fuzzy set Qualitative Comparative Analysis (fsQCA). Su and Ding (2024) [28] analyzed the low-carbon transformation configuration paths of heavily polluting enterprises based on the TOE framework. Zhu and Peng (2024) used the TOE framework to analyze the factors affecting CEI at the provincial [29]. These studies reflect the applicability of the TOE framework in analyzing the factors affecting corporate CEI.

Model Construction

First, from a technological perspective, digital transformation and green technological innovation represent the latest advancements in technology and innovative practices within organizations, respectively. Technological progress can indirectly reduce carbon emissions by reducing energy consumption [15, 30]. Digital transformation can reduce manufacturing enterprises' carbon emissions by increasing the level of government green subsidies, promoting technological progress [9], and improving corporate social responsibility [31]. The quality and quantity enhancement from green technological innovation can significantly reduce carbon emissions [32, 33].

Second, from an organizational perspective, dual-carbon leadership and financial redundancy reflect an organization's strategic decision-making and resource allocation capabilities. Dual-carbon leadership demonstrates the management and strategic direction of enterprises in carbon reduction, ensuring that carbon reduction activities are effectively implemented within the organization. Simultaneously, financial redundancy provides the necessary funding support for enterprises to undertake technological transformation and innovation [34], reflecting their resource-buffering capability in response to environmental pressures.

Finally, from an environmental perspective, formal environmental regulatory pressures and informal environmental pressures influence CEI in the external environment [35]. Formal environmental regulatory pressures have set clear external requirements for corporate emission reductions, such as government regulations and policies, international agreements, and industry standards. These provide policy incentives and constraints for the technological transformation and innovation of enterprises' carbon reduction activities [36], thereby enhancing the level of corporate environmental information disclosure, environmental management concepts, and resource allocation efficiency [37]. Simultaneously, informal environmental pressures arising from public concern provide positive market signals to enterprises, strengthening the government's implementation of environmental regulatory policies [38] and influencing corporate environmental behaviors through market mechanisms [39].

As mentioned above, this study, based on the TOE theory combined with a systems perspective, investigated the impact of the interactions and synergistic effects among digital transformation, green technological innovation, dual-carbon leadership, financial redundancy, formal environmental regulation pressures, and public environmental concern variables on enterprise CEI.

Technological Factors

Digital Transformation

Digital transformation referred to the use of digital technologies and data as key elements in reforming enterprise management, business, and commercial models. By integrating digital technologies into production, management, and logistics processes, enterprises can monitor carbon emissions in real time, optimize production and supply chain management, and effectively reduce supply chain carbon emissions and emission reduction risks [40]. Additionally, integrating digital transformation into manufacturing processes can improve the ability of companies to acquire, transmit, and store analytical data, which in turn improves production management and optimizes resource allocation efficiency, thereby reducing carbon emissions [9]. However, the digital transformation process requires a lot of data management support and is full of uncertainties, which may trigger energy rebound effects and ultimately increase carbon emissions [41]. Additionally, some studies have indicated that digital transformation may indirectly affect carbon emissions through increased electricity consumption, exhibiting an inverted U-shaped relationship with carbon emissions [9]. This suggests that digital transformation should be combined with other factors, such as resource allocation and environmental policies, to promote carbon emission reduction activities in enterprises effectively.

Green Technology Innovation

Green technology innovation encompasses green product innovation, green process innovation, end-of-pipe treatment technology innovation, and clean production technology innovation [42]. For example, enterprises can effectively reduce product carbon emissions by adopting green technology innovations such as eco-friendly materials, energy-saving technologies, and clean production processes [43-46]. Through green technology innovation, enterprises can achieve end-of-pipe resource recycling and waste treatment, thereby reducing carbon emissions [47]. However, some studies have indicated that a complex relationship may exist between green technology innovation and carbon emissions. Miao et al. (2024) [33] showed that both the quantity and quality of green technology innovation can significantly reduce the carbon emissions of high-energy-consuming manufacturing enterprises. Lyu et al. (2024) [34] believe that green technology innovation can introduce advanced equipment, continuously optimize the production process, improve the energy efficiency of enterprises, and reduce the carbon intensity of enterprises.

Organizational Factors

Dual-Carbon Leadership

Dual-carbon leadership referred to the comprehensive leadership capabilities and management levels demonstrated by enterprises in addressing climate change and achieving carbon peak and carbon neutrality goals. This leadership was reflected not only in the enterprise's deep understanding and long-term planning of carbon strategies but also in how effectively it organized resources, formulated and implemented carbon action plans, and addressed risks and opportunities related to carbon goals. Enterprises with higher levels of carbon leadership had senior managers who actively formulated and promoted strategies, policies, and measures closely related to carbon reduction, ensuring that carbon emission issues were thoroughly considered in daily operations. This leadership could guide the entire organization in forming a consensus and environment for low-carbon development, thereby significantly reducing the enterprise's CEI.

Financial Redundancy

Financial redundancy referred to the financial resources available for management's discretionary use after meeting necessary financial expenditures [48]. On the one hand, enterprises with ample financial redundancy are potentially more capable of bearing the risks and costs associated with transformation, making it easier for them to transition from high-carbon emission industries to low-carbon emission industries [49]. On the other hand, when enterprises face resource constraints, sufficient financial redundancy could serve as a buffer, helping to resolve internal conflicts, protect core technologies, promote innovation, and positively impact corporate social responsibility performance [49]. Therefore, financial redundancy serves as an internal resource buffer, providing the necessary financial support for enterprises to deal with external environmental changes.

Environmental Factors

Environmental Regulatory Pressure

Environmental regulatory pressure referred to the environmental laws and regulations issued by the government and market-based regulatory mechanisms [50]. Formal environmental regulatory pressure reflected the command-and-control and market-driven regulatory approaches. Faced with stringent environmental regulations and policies, manufacturing enterprises must adjust their production methods and business strategies to comply with environmental regulatory requirements. Environmental regulation can reduce enterprise carbon emissions by enhancing the level of environmental disclosure and environmental management concepts and accelerating the establishment of corporate environmental systems [40, 50]. Additionally, environmental regulation is of significant importance for green technology innovation in manufacturing. Appropriate environmental regulations have forced enterprises to reduce pollution emission costs, thereby promoting green technology innovation and serving as an important driver for the government to address environmental pollution issues [37]. Thus, formal environmental regulatory pressure is an important antecedent environmental factor that influences manufacturing enterprises' CEI.

Public Environmental Concern

Public environmental concern, as an informal environmental regulatory pressure [51], has become another important method of environmental governance in China [52]. Through mechanisms such as opinion pressure, low-carbon consumers, and environmentally friendly choices, the public could effectively reduce the likelihood of polluting enterprises entering the market, thereby achieving source control of pollution emissions [52]. Additionally, public environmental concerns can effectively promote enterprises' green technology innovation and enhance their carbon performance levels [53, 54]. It also helps amplify the suppressive effect of environmental regulations on enterprise carbon emissions [51]. Therefore, public environmental concerns have a significant impact on manufacturing enterprises' CEI.

Research Methods

NCA indicates the conditions necessary for the production of a specific result; without these conditions, the corresponding result cannot be achieved [55, 56]. fsQCA posits that, in analyzing a particular outcome, the combination of multiple conditions jointly determines the occurrence of the result rather than a single factor acting in isolation [57, 58]. It excels in elucidating successful pathways under different combinations of conditions and assists researchers in identifying the necessary and sufficient conditions within these combinations. Furthermore, it emphasizes the configuration of causal conditions, allowing for the equivalence of different pathways and rendering it suitable for analyzing complex phenomena and interdependent relationships [59]. In addition, machine learning, with its flexible model structure, can reveal complex nonlinear relationships between explanatory variables and outcomes rather than the net effects of individual variables [55]. Through measures of variable importance, machine learning methods facilitate the identification of explanatory variables that play a crucial role in predicting outcomes, providing researchers with indications of factors that warrant in-depth analysis. This approach is not only applicable to large datasets but also informs small-sample studies [60].

This study combines NCA, fsQCA, and machine learning algorithms for complementary analysis. NCA focuses on the necessity analysis of antecedents, whereas fsQCA focuses on the combination of sufficient conditions for antecedents. However, neither of these can rank the importance of the variables in the results. To solve this problem, this study draws on the mixed analysis method proposed by Jiang et al. (2023) [55] and incorporates a machine learning analysis to compensate for the shortcomings of NCA and fsQCA. This approach reveals the variables that play a critical role in influencing outcomes, making it an effective complement to the NCA and fsQCA.

The NCA identifies the necessity of antecedent conditions, assesses the effect size and statistical significance of these conditions, and determines the extent to which predictive antecedent conditions act as bottlenecks for the outcome variables [56]. However, the NCA does not provide an analysis of data sufficiency and does not offer detailed descriptions of the empirical cases. In contrast, fsQCA is suitable for analyzing complex causal relationships and interactions under multiple conditions. It explores how multiple concurrent causal relationships lead to the formation of complex social issues from a holistic perspective, explains complex real-world phenomena from a configurational perspective, and identifies antecedent conditions as necessary conditions for outcome variables [57]. To analyze the necessary and sufficient causal relationships for CEI in manufacturing enterprises,

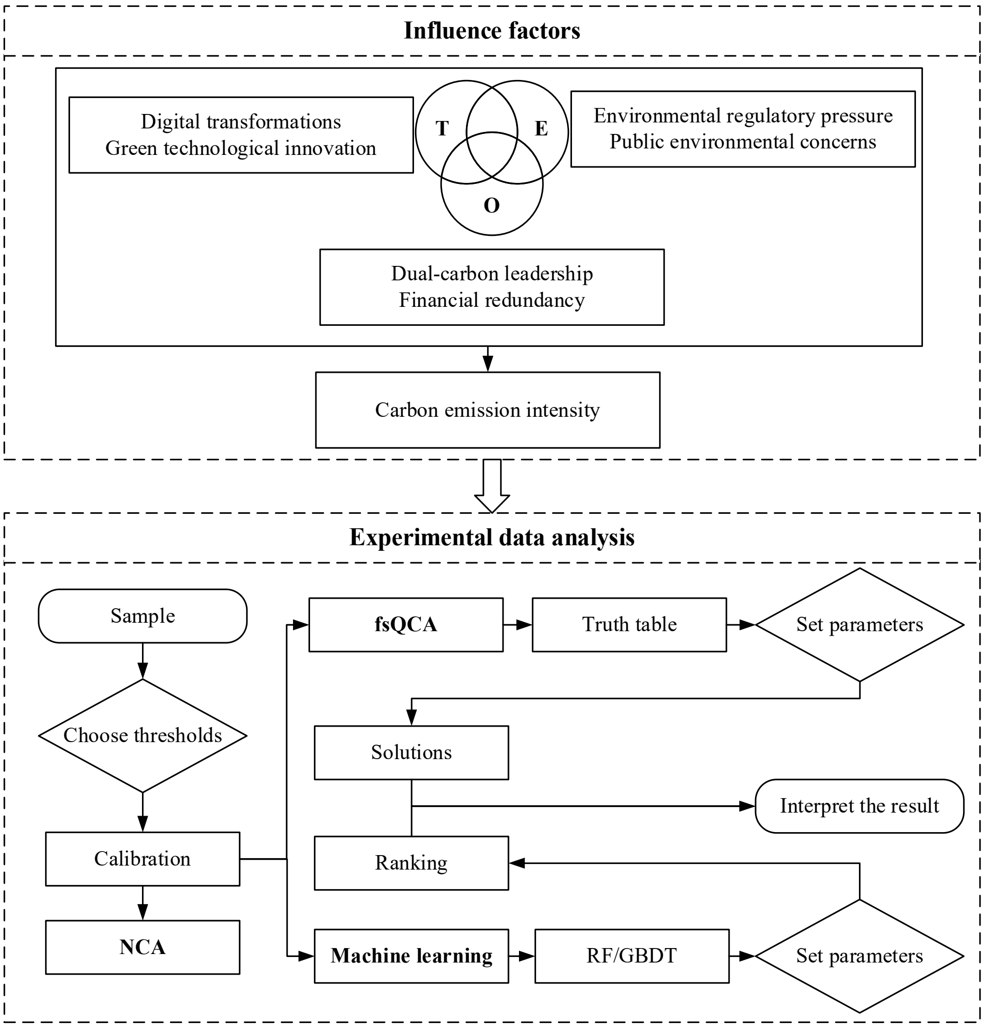

Fig. 1. Structural diagram of this study.

we combined NCA and fsQCA. The NCA identifies the conditions necessary for the CEI, whereas the fsQCA examines the impact of these conditions under different combinations on the CEI.

Subsequently, we used a tree-based ensemble learning method to predict the importance of the antecedent variables. This method predicts the target variable by constructing multiple decision trees and combining their results. It also excels at capturing complex nonlinear relationships and interactions [55]. We choose the random forest algorithm to identify the antecedent variables that are most important for predicting the CEI and use gradient-boosted decision trees for robustness checks. The integrated analytical approach used in this study provides a comprehensive perspective on complex causal relationships, and the complementarity of these methods enhances the understanding and predictive ability of complex phenomena. The technical routes used in this study are illustrated in Fig. 1.

Variable Measurement

For the CEI variable, the data come from the 2021 and 2022 rankings of carbon emissions for China's top 100 listed companies published by Caijing magazine. We calculated the CEI of each listed company by using the ratio of annual carbon emissions to annual business income.

In terms of technological condition variables, this study constructs an indicator for enterprise digital transformation by analyzing the frequency of keywords related to digital transformation in the annual reports of publicly listed companies. Specifically, we referred to the study by Yang et al. (2023) [61]. Using Python web scraping technology, we systematically collected annual report information from the CNINFO website. We then performed word segmentation using Jieba, incorporating stop words and a custom dictionary, to count the frequencies of keywords related to artificial intelligence technology, big data technology, cloud computing technology, blockchain technology, and the application of digital technologies across the five dimensions. We measured the degree of enterprise digital transformation by adding one to the counted frequencies and taking the natural logarithm. For green technological innovation, we assessed the level of innovation by adding one to the number of green technology patent applications of listed companies and taking the natural logarithm [62].

In terms of organizational condition variables, for dual-carbon leadership, we utilized the dual-carbon leadership data of China's top 100 listed companies published by Caijing magazine. This indicator identifies the various elements that enterprises need to have under the dual-carbon goals, including eight dimensions: strategic planning, management mechanisms, action plans, rules and regulations, support tools, assessment and constraints, brand promotion, and capacity building. Additionally, it incorporates recommendations from the Task Force on Climate-related Financial Disclosures (TCFD), including identifying, assessing, and managing climate risks and opportunities, integrating these requirements into the evaluation system, and assigning different weights to different dimensions. Ultimately, the dual-carbon leadership evaluation system for listed enterprises covers 10 key issues, 35 dimensions, and more than 120 sub-indicators, classifying dual-carbon leadership into excellent, very good, good, medium, and average levels. We converted these levels into corresponding numerical values ranging from 5 to 1, representing the levels from high to low. Additionally, for the financial redundancy variable, we used the enterprise financial ratio (the ratio of cash and cash equivalents to total assets). We measured an enterprise's financial redundancy by subtracting the average financial ratio of the total sample [63].

Regarding environmental condition variables, for formal environmental regulatory pressure, this study employs the proportion of industrial pollution control

Table 1. Sample descriptive statistics.

Variable	Mean	SD	Max	Min	N	Mean	SD	Max	Min	N
Year	2021					2022				
CEI	7.092	6.494	25.72	1.630	40	6.912	5.988	22.82	1.160	40
DT	1.481	1.045	4.543	0.000	40	1.364	0.997	4.094	0.000	40
GTI	1.386	1.334	3.466	0.000	40	1.284	1.217	3.497	0.000	40
DCL	2.200	0.992	5.000	1.000	40	2.725	0.877	5.000	1.000	40
FR	-0.030	0.054	0.143	-0.137	40	-0.038	0.048	0.097	-0.161	40
ERP	0.841	0.793	2.734	0.047	40	0.841	0.793	2.734	0.047	40
PEC	130.300	134.700	511.300	1.449	40	120.9	108.2	391.3	2.507	40

Note: CEI denotes carbon emission intensity; DT denotes digital transformation; GTI denotes green technology innovation; DCL denotes dual-carbon leadership; FR denotes financial redundancy; ERP denotes environmental regulatory pressure; PEC denotes public environmental concern. The abbreviations for the variables in the following tables have the same meanings as those in this table.

Table 2. Fuzzy-set membership calibrations.

Variables	Calibrations					
	2021			2022		
	Fully out	Crossover	Fully in	Fully out	Crossover	Fully in
CEI	18.783	3.660	2.287	17.837	3.800	2.175
DT	2.815	1.609	0.000	2.786	1.386	0.000
GTI	3.332	1.242	0.000	2.898	1.354	0.000
DCL	4.000	2.000	1.000	4.000	3.000	2.000
FR	0.047	-0.043	-0.111	0.027	-0.039	-0.115
ERP	2.734	0.540	0.048	2.734	0.540	0.048
PEC	511.337	95.406	13.605	391.317	101.132	15.693

investment in the secondary industry in the province where the listed company is registered as an indicator of the environmental regulatory pressure intensity faced by the enterprise [64]. To evaluate public environmental concerns, we used the Baidu search engine to conduct the keyword searches. We collected the average daily search volume for the terms "environmental pollution" and "smog" in various prefecture-level cities from 2021 to 2022 as the measurement standard [51]. Table 1 presents the descriptive statistics of the variables.

Data Calibration

Data calibration is the basis of the configurational analysis in QCA. In this study, the direct calibration method was utilized with a full membership set at 95%, crossover point at 50%, and full non-membership at 5%, thus converting the original variable data into fuzzy membership values between 0 and 1 [58]. Table 2 provides the details of the calibration data for each antecedent and outcome variable. To avoid samples with a fuzziness of 0.5 in the analysis, we follow standard practice and add a small constant (0.001) to each member with a fuzziness of 0.5 for configurational analysis, thus ensuring the accuracy of the QCA analysis [58].

Results and Discussion

Necessary Condition Analysis

In the necessity analysis, we combined NCA and fsQCA to identify the necessary conditions, as they employ different methods and criteria for calculating the necessary conditions. NCA analyzes the degree of necessity of conditions using quantitative methods, clearly indicating the importance of specific conditions at various levels for the outcome, whereas fsQCA employs qualitative methods to determine whether conditions are necessary without addressing the "quantitative" analysis of the degree of necessity of antecedent variables for the outcome. In other words, NCA focuses on quantitatively assessing the degree of influence of conditions, whereas fsQCA emphasizes the combination and existence of conditions. Therefore, the combined analytical approach of both methods can provide more concrete insights into the complex relationship between antecedent and outcome variables.

First, we chose the NCA for the necessity analysis. NCA not only helps us identify which conditions are essential for a specific outcome but also reveals the minimum standards required for these conditions to produce the outcome [55, 56]. To apply NCA, we employed two analytical methods to assess effect sizes: ceiling regression (CR) and ceiling envelopment (CE). To determine whether antecedent conditions are necessary for the outcome, the effect size of these antecedent conditions must be greater than 0.1, and the p-value of the effect size must be less than 0.01 after Monte Carlo simulation permutation tests [56]. Table 3 presents detailed results of the necessity analysis for each antecedent condition using the NCA method. The data in the table indicate that all the variables have effect sizes less than or equal to 0.1, and the p-values are not significant. This suggests that, in our study, these antecedent conditions are not necessary for the intensity of enterprise CEI. This finding provides an important direction for subsequent configurational analysis; specifically, we need to focus on the combinations and interactions between these conditions to gain a more comprehensive understanding of how they collectively impact enterprise CEI.

Next, to further understand the relationship between antecedent conditions and the outcomes of low or high CEI in enterprises, we conducted a necessity analysis using the fsQCA. In a necessity analysis, a condition is deemed necessary for an outcome if the consistency score between the condition and the outcome exceeds 0.9 [59]. Table 4 presents the results of the necessity tests. The results indicate that the consistency score for each condition is below 0.9, suggesting that no single factor constitutes a necessary condition for enterprises

Table 3. Analysis results of NCA method necessary conditions.

Year	Variable	Ceilings	Accuracy	Ceiling zone	Scope	Effect size	p-value
2021	DT	CR	100%	0.004	0.930	0.004	0.707
		CE	100%	0.008	0.930	0.009	0.701
	GTI	CR	100%	0.002	0.890	0.002	0.601
		CE	100%	0.003	0.890	0.004	0.601
	DCL	CR	100%	0.000	0.920	0.000	1.000
		CE	100%	0.000	0.920	0.000	1.000
	FR	CR	100%	0.004	0.960	0.004	0.938
		CE	100%	0.007	0.960	0.007	0.934
	ERP	CR	92.5%	0.088	0.880	0.100	0.070
		CE	100%	0.077	0.880	0.087	0.033
	PEC	CR	87.5%	0.052	0.900	0.058	0.373
		CE	100%	0.031	0.900	0.034	0.319
2022	DT	CR	100%	0.003	0.920	0.003	0.669
		CE	100%	0.005	0.920	0.006	0.669
	GTI	CR	100%	0.000	0.900	0.000	1.000
		CE	100%	0.000	0.900	0.000	1.000
	DCL	CR	100%	0.008	0.970	0.008	0.823
		CE	100%	0.015	0.970	0.016	0.788
	FR	CR	100%	0.009	0.960	0.009	0.864
		CE	100%	0.018	0.960	0.019	0.807
	ERP	CR	100%	0.038	0.870	0.044	0.249
		CE	100%	0.050	0.870	0.057	0.095
	PEC	CR	100%	0.018	0.890	0.020	0.530
		CE	100%	0.018	0.890	0.013	0.625

with either low or high CEI within the scope of this study.

Configuration Analysis

After the necessity analysis, truth tables were constructed to assess the sufficiency of the various condition configurations. Pappas and Woodside (2021) [58] showed that the consistency level for sufficiency should not fall below 0.75, with the frequency threshold for cases set at 1 for small samples and greater than 1 for large samples. In our study, we established a frequency of 1 for the sample, set the original consistency of the configuration at 0.8, and fixed the consistency for the prime implicants at 0.75. Intermediate and parsimonious solutions have been integrated to report configurations [59]. The results for these configurations are presented in Table 5.

Configurational Analysis of Low CEI

Based on the results presented in Table 5, we observed that a total of 11 pathways with low CEI were identified for 2021 and 2022. The consistency of all pathways exceeded 0.800, indicating that these pathways were sufficient conditions for a low CEI. This further confirms that various factors and their configurations influence the reduction in corporate CEI. Notably, green technological innovation is a core condition in all ten configuration pathways for achieving a low CEI. These findings support the view of Lee et al. (2022) [47] that green technological innovation is a crucial driving force for low-carbon transformation. We classified the 11 configuration pathways into five distinct modes of low CEI based on the distribution characteristics of the core conditions: technology-driven type, green technology innovation-led type, resource and public concern-driven type, technology-organization-environment

Table 4. Consistency and Coverage of Individual Condition Variables.

Year	Variables	Low CEI		Variables	High CEI	
		Consistency	Coverage		Consistency	Coverage
2021	DT	0.655	0.731	DT	0.523	0.512
	dt	0.563	0.574	dt	0.725	0.648
	GTI	0.719	0.814	GTI	0.389	0.386
	gti	0.458	0.461	gti	0.812	0.716
	DCL	0.661	0.696	DCL	0.631	0.582
	dcl	0.604	0.651	dcl	0.671	0.634
	FR	0.795	0.748	FR	0.599	0.493
	fr	0.461	0.567	fr	0.694	0.748
	ERP	0.502	0.576	ERP	0.739	0.743
	erp	0.776	0.772	erp	0.578	0.504
	PEC	0.553	0.725	PEC	0.511	0.588
	pec	0.686	0.615	pec	0.761	0.598
2022	DT	0.649	0.683	DT	0.582	0.566
	dt	0.588	0.603	dt	0.674	0.639
	GTI	0.681	0.761	GTI	0.417	0.430
	gti	0.490	0.477	gti	0.768	0.690
	DCL	0.457	0.630	DCL	0.495	0.631
	dcl	0.733	0.611	dcl	0.710	0.547
	FR	0.683	0.688	FR	0.670	0.624
	fr	0.627	0.673	fr	0.665	0.659
	ERP	0.542	0.607	ERP	0.697	0.720
	erp	0.750	0.373	erp	0.619	0.555
	PEC	0.568	0.712	PEC	0.482	0.559
	pec	0.648	0.576	pec	0.752	0.616

Note: Uppercase letters indicate the presence of condition variables; lowercase letters indicate their absence.

collaborative type, and technology-environment-driven type. The detailed analysis is as follows.

Technology-driven type (C1a, C1b): Configuration C1a indicates that digital transformation and green technology innovation exist as core conditions, while dual-carbon leadership serves as a peripheral condition, and financial redundancy in the absence of peripheral condition. This suggests that enterprises can successfully achieve a low CEI through high levels of digital transformation and green technological innovation combined with appropriate dual-carbon leadership. Configuration C1b shows that high digital transformation and green technological innovation exist as core conditions, with financial redundancy as a peripheral condition, and environmental regulation and public environmental concern in the absence of peripheral conditions. In this configuration, enterprises can achieve a low CEI. Compared to Configuration C1a, Configuration C1b indicates that when green technological innovation and digitalization reach high standards, financial redundancy and dual-carbon leadership are interchangeable in the process of achieving a low CEI in the technology-driven type. The technology-driven model underscores the importance of enterprises achieving a low CEI through their own digital transformation, green technological innovation, high dual-carbon leadership, and strong financial support in the absence of external environmental pressures. This configuration path highlights the indispensability of green technological innovation and digital transformation for proactive implementation of low-carbon emissions by enterprises.

Green technology innovation-led (C2a, C2b): Configuration C2a indicates that high green technology innovation serves as a core condition, whereas digital transformation and financial redundancy are absent as peripheral conditions. Even when dual-carbon leadership and environmental regulations are missing core conditions, a low CEI can still be achieved. Similarly, Configuration C2b shows that high green technology innovation is a core condition, with digital transformation, environmental regulation, and public environmental concern absent as peripheral conditions. When dual-carbon leadership and financial redundancy are missing as core conditions, manufacturing enterprises can achieve a relatively low CEI. The green technology innovation-led model suggests that green technology innovation plays a leading role in driving low-carbon transformation and maintaining effective carbon reduction even in the absence of various conditions. This indicates that green technology innovation has a sufficient driving force to compensate for the lack of other conditions.

Resource and public concern-driven type (C3): Configuration C3 indicates that high dual-carbon leadership, high financial redundancy, and strong public environmental concerns serve as core conditions, while digital transformation acts as a peripheral condition. Even when environmental regulation is absent as a peripheral condition, enterprises can successfully achieve low carbon emissions. The resource and public concern-driven model suggests that dual-carbon leadership, as an enterprise's capability and strategy for setting and implementing dual-carbon goals combined with substantial financial support and external public environmental concern, incentivizes enterprises to adopt proactive environmental protection measures. Digital transformation as a peripheral condition further supports enterprises in optimizing resource management, thereby promoting the achievement of a low CEI.

Technology-organization-environment collaborative type (C4, C5a, C5b): Configuration C4 indicates that with high levels of green technology innovation, high financial redundancy, and strong public environmental concern as core conditions, the presence of environmental regulation as a peripheral condition, and the absence of digital transformation as a peripheral condition, enterprises can still successfully achieve a low CEI. Configuration C5a shows that when enterprises have high levels of green technology innovation, high dual-carbon leadership, substantial financial resources, and strong public environmental concerns as core conditions, with digital transformation absence as a peripheral condition, manufacturing enterprises can still achieve a low CEI. Configuration C5b, similar to C5a, also emphasizes the importance of high levels of green technology innovation, high dual-carbon leadership, substantial financial resources, and high environmental concern as core conditions. The technological, organizational, and environmental synergy models reflect the interdependence and synergistic effects of technological, organizational, and environmental factors in achieving a low CEI within enterprises. Green technology innovation and dual-carbon leadership are core drivers, while financial resources and public environmental concerns provide support and incentives. Even when certain peripheral conditions are absent, enterprises can successfully achieve a low CEI, as long as the core conditions are met. This underscores the importance of the synergistic action of multiple factors in achieving a low CEI.

Technology-environment-driven type (C6a, C6b, C7): Configuration C6a indicates that with high levels of digital transformation, high green technology innovation, and strong public environmental concern existing as the core conditions and dual-carbon leadership existing as a peripheral condition, even in the absence of environmental regulation as a core condition, enterprises can still achieve a low CEI. Configuration C6b shows that with high levels of digital transformation, high green technology innovation, and strong public environmental concern existing as core conditions and financial redundancy existing as a peripheral condition, while environmental regulation is absent as a core condition, enterprises can still establish pathways to drive a low CEI. These two configurations suggest that enterprises can create effective low-carbon emission pathways by leveraging digital tools and innovations in green technology, combined with public environmental awareness and support. Despite the lack of environmental regulations, enterprises can achieve low-carbon goals by enhancing their internal management efficiency and innovative practices. Comparing configurations C6a and C6b, we observe that financial redundancy and dual-carbon leadership are interchangeable in these technological and environmental driving models, respectively. Configuration C7 indicates that when digital transformation is absent as a core condition, but high green technology innovation and environmental regulation are present as core conditions and financial redundancy exists as a peripheral condition, enterprises can still form pathways to drive low CEI in the absence of dual-carbon leadership and public environmental concerns. This pathway demonstrates the core role of green technology and environmental policies in achieving low-carbon goals. The technological and environmental drive model highlights that manufacturing enterprises with strong digital transformation and green technological innovation capabilities can adopt various strategies to achieve a low CEI under moderate external incentives and regulations.

To analyze whether these configurations evolve over time, we conducted an evolutionary analysis of the configurations that lead to a low CEI. A comparison of all the low CEI configurations in Table 5 between 2021 and 2022 reveals several significant trends. First, the green technology innovation-led (C2a and C2b) demonstrate stability over time, with configurations C2a appearing in 2021 and C2b in 2022. Second, the technology-driven pathways (C1a and C1b) gradually evolved into technology-environment-driven types

(C6a and C6b), reflecting the growing public attention to carbon emission issues. Finally, the technology-organization-environment collaborative type (C5a and C5b) showed stability and maintained consistency over time.

Configuration Analysis of High CEI

Comparing the results in Table 5, we can see that among the various configurational pathways leading to high CEI, informal environmental regulation (public environmental issues) appears as a core condition in multiple configurational pathways (C8a, C8b, C10), while green technology innovation is absent as a core condition (C8a, C8b, C9, C10). This implies that the absence of green technology innovation in enterprises may lead to a high CEI, and a high CEI will arouse more public environmental concern. These regulations and oversight are particularly pronounced when enterprises exhibit a high CEI. From the information in Table 5, we find that in 2021 and 2022, there are four driving pathways leading to a high CEI, all of which have consistency greater than 0.800. These four pathways were sufficient to form a high CEI. Based on the distribution of core conditions in these pathways, we categorized them into three high CEI patterns: technology capability-constrained type, technology environment-lacking type, and green technology innovation-deficient type. The detailed analysis is as follows.

Technology capability-constrained type (C8a, C8b): These two configuration pathways indicate that, even with strong public environmental concern as a core driving force, the absence of core conditions, such as enterprise digital transformation and technological innovation, along with the lack of peripheral conditions, such as dual-carbon leadership or financial redundancy, results in a high CEI. This configuration indicates that high CEI has drawn significant public attention to the issue of carbon emissions. However, in the absence of necessary technological capabilities and resource support, companies struggle to address this challenge effectively, resulting in the persistence of high CEI levels. In this context, companies face the dual challenges of environmental pressure and limitations in technological resources, hindering their ability to reduce carbon emissions rapidly. Failing to meet public expectations may result in reputational damage.

Technology environment-lacking type (C9): This configuration pathway indicates that when high dual-carbon leadership is present as a core condition, with digital transformation and environmental regulation as supporting conditions, and the absence of green technology innovation and public environmental concern as core conditions, enterprises face the risk of a high CEI. This pathway suggests that a lack of green technology leads to a technological innovation lag, failing to reduce carbon emissions effectively. Additionally, the absence of external pressure to drive environmental actions limits an enterprise's adaptability to policy requirements, ultimately impairing its long-term competitiveness and sustainable development capabilities.

Green technology innovation-deficient type (C10): This configuration pathway indicates that when high financial redundancy, strict environmental regulations, and high public environmental concern are present as core conditions with dual-carbon leadership as a peripheral condition, the absence of green technology innovation as a core element, along with the lack of digital transformation as a peripheral condition, still results in a high CEI. This pathway suggests that the lack of green technology innovation restricts the application and development of low-carbon technologies, and the absence of digital transformation prevents the optimization of production processes and energy management. Although financial resources, external policies, and public pressure provide impetus, the lack of technological means makes it difficult for enterprises to achieve effective carbon reduction.

Robustness Test

This study tested the robustness of the results by adjusting the consistency criteria. First, the consistency threshold was raised from 0.80 to 0.85, and second, the PRI value was increased from 0.75 to 0.8, with specific results shown in Table 6. Table 6 indicates that the single and overall consistencies of both antecedent variables were above 0.9. One pathway from 2021 was reduced in the low CEI pathway, whereas the others remained consistent. However, 2022 saw significant changes, retaining only one pathway, with the new pathway C5 similar to pathway C6a from the original Table 5, indicating a shift in one of the core conditions [65]. Regarding the high CEI pathways, the 2021 pathways are very similar, while those from 2022 show some similarities, meaning that most core conditions remain stable, although other core and peripheral conditions have changed [65]. Overall, the results were considered reliable.

Importance Analysis of Influencing Factors

This study utilizes random forest and gradient boosting decision tree algorithms to rank the importance of the influencing factors. Random forest and gradient boosting decision tree algorithms are widely recognized as versatile methods capable of generating rankings for variable importance [60]. Unlike the fsQCA method, which identifies multiple pathways to low CEI, machine learning methods aim to build an optimal predictive model based on multiple influencing factors to determine the outcomes [55]. Considering the sample size requirements of machine learning, we used data from 2021 and 2022 as training samples and optimized the model parameters using a grid search while employing 10-fold cross-validation to reduce model bias. Using six antecedents from the TOE framework as input

Table 5. Configuration results of enterprise carbon emission intensity.

Variable	Low CEI											High CEI			
Year	2021						2022					2021		2022	
Configuration	C1a	C1b	C2a	C3	C4	C5a	C2b	C5b	C6a	C6b	C7	C8a	C8b	C9	C10
DT	●	●	⊗	•	⊗	⊗	⊗		●	●	⨂	⨂	⨂	•	⊗
GTI	●	●	●		●	●	●	●	●	●	●	⨂	⨂	⨂	⨂
DCL	•		⨂	●		●	⨂	●	•		⊗		⊗	●	•
FR	⊗	•	⊗	●	●	●	⨂	●		•	•	⊗			●
ERP		⊗	⨂	⊗	•		⊗		⨂	⨂	●	•	•	•	●
PEC		⊗		●	●	●	⊗	●	●	●	⊗	●	●	⨂	●
Consistency	0.989	0.956	0.982	0.971	0.940	0.975	0.929	0.950	0.975	0.932	0.937	0.983	0.979	0.979	0.927
Raw coverage	0.270	0.320	0.233	0.241	0.191	0.200	0.050	0.255	0.210	0.252	0.227	0.271	0.298	0.143	0.212
Unique coverage	0.072	0.095	0.072	0.061	0.022	0.042	0.219	0.051	0.007	0.021	0.046	0.037	0.063	0.017	0.085
Overall solution consistency	0.947						0.933					0.981		0.932	
Overall solution coverage	0.633						0.455					0.335		0.229	

Note: Large black circle (●) denotes the core presence of a condition; Large cross-out circle (⨂) denotes the core absence of a condition; Small black circle (•) denotes the peripheral presence of a condition; Small cross-out circle (⊗) denotes the peripheral absence of a condition; Blank spaces imply that the conditions can be either present or absent; solutions with the same core conditions are differentiated by the suffix “a/b/c”.

Table 6. Configuration results of enterprise carbon emission intensity.

Variable	Low CEI						High CEI			
Year	2021					2022	2021		2022	
Configuration	C1a	C1b	C2a	C3	C4	C5	C6a	C6b	C7a	C7b
DT	●	●	⊗	•	⊗	●	⨂	⨂	•	⊗
GTI	●	●	●		●	●	⨂	⨂	⨂	⨂
DCL	•		⨂	●	●	●			●	●
FR	⊗	•	⊗	●	●				●	●
ERP		⊗	⨂	⊗		⨂	•	•	●	●
PEC		⊗		●	●	●	●	●	⊗	•
Consistency	0.989	0.956	0.982	0.971	0.975	0.975	0.979	0.983	0.965	0.979
Raw coverage	0.270	0.320	0.234	0.241	0.200	0.210	0.298	0.037	0.189	0.144
Unique coverage	0.072	0.095	0.084	0.061	0.047	0.210	0.063	0.272	0.062	0.017
Overall solution consistency	0.960					0.975	0.981		0.968	
Overall solution coverage	0.610					0.210	0.335		0.205	

Note: Large black circle (●) denotes the core presence of a condition; Large cross-out circle (⨂) denotes the core absence of a condition; Small black circle (•) denotes the peripheral presence of a condition; Small cross-out circle (⊗) denotes the peripheral absence of a condition; Blank spaces imply that the conditions can be either present or absent; solutions with the same core conditions are differentiated by the suffix “a/b/c”.

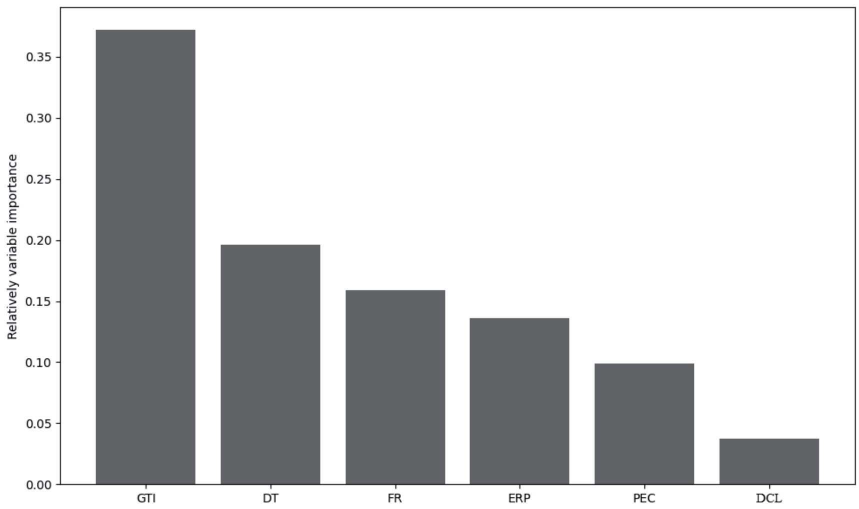

Fig. 2. Importance of random forest algorithm.

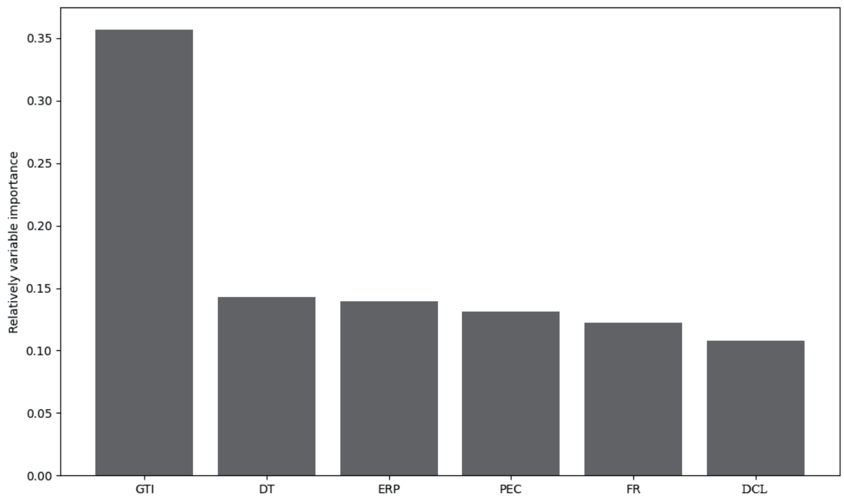

Fig. 3. Importance of gradient boosting decision tree algorithm.

variables, we constructed predictive models for CEI using random forest and gradient-boosting decision tree regressions. Fig. 2 displays the results of the random forest algorithm, and Fig. 3 presents the results of the gradient boosting decision tree. Both machine learning algorithms indicate that, compared to other influencing factors, green technology innovation has the highest importance for enterprise CEI. This result corresponds with the fsQCA analysis, which also identifies green technology innovation as a core condition appearing in multiple configurational pathways. Although dual-carbon leadership has the lowest relative importance, it still plays a significant role in configurational pathways. All six elements contribute to reducing enterprises' CEI.

Conclusions

This study aimed to reveal the multifaceted drivers of CEI in manufacturing enterprises. Our findings suggest that no single factor is sufficiently deterministic to achieve a low CEI, as indicated by the NCA and fsQCA necessity conditions. Furthermore, fsQCA reveals that reductions in CEI stem from the complex interplay and synergistic coordination among the technological, organizational, and environmental dimensions. We identified 11 configurational pathways leading to a low CEI, with green technology innovation playing a pivotal role in ten of these pathways. These pathways were classified into five categories based on their core conditions: technology-driven type, green technology innovation-led type, resource and public concern-driven type, technology-organization-environment collaborative type, and technology-environment-driven type. Conversely, four configurational pathways were associated with a high CEI. Public environmental concern emerges as a core condition in three of these pathways, whereas the absence of green technology innovation correlates with an increased CEI. We categorized these configurational pathways as technological capability constraints, technological and environmental absence, and green technology innovation absence patterns. Machine learning algorithms further corroborate the preeminent role of green technology innovation in diminishing CEI within the sector, underscoring its relative importance compared with other factors.

Theoretical and Management Implications

Our study makes three main theoretical contributions. First, we provide a more comprehensive and detailed pathway for reducing the CEI of manufacturing enterprises. Previous studies have mostly focused on individual factors, such as the impact of digital transformation [2, 9, 15, 31, 66, 67], green technological innovation [30, 32, 33, 36, 68, 69], and environmental regulations [37, 39, 70] on corporate carbon emissions. However, carbon emissions in enterprises represent a complex system that is subject to multiple constraints, such as technological capabilities, organizational resources, and external environments [18]. Based on the existing literature and the TOE framework, we shifted from a single-perspective approach to a systemic perspective by collecting longitudinal carbon emission data from manufacturing enterprises listed on the Chinese stock market. From the technological, organizational, and environmental dimensions, we identified the synergistic effects among different factors, emphasizing the impact of multifactor combinations on the CEI. This study addressed the limitations of previous research [71], which primarily focused on single factors.

Second, our findings enrich the literature on carbon emissions from manufacturing enterprises. Specifically, published literature [20] pointed out that the CEI of manufacturing enterprises is closely related to green technological advancements, organizational strategic support, and the regulatory role of the policy environment. However, they did not consider the significant impact of digital transformation and dual-carbon leadership on manufacturing enterprises' carbon emissions. Furthermore, in our configuration path analysis, we incorporated temporal effects to provide enterprises with dynamic strategies for reducing emissions. More importantly, against the backdrop of carbon neutrality goals, we were the first to investigate the effect of dual-carbon leadership on carbon emissions, offering a new perspective for the development of the literature on dual-carbon leadership in carbon emission studies.

Third, by integrating NCA, fsQCA, and machine learning, we provide a more abundant method to supplement the existing research literature on enterprise carbon emissions. The conclusions of these three methods can be mutually verified, which not only improves the accuracy and reliability of the research conclusions but also provides a multidimensional perspective for the study of the CEI. This enables researchers to make comprehensive use of different analytical tools when exploring complex phenomena, responding to the recent call for multi-method research on corporate carbon emissions [18], and promoting the trend of widespread adoption of multi-method research in this field.

Limitations and Future Research Directions

Our study had some limitations. First, from a theoretical perspective, although the study employs the TOE framework to investigate the technological, organizational, and environmental determinants of enterprise CEI, it could benefit from a deeper exploration of additional factors to expand this theoretical framework. Second, regarding the research subjects, this study's case samples were manufacturing enterprises from China's carbon emissions rankings, and the conclusions may only apply to manufacturing enterprises' carbon emissions issues. According to China's carbon emission ranking, the electricity sector is the largest emitter. Future research could explore the pathways that drive carbon emissions in the electricity sector. Finally, future studies could employ dynamic qualitative comparative analysis to uncover the intricate and evolving causal relationships between different antecedents, their configurations, and manufacturing enterprises' CEI.

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Conflict of Interest

The authors declare that they have no conflicts of interest.

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