

Article

Carbon Reduction Effects in Transport Infrastructure: The Mediating Roles of Collusive Behavior and Digital Control Technologies

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Abstract: Many countries have committed to carbon reductions and carbon neutrality targets in response to the Paris Agreement and Sustainable Development Goals (SDGs). With economic development, the transportation sector has become a major source of carbon emissions. In China, transport infrastructure—as an important carrier of the transportation sector—is important for controlling carbon emissions from this sector and achieving carbon neutrality and the targets of the SDGs. However, most studies have focused on transport vehicles and neglected transport infrastructure. Furthermore, the influences of collusive behavior and digital control technologies on the carbon reduction process have not yet been examined. This study aimed to analyze the influencing factors in the carbon reduction process in transport infrastructure. This study uses partial least squares structural equation modeling (PLS-SEM) to analyze the factors influencing carbon reductions in transport infrastructure and the mediating roles of collusive behavior and digital control technologies in the carbon reduction process. Low-carbon technologies, digital control technologies, and collusive behavior have positive direct and indirect effects on the carbon reduction effect. Digital control technologies have a positive effect on low-carbon regimes. Low-carbon technologies influence carbon reduction effects. Collusive behavior plays a mediating role in low-carbon regimes. Finally, the industrial structure influences carbon reduction effects. This study extends China’s carbon emission research in the transportation sector by focusing on infrastructure rather than vehicles. Additionally, this is the first study to incorporate collusive behavior and digital control technologies into the framework to analyze the impact of carbon reductions. The study also employs PLS-SEM to explore effective carbon reduction paths. The findings provide decision-making support for controlling carbon reductions in transport infrastructure.

Keywords: carbon neutrality; transport infrastructure; carbon reduction; digital control technologies; collusive behavior; PLS-SEM; sustainable transport



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1. Introduction

Energy demand is expected to increase by 34% by 2035 as the world’s population grows rapidly and urbanization occurs [1]. The resulting increase in energy consumption will substantially enhance carbon emissions and accelerate climate change, which is a major threat to society. To address climate threats, both the Paris Agreement and the Sustainable Development Goals (SDGs) have proposed long-term greenhouse gas reduction strategies, and many scholars have proposed various initiatives to reduce carbon emissions [2]. Most researchers believe that carbon neutrality refers to a state of net-zero emissions following efforts to reduce or offset carbon emissions [3,4].

Transport has become the second largest source of carbon emissions, accounting for over 24% and continuing to grow rapidly [1]. Enhancing the carbon reduction effect (CRE) in transport infrastructure and understanding the factors influencing this effectiveness have

sparked the interest of many researchers. The literature identifies several factors influencing the effectiveness of carbon reduction strategies. These factors fall into three main categories: economic, institutional, and technological. Most studies have focused on energy and industry while placing less emphasis on transport infrastructure; moreover, they have not examined the impact of the social environment and use of digital control technologies (DC) on the effectiveness of carbon reduction strategies [5–7]. Khan et al. [8] showed that low-carbon targets can be achieved by improving the capacity and effectiveness of energy management. Therefore, maximizing carbon reductions and improving carbon emission management are important for achieving carbon neutrality targets and promoting the sustainable development of transport infrastructure. Alola et al. [9] noted that low-carbon awareness contributes to sustainable social development. Chen et al. [5] pointed out that DC have a positive effect on the achievement of carbon neutrality targets. However, the contributions of the various influencing factors behind the effectiveness of carbon reductions in transport infrastructure remain unexamined. The literature on the role of the social environment and DC in the carbon reduction process within transport infrastructure is inadequate. Finding answers to these questions thus requires further research.

Many countries have committed to carbon reduction and neutrality in response to the Paris Agreement and to achieve the Sustainable Development Goals (SDGs). With economic development, the transportation sector has become an important source of CO₂ emissions. As an important carrier of the transport industry, the transport infrastructure is of great significance in controlling carbon emissions from this sector and achieving carbon neutrality and the SDGs targets. However, most studies have focused on transport vehicles and neglected the transport infrastructure itself. Furthermore, the influence of collusive behavior and digital control on the process of carbon reduction has also not been examined. The novelties of this paper are as follows: (1) the subject of the study is the transport infrastructure, rather than the common vehicle, extending the existing research perspectives; and (2) in the construction of the research model, the consideration of collusive behavior and the impact of digital regulation is incorporated.

This study aims to address the following questions:

Do economic, institutional, and technological factors still play a role in the carbon reduction process in transport infrastructure?

Does collusive behavior mediate the relationships among industrial structure, low-carbon regimes, and the effectiveness of carbon reductions?

Do DC mediate the effects of low-carbon regimes and LCTs on carbon reductions?

In the second part of this study, a literature review is conducted to summarize the relevant studies on carbon emission reduction in transport infrastructure, which provides the basis for model construction; in the third part, the basic hypotheses of the study are put forward on the basis of the analysis of the literature; in the fourth and fifth parts, the constructed model is analyzed and verified by using the PLS-SEM method, and the conclusions are obtained; and in the sixth part, the conclusions are summarized, recommendations are made for the research issues, and the limitations of the study are explained. problems, and the limitations of the study are explained.

2. Literature Review

2.1. Carbon Neutrality Studies

Growing energy demand has impacted global climate change. In response to climate change, many countries worldwide have proposed carbon neutrality targets, and more than 30 have established explicit carbon emission plans [10]. Carbon neutrality is the achievement of net-zero carbon emissions within a specified period [11] (IPCC, 2020). However, many other countries have not yet set carbon neutrality goals. Australia and New Zealand were the first countries to develop and implement carbon-neutral systems (called “zero-carbon emission systems” in New Zealand). Only a few countries, such as Norway and Denmark, refer to their carbon neutrality goals as “climate neutral”, and

most countries, including China, refer to them as a “carbon neutrality target” in their policies [12].

Many scholars have studied methods of achieving carbon neutrality. The path to achieve the dual carbon goal comprises the following two steps: first, reduce carbon sources and greenhouse gas emissions, mainly carbon; second, increase carbon sinks through various means and technologies to increase the amount of carbon absorbed [13]. Regarding infrastructure, using energy-efficient materials and technological innovations can reduce carbon emissions, while cutting-edge technology is essential for achieving carbon neutrality goals [14].

Worldwide, countries are gradually turning carbon neutrality targets into national strategies and actively adopting carbon reduction measures to achieve net-zero carbon emissions within a specified period. Therefore, it is of theoretical and practical significance to explore the factors influencing carbon reductions. Only a few scholars have focused their carbon reduction research on the main body of transport infrastructure under the carbon neutrality target. Most have studied the factors influencing carbon reductions from power, transportation, steel, and other industries [15–17]. These show that a carbon neutrality target can only be achieved through the combined effect of technological innovation and industrial restructuring [18,19].

2.2. Carbon Emissions from Transport Infrastructure

In the transport industry, transport infrastructure not only plays an important role in supporting and guaranteeing socioeconomic development but is also a major source of carbon emissions [20]. Transport infrastructure generates large amounts of carbon emissions during the construction, operation, and maintenance phases, which increase with the increase in such infrastructure. Further, with continuous economic development, demand for transport infrastructure will grow rapidly. To accommodate this rising demand, controlling carbon emissions from transport infrastructure has become an urgent issue. Therefore, the control and management of carbon emissions from transport infrastructure can help promote overall carbon reduction [21,22]. Carbon emissions from transport include not only emissions from transport infrastructure, which are fixed sources such as roads, ports, airports, etc., but also emissions from transport equipment, which are mobile sources such as cars, trains, and lorries, and the factors influencing carbon emissions from transport infrastructure are more related to the infrastructure itself [23,24]. Therefore, the factors influencing them are also quite different. Carbon reduction in transport infrastructure can also be achieved through the promotion of sustainable modes of transport, with scholars focusing on emissions modeling, travel patterns, shared mobility, and environmental monitoring of roads for sustainable transport [25–27]. However, most existing studies have focused on measuring carbon emissions and analyzing the factors influencing them in the transportation sector, including exploring the impact of the type of transport, volume of transport, and mode of energy supply (e.g., oil, electricity) on carbon emissions [24]. By contrast, only a few scholars have focused on the factors influencing carbon emissions in transport infrastructure.

2.3. Carbon Emission-Related Digital Control Technologies

Since DC play an important role in the real-time monitoring of carbon emissions in energy production, transportation, and consumption, it can be assumed that they help achieve carbon neutrality. With the continuous advancement of research on this topic, emerging technologies such as big data, digital twins, artificial intelligence, and blockchain technology have been increasingly adopted to mitigate carbon emissions.

In practical applications, DC can regulate carbon emissions by analyzing the capacity for carbon capture [3,28]. On this basis, a carbon emission trading platform can be constructed based on the principles of “decentralization, transparency, security, non-tampering, and traceability” of Internet and blockchain technology [3]. Enterprises with carbon emissions above or below the set quota can buy or sell carbon offsets on the plat-

form [29]. However, the use of DC also generates carbon emissions owing to their high power consumption and high dependence on energy localization [30]. Research largely ignores carbon emissions from digital technology, which lowers the efficiency of carbon reduction processes.

2.4. Impact of Collusive Behavior on Carbon Emissions

Infrastructure construction suffers from a high incidence of collusion. In carbon emission regulation, there is not only government–enterprise collusion but also collusion between enterprises and third-party institutions. The occurrence of these behaviors adversely affects the control of carbon emissions. Collusive behavior is defined in this paper as “two or more entities colluding to violate relevant policies and engage in carbon-intensive behaviors in order to achieve higher revenues for themselves without being penalized.” Research reveals a dynamic relationship between regional collusion and carbon emissions in developing countries: regional collusion first leads to an increase in carbon emissions, which is unfavorable to carbon reductions, and then drives up carbon emissions [31]. Third-party verification agencies collude with companies to falsely report carbon emissions for profit, which seriously hinders the carbon reduction process [32]. However, research largely focuses on preventing the occurrence of collusive behavior and formulating punitive measures for when it occurs, as the occurrence of such behavior results in economic losses and reduced environmental performance that are difficult to recover from even if they are remedied. Therefore, detecting ongoing collusion and combating it remains challenging.

The existing literature on the reduction of carbon emissions in the field of transport has been reviewed, and it can be seen that the majority of research has focused on vehicles, traveling modes, planning, and other related issues. There is, however, a paucity of studies on the impact of emission reduction on transport infrastructure. Furthermore, there is a dearth of research that has sought to design how multiple factors work together in order to achieve emission reduction. This research paper seeks to address these shortcomings.

3. Research Hypotheses

3.1. Impact of the Industrial Structure on Carbon Reductions

The traditional high-carbon industrial structure (IS) and development model are major drivers of the increased carbon emissions in China. In the context of carbon neutrality, traditional generation structures and development models urgently need to be optimized and updated. The term “industrial structure” refers to the composition, interrelationships, proportions, and links among industries in the national economy of a country or region. The IS has a direct impact on the energy consumption and carbon emissions of each industry. By optimizing and adjusting the industrial structure, the overall industrial system can generate economic benefits while reducing environmental pressure, thus achieving the low-carbon transformation of the industrial chain [33]. The increase in the share of the tertiary sector and economic growth play important roles in curbing carbon emission intensity [34]. Therefore, the rationalization of the IS can improve carbon efficiency and reduce carbon emissions, which are the key drivers of carbon reductions [35,36]. Zhou et al. [37] pointed out that industrial restructuring can reduce carbon emissions. However, during industrial restructuring, the IS is influenced by the collusion of economic agents bound by a uniform scale of competition [38]. Therefore, collusive behavior during industrial restructuring is not conducive to the development of a structure toward rationalization [39]. Controlling collusive behavior can thus help drive the IS in a low-carbon direction. Based on the foregoing, we propose the following hypotheses:

Hypothesis 1 (H1): The IS affects carbon reductions.

Hypothesis 2 (H2): The IS affects collusive behavior.

3.2. Impact of Low-Carbon Technologies on Carbon Reductions

In transport infrastructure, low-carbon technology (LCT) refers to the methods used in the design, construction, operation, and maintenance of transport infrastructure projects that reduce carbon emissions. Increased spending on technology can reduce carbon emissions to a limited extent; however, in today's climate, breaking the technology bottleneck and developing LCTs are the key factors to reducing carbon emissions from infrastructure [6]. However, if it is not economical to adopt low-carbon technologies, the transition to alternative technologies such as low-carbon fuel substitution technologies will occur, not only to reduce carbon intensity but also to help dispose of waste. In the context of carbon neutrality goals, the implementation of LCTs can enhance infrastructural development, making it necessary to promote the innovation and deployment of low-carbon technologies and replace current high-carbon technologies with these alternatives to reduce energy and carbon intensities [40]. Therefore, adopting LCTs can reduce carbon emission intensity and achieve greater carbon reductions; however, LCTs are affected by policies, expenditure, and application prospects.

DC (e.g., digital management platforms and carbon emission monitoring systems) can be used to control carbon emissions. Such technologies provide safe and reliable technical support for energy production, promote the innovation of low-carbon technologies, and establish a digital operation and control system, which can also monitor and manage greenhouse gases, thus helping reduce carbon emissions [3]. In addition, the application of LCTs in transport infrastructure has been found to reduce the cost of government and improve its efficiency, thus effectively avoiding collusive behavior between local governments and enterprises and prompting enterprises to reduce emissions [41]. Consequently, LCTs, DC, and collusive behavior also play a role in promoting carbon reductions. Based on the foregoing, we propose the following hypotheses:

Hypothesis 3 (H3): LCTs affect the effectiveness of carbon reductions.

Hypothesis 4 (H4): LCTs affect DC.

Hypothesis 12 (H12): LCTs indirectly affect the effectiveness of carbon reductions through collusive behavior.

3.3. Impact of Low-Carbon Regimes on Carbon Reductions

Transport infrastructure continues to have high levels of energy consumption and emissions. Reducing carbon in transport infrastructure requires the joint action of multiple factors. Many researchers have investigated whether current low-carbon policies can help achieve carbon reduction goals and the reasons that hinder the implementation of low-carbon policies. From the government's perspective, inadequate laws and regulations related to carbon taxes and the insufficient implementation of low-carbon policies are the main factors restricting the development of low-carbon buildings [42]. Limited investment budgets and a lack of knowledge and experience of LCTs are thus important reasons for this inability to implement low-carbon policies [43]. However, most scholars believe that low-carbon policies can reduce the carbon emissions of enterprises.

When enterprises carry out production activities under a low-carbon system, an overly strict carbon trading system weakens enterprises' carbon reductions. In this regard, to compensate for their reduced profits, in the absence of prior communication, jointly choose the strategy of raising prices to avoid losses. The choice of enterprises to follow low-carbon policy is not constrained only by the carbon reduction target, as the government's DC significantly mediate the effect of an enterprise's carbon reductions. DC, which the government uses to review the carbon emissions of enterprises to calculate real carbon emission data as well as avoid collusion between enterprises and third-party verification agencies.

DC provides the basic support for the application of LCTs and the implementation of LCRs. After the development of LCRs, strong implementation is still needed to play

a proper role, so it is necessary to provide a guarantee for them through DC, and the development of LCRs will also promote the application of DCs. The existence of DC will suggest the effect of LCTs in the role of CRE.

Based on the aforementioned, the following hypotheses are proposed:

Hypothesis 5 (H5): Low-carbon regimes affect carbon reductions.

Hypothesis 6 (H6): Low-carbon regimes affect DC.

Hypothesis 7 (H7): Low-carbon regimes affect collusive behavior.

Hypothesis 11 (H11): Low-carbon regimes indirectly affect carbon reductions through collusive behavior.

3.4. Impact of Digital Control Technologies on Carbon Reductions

As DC continue to develop in the environmental field, their role in achieving carbon neutrality goals is receiving increasing attention. DC are not as dependent on natural resources as traditional production technologies are. Hence, their innovation can help set carbon accounting standards, promote the application of new energy technologies, and develop carbon absorption systems. Therefore, low-carbon systems can function better and solve the difficulties of low-carbon development, thus promoting the achievement of carbon neutrality goals [4,44]. Liu et al. [45] found that DC can not only reduce local carbon emissions but also promote carbon reductions in neighboring cities. Therefore, innovation in DC reduces carbon emissions intensity nationally, and when technological development reaches a certain threshold, the effectiveness of carbon reductions gradually becomes obvious [46,47]. Promoting DC based on artificial intelligence and blockchain can thus promote carbon reductions in transport infrastructure. Based on the foregoing, we propose the following hypotheses:

Hypothesis 8 (H8): Low-carbon regimes indirectly affect carbon reductions through DC.

Hypothesis 9 (H9): LCTs indirectly affect carbon reductions through DC.

Hypothesis 10 (H10): DC affect carbon reductions.

3.5. Impact of Collusive Behavior on Carbon Reductions

The presence of collusive behavior impacts the implementation of government policies and the intensity of management and control, as well as the effectiveness of carbon reductions in infrastructure. Achieving the SDGs and dual carbon goal simultaneously can promote industrial upgradation at the macro level; however, it can damage the economic benefits of enterprises using the original high-carbon development model in the short term. Therefore, companies may be motivated to adopt collusion strategies that hinder the implementation of low-carbon policies. Third-party institutions in carbon emission regulations play an important role in maintaining the global carbon market [48]. Their supervision can help enterprises mitigate carbon emissions, while they can also establish a carbon emission management system and provide data support for the carbon trading market. Early carbon verification is crucial because it affects the allocation of carbon quotas to enterprises.

If an enterprise chooses to collude with a third-party organization, it can obtain more carbon allowances by increasing the falsely reported carbon emissions of industries that have been eliminated, thereby increasing income. Therefore, using DC can control collusion in the processes of carbon emission regulation and reduction. Using LCTs to create an open, transparent, and democratic environment can reduce this degree of collusion [49]. However, some studies have found that enterprises are more likely to collude when

third-party verification agencies are too strict. At this time, the government should build multilevel safeguards to reduce collusive behavior [32]. Based on the foregoing, the following hypothesis is proposed:

Hypothesis 13 (H13): Collusive behavior affects carbon reductions.

4. Materials and Methods

4.1. Model Design

A research model was constructed using the factors affecting the reduction of carbon emissions from transport infrastructure based on the foregoing literature review and hypotheses. This is illustrated in Figure 1.

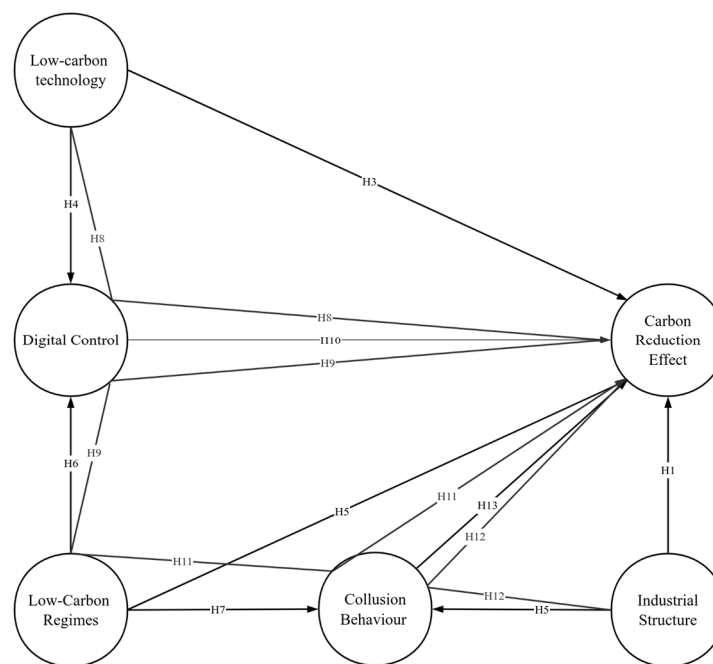


Figure 1. Theoretical model.

4.2. Questionnaire Design

Through group discussions, expert interviews, and on-site and online collections, this study designed a questionnaire on the effectiveness of carbon reductions. It was pre-tested in Changsha, and the questionnaire was adjusted and improved based on the results to reflect respondents' opinions more comprehensively and correctly. The questionnaire included items based on the following six latent variables: the IS, LCTs, low-carbon regimes, DC, collusive behavior, and CRE; the survey language was Chinese (Table 1). All the items were obtained from previous studies to ensure the validity of the questionnaire. A five-point Likert scale (5 = strongly disagree, 4 = disagree, 3 = no opinion, 2 = agree, and 1 = strongly agree) was used for responses. The gender, occupation, and years of experience of respondents were also recorded. Participation in the questionnaire was voluntary, and the purpose of the study was explained to all participants. Participants' information and responses were kept confidential during the survey to reduce the threat of common method bias [50].

Table 1. Latent and observed variables.

Latent Variable	Observed Variable	Reference(s)
IS	The stage at which the industry is developing R&D investment in low-carbon technologies Percentage of high-carbon industrial development patterns	Jiang et al. [51]; Nurgazina et al. [52]; Lin et al. [53]; Wang et al. [54]
LCT	Carbon reduction capacity of alternative technologies Prospects for the application of low-carbon technologies Level of deployment of low-carbon technologies Difficulty of trading low-carbon technologies	Cary [55]; Gao et al. [56]; Xin et al. [57]; Wei et al. [58]
LCR	Expenditure on low-carbon subsidies High-carbon development model inertia	Jin [59]; Chen, Y. et al. [5]; Zhang et al. [60]
DC	Application of digital control technologies Construction and operation of digital control technologies Transformation of the digital management model	Liu et al. [45]; Zeng et al. [61]; Chen et al. [62]
CB	Government–business collusion and policy implications Regional collaborative behavior	Yang et al. [63]; Gao et al. [64];

Note: Collusion behavior, CB; Digital control technologies, DC; Industrial structure, IS; Low-carbon technology, LCT; Low-carbon regimes, LCR.

4.3. Demographic Information

The research team conducted the research from October 2021 to July 2022 with government agencies and companies related to transport infrastructure. An effective response rate of 93.9% was achieved based on 430 questionnaires returned.

The occupational distribution of the respondents was as expected, comprising 6.19% working in the government, 53.46% in transport infrastructure (investment, construction, and operation), 18.32% in research, 15.84% in carbon emissions supervision and management, and 6.19% other. Of the respondents, 59.4% had more than five years of work experience. SPSS AU was used to collate the data. Table 2 presents the characteristics of the surveyed population.

Table 2. Characteristics of the surveyed population.

Variable	Type	Value	Proportion
Occupation	Government	25	6.19%
	Transport infrastructure investment	48	11.88%
	Transport infrastructure construction	78	19.31%
	Transport infrastructure operations	90	22.28%
	Research	74	18.32%
	Carbon emission supervisors and managers	64	15.84%
	Other	25	6.19%
Years of working	<5	44	10.89%
	5–10	120	29.7%
	10–15	164	40.59%
	>15	76	18.81%

4.4. Methodological Options

Structural equation modeling (SEM) is a second-generation statistical modeling method that allows the quantitative analysis of unobservable variables and can be used to assess the initial assumptions of causal models [65]. Common SEM methods include covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) [66,67]. Both methods have their applications and limitations. CB-SEM is mainly used for testing and confirming hypotheses; it emphasizes fit indices and is suitable for analyzing large samples. PLS-SEM is usually used to analyze the correlations between relevant hypotheses and theories and is more concerned with predicting causality and assessing quality. It is used when (1) a theoretical framework is being tested from a predictive perspective, (2) a complex problem is being addressed through the exploration of established theories, and (3) minority groups limit the

number of participants. According to the above, PLS-SEM can be used to test the validity of the model and to analyze the causal relationship between variables that are difficult to observe, which is in line with this paper's analysis of the relationship between LCT, DC, LCR, CB, IS, and CRE; at the same time, according to the existing research, PLS-SEM is more reliable in the case of multi-structures, which meets the requirements of the model setting in this paper. Considering the characteristics of the subjects analyzed, purpose of the study, and quality of the data, PLS-SEM was chosen as the research method for this study.

5. Result

5.1. Methods

To enhance the model's ability to handle complexity and establish predictive validity, this study used the bootstrapping technique of PLS-SEM to test and examine the measurement and structural models [67–69]. This study was analyzed using SmartPLS 3 software.

For the measurement model, the focus was on analyzing its reliability. We assessed the Cronbach's alpha, a method of measuring the reliability of a scale or test that overcomes the shortcomings of the partial halving method and is the most commonly used method of reliability analysis in scientific research, composite reliability (CR; the reliability of a composite score, a new variable consisting of the sum of more than one variable), t-statistics, factor loadings (used to assess the reliability and credibility of the strategy model, indicating the strength of the relationship between the measure and the latent variable), and covariance structures of the model to examine its reliability. In an exploratory analysis, when Cronbach's $\alpha > 0.7$ and CR > 0.7 , the results are reliable; hence, our measurement model had good reliability [70]. Moreover, all the factor loadings in this study were above 0.5, suggesting that the variables were explained reasonably well. The model also had a variance inflation factor (VIF) below 5 [71], meeting the requirements in this regard. Finally, we found that the observed variables were linearly related to the latent variables, which makes the latent variables easier to understand.

The goodness-of-fit concept commonly used in CB-SEM does not have a universal value for PLS-SEM models. Hence, the standardized root mean square residual (SRMR), heterotrait-monotrait (HTMT) ratio, and normed fit index (NFI) were selected for this study [72] (see Tables 3 and 4).

Table 3. Goodness-of-fit.

Indicator	Value	Criterion	Reference(s)
SRMR	0.054	<0.08	Bentler and Bonett [73]; Shmueli et al. [72]
NFI	0.875	>0.85	Junliang et al. [74]; Rong [75]; Wu [76]; Wu et al. [77]; Xiong [78]

Note: standardized root mean square residual, SRMR; normed fit index, NFI.

Table 4. HTMT ratio.

	IS	LCR	LCT	CB	DC	CRE
IS						
LCR	0.808					
LCT	0.759	0.803				
CB	0.720	0.778	0.755			
DC	0.710	0.762	0.742	0.724		
CRE	0.645	0.752	0.696	0.671	0.648	

Note: Collusion behavior, CB; Carbon reduction effects, CRE; Digital control technologies, DC; Industrial structure, IS; Low-carbon technology, LCT; Low-carbon regimes, LCR.

The closer the NFI is to 1, the better is the fit of the model. However, a major disadvantage is that it does not penalize for model complexity. The higher the number of parameters in the model, the larger (i.e., better) the NFI result. A threshold of above

0.9 has been selected by some scholars as a good NFI, with >0.8 or >0.85 an acceptable goodness-of-fit criterion in some studies; other scholars also consider it acceptable when the NFI is between 0.7 and 0.9. In this study, the NFI was 0.875. Considering the study and survey characteristics, this indicator was thus considered acceptable.

However, Hair et al. [79] pointed out that using the NFI for analyzing models in PLS-SEM is not recommended. Therefore, we also used additional metrics to determine the reliability of the model (i.e., SRMR and HTMT). As shown in Table 3, the SRMR and HTMT values of the model met the requirements, suggesting that the model had sufficient discriminant validity (Table 4). After the comparison of several indicators, we concluded that the proposed model was suitable for use in the subsequent analysis.

We subsequently calculated the factor loadings and R^2 values of the model (Figure 2) to analyze its reliability and construct validity. We found that the reliability, convergent validity, discriminant validity, and significance level of the model were acceptable. According to existing studies, the conclusions of a model are reliable when Cronbach's α and CR are above 0.7 in PLS-SEM [70]. In the model, all the items had VIFs below 5, which met the requirements without further adjustments to the model (Table 5). We can measure the convergent and discriminant validity of a PLS-SEM model using the AVE, which should be above 0.5; further, the square root of the AVE should be above the correlation coefficients of the other latent variables (Tables 6 and 7). Hence, it was concluded that the measured variables explained the latent variables well and that the model construction was reasonable.

Table 5. Model items.

Latent Variable	Cronbach's α	Composite Reliability	t	p	VIF	Item
IS	0.876	0.897	19.725	<0.001	2.323	IS1
			21.026	<0.001	2.312	IS2
			23.618	<0.001	3.375	IS3
LCR	0.854	0.870	18.454	<0.001	2.244	LCR1
			19.631	<0.001	2.244	LCR2
LCT	0.895	0.906	18.867	<0.001	2.266	LCT1
			21.855	<0.001	2.323	LCT2
			20.139	<0.001	2.653	LCT3
			22.120	<0.001	4.898	LCT4
CB	0.872	0.939	18.768	<0.001	2.484	CB1
			23.174	<0.001	2.484	CB2
DC	0.876	0.898	22.509	<0.001	2.245	DC1
			26.723	<0.001	2.449	DC2
			24.300	<0.001	3.553	DC3
CRE	1.000	1.000	20.572	<0.001	1.000	CRE1

Note: Collusion behavior, CB; Carbon reduction effects, CRE; Digital control technologies, DC; Industrial structure, IS; Low-carbon technology, LCT; Low-carbon regimes, LCR.

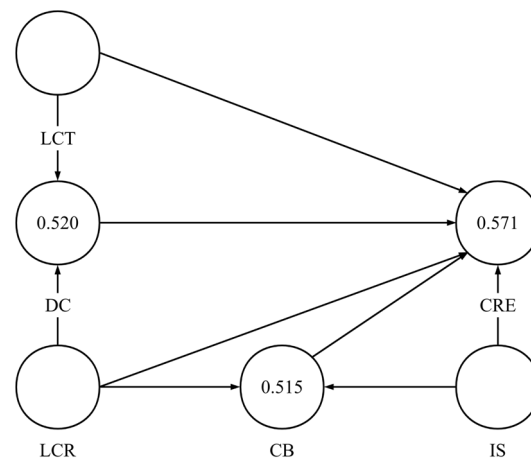


Figure 2. Measurement model with the R^2 values.

Table 6. Average variance values of the latent variables.

Latent Variable	Average Variance Extracted
IS	0.802
LCR	0.872
LCT	0.762
CB	0.886
DC	0.802
CRE	1.000

Note: Collusion behavior, CB; Carbon reduction effects, CRE; Digital control technologies, DC; Industrial structure, IS; Low-carbon technology, LCT; Low-carbon regimes, LCR.

Table 7. Correlation coefficients between the square root of the AVE and latent variables (Fornell–Larker).

Latent Variable	CB	CRE	DC	IS	LCR
CB	0.941				
CRE	0.632	1			
DC	0.643	0.612	0.895		
IS	0.640	0.610	0.630	0.896	
LCR	0.681	0.699	0.667	0.706	0.934

Note: Collusion behavior, CB; Carbon reduction effects, CRE; Digital control technologies, DC; Industrial structure, IS; Low-carbon regimes, LCR.

Discriminant validity is an important method of assessing the validity of a PLS-SEM model to determine whether there is a difference between constructs in a research model. The Fornell-Larcker criterion is an important method of assessing discriminant validity, where the AVE for each construct should be greater than the correlation coefficient between that construct and the rest of the constructs in the model. It ensures that there is no overlap between constructs. According to Table 7, it can be found that the indicators in the constructed model are independent from each other.

R^2 is usually used to evaluate the degree to which the independent variables of a model explain the variance of the dependent variable, while Q^2 is used to evaluate the predictive relevance of the model and analyze the relationship between the power of the full measurement model and the quality of the full structural model by calculating the goodness-of-fit [5,80]. The model in this study had a good fit (0.582); values over 0.26 indicate that a model has a high goodness-of-fit, which suggests good applicability to social surveys. The R^2 values for collusive behavior, CRE, and DC were 0.512, 0.566, and 0.517, respectively, indicating that the model explained a moderate degree of variance. Further, the Q^2 was above zero, indicating that the model had good predictive relevance and that the structural model used in this study was robust (see Table 8).

Table 8. R^2 , Q^2 , and cross-validated communality and redundancy.

Latent Variable	R^2	Q^2	Cross-Validated Communality	Cross-Validated Redundancy
CB	0.512	0.510	0.540	0.447
CRE	0.566	0.543	1.000	0.558
DC	0.517	0.514	0.575	0.409
IS			0.576	
LCR			0.511	
LCT			0.594	

Note: Collusion behavior, CB; Carbon reduction effects, CRE; Digital control technologies, DC; Industrial structure, IS; Low-carbon technology, LCT; Low-carbon regimes, LCR.

5.2. Analysis of the Results

When using PLS-SEM, we typically test hypotheses by analyzing the t - and p -values of the paths [80]. In the analysis of the path coefficients, statistical significance was assessed using the t -value, where $t > 1.96$ reached a significance level of $p < 0.05$, $t > 2.58$ reached a significance level of $p < 0.01$, and $t > 3.29$ reached a significance level of $p < 0.001$. As shown in Figure 3, Tables 9 and 10, the coefficients of the paths between the IS and collusive behavior as well as between the IS and carbon reductions were 0.074 ($t = 1.498 < 1.96$) and 0.317 ($t = 6.619 > 1.96$), respectively, indicating that Hypothesis 1 was not supported and Hypothesis 2 was supported. However, Table 10 shows that the coefficient of $IS \rightarrow CB \rightarrow CRE$ was 0.05 ($t = 2.74 > 1.96$), supporting Hypothesis 12. The results indicate that the IS does not directly affect the effectiveness of carbon reductions but can promote it through its effect on the social environment. This is consistent with the findings of Chen et al. [5] that the social environment positively affects the control of carbon emissions. The coefficients of the paths from low-carbon technologies to the effectiveness of carbon reductions and DC were 0.200 ($t = 3.900 > 1.96$) and 0.386 ($t = 8.095 > 1.96$), respectively, supporting Hypotheses 3 and 4. LCTs affect carbon reductions and DC. When low-carbon technologies are applied, DC and the effectiveness of carbon reductions improve to a greater extent. The coefficients of the paths from low-carbon systems to the effectiveness of carbon reductions, digital control technologies, and collusive behavior were 0.318 ($t = 5.525 < 1.96$), 0.394 ($t = 8.555 > 1.96$), and 0.457 ($t = 9.997 > 1.96$), respectively. Hence, low-carbon systems can promote the social environment and progress in DC, enhancing the effectiveness of carbon reductions. Hypotheses 6 and 7 were supported. The effect of DC on carbon reductions was 0.119 ($t = 2.340 > 1.96$), supporting Hypothesis 10. Thus, the application of low-carbon technologies directly affects carbon reductions. The coefficient of the path between the social environment and the effectiveness of carbon reductions was 0.157 ($t = 3.106 > 1.96$); hence, Hypothesis 13 was supported.

Table 9. Hypothesis testing results.

Hypothesis	Relationship	Path Coefficient	t	p	Result
H1	$IS \rightarrow CRE$	0.074	1.498	0.134	Reject
H2	$IS \rightarrow CB$	0.317	6.619	<0.001	Accept
H3	$LCT \rightarrow CRE$	0.200	3.900	<0.001	Accept
H4	$LCT \rightarrow DC$	0.386	8.095	<0.001	Accept
H5	$LCR \rightarrow CRE$	0.318	5.525	<0.001	Accept
H6	$LCR \rightarrow DC$	0.394	8.555	<0.001	Accept
H7	$LCR \rightarrow CB$	0.457	9.997	<0.001	Accept
H10	$DC \rightarrow CRE$	0.119	2.340	0.019	Accept
H13	$CB \rightarrow CRE$	0.157	3.106	0.002	Accept

Note: Collusion behavior, CB; Carbon reduction effects, CRE; Digital control technologies, DC; Industrial structure, IS; Low-carbon technology, LCT; Low-carbon regimes, LCR.

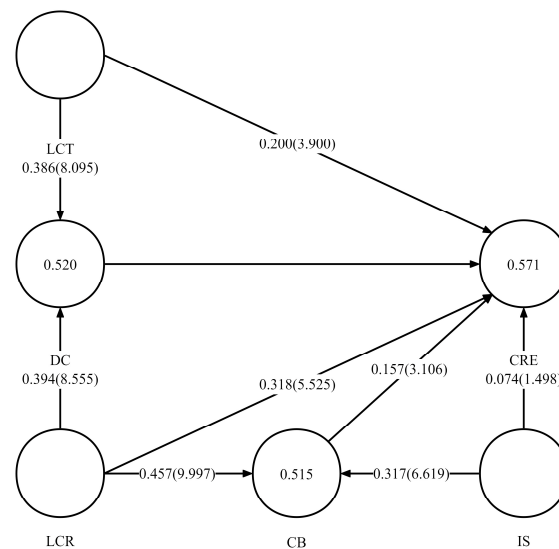


Figure 3. Structural model.

Table 10. Results of the mediation analysis.

Hypothesis	Relationship	Path Coefficient	t	p	Result
H8	LCR → DC → CRE	0.047	2.212	0.027	Accept
H9	LCT → DC → CRE	0.046	2.247	0.025	Accept
H11	LCR → CB → CRE	0.072	2.952	0.003	Accept
H12	IS → CB → CRE	0.05	2.74	0.006	Accept

Note: Collusion behavior, CB; Carbon reduction effects, CRE; Digital control technologies, DC; Industrial structure, IS; Low-carbon technology, LCT; Low-carbon regimes, LCR.

Next, DC and collusive behavior played mediating roles in the relationships among LCTs, low-carbon regimes, and CRE. This implies that with better DC and less collusive behavior, LCTs and low-carbon regimes play greater roles in reducing carbon emissions.

While the use of low-carbon technologies will contribute to a reduction in carbon emissions, the initial research and development phase will entail additional costs for enterprises compared to the use of high-carbon technologies. Furthermore, due to the lack of sufficient validation, there are reliability and market acceptance issues with low-carbon technologies at this early stage of their application, which will hinder their adoption. The use of digital control technology in regulation allows for a more comprehensive and rigorous control process. It reduces the likelihood of companies taking chances and influencing their choice of low-carbon behavior; it reduces long-term costs for the regulator.

6. Discussion and Limitations

6.1. Discussion

This study verifies that LCT, DC, and collusive behavior have positive direct and indirect impacts on CRE; DC can enhance the effectiveness of carbon emission reduction by effectively enhancing the effectiveness of the measures, whereas CB will firstly exacerbate carbon emissions and inhibit the effectiveness of carbon emission reduction to a certain extent, consistent with the literature [57,58]. First, low-carbon and DC directly affect the technologies available to transport infrastructure companies in the carbon reduction process and the cost of technology use, which can significantly influence the possibility and cost of using carbon reduction technologies. Simultaneously, the application of DC increases the cost of non-compliance for these enterprises and enhances the possibility that their operations are standardized. When most enterprises choose to operate at a low-carbon level, high-carbon enterprises will also transform, thus improving the overall effectiveness of carbon reductions across society. Meanwhile, the IS does not directly affect

CRE. Transport infrastructure companies at the end of the chain lack a comprehensive and correct understanding of the IS and policies of the whole industry. Therefore, the IS can only influence the decisions of transport infrastructure companies through other factors that can be perceived by them.

DC are shown to mediate the process by which low-carbon regimes and LCTs influence CRE. This mediating role of DC was also found by previous studies [61,62]. First, the implementation of low-carbon regimes requires the involvement of controls, and DC can improve the efficiency of controls and process compliance. This increases the likelihood of detecting high carbon emissions by transport infrastructure companies and raises the cost of non-compliance, all of which can improve CRE. Collusive behavior also plays a mediating role in the influence of low-carbon regimes and the IS on CRE. This demonstrates that external IS and the introduction of low-carbon regimes can affect the low-carbon behavior of transport infrastructure firms by influencing the social environment. This finding has both theoretical and practical implications. In particular, it deepens previous research on the causes of enterprises' low-carbon behavior and explains that the social environment and DC play a role in enhancing CRE, which can provide a basis for future policy formulation.

These findings provide a strong theoretical basis and useful perspectives for the improvement of environmental quality and public welfare in China as well as the mitigation of climate change. First, the IS, LCTs, low-carbon systems, and low-carbon regimes all affect CRE directly or indirectly. On the one hand, this means that enterprises can control carbon emissions within the government's limit and meet the dual carbon goal. On the other hand, enterprises can reduce their expenditure on carbon taxes. Further, the government can gradually achieve the goals to which China committed at the UN General Assembly, reflecting the country's responsibility as a great power. For the public, reducing collusive behavior can improve social welfare, while effective carbon reductions can improve the quality of people's living environment.

Second, LCTs, DC, and collusive behavior have a direct impact on CRE. The government and relevant departments, with the support of national development strategy, should continue to promote the development of low-carbon and DC in transport infrastructure, thus improving the effectiveness of carbon reductions in society and making China's economic development sustainable and healthy. Moreover, collusive behavior is shown to play a mediating role in the effect of low-carbon regimes and the IS on CRE. In areas with low carbon reductions, local governments and related departments should strictly control the relocation of highly polluting enterprises to these areas; in areas with high carbon reductions, it is necessary to develop and introduce LCTs that match the IS as well as gradually improve the effectiveness of carbon reductions through continuous exchanges among cooperative enterprises.

6.2. Limitations

This study validated the direct and indirect factors influencing CRE; however, it has certain limitations. First, as it is only a preliminary study of the factors influencing CRE in transport infrastructure, the measures and influencing factors may be less than perfect. Future research could aim to refine the items of the influencing factors. Second, while this study examines the mediating roles of DC and collusive behavior on CRE, other mediating variables could impact CRE, which future research could pursue. Third, this study is based in China; future research could expand the scope of the research to verify the theory proposed in this study.

7. Conclusions

In this study, PLS-SEM was used to analyze the factors influencing CRE in transport infrastructure and explore the mediating roles of these influencing factors. Based on the analysis, two main conclusions can be drawn. First, low-carbon technologies, DC, and collusive behavior have direct and positive influences on CRE. The coefficients of the paths from low-carbon technologies to the effectiveness of carbon reductions and DC

were 0.200 ($t = 3.900 > 1.96$) and 0.386 ($t = 8.905 > 1.96$), respectively. Hence, LCT affect carbon reductions and DC. The coefficients of the paths from low-carbon systems to CRE, DC, and collusive behavior were 0.318 ($t = 5.525 > 1.96$), 0.394 ($t = 8.555 > 1.96$), and 0.457 ($t = 9.997 > 1.96$), respectively. Hence, low-carbon systems can promote the social environment and innovation in DC, enhancing the effectiveness of carbon reductions.

Second, DC were shown to play a mediating role in the influence of low-carbon regimes and LCTs on CRE, while collusive behavior also mediated the influence of low-carbon regimes and the IS on CRE. The coefficients of the paths from the IS to collusive behavior and carbon reductions were 0.074 ($t = 1.498 < 1.96$) and 0.317 ($t = 6.619 > 1.96$), respectively. The coefficient of IS $\rightarrow$ CB $\rightarrow$ CRE was 0.05 ($t = 2.74 > 1.96$). Finally, the IS does not directly influence the CRE but does promote it through its effect on the social environment.

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