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How Business Model Innovation Affects Carbon Performance of Mobile Phone Industry Chain Enterprises: The Mediating Role of Artificial Intelligence and Green Technology

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Abstract

The question of how enterprises can achieve both economic gains and carbon reduction goals through business model innovation has become an urgent issue requiring attention, as the sector currently navigates a critical period of dual transformations toward intelligence and green development. Using a sample of 133 Chinese smartphone industrial chain enterprises from 2015 to 2022, this study employs methodologies including the two-way fixed effects model, term frequency analysis. It aims to provide both a comprehensive theoretical framework and micro-level empirical evidence for the proposition that business model innovation impacts corporate carbon performance. Regression results demonstrate that business model innovation significantly enhances corporate carbon performance, a result robust to a battery of tests. Mechanism analysis demonstrates that the application of artificial intelligence and green technology innovation serve as mediating channels between business model innovation and carbon performance. Heterogeneity analysis indicates that the carbon performance enhancement effect of business model innovation is more pronounced in state-owned enterprises, firms facing stronger financing constraints, and enterprises positioned in the upstream segments of the supply chain. Continuous efforts in areas such as government guidance and enterprise-driven innovation will be essential in the future to facilitate the achievement of the dual carbon goals.

Keywords: Business Model Innovation, Carbon Performance, Artificial Intelligence, Green Technology.

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1. Introduction

Against the background of global climate change getting worse and carbon neutrality goals being pushed forward faster, companies, as the main players in the market, urgently need to integrate low-carbon ideas into their whole production and operation process and contribute to achieving carbon neutrality goals (Wang et al., 2011). More and more companies start to publish sustainable development reports, ESG reports and so on, which shows that they pay attention to sustainable development. However, most companies still face the problem of not having enough motivation to reduce carbon emissions. On the one hand, the costs of low-carbon transformation and technical problems limit companies' short-term decisions, making it hard for them to balance environmental protection investment and economic performance. On the other hand, they lack effective business models to turn emission reduction pressure into sustainable competitiveness, so their green innovation only stays at the level of meeting rules and it is hard to form a long-term mechanism (Liu and Lu, 2024). This problem is especially serious for companies in the smartphone industry chain. Although international brands like Apple and Samsung have set carbon neutrality goals for their whole supply chains, in reality, many of their suppliers face growing risks of carbon control because of their high energy consumption and high carbon emission production processes, such as processing precision structural parts, making display modules and manufacturing batteries. Policies like the EU's Carbon Border Adjustment Mechanism have turned from theoretical risks into real trade barriers, which directly threaten these companies' export competitiveness and survival space. Whether companies can turn carbon constraints into innovation signals through business model innovation, and then optimize resource allocation systematically and encourage technological progress, has become a key issue that affects their carbon performance and long-term competitiveness (Zott and Amit, 2010). At the same time, as a new round of technological revolution characterized by intelligence and green development speeds up, intelligent transformation and green transformation have become the key to solving environmental and resource constraints and promoting high-quality development of companies (Liu et al., 2024). In view of this, against the background of the dual transformation of intelligence and green development, deeply exploring the impact mechanism of business model innovation on companies' carbon performance has become an urgent problem to solve.

At present, qualitative research is still the main way to measure business model innovation, and there are few studies using quantitative methods. In terms of qualitative research, questionnaires, grounded theory and case studies are the three most widely used methods to measure business model innovation at present (Wang,2025; Wang, 2025; Jiang and Pang, 2025). Most of these studies focus on groups with strong innovation vitality, such as technology-based companies, Internet companies and start-ups (Chen et al. 2025, Zhang et al. 2025). Although these methods have advantages in revealing the details of mechanisms in specific situations and exploring hidden connections, they are limited by the representativeness of samples and the particularity of research scenarios. In contrast to the wide use of qualitative methods, quantitative research is still in the stage of scattered exploration in measuring business model innovation. Only a few scholars have tried to reveal the causal relationships between variables through quantitative analysis. For example, Liu Zhengyang and other researchers used corporate financial indicators and the principal component analysis method to build an evaluation model, which realized the quantitative measurement of the level of business model innovation (Liu et al, 2019).

Corporate performance is a comprehensive concept. It mainly focuses on the economic and financial aspects of a company. Corporate carbon performance, based on corporate performance, is a comprehensive reflection of the efficiency and results of managing, controlling and improving greenhouse gas emissions from its business activities in a specific period. However, existing studies have not reached a consistent conclusion on how business model innovation affects corporate carbon performance. Relevant discussions mainly focus on the relationship between business model innovation and corporate (financial) performance, such as return on total assets (Amores et al., 2014), Tobin's Q (Ha et al., 2024), return on total assets (Xie and Zhu, 2021) and so on. The discussion on its environmental effects is still in the initial stage (Jing and Jiang, 2024). As global attention to addressing climate change continues to rise, the relationship between companies and carbon emissions has attracted more and more attention. Some scholars have begun to study the environmental benefits brought by business model innovation. For example, Fora believes that green business models perform well in improving environmental benefits and creating sustainability (Fora, 2025). Yun Lexin and other scholars further systematically explore the role of business model innovation in corporate sustainable performance. They find that business model innovation can significantly improve corporate sustainable performance, and this promoting effect is more obvious in state-owned enterprises (Yun et al., 2025).

The internal transmission mechanism of business model innovation performance has not yet been systematically elucidated. Existing research is mostly confined to the dimension of internal resource capabilities within enterprises, examining their mediating effects between business model innovation and corporate economic performance. Core research perspectives encompass key variables such as corporate dynamic capabilities, ambidextrous innovation, and leadership behavior. Li (2019), found that exploitative innovation exerts a partial mediating effect in the relationship between efficiency-oriented business model innovation and corporate financial performance; exploratory innovation exhibits a full mediating effect in the association between novelty-oriented business model innovation and financial performance; and exploratory innovation acts as a partial mediator in the transmission path from novelty-oriented business model innovation to market performance (Li, 2019). In addition, although some studies have pointed out that technological factors may serve as a linking nexus between business model innovation and corporate performance (Chesbrough, 2010), existing findings remain largely at the level of qualitative judgment. They neither clarify the mechanistic effects of technological factors nor empirically verify their mediating or moderating effects between the two types of variables, resulting in the unclear transmission logic and boundaries of effect of the technological path. This further highlights that research on the mechanism through which business model innovation influences corporate performance still needs to be further deepened.

In summary, although existing literature has conducted relatively in-depth research on issues related to business model innovation and corporate carbon performance, the following shortcomings still exist: First, existing studies mainly adopt qualitative methods such as grounded theory and case studies to measure business model innovation, while relevant explorations on the quantitative measurement of business model innovation remain relatively scarce. Second, existing literature focuses on investigating the impact of business model innovation on firms' traditional economic performance; although a small number of studies have taken environmental benefits into account, they fail to explore the effect of business model innovation on corporate carbon performance. Third, most existing studies take internal enterprise resource capabilities (e.g., dynamic capabilities) as the mediating mechanism influencing business model innovation, and have not yet explored the mediating role of artificial intelligence and green technologies from the perspective of the dual transformation of intelligence and greening. Based on this, the marginal contributions of this paper may lie in the following three aspects: (1) This paper combines the construction of an indicator system with the technological distance reference method to measure business model innovation, enriching the quantitative measurement methods of business model innovation. (2) Focusing on the carbon performance of enterprises in the mobile phone industry chain, this paper expands the research scope of the impact of business model innovation on corporate carbon performance. (3) Against the backdrop of the synergistic transformation of intelligence and greening, this paper unpacks the mediating role of artificial intelligence technology and green technology innovation, deepening the influence mechanism of business model innovation on corporate carbon performance.

2. Theoretical Mechanisms and Research Hypotheses

2.1 Business Model Innovation and Corporate Carbon Performance

Business model innovation drives the systematic improvement of financial performance, environmental performance, and corporate social responsibility (CSR) by restructuring enterprises' value creation systems (Seman et al., 2019). According to Dynamic Capabilities Theory, business model innovation can not only enhance economic benefits through resource optimization and efficiency innovation but also achieve multi-dimensional compatibility with sustainable development goals (SDGs) via green technology embedding and stakeholder collaboration (Bocken and Geradts, 2020). Business model innovation constructs platform ecosystems (Alt et al.,2015), which are essentially resource value co-creation mechanisms that integrate the resources of multiple stakeholders. Through this mechanism, enterprises can not only achieve data-driven precise matching of consumers' low-carbon demand but also strengthen their social image and consumer trust through the delivery of green products and services (Ding and Ding,2010). The improved image, in turn, incentivizes enterprises to maintain low-carbon operations, forming a closed loop of platform resource integration, low-carbon demand satisfaction, and carbon performance optimization.

From the perspective of Externality Theory, the core of the dual carbon goals lies in addressing the environmental negative externalities of corporate operations (Teece, 2010). In this context, business model innovation builds green competitive advantage by mitigating environmental negative externalities, and the core manifestation of green competitive advantage is precisely the improvement of carbon performance - such as reduced carbon emissions and improved carbon compliance levels. Meanwhile, business model innovation optimizes production processes, adopts clean energy, and promotes the circular economy in value creation links (Ye et al., 2022), which is essentially a restructuring of the firm's internal resources (e.g., energy resources and production resources) based on the Resource-Based View (RBV). This restructuring not only reduces resource consumption and waste emissions to directly improve carbon performance but also enhances resource utilization efficiency through cost savings. Moreover, improved carbon performance itself constitutes a scarce resource (Xia et al., 2025), further aligning with the logic of resource advantage leading to performance improvement proposed in the Resource-Based View.

Based on the above analysis, this paper proposes the following hypothesis:

Hypothesis H1: Business model innovation can significantly improve corporate carbon performance.

2.2 The Mechanistic Role of Artificial Intelligence

In today's rapidly evolving business environment, a new round of technological revolution centered on intelligent technologies serves as a bridge, facilitating the integration of business model innovation and corporate carbon performance (Lu, 2022). Technology Innovation Theory emphasizes that breakthrough technologies such as artificial intelligence (AI) drive enterprises to transform from "high energy consumption and high pollution" to "green and efficient" by revolutionizing production and management models. This transformation constitutes the core of "operational link innovation" in business models and directly serves the improvement of carbon performance.

First, artificial intelligence (AI) technology significantly empowers the dynamic adjustment of business strategies and the systematic improvement of carbon performance by restructuring enterprises' value networks. In the process of value network restructuring, AI, relying on its multi-source data analysis capabilities, precisely deconstructs user behavior patterns and product life-cycle carbon footprints, driving enterprises to form differentiated low-carbon value propositions (Acemoglu and Restrepo, 2022). On the one hand, it develops customized low-carbon solutions through demand-side insights - for example, flexible pricing services based on user carbon sensitivity (Bankins et al., 2024), on the other hand, it realizes intelligent resource orchestration on the supply side, and significantly improves green resource allocation efficiency by real-time coordination of material and energy flows among supply chain nodes. More critically, the collaborative networks constructed by AI foster new value creation mechanisms: the embedded carbon data streams establish a closed loop from product design to recycling and reuse, enabling enterprises to dynamically adjust capacity layout and process parameters based on carbon constraints, thereby reducing carbon emission intensity per unit of economic output through operational flexibility.

Second, the application of artificial intelligence (AI) technology facilitates enterprises' efficient energy utilization and management, providing efficient solutions for corporate pollution control and carbon reduction (Wang and Li, 2024). As microscopic entities in technological innovation, enterprises can leverage new-generation AI technologies such as machine learning, natural language processing, and computer vision to provide auxiliary support for decision-making systems, drive organizational structure transformation, and promote product and service innovation (Chen et al., 2025). AI can monitor corporate carbon emissions accurately and efficiently, track carbon footprints in real time, collect data throughout the entire industrial chain, and enhance the accuracy of monitoring. Thereby, it promotes smart manufacturing and green production, improves enterprises' capacity and level in reducing pollutant emissions, and enables a major transformation of enterprises from high-pollution and high-consumption production to green production (Zhong et al., 2024).

Based on the above analysis, this paper proposes the following hypothesis:

Hypothesis H2: Artificial intelligence technology plays a mechanistic role in the improvement of corporate carbon performance driven by business model innovation.

2.3 The Mechanistic Role of Green Technologies

Corporate green innovation refers to innovative activities in which enterprises develop and create new products, processes, services and market solutions through R&D (Research and Development), aiming to reduce dependence on and consumption of natural resources, mitigate the negative impacts on the ecological environment, and ultimately achieve green development goals (Sun and Shen, 2021). This innovative concept drives enterprises to rethink their business models and operate in a more environmentally friendly and efficient manner. However, existing research reveals that enterprises still face problems such as the mismatch of innovative resources, insufficient R&D investment, and insufficient motivation for green innovation in the field of green technology innovation, which limit enterprises' ability to achieve green transformation (Wan et al., 2022).

On the one hand, business model innovation reshapes value propositions and profit-making logic, providing economic incentives and resource guarantees for green technology innovation. Traditional end-of-pipe treatment models often regard environmental protection investment as a cost, resulting in insufficient motivation for enterprises to engage in green innovation. However, green value-centered business model innovation transforms "low-carbon" and "environmental protection" from external constraints into the core value propositions and differentiated competitive advantages of enterprises. For instance, through product servitization or circular economy models, enterprises can directly obtain economic returns from green performance. This fundamental shift in the value realization path effectively addresses the dilemma of "high investment, long cycle, and low expected returns" in green innovation (Hu et al., 2021), incentivizing enterprises to continuously allocate resources to the R&D of green processes and products.
On the other hand, the collaborative networks constructed by business model innovation amplify and accelerate the emission reduction effects of green technology innovation, which highly aligns with the core tenets of Resource Dependence Theory. This theory holds that enterprises need to integrate external resources through network relationships to reduce the risk of dependence on critical resources, and the limitations of green technology innovation can be precisely broken through network collaboration. By building platform ecosystems or integrating supply chains, business model innovation can embed green technologies into the full life cycle management spanning raw material procurement, production and manufacturing to product recycling (Yan and Cheng, 2024). This not only creates a multiplier effect for the emission reduction outcomes of green technologies across the industrial chain but also reduces the costs of technology application and diffusion through standardization and modularization, thereby improving the input-output efficiency of green technology innovation. Therefore, according to the Resource-Based View (RBV), green innovation enables enterprises to form unique resources that are differentiated, scarce, and difficult to replicate, strengthening corporate competitive advantages and improving corporate carbon performance.
Based on the above analysis, this paper proposes the following hypothesis:

Hypothesis H3: Green technology innovation plays a mechanistic role in the improvement of corporate carbon performance driven by business model innovation.
Based on the above analysis, this paper constructs the theoretical framework as shown in Figure 1.

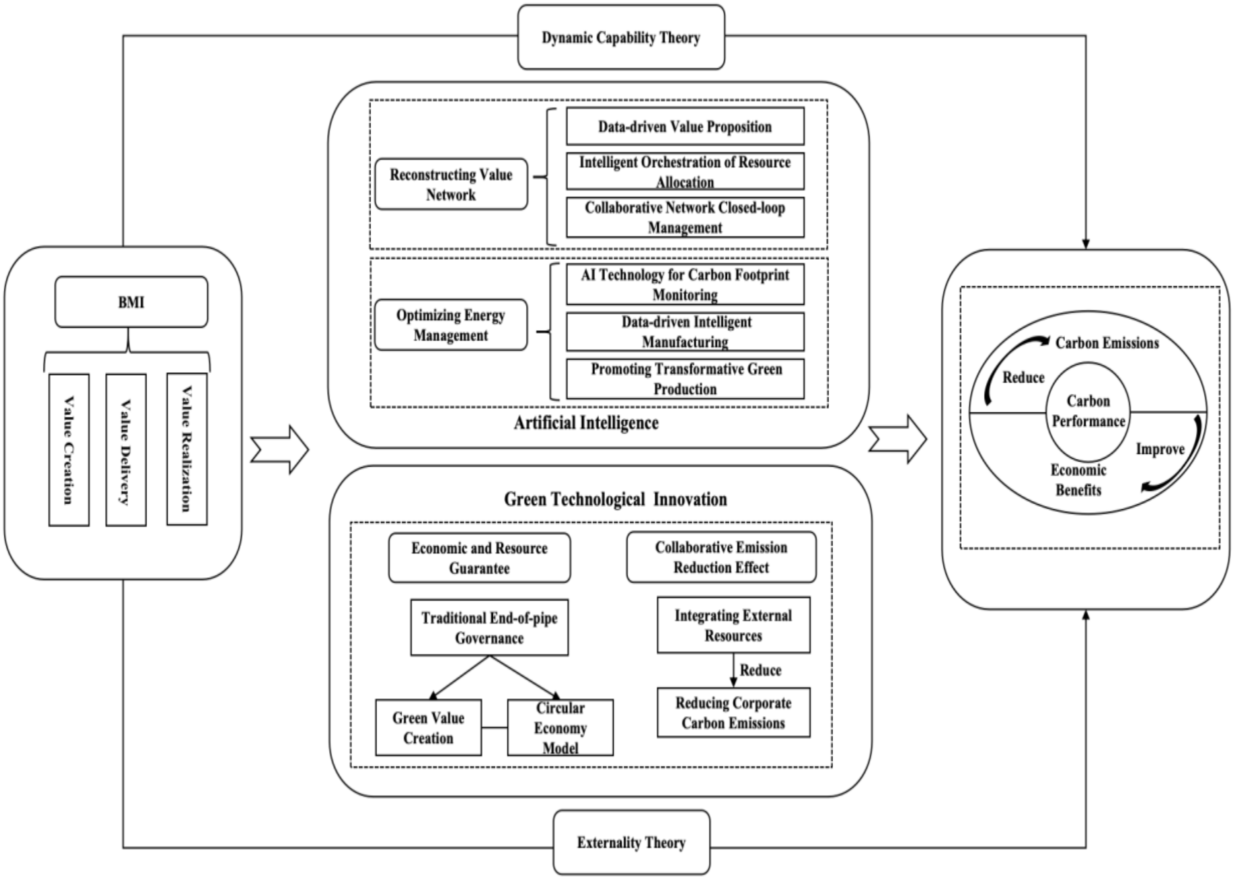

Figure 1: Theoretical Framework of the Impact of Business Model Innovation on Corporate Carbon Performance

3. Research Design

3.1 Sample Selection and Data Sources

This paper takes listed companies in China's smartphone industry chain as its research object. Samples are selected through the following steps: First, drawing on the research of Wen Xiaojun and considering the availability of data on Chinese listed companies, the industry chain is divided into five major segments: chips, display panels, supporting components, complete machine design and manufacturing, and brand channels and application services (Wen, 2013). Second, learning from the research experience of Zhang Mingzhi et al., this paper carefully reviews the annual reports of A-share listed companies on the Shanghai and Shenzhen Stock Exchanges, screens out enterprises whose core businesses involve these five segments, and excludes companies with low relevance or small business volume (Zhang et al., 2024). Finally, 133 listed companies in the smartphone industry chain from 2015 to 2022 are identified as the research sample, with a total of 1,064 sample observations. Firm-level data in this paper are obtained from the

Wind Database; carbon performance data are calculated based on relevant data from the China Energy Statistical Yearbook and the China Statistical Yearbook. Some missing values in the sample data are handled using the interpolation method. To eliminate the influence of different dimensions among variables, all financial data are standardized.

3.2 Variable Measurement

3.2.1 Dependent Variable

Corporate Carbon Performance (CP):Carbon performance refers to the performance achieved by enterprises in the form of compliance, profitability, or carbon assets through reducing carbon dioxide emissions during operations. In constructing a carbon performance rating system, some scholars examine carbon emission-related indicators involved in the input and output processes of research subjects, while others use corporate financial indicators such as carbon asset turnover and carbon emissions per unit profit to comprehensively reflect enterprises' financial and low-carbon capabilities. Given that China does not yet have a relatively mature corporate carbon emission database, this paper draws on the practices of Clarkson et al. and He Yu et al. to measure carbon performance using the logarithm of operating income per unit carbon emissions (Clarkson et al., 2011; He et al., 2017). The specific calculation logic is as follows: First, the smartphone industry chain is identified as belonging to the Manufacture of Computers, Communication and Other Electronic Equipment (C39) in the National Economic Industry Classification. Second, industry carbon emissions are calculated. This paper selects data on the consumption of 9 types of energy (coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas, and electricity) for calculation. Energy carbon emission coefficients are obtained by consulting the Guidelines for the Compilation of Provincial Greenhouse Gas Inventories (Trial) and the General Principles for Calculation of Comprehensive Energy Consumption (GB/T2589-2020), and energy consumption data are sourced from the China Energy Statistical Yearbook. For carbon emissions generated by electricity consumption, this paper follows the practice of Glaeser and Kahn: each regional power grid has only one emission factor (Glaeser and Kahn, 2010). Different from previous studies, this paper refines the calculation of power carbon emissions with the following measures: China's power grid is divided into six major regional power grids (North China, Northeast China, East China, Central China, Northwest China, and South China), and the carbon emissions from electricity consumption in the manufacture of computers, communication and other electronic equipment are calculated using the baseline emission factors of each regional power grid and urban electricity consumption. Finally, drawing on the practice of Yan Huahong et al., this paper converts corporate carbon performance using industry operating costs, corporate operating income, and corporate operating costs (Yan et al., 2019). A larger value of corporate carbon performance indicates that the enterprise obtains higher economic benefits from implementing carbon emission reduction strategies. Equation (1) presents the calculation formula for corporate carbon performance.

$$\text{CP} = \frac{ER}{\frac{SCE}{ICOC} \times CCR} \tag{1}$$

Where: CP denotes corporate carbon performance; ER denotes corporate operating income; SCE denotes industry carbon emissions; ICOC denotes industry main business costs; CCR denotes corporate operating costs.

3.2.2 Independent Variable

Business Model Innovation (BMI): The core connotation of business model innovation lies in driving the systematic improvement of financial performance, environmental performance, and corporate social responsibility (CSR) by restructuring enterprises' value creation systems. Existing literature predominantly adopts qualitative research methods as core tools—for example, exploring the evolutionary dimensions of business model innovation through grounded theory and analyzing the practical paths of business model innovation via case study methods. Although such methods can deeply reveal the internal operational logic of business model innovation, they have limitations in the systematicity of measurement dimensions and the quantitative adaptability of indicator design, making it difficult to meet the precision requirements for measurement tools in large-sample empirical research.

Different from existing studies, this paper integrates and draws on the theoretical analysis framework of business model innovation proposed by Liu Zhengyang and the quantitative measurement approach developed by Ding Luyang et al. Based on the perspective of Value Network Theory, it avoids the one-sidedness of the measurement system from a single perspective and constructs a multi-dimensional and quantifiable measurement system for corporate business model innovation (Ding and Li, 2025). First, from the perspective of the value network, a comprehensive measurement system for corporate business model innovation is constructed, with three primary indicators: value creation, value delivery, and value realization. Under each primary indicator, three secondary financial indicator variables are set (see Table 1).

Table 1: Business Model Innovation Indicator System

	Dimension	**Indicator Name**	**Indicator Description**
Business Model	**Value Creation**	**Quick Ratio**	**Current Assets/Current Liabilities**
		Debt Coverage Ratio	Net Cash Flow from Operating Activities / Total Liabilities
		Equity-to-liability ratio	Equity/Total Liabilities
	Value Transfer	Inventory turnover ratio	Cost of sales / Average inventory
		Accounts receivable turnover ratio	Sales Revenue/Average Accounts Receivable
		Total asset turnover ratio	Sales Revenue / Average Total Assets
	Value Realisation	Year-on-year growth rate of operating revenue	Current Year Operating Revenue / Previous Year Operating Revenue - 1
		Net profit growth rate	Current Year Net Profit / Previous Year Net Profit - 1
		Main business profit margin	Operating profit / Operating revenue

Second, drawing on the technology distance measurement method, this paper constructs a vector for measuring business model innovation. Equation (2) presents the calculation formula for business model innovation:

$$BMI_i=1-\frac{D_i \cdot D_a^T}{\sqrt{D_i \cdot D_i^T \cdot D_a \cdot D_a^T}} \tag{2}$$

Where: D_i and D_i^T respectively denote the vector and transpose matrix of the nine indicators of business model innovation for firm i among the sample listed companies in the smartphone industry chain; D_a and D_a^T respectively denote the vector and transpose matrix of the average values of the nine indicators of business model innovation for the sample listed companies in the smartphone industry chain. The calculation result of BMI ranges from (0, 1). The closer the calculation result of business model innovation for a smartphone industry chain enterprise is to 1, the higher its business model innovation level is compared with the average level of the smartphone industry chain.

3.2.3 Mediating Variable

Artificial Intelligence Application (AI): Artificial intelligence plays a key role in improving enterprise production efficiency and driving economic growth. Existing studies measuring the level of artificial intelligence application mostly rely on indicators such as the number of technology patents and the scale of robots, but such measurement methods fail to comprehensively and accurately reflect the actual application degree of artificial intelligence in the entire process of enterprise operations. In recent years, many studies have begun to take enterprise annual reports as the data source and comprehensively depict the overall application level of artificial intelligence technology at the enterprise level by identifying the frequency of keywords related to "artificial intelligence application". Therefore, this paper draws on the practice of Yao Jiaquan et al. Based on a dictionary containing a total of 73 words including "artificial intelligence, AI products, AI chips, deep learning, machine learning, and human-computer interaction", this paper extracts the number of relevant feature words through word segmentation and text mining via Python, and finally obtains the enterprise artificial intelligence application indicator after summing up and logarithmic processing (Yao et al., 2024).

Green Technology Innovation (Patent): High-quality green invention patents tend to have higher citation counts. Therefore, this paper uses the citation counts of green invention patents applied for by enterprises in the current year as a proxy indicator for green technology innovation (Lahiri, 2010). Considering that patents applied for earlier tend to accumulate more citations, and failing to restrict the time window will lead to estimation bias, this paper draws on the method of Liu Bai and manually collates the total citation counts of green invention patents applied for by enterprises in the current year within the next two years based on the enterprise green invention patent citation data from the National Intellectual Property Administration (NIPA) to measure corporate green technology innovation (Liu et al., 2023). In the empirical analysis, the green technology innovation variable is processed by adding 1 and taking the natural logarithm to address the issue of right-skewed distribution in green patent data.

3.2.4 Control Variable

To mitigate endogeneity issues caused by omitted variables, this paper selects five variables as control variables that may affect the carbon performance of firms in the smartphone industry chain: firm size (Size), firm age (Age), ownership structure (Fsr), board size (Dep), and intangible assets (Intasset). Specifically: Firm size (Size) is measured as the natural logarithm of a firm’s total assets; Firm age (Age) is measured as the natural logarithm of the difference between the sample observation year and the firm’s year of establishment; Ownership structure (Fsr) is measured as the ratio of the total shareholding of the firm’s top ten shareholders to its total share capital; Board size (Dep) is measured as the natural logarithm of the number of directors on the firm’s board; Intangible assets (Intasset) is measured as the ratio of a firm’s intangible assets to its total tangible assets.

Table 2: Variable Description and Definition

Variable Type	Variable Name	Symbol	Variable Measurement
Explanatory Variable	Business Model Innovation	BMI	A vector covering four dimensions: value creation, value delivery, and value realization.
Explained Variable	Corporate Carbon Performance	CP	The natural logarithm of: Corporate operating revenue / [(industry carbon emissions / total industry operating costs) × corporate operating costs]
Mediating Variable	Artificial Intelligence Application	AI	Word frequency of relevant terms in corporate annual reports
	Green Technological Innovation	Patent	The natural logarithm of the number of green patent applications
Control Variable	Firm Size	Size	The natural logarithm of a firm's total assets
	Firm Age	Age	The natural logarithm of the difference between the sample observation year and the firm's founding year
	Ownership Structure	Fsr	The proportion of total shares held by the top ten shareholders relative to total share capital
	Board Size	Dep	The natural logarithm of the number of directors
	Intangible Assets	Intasset	The ratio of intangible assets to the total amount of tangible assets

3.3 Model Specification

3.3.1 Baseline Regression Model

To examine the impact of business model innovation (BMI) on the carbon performance of firms in the smartphone industry chain, this paper establishes the following baseline regression model, as shown in Equation (3). To control for the influence of unobservable time-varying factors and firm heterogeneity, time fixed effects (d_{Year}) and firm fixed effects ($d_{Industry}$) are introduced.

$$CP_{it} = \alpha_0 + \alpha_1 BMI_{it} + \alpha_2 Controls_{it} + d_{Year} + d_{Industry} + \varepsilon_{it} \tag{3}$$

Where: i and t denote the firm in the smartphone industry chain and the year, respectively; α_0, α_1, and α_2 are constant terms; ε_{it} is the stochastic disturbance term. CP_{it} represents the carbon performance of firm i in the smartphone industry chain in year t; BMI_{it} represents the level of business model innovation of firm i in the smartphone industry chain in year t; Controlsit denotes the control variables in this paper, including firm size, firm age, board size, ownership structure, and intangible assets.

3.3.2 Model specification

The mainstream approaches for constructing mediation effect models in current research can be summarized as the two-step method and the three-step method. The three-step method has significant limitations: the multiple regression equations on which it relies are susceptible to interference from endogeneity issues such as omitted variables and reverse causality, which may lead to bias in the results of mediation effect tests (Wen, 2014). In contrast, the two-step method simplifies the testing process and explicitly requires theoretical demonstration of the key causal paths in the model, which can effectively avoid mechanical testing of paths with severe endogeneity correlations and thus better embody the principle of rigor in causal inference (Jiang, 2022). Based on this, to test Hypotheses H2 and H3, this study adopts the two-step mediation effect model to examine the mediating effects of artificial intelligence (AI) application level and green technology innovation on the relationship between business model innovation (BMI) and corporate carbon performance (CP), respectively.

$$M_{it} = \beta_0 + \beta_1 \mathrm{BMI}_{it} + \beta_2 Controls_{it} + d_{Year} + d_{Industry} + \varepsilon_{it} \tag{4}$$

Where: t denotes the firm in the smartphone industry chain, and t denotes the year; β_0 、β_1 and β_2 are constant terms; εit is the stochastic disturbance term. BMit denotes the corresponding mediating variable, including artificial intelligence (AI) application level and green technology innovation (Patent). The meanings of the remaining variables are the same as those in Equation (3).

4. Empirical Results and Analysis

4.1 Descriptive Statistical Analysis

Table 3 presents the descriptive statistical results of the main variables for listed companies in the smartphone industry chain. The mean value of corporate carbon performance (CP) is 10.2430, with a minimum of 8.6220, a maximum of 10.9600, and a standard deviation of 0.2800; the mean value of corporate business model innovation (BMI) is 0.0560, with a minimum of 0.0030, a maximum of 0.5710, and a standard deviation of 0.0610. The data for the main control variables, such as ownership structure (Fsr, mean = 0.5010), firm size (Size, mean = 22.5280), firm age (Age, mean = 2.9980), board size (Dep, mean = 2.0700), and intangible assets (Intasset, mean = 0.0740), all fall within reasonable ranges.

Table 3: Descriptive Statistics Results

Variable	Sample Size	Mean	Standard Deviation	Minimum	Maximum
CP	1064	10.2430	0.2800	8.6220	10.9600
BMI	1064	0.0560	0.0610	0.0030	0.5710
AI	1064	1.8250	1.4730	0	5.6130
Patent	1064	0.6180	1.1160	0	5.8320
Age	1064	2.9980	0.2890	1.9460	3.7380
Dep	1064	2.0700	0.1940	1.6090	2.6390
Size	1064	22.5280	1.3810	19.6400	27.1920
Intasset	1064	0.0740	0.5310	-14.6810	6.7040
Fsr	1064	0.5010	0.1460	0.0880	0.9940

4.2 Analysis of Baseline Regression Results

The regression results between business model innovation and corporate carbon performance are shown in Table 4. Specifically, Column (1), Column (2) and Column (3) in the table show the multiple regression results of Formula (3) under different settings respectively. The main difference between these settings is whether individual and time fixed effects are controlled and whether control variables are added. Column (1) shows the regression results without controlling individual and time fixed effects and without adding control variables. In this case, the regression coefficient between business model innovation and corporate carbon performance is 0.3660, and this coefficient passes the test at the 1% significance level. This shows that without considering other potential influencing factors, business model innovation has a significant positive impact on corporate carbon performance. Column (2) shows the regression results after adding control variables. At this time, the regression coefficient of business model innovation on corporate carbon performance is 0.3456, which is significant at the 5% significance level. This result shows that after considering factors such as firm size and ownership structure, the positive impact of business model innovation on corporate carbon performance still exists significantly. Column (3) shows the complete regression results after controlling individual and time fixed effects and adding control variables. Under this setting, the regression coefficient between business model innovation and corporate carbon performance reaches 0.4279, which is significant at the 1% significance level, verifying Hypothesis H1.

Table 4: Baseline Regression Analysis Results

Variable	(1)	(2)	(3)
	CP	CP	CP
BMI	0.3660***	0.3456**	0.4279***
	(2.6746)	(2.5708)	(6.5008)
Control Variables	NO	YES	YES
Constant	9.7501***	9.5702***	9.6027***
	(864.3355)	(60.5855)	(33.1793)
ID	NO	NO	YES
Year	NO	NO	YES
N	1064	1064	1064
R^2	0.007	0.071	0.917
F	7.154	13.516	10.876

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are reported in parentheses.

4.3 Robustness Checks

4.3.1 Excluding Municipalities Directly Under the Central Government

Municipalities directly under the central government have significant economic and political particularities. The impact of business model innovation (BMI) on corporate carbon performance (CP) may differ from that in other cities, thereby interfering with the results of the baseline regression analysis. To rule out this potential influence, this paper excludes the samples of the four municipalities directly under the central government - Shanghai, Beijing, Tianjin, and Chongqing - and re-runs the regression analysis, obtaining the regression results shown in Column (1) of Table 5. The regression coefficient between business model innovation (BMI) and corporate carbon performance (CP) is 0.4219, which is statistically significant at the 1% level. This result further strengthens the conclusion that business model innovation can improve the level of corporate carbon performance, and this conclusion is robust and not affected by regional differences in economic development.

4.3.2 Replacing the Core Independent Variable

In the previous analysis, the technology distance measurement method was adopted to measure business model innovation (BMI). To verify the robustness of the conclusion, this paper further draws on the method of Liu Zhengyang et al. and uses Principal Component Analysis to calculate the composite score, which serves as the indicator level for measuring the degree of business model innovation (BM). Using this new measurement standard, the regression analysis is re-run, and the regression results shown in Column (2) of Table 5 are obtained. After measuring business model innovation with the new method, the regression coefficient between business model innovation (BM) and corporate carbon performance (CP) is 0.2117, which is statistically significant at the 1% level. This result once again confirms the existence of a significant positive correlation between business model innovation and corporate carbon performance.

4.3.3 Lagging the Core Independent Variable by One Period

Considering that the outcomes of business model innovation implementation by firms in the smartphone industry chain may exhibit a time lag, and that endogeneity may arise from reverse causality between the core independent variable (business model innovation, BMI) and the dependent variable (corporate carbon performance, CP)—specifically, firms with higher carbon performance may be more inclined to implement business model innovation, meaning carbon performance could be the cause rather than the outcome of business model innovation. To mitigate the endogeneity issue caused by reciprocal causality between the independent and dependent variables, this paper uses the first-order lag term of business model innovation as the core independent variable for regression analysis. Column (3) of Table 5 shows that after lagging business model innovation by one period, it still has a significant positive impact on corporate carbon performance. After accounting for the lag of the core independent variable, business model innovation still promotes the improvement of corporate carbon performance, and the conclusion is consistent with the previous findings.

4.3.4 GMM Instrumental Variables

Corporate carbon performance (CP) exhibits a cumulative nature, as the carbon performance of the previous period significantly affects that of the current period. Therefore, the System GMM model is adopted for the endogeneity test, which can effectively mitigate the endogeneity of the model. First, the p-value of the first-order serial correlation test is 0.087, and the p-value of the second-order serial correlation test is 0.127, indicating the existence of first-order serial correlation but no second-order serial correlation, thus passing the test. Second, the instrumental variables of the model pass both the Sargan test and the Hansen test (corrected from the typo "Henson test"), demonstrating that the selection of instrumental variables is reasonable and satisfies the exogeneity assumption. The regression results of the model are shown in Column (4) of Table 5. The impact of the lagged one-period corporate carbon performance on current carbon performance is substantial, with a coefficient of 0.5644 that is statistically significant at the 1% level. The impact of business model innovation (BMI) remains positive and passes the test at the 10% significance level. This indicates that the baseline regression of this paper is relatively credible, and business model innovation can significantly improve corporate carbon performance.

Table 5: Robustness Check Results

	(1)	(2)	(3)	(4)
	CP	CP	CP	CP
BMI	0.4219***			0.3015*
	（6.1560）			(1.8619）
BM		0.2117***		
		（5.9170）		
L.BMI			0.1256*	
			（1.6707）	
L.CP				0.5643***
				(6.7120)
Control Variable	YSE	YSE	YSE	YSE
Constant	10.0458***	9.9571***	9.5205***	55.4855***
	(31.1164)	(34.0498)	(24.8465)	(3.2445)
ID	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	960	1064	931	931
R^2	0.915	0.911	0.899	
F	10.166	9.772	1.692	

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are reported in parentheses.

4.4 Mechanism Analysis1

4.4.1 The Mechanistic Role of Artificial Intelligence

Different links of business model innovation rely on a large amount of data, such as optimizing operations, matching supply and demand, forecasting demand, and managing complex networks, thereby driving enterprises' demand for and depth of application of artificial intelligence (AI) technology. AI technology is widely applied in various links of firms in the smartphone industry chain. In the manufacturing link of the smartphone industry chain, AI can improve production efficiency. Existing studies show that AI technology substitutes for routine and repetitive labor positions, while complementing non-routine and non-repetitive labor positions. Therefore, enterprises exert the productivity effect of AI by reducing demand for routine low-skilled labor and increasing demand for non-routine high-skilled labor (Xu et al., 2022). In the intelligent logistics and supply chain link, AI can optimize routes and enhance efficiency. ZTE Corporation combines AI technology with traditional industries to unlock the data value of the entire field, improve the productivity of the whole process, reduce energy consumption across the entire chain, and achieve a win-win situation between development and emission reduction (ZTE Zero Carbon Strategy White Paper, 2024). In the product manufacturing link, AI technology empowers the product manufacturing process, significantly reducing energy consumption and carbon emissions. For example, BOE focuses on the intelligentization of core manufacturing units, and has achieved breakthroughs in key AI industrial software systems such as industrial quality inspection and knowledge Q&A through AI technology, resulting in better efficiency, lower costs, and higher yield rates (BOE 2024 Sustainable Development Report, 2024). According to existing research, this paper uses the keyword frequency in enterprise annual reports to characterize the level of AI technology. Column (1) of Table 6 reports the mediating effect of the AI level between business model innovation (BMI) and corporate carbon performance (CP). It can be seen that business model innovation has a significant positive impact on corporate carbon performance, with a coefficient of 0.7580 that is statistically significant at the 1% level. This indicates that the level of AI can enhance business model innovation to promote the improvement of corporate carbon performance, verifying Hypothesis H2.

4.4.2 The Mechanistic Role of Green Technology Innovation

Green technology innovation includes the incremental improvement of technologies such as clean production processes, energy-saving equipment, environmentally friendly materials, renewable energy technologies, and carbon capture technologies, bringing about fundamental changes in products, services, or processes. This provides enterprises with the opportunity to construct brand-new value propositions centered on "green" or "low-carbon". Green technology innovation also enables enterprises to effectively comply with increasingly stringent environmental regulations and meet consumers' growing green consumption preferences, creating huge market demand for green products and services. Leading green technologies can serve as a powerful differentiation tool, enabling enterprises to distinguish themselves from competitors, win over specific customer groups, and potentially obtain a green premium, thereby improving corporate carbon performance. The mediating effect of green technology innovation is reported in Column (2) of Table 6. The results show that green technology innovation has a significant positive impact on corporate business model innovation (BMI), with a coefficient of 0.7575 that is statistically significant at the 1% level. This indicates that enterprises can enhance business model innovation through green technology innovation to promote the improvement of corporate carbon performance (CP), verifying Hypothesis H3.

Table 6: Mechanism Analysis Results

	(1)	(2)
	Mediating Variable	Green Technology Innovation
	AI	Patent
BMI	0.7580***	0.7575***
	(2.5097)	(2.0184)
Control Variable	YES	YES
Constant	-0.5473	-5.7140*
	(-1.5422)	(-1.8627)
ID	YES	YES
Year	YES	YES
N	1064	1064
R^2	0.052	0.625
F	9.650	2.982

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are reported in parentheses.

5. Heterogeneity Analysis

5.1 Heterogeneity Analysis Based on Firm Characteristics

5.1.1 Firm Ownership

Property Rights Theory holds that the ownership nature of a firm affects its production management and innovation activities. Accordingly, the carbon reduction effect of business model innovation (BMI) may differ across firms with different ownership types. Therefore, this paper divides the firm sample into two groups - state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) - based on firm ownership nature for in-depth analysis. Columns (1) and (2) of Table 7 present the heterogeneity regression results for different firm ownership types. The results show that business model innovation promotes corporate carbon performance (CP) in both SOEs and non-SOEs, with a stronger effect in the former. Specifically, the coefficient of business model innovation on corporate carbon performance is 0.4798 for SOEs, significant at the 1% level; the coefficient is 0.3966 for non-SOEs, also significant at the 1% level. Compared with non-SOEs, SOEs are more resolute in implementing government policies and more responsive to policy guidance. On the one hand, SOEs' advantages in capital scale, R&D teams, and supply chain control capability support them in carrying out high-investment, long-cycle carbon reduction-oriented business model innovation. On the other hand, relying on collaborative networks with government departments and research institutions, SOEs can more quickly access key elements such as low-carbon technologies and carbon management standards, reducing the adaptation cost between business model innovation and carbon reduction goals (Ma et al., 2025).

Although non-SOEs have the flexibility of market-oriented innovation, they are constrained by financial limitations and narrow channels for technology acquisition. Their business model innovation mostly focuses on the application of low-carbon technologies, resulting in a relatively limited driving effect on carbon performance.

5.1.2 Heterogeneity of Financing Constraints

Firms with weaker financing constraints usually have easy access to sufficient financial support to optimize the input of production factors, improve production efficiency, and expand investment in emission reduction equipment. Therefore, such firms may be less affected by the factor input optimization effect, productivity effect, and emission reduction equipment investment effect released by foreign investment openness in reducing pollution emission intensity. The SA index is designed to measure the ease with which firms obtain external financing, i.e., the strength of financing constraints. Following the research of Sudan Ni and Sheng Bin, this paper divides the sample into two groups - firms with strong financing constraints and firms with weak financing constraints - based on the mean value of the SA index. The results are shown in Columns (3) and (4) of Table 7. The results show that business model innovation (BMI) has a significant positive impact on corporate carbon performance (CP) in both firms with strong and weak financing constraints, and the effect is significant at the 1% level. However, in terms of the coefficient, the impact of business model innovation on carbon performance is greater for firms with strong financing constraints. This further indicates that financing constraints may act as a forcing mechanism, forcing firms to allocate limited resources more precisely and efficiently to business model innovation activities that can directly and significantly improve carbon performance. It also reflects that under resource-constrained conditions, successful business model innovation tends to have stronger resource-saving and leverage effect characteristics, with a higher marginal contribution to carbon emission reduction, highlighting the differences in carbon emission reduction paths among heterogeneous firms.

Table 7: Heterogeneity Results Based on Firm Characteristics

	Firm Ownership		**Financing Constraints**	
	SOEs	**non-SOEs**	**Strong**	**Weak**
	(1)	(2)	(3)	(4)
BMI	0.4798***	0.3966***	0.3923***	0.3852***
	(4.8912)	(4.7540)	(5.1020)	(2.9769)
Control Variable	YES	YES	YES	YES
Constant	9.7764***	9.5873***	9.2094***	8.6982***
	(22.4867)	(26.2489)	(21.6504)	(6.8071)
ID	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	264	800	548	491
R^2	0.938	0.913	0.942	0.918
F	6.563	6.843	5.995	2.171

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are reported in parentheses.

5.2 Heterogeneity Analysis Based on Industry Chain Links

This paper divides firms in the smartphone industry chain into five major links: chips, display screens, supporting components, complete machine design and manufacturing, and brand channels & application services. Differences across these links may also affect the degree to which business model innovation (BMI) influences corporate carbon performance (CP). Therefore, this paper divides the sample into these five links for grouped regression, with the results presented in Table 8.

The regression results show that the improvement of business model innovation (BMI) in the chips, display screens, and supporting components links of the smartphone industry chain has a significant promoting effect on corporate carbon performance (CP), while business model innovation in the complete machine design and manufacturing, and brand channels & application services links has no significant impact on carbon performance.

The possible reasons are as follows: As upstream links, chips, display screens, and supporting components have a high emission base and strong technological traction, making business model innovation a key leverage point for driving the leap of the industry chain's carbon performance. The research by Fang Yuxia et al. also shows that at the upstream end, product R&D and design realize personalized customization through digital platforms to accurately meet customer needs, thereby avoiding resource waste and reducing carbon emissions; while innovation in the middle and downstream links focuses more on value capture and market efficiency, with a relatively indirect and weak carbon reduction effect (Fang et al., 2024).

Table 8: Heterogeneity Results Test Based on Industry Chain Links

	(1)	(2)	(3)	(4)	(5)
	Chips	**Display Screens**	**Supporting Components**	**Complete Machine Design and Manufacturing**	**Brand Channels & Application Services**
BMI	0.8217***	0.4087**	0.4211***	0.4803	0.2657
	(4.1296)	(2.4266)	(4.9909)	(1.6412)	(1.3896)
Control Variable	YES	YES	YES	YES	YES
Constant	8.1724***	10.4231***	9.2330***	3.0818***	9.3964***
	(11.2785)	(10.2665)	(26.8496)	(4.3556)	(5.4166)
ID	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
N	128	120	576	32	208
R^2	0.919	0.894	0.927	0.960	0.921
F	4.867	3.192	9.825	1.243	2.133

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. t-statistics are reported in parentheses.

6. Conclusions and Implications

Against the backdrop of the parallel advancement of green and intelligent transformation, business model innovation (BMI), as a key driver of corporate reform and technological innovation, is of great significance for enterprises to achieve both economic benefits and carbon reduction goals. Based on data from 133 listed companies in China’s smartphone industry chain from 2015 to 2022, this study adopts methods such as two-way fixed effects, instrumental variable approach, mechanism test, and text mining to investigate the impact of business model innovation (BMI) on corporate carbon performance (CP), as well as the mechanism of artificial intelligence (AI) level and green technology innovation (Patent). The main conclusions are as follows: The baseline regression reveals that business model innovation (BMI) of firms in the smartphone industry chain has a significant positive impact on corporate carbon performance (CP), meaning that BMI can promote the improvement of CP, and this conclusion is validated through a series of robustness and endogeneity tests. Mechanism analysis shows that business model innovation (BMI) can significantly improve corporate carbon performance (CP) through two channels: artificial intelligence (AI) level and green technology innovation (Patent). Heterogeneity analysis indicates that the positive effect of business model innovation (BMI) on corporate carbon performance (CP) is more pronounced for state-owned enterprises (SOEs), firms with strong financing constraints, and enterprises in the upstream industry chain links (chips, display screens, and supporting components).

Based on the above conclusions, the following implications are drawn:
(1) Enterprises should actively optimize business model innovation (BMI) and deeply integrate corporate carbon performance (CP) into their BMI strategies. As high-tech enterprises, firms in the smartphone industry chain need to carefully design clear carbon reduction paths when carrying out innovative practices such as digital platform development, servitization transformation, and exploration of circular economy models. By establishing low-carbon attributes as the core value proposition of new business models, enterprises can build unique differentiated competitive advantages to stand out in market competition. At the same time, it is crucial to strengthen close cooperation with suppliers and customers. Enterprises should establish cross-departmental collaboration mechanisms to break down departmental barriers, promote information flow and resource sharing, ensure efficient coordination among all links of the industry chain, and quickly transform carbon reduction concepts and technologies into commercially feasible solutions to accelerate the green transformation process. In addition, enterprises should set up green innovation projects and corresponding incentive mechanisms to encourage employees to actively participate in green innovation practices and integrate green concepts into every link of daily work.
(2) Enterprises need to implement business model innovation (BMI) in a differentiated manner based on their own characteristics and industry chain positioning to improve corporate carbon performance (CP). State-owned enterprises (SOEs) should play a demonstration and leading role, strengthen policy guidance and institutional design, and incorporate carbon performance (CP) into the management assessment system. Non-state-owned enterprises (non-SOEs) should build industry-university-research collaboration platforms to promote the in-depth integration of business model innovation (BMI) and green technology innovation (Patent). Enterprises facing financing constraints need to convert resource pressure into innovation motivation and accurately allocate limited resources to business model innovation activities with high carbon emission reduction benefits. Governments and financial institutions should work together to expand green financing channels. At the industry chain level, upstream enterprises (chips, display screens, and supporting components) need to deepen business model innovation (BMI), focus on exploring circular economy and servitization transformation paths, realize personalized customization and resource optimization through digital platforms, and strengthen collaborative innovation in the industry chain. Downstream complete machine manufacturing and brand service enterprises still need to actively explore adaptive paths such as production process optimization and green logistics, and take the initiative to connect with upstream technological innovation achievements to indirectly improve carbon performance (CP) through industry chain collaboration. Ultimately, through full-chain collaboration, the systematic empowerment of business model innovation (BMI) on carbon emission reduction can be achieved.
(3) Governments should guide enterprises to firmly adhere to the strategic direction of intelligent and green transformation. This study finds that the application of

artificial intelligence (AI) and green technology innovation (Patent) can further amplify the impact of business model innovation (BMI) on corporate carbon performance (CP), providing new ideas and paths for enterprises to achieve a win-win situation between economic benefits and environmental benefits on the path of low-carbon development. Governments can adopt a series of policy measures such as providing financial subsidies and implementing tax incentives to effectively reduce the cost input and risk pressure faced by enterprises in the process of AI innovation and green technology innovation application. They should guide enterprises to firmly pursue the strategic transformation of intelligence and greening, deeply integrate cutting-edge AI technologies and green technology innovation into corporate business needs, realize the organic integration and coordinated development of technology and business, thereby effectively improving enterprise production efficiency, enhancing core competitiveness in the market, and promoting enterprises to achieve high-quality development driven by the dual wheels of intelligence and greening.

Although this study has made innovations in research methods, perspectives, and mechanisms, it still has certain limitations in data collection and indicator measurement. On the one hand, in the process of collecting corporate carbon emission data, constrained by the fact that a unified and complete construction system for domestic corporate carbon emission databases has not yet been formed, this study relies on industry-level carbon emission statistics for firm-level conversion, which may lead to deviations in carbon performance (CP) measurement results and make it difficult to accurately reflect the real carbon emission reduction achievements of individual enterprises. Future research can further refine the collection and sorting of micro-level corporate carbon emission data and construct a firm-level carbon emission panel database, thereby improving the accuracy and micro-level distinguishability of carbon performance measurement. On the other hand, in the measurement of corporate artificial intelligence (AI) level, this study adopts the proxy variable method of taking the logarithm of keyword frequency. Although this method can ensure indicator availability by relying on public text data, it may give rise to the risk of AI-washing. Future research can explore measurement paths that are more in line with the essence of AI application, such as constructing a weighted comprehensive evaluation system by combining multi-dimensional indicators such as the number of AI-related patent applications and the number of landing cases of AI technologies in multiple scenarios, to reduce the interference of AI-washing risk on the robustness of research conclusions.

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