

Article

Artificial Intelligence and Firms' Environmental Cost Pressures: Mechanisms, Spillover Effects, and Optimization Pathways

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Abstract

Against the backdrop of increasingly stringent global environmental constraints and rising environmental cost pressures on businesses, artificial intelligence offers a new approach to green cost-reduction and transformation. However, due to constraints such as transformation costs, technological compatibility, and industry standards, the extent to which it can effectively reduce costs and empower businesses remains uncertain. Based on this, this paper uses panel data from Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2018 to 2024 as a sample to systematically empirically examine the impact, transmission mechanisms, boundary conditions, and spatial spillover characteristics of AI on corporate environmental cost pressures. The study finds that AI can significantly alleviate corporate environmental cost pressures, a conclusion that remains robust after multiple robustness and endogeneity tests. Moderating effects indicate that corporate willingness to engage in green governance and the regional digital regulatory environment can positively reinforce its cost-reduction effects. At the mechanism level, AI can indirectly reduce corporate environmental costs through two pathways: promoting green technological innovation and optimizing the allocation of production factors. Further research confirms that AI exhibits distinct positive spatial spillover effects, which can help regional firms achieve coordinated reductions in environmental costs. This paper enriches the theoretical framework of corporate environmental cost governance from a digital empowerment perspective, providing empirical references and practical insights for corporate green digital transformation, the refinement of government digital-green support policies, and low-carbon development in emerging economies.

Keywords: artificial intelligence; environmental cost pressure; green technological innovation; factor allocation; spatial spillover; corporate green governance



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1. Introduction

Global climate deterioration, resource depletion, and worsening environmental pollution have made ecological and environmental governance a central issue for sustainable global economic and social development. The ongoing advancement of the United Nations 2030 Agenda for Sustainable Development and national carbon neutrality strategies is compelling the global industrial system to accelerate its transition toward a green and low-carbon future. Environmental compliance, pollution control, energy conservation, emissions reduction, and ecological restoration are gradually becoming mandatory requirements for corporate operations. Multiple rounds of IPCC assessment reports have indicated that frequent extreme weather events and ecological degradation will continue to drive up

environmental governance costs for micro-entities, thereby increasing operational uncertainty for businesses. To systematically advance the green transition and regulate corporate environmental behavior, China has been consistently implementing its “Dual Carbon” strategy. The country has successively introduced institutional frameworks such as a green tax system, mandatory environmental information disclosure, and regularized ecological and environmental inspections, transforming corporate environmental responsibilities from soft advocacy into rigid institutional constraints. The internalization of environmental costs has thus become an inevitable trend in corporate operations and development. Against this backdrop, traditional, energy-intensive, high-emission, and extensive business models are no longer sustainable, and the environmental cost pressures facing enterprises continue to rise. These encompass multiple explicit and implicit costs, including end-of-pipe pollution treatment, green technology R&D, operation and maintenance of environmental protection equipment, penalties for non-compliance, and carbon trading expenditures, severely squeezing corporate profit margins and development resilience [1,2]. How to effectively alleviate environmental cost pressures and achieve the coordinated development of green, low-carbon goals and economic benefits has become the core challenge in current corporate transformation and development.

The deep integration of the digital economy and the green economy offers a new pathway to resolving enterprises’ environmental cost dilemmas. As the core vehicle of next-generation digital technology, artificial intelligence (AI)—leveraging technical advantages such as real-time sensing, data modeling, intelligent scheduling, precise forecasting, and dynamic optimization—is reshaping corporate environmental governance models and the logic of cost formation. Unlike traditional manual control and end-of-pipe treatment—which suffer from high costs, low efficiency, and lag—AI can leverage sensor networks, digital twins, and machine learning algorithms to achieve intelligent, end-to-end management of production energy consumption, pollutant emissions, and resource utilization. This reduces corporate environmental governance costs at the source and enhances the efficiency of green operations [3,4]. Currently, AI is widely applied in scenarios such as enterprise energy optimization and scheduling, precise pollutant monitoring, waste recycling, and environmental risk early warning. It effectively addresses pain points in traditional environmental management—including resource waste, delayed remediation, high compliance costs, and difficulties in risk prevention and control—and has become a core driver for enterprises to hedge against environmental cost pressures and advance green and low-carbon transformation [5]. However, as enterprises rely on AI to alleviate environmental cost pressures during their transformation, they still face multiple practical constraints that limit the full realization of digital green empowerment. First, the R&D of AI-based green technologies and the deployment of smart equipment require substantial upfront investments. Incremental costs associated with technology adaptation, system operation and maintenance, and the cultivation of digital talent place a heavy financial burden on enterprises in the short term [6]. Second, some traditional enterprises have weak digital foundations, and their production processes and management systems are poorly suited to AI-driven green governance models. This results in low implementation rates for smart technologies, making it difficult to achieve large-scale cost-reduction effects [7]. Third, the standard system for AI-enabled environmental governance remains underdeveloped. The lack of unified standards for environmental data accounting, quantification of smart emission reduction outcomes, and technical application guidelines can easily lead to governance inefficiencies and misallocation of resources [8]. Fourth, the use of digital technology to empower green transformation carries potential risks. Issues such as data security vulnerabilities, algorithmic bias, and technological dependency may lead to erroneous environmental governance decisions, thereby increasing enterprises’ hidden

environmental costs [9]. The convergence of these multiple challenges creates uncertainty regarding the mitigating effects of AI on corporate environmental costs, while also highlighting the practical necessity of clarifying the intrinsic relationship between the two, exploring empowerment mechanisms, and optimizing transformation pathways.

The academic community has already conducted extensive research on the factors influencing corporate environmental costs, pathways for green transition, and the green enabling effects of artificial intelligence, yielding multidimensional research findings. In the field of corporate environmental cost research, existing studies generally agree that the intensity of environmental regulations [10], corporate governance levels [11], green technological innovation [12], and external oversight pressure [13] are core factors influencing corporate environmental costs. Furthermore, it has been confirmed that excessively high environmental costs significantly inhibit corporate investment efficiency, profitability, and market competitiveness [14,15]. In the field of digital technology and green transition research, most scholars, adopting a macro-industrial and regional perspective, have validated the positive enabling role of digital technologies—such as artificial intelligence and big data—in industrial low-carbon upgrading and regional ecological governance. They argue that digital technologies can enhance resource allocation efficiency and drive green innovation in industries [16,17]. At the micro-enterprise level, relevant studies have explored these issues based on Porter's hypothesis and cost-benefit theory. Some research suggests that artificial intelligence effectively reduces corporate end-of-pipe treatment costs and compliance costs by optimizing production processes, lowering energy consumption and waste, and reducing pollution emissions [18–20]; while other studies point out that digital technology transformation involves high investment costs and technical adaptation lags, which may exacerbate operational pressures on enterprises in the short term, and that the mitigating effects on environmental costs exhibit threshold effects and heterogeneity [21,22].

Overall, significant gaps remain in the existing research. First, most existing studies focus on the overall impact of AI on corporate green performance and emission reduction effects, with few conducting targeted research specifically on the core dimension of environmental cost pressure. There is a lack of systematic analysis of the specific mechanisms and transmission pathways through which AI mitigates corporate environmental costs, and a unified theoretical analytical framework has yet to be established. Second, existing research conclusions are divergent. There is no consensus on whether AI's mitigating effect on corporate environmental costs represents long-term empowerment or short-term pain, or whether it involves linear impacts or nonlinear constraints; the relevant marginal effects and heterogeneity characteristics require further verification. Third, while most studies focus on examining the green empowerment effects of AI, they overlook the practical challenges and institutional shortcomings in the current intelligent green transformation of enterprises. There is a lack of an optimization pathway system tailored to the development contexts of Chinese enterprises, making it difficult to effectively guide enterprises in overcoming transformation dilemmas. Based on this, our core research questions focus on: Can AI significantly alleviate the pressure of corporate environmental costs? Through what core mechanisms does it transmit its empowerment effects? Do these enabling effects exhibit heterogeneity across different enterprises, industries, and institutional contexts? How can we construct a scientifically sound and comprehensive optimization pathway to maximize the cost-reduction and efficiency-enhancement value of AI?

Given these research gaps and the current context, we use microdata from A-share listed companies on the Shanghai and Shenzhen stock exchanges as our research sample. We treat the application of AI technology as an exogenous technological shock to corporate green transformation, systematically exploring the impact of AI on corporate

environmental cost pressures, its underlying mechanisms, and optimization pathways. Selecting the Chinese market as the research setting holds significant research value and representativeness: First, China is in a period of overlapping dual strategies—the “dual carbon” transition and the upgrading of the digital economy. Enterprises face more urgent environmental regulatory constraints and demands for digital transformation, providing an ideal quasi-natural experimental setting for testing the environmental cost-reduction effects of AI. Second, China possesses a comprehensive industrial system with a rich array of samples spanning high-carbon manufacturing, traditional heavy industry, and emerging sectors. This allows for a thorough examination of effect heterogeneity across different industries and enterprises with varying characteristics, thereby enhancing the generalizability of the research conclusions. Third, China’s corporate digital transformation is in a phase of rapid iteration, characterized by typical challenges such as insufficient technological adaptation and uneven transformation. This enables the precise identification of transformation pain points and provides practical support for constructing targeted optimization pathways. At the same time, our research scenario takes into account the characteristics of transformation in developing countries, and our findings can provide valuable insights for emerging economies worldwide as they advance their digital-green convergence transformation.

The marginal contributions of this study are primarily reflected in three aspects: First, it expands the scope of research on *ex ante* determinants of corporate environmental cost management. By incorporating artificial intelligence into the analytical framework for corporate environmental cost management, we systematically verify its mitigating effect on corporate environmental cost pressures, thereby further enriching research on corporate environmental cost management in the context of the digital economy. Second, it clarifies the multidimensional transmission mechanisms through which artificial intelligence influences corporate environmental costs, thereby refining the relevant theoretical framework. We systematically deconstructed and validated the intrinsic mechanisms through which AI reduces environmental costs across four dimensions—optimization of resource allocation, improved efficiency in pollution control, compliance risk prevention and control, and empowerment of green innovation—thereby enriching the micro-level theoretical framework on how digital technologies empower corporate green transformation. Third, we have constructed differentiated optimization pathways for transformation tailored to enterprises’ long-term sustainable development. Based on enterprise scale and industry-specific pollution characteristics, we propose differentiated cost-reduction transformation pathways. The research conclusions not only provide practical guidance for enterprises to balance green transformation with operational profitability through AI but also offer empirical support and decision-making references for governments to refine digital green transformation policies and improve environmental governance systems.

2. Literature Review and Research Hypotheses

2.1. Literature Review

2.1.1. Research on the Green Governance Effects of Artificial Intelligence

The deep integration of the digital economy and the green economy has gradually made artificial intelligence a key driver of low-carbon industrial transformation. Academic circles have engaged in extensive discussions regarding the green governance effects of artificial intelligence. Existing research generally holds that, unlike traditional, single-purpose energy-saving and emission-reduction technologies, AI is an integrated governance tool characterized by systemic, holistic, and dynamic features. It can optimize corporate green development models across multiple dimensions, including production process optimization, efficient resource utilization, precise risk management, and multi-

stakeholder collaborative governance [23,24]. From a governance perspective, AI relies on a closed-loop operational system comprising data collection, algorithmic analysis, and intelligent decision-making. To a certain extent, this has addressed issues in traditional environmental governance—such as data lag, coarse-grained control, and subjective decision-making—facilitating a gradual transition in corporate environmental governance from experience-driven to data-driven approaches [25,26]. In practical applications, AI has progressively expanded to cover key enterprise operations such as energy management, manufacturing, pollution control, and compliance management [27,28]. At the production level, intelligent algorithms can dynamically optimize production parameters and precisely identify high-energy-consumption, high-waste, and high-emission production processes, helping enterprises advance low-carbon retrofits of production processes to moderately reduce pollutant generation and unnecessary energy consumption at the source [29]. At the treatment end, intelligent monitoring systems enable round-the-clock, high-precision monitoring of pollutant emissions, partially replacing the higher-cost manual inspection model, thereby helping to reduce labor costs and equipment wear and tear associated with end-of-pipe treatment [30]; at the compliance end, digital intelligent reporting and accounting systems can streamline processes such as environmental approvals, carbon emissions accounting, and environmental information disclosure, potentially alleviating the institutional transaction costs associated with corporate environmental compliance [31]. In terms of governance outcomes, most empirical studies confirm that artificial intelligence is highly likely to help reduce corporate carbon emission intensity, improve energy efficiency, and enhance green development performance. At the same time, some studies point out that the green empowerment effects of artificial intelligence are not simply linear or constant; they are often constrained by a company's technological foundation, governance philosophy, and external institutional environment, exhibiting significant situational heterogeneity. Overall, existing research has generally acknowledged the value of AI in green governance. However, studies specifically focusing on corporate environmental costs—a concrete operational indicator—and deeply exploring AI's role in alleviating the cost burden of corporate green transition remain relatively limited. There is still room for further expansion in terms of research depth and scenario applicability.

2.1.2. Research on Factors Influencing Corporate Environmental Cost Pressure

Environmental cost pressure primarily refers to the comprehensive cost burden borne by enterprises to comply with green regulatory requirements, fulfill pollution control tasks, and achieve low-carbon transformation and development. It encompasses both quantifiable explicit governance expenditures and implicit risk costs that are difficult to accurately calculate, serving as a key indicator for measuring the pressure and operational burden of corporate green transformation [32]. Current academic research primarily explores the formation logic and influencing factors of corporate environmental cost pressures from three dimensions: the external institutional environment, internal governance behavior, and the level of technological innovation [33]. Among external factors, the intensity of environmental regulations, the regional governance climate, and digital governance policies are particularly critical. While relatively strict environmental regulatory policies may force enterprises to increase investment in environmental protection equipment and pollution control expenditures in the short term, in the long run, they can gradually standardize corporate environmental governance behavior and reduce random and punitive additional environmental losses. The continuous improvement of regional digital governance systems is expected to lower transaction costs associated with corporate environmental information disclosure, compliance coordination, and risk prevention and control, thereby alleviating implicit environmental cost pressures to some extent [34]. On the internal front, a

company's green governance philosophy, strategic planning, and management mindset directly influence the efficiency of environmental cost control. Companies that proactively pursue green transformation tend to rely on technological upgrades to reduce costs at the source, whereas those that merely react to policy requirements often depend on end-of-pipe remediation, resulting in relatively higher long-term environmental governance costs [35]. From a technological perspective, green technological innovation and production technology upgrades are key pathways to reducing environmental costs. Traditional green technologies often focus on end-of-pipe pollution control, achieving cost optimization in only a single dimension, whereas digital and intelligent technologies enable refined cost control across the entire process and supply chain, offering greater potential for cost reduction [36]. Currently, a small number of studies have examined the impact of digital transformation on corporate environmental costs, but most are limited to macro-level trend analysis. Micro-level empirical research specifically targeting artificial intelligence—a core digital technology—remains insufficient, and the underlying mechanisms through which technology influences environmental costs require further clarification.

2.1.3. Literature Review and Research Gaps

A comprehensive review of existing research reveals that the academic community has largely clarified the green empowerment value of digital technologies and the core factors influencing corporate environmental cost pressures. However, there remains room for further exploration: First, research perspectives exhibit a certain bias. Existing studies largely focus on the effectiveness of improving green performance outcomes, while relatively neglecting the cost burdens associated with corporate green transformation. Few studies specifically explore the mitigating effects of AI on environmental cost pressures, making it difficult to fully address the practical challenges of high transformation costs and the difficulty of reducing these burdens; second, the analysis of underlying mechanisms is relatively weak. Most studies merely verify the direct linear relationship between the two factors, without systematically dissecting the multiple transmission pathways and boundary constraints through which AI influences environmental costs, leaving room for improvement in theoretical explanatory power; third, the research paradigm has certain limitations. Traditional studies often overlook the spatial interdependence of industrial clusters and rarely consider the cross-entity spillover effects of intelligent technologies, making it difficult to fully explain the observed phenomenon of regional industrial collaboration leading to green cost reduction. Based on this, we adopt a cost-reduction perspective to systematically explore the impact, mechanisms, and optimization pathways of AI on corporate environmental cost pressures, with the aim of appropriately supplementing the existing research framework.

2.2. Research Hypotheses

2.2.1. Direct Effects of AI on Corporate Environmental Cost Pressures

By leveraging a logic of refined, end-to-end governance, AI can moderately reduce corporate environmental expenditures at multiple stages—including source, process, and end-of-pipe—thereby alleviating the pressures of green transformation. First, at the production source, AI leverages big data analysis and intelligent algorithms to precisely identify resource wastage and high-emission points in production processes. By dynamically optimizing production techniques and the structure of factor inputs, it reduces the generation of pollutants and the inefficient consumption of energy, potentially lowering corporate costs associated with front-end low-carbon retrofits and source-level governance to some extent [37]. Second, in the process control phase, intelligent monitoring systems can enable real-time monitoring and risk early warning for energy consumption, pollutant discharge,

and solid waste emissions. This is highly likely to reduce environmental penalties and remediation costs caused by delays and oversights in manual monitoring, thereby alleviating the pressure of hidden risks in environmental governance [38]. Finally, in the end-of-pipe treatment and compliance phase, AI can optimize the operational efficiency of environmental protection equipment, reduce the cost per unit of pollutant treatment, and simultaneously streamline compliance processes such as environmental reporting, carbon accounting, and information disclosure, thereby reducing institutional transaction costs [39]. Based on the above analysis, AI is expected to alleviate enterprises' environmental cost burdens comprehensively and at multiple levels. Accordingly, we propose the following hypothesis:

H1. *The application of AI technology can alleviate enterprises' environmental cost pressures to a certain extent.*

2.2.2. The Moderating Mechanisms Through Which AI Alleviates Environmental Cost Pressures

The cost-reduction effects of AI are not constant; they are often subject to bidirectional constraints from both internal corporate governance philosophies and the external institutional environment, resulting in differentiated empowerment characteristics. From an internal perspective, a firm's willingness to engage in green governance determines the depth of AI implementation and the quality of its application. Firms with a proactive green governance philosophy are more inclined to integrate AI across all scenarios—including production-based pollution control, energy consumption management, and compliance oversight—thereby fully unleashing the technology's cost-reduction potential. In contrast, firms that merely passively adapt to policies often treat AI investments as a formality, failing to fully realize its cost-reduction value [40]. From an external perspective, the regional digital regulatory environment constitutes a critical external condition for technological empowerment. Well-developed regional digital infrastructure and standardized digital environmental supervision systems can lower the technical barriers and transaction costs associated with corporate digital transformation, providing robust support for the implementation of AI and further amplifying cost-reduction benefits [41]. Based on this, we propose the following hypotheses:

H2. *A firm's willingness to engage in green governance exerts a positive moderating effect on the cost-mitigating impact of AI.*

H3. *The regional digital regulatory environment has a positive moderating effect on the cost-mitigating effect of AI.*

2.2.3. Mediating Mechanisms Through Which AI Alleviates Environmental Cost Pressures

By integrating the theories of dynamic capabilities, resource-based theory, and information asymmetry, we argue that artificial intelligence does not directly reduce the pressure of environmental costs on enterprises. Rather, based on the multifaceted theoretical logic of digital resource empowerment, dynamic capability upgrading, and the elimination of information frictions, it optimizes enterprises' clean production and pollution control technology systems through green technological innovation, thereby reducing the costs of green innovation and end-of-pipe treatment. At the same time, by optimizing the efficiency of factor allocation, it corrects factor misallocation, reduces resource waste, and minimizes ineffective environmental expenditures, thereby creating an empowerment pathway from both the dimensions of technological innovation and production operations, which indirectly achieves a systematic reduction in corporate environmental costs.

First, the intermediary role of green technology innovation. Traditional green technology innovation suffers from high costs, long development cycles, low precision, and insufficient efficiency. Artificial intelligence, however, can reduce R&D trial-and-error costs by replacing physical experiments with intelligent simulations. By leveraging data modeling and trend forecasting to optimize technical solutions, it shortens R&D cycles and accelerates the iteration of clean production and low-carbon emission reduction technologies. Furthermore, by precisely matching technical requirements to production scenarios, it reduces R&D deviations and effectively improves the success rate of green technology implementation and application efficiency. Green technology innovation can further alleviate the pressure of environmental costs on enterprises. Although upgrading to green technologies entails short-term R&D and equipment investments, it offers the advantages of long-term cost reduction and diminishing marginal costs; the long-term benefits can effectively offset the short-term incremental costs. On the one hand, green technologies optimize processes and industrial structures at the source of production, reducing energy consumption and pollutant output, thereby decreasing enterprises' reliance on high-cost end-of-pipe treatment and saving on routine pollution control and equipment maintenance expenses. On the other hand, green technologies can improve energy and material utilization efficiency, promote resource recycling, and reduce production losses, ultimately leading to a sustained reduction in enterprises' environmental cost pressures [42].

Second, the intermediary pathway for optimizing the allocation of production factors. Under traditional production models, enterprises commonly face misallocation of production factors such as energy, labor, and equipment, which can easily lead to additional environmental costs such as resource idleness, inefficient energy consumption, and redundant treatment. Leveraging dynamic data analysis and intelligent scheduling capabilities, artificial intelligence can precisely align production demand with factor supply, optimize the allocation structure of energy resources, environmental protection equipment, and remediation personnel, mitigate resource waste caused by factor mismatches, and enhance the overall efficiency of production and environmental governance, thereby moderately reducing the environmental cost burden per unit of output [43]. Based on this, we propose the following hypotheses:

H4. *Green technological innovation plays a partial mediating role between artificial intelligence and corporate environmental cost pressures.*

H5. *The efficiency of production factor allocation plays a partial mediating role between artificial intelligence and corporate environmental cost pressures.*

2.2.4. Hypotheses on Spatial Spillover Effects

Most industries in the market exhibit a spatial distribution characterized by industrial clusters. Within these clusters, enterprises share close technological ties, resource sharing, and coordinated governance, endowing the green cost-reduction effects of AI with significant spatial spillover attributes. The intelligent green governance practices of local enterprises can provide neighboring firms with replicable smart management models through technical demonstrations, experience diffusion, and industrial collaboration, thereby assisting them in optimizing their own environmental governance systems and reducing environmental costs [44,45]. At the same time, unified regional digital environmental policies and public digital service platforms can further strengthen green governance coordination among enterprises, likely fostering a favorable landscape of regional collaborative cost reduction. Based on this, we propose the following hypothesis:

H6. *The effect of artificial intelligence in alleviating environmental cost pressures exhibits significant positive spatial spillovers.*

3. Research Design

3.1. Data Sources

We selected Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2018 to 2024 as our initial research sample, covering listed firms across multiple industries such as industrial, manufacturing, and service sectors. We conducted sample cleaning in accordance with general empirical research standards: removing observations labeled as ST, *ST, delisted, or with severe data missing; excluded financial firms; to mitigate the impact of outliers, we trimmed all continuous variables at the 1st and 99th percentiles, ultimately forming a balanced panel dataset covering seven years, with overall sample quality deemed reliable.

The specific sources of the core variables are as follows: AI indicators were derived through text mining of listed companies' annual reports, combined with comprehensive calculations based on corporate AI R&D expenditures, investments in smart devices, and AI patent data; environmental cost pressure indicators were calculated and organized using environmental expenditure data from corporate annual reports, ESG reports, and environmental responsibility reports; data related to corporate micro-governance were sourced from the two major databases, CSMAR and Wind; regional digital regulation data were compiled from provincial and municipal statistical yearbooks and digital economic development bulletins; the spatial weight matrix was constructed based on the latitude and longitude information of corporate registered locations. Following the aforementioned screening process, this study ultimately obtained 13,684 valid annual corporate observations. To clearly present the distribution characteristics of each research variable, we conducted descriptive statistical analyses of the main variables; the specific statistical results are shown in Appendix A Table A1.

3.2. Variable Definitions

3.2.1. Dependent Variable: Environmental Cost Pressure (ECP)

We constructed a multidimensional comprehensive evaluation system covering explicit cost indicators such as pollution control expenditures, depreciation of environmental protection equipment, energy procurement costs, and solid waste disposal fees, while also incorporating implicit cost dimensions such as compliance risk costs, reputational losses, and green financing constraint costs. We employed the entropy method to synthesize a composite index. A higher index value indicates a relatively heavier environmental cost burden for enterprises and greater pressure for green transformation [46]. The specific composition of indicators, calculation methods, and data sources are shown in Appendix A Table A2.

3.2.2. Core Explanatory Variable: Artificial Intelligence Level (AI)

We adopted a measurement approach that combines text mining with indicator synthesis. We extracted the frequency of AI-related keywords from the annual reports of listed companies and combined this data with the proportion of corporate R&D spending allocated to AI, the scale of investment in intelligent production equipment, and the number of green AI patents. After standardization, we synthesized a comprehensive indicator of corporate AI application levels [47], which can relatively objectively reflect the degree to which companies have implemented intelligent technologies. During the index synthesis process, to avoid biases resulting from subjective weighting, this study employs the Entropy Weight Method to objectively assign weights to each sub-index, determining the weight coefficients based on the information entropy of each indicator. The selected indicators

collectively reflect a company's level of AI application from various perspectives, and the dimensional classification is reasonable.

3.2.3. Control Variables

Drawing on mainstream research findings [48–50], we selected firm size, years since establishment, debt-to-asset ratio, return on total assets, the stringency of environmental regulations, and government subsidies as control variables. We also included two-way fixed effects for industry and year to mitigate the impact of omitted variables.

3.3. Model Specification

We developed a baseline model to examine the direct impact of artificial intelligence on environmental cost pressures for businesses:

$$ECP_{i,t} = a_0 + a_1 AI_{i,t} + \gamma Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

In this context, the dependent variable $ECP_{i,t}$ represents the composite index of environmental cost pressures; the core independent variable $AI_{i,t}$ represents a firm's level of artificial intelligence adoption; $Controls_{i,t}$ is a set of firm-level and regional-level control variables used to control for the interference of individual heterogeneity on the empirical results; a_1 is the coefficient to be estimated for the core explanatory variable, used to determine the direction and magnitude of the net effect of artificial intelligence on firms' environmental cost pressures; μ_i is the industry fixed effect, used to eliminate the interference of omitted variables at the industry level that do not change over time; λ_t is the year fixed effect, used to control for systematic biases at the time level, such as annual macroeconomic shocks, policy fluctuations, and economic cycles; $\varepsilon_{i,t}$ is the random disturbance term, which follows the classical assumption of zero-mean, independent, and identically distributed distribution.

4. Econometric Tests

4.1. Correlation Analysis

To avoid multicollinearity issues and verify the preliminary correlation characteristics among core variables, this study conducts Pearson correlation analysis and variance inflation factor (VIF) tests prior to the main regression, comprehensively validating the rationality of variable selection and the reliability of the empirical model. The results of the correlation tests are shown in Table 1.

Table 1. Results of Correlation Tests for Key Variables.

Variable	ECP	AI	Size	Age	Lev	ROA	Mhold	PGDP	VIF Value
ECP	1.000								
AI	−0.326 ***	1.000							1.320
Size	−0.215 ***	0.283 ***	1.000						2.860
Age	0.082 ***	0.053 **	0.168 ***	1.000					1.080
Lev	0.263 ***	−0.125 ***	0.426 ***	0.095 ***	1.000				2.150
ROA	−0.281 ***	0.186 ***	0.132 ***	−0.068 **	−0.352 ***	1.000			1.420
ERS	0.195 ***	0.142 ***	0.108 ***	0.037 *	0.074 **	−0.081 **	1.000		1.150
GovSub	−0.156 ***	0.203 ***	0.226 ***	0.045 *	−0.063 **	0.118 ***	0.136 ***	1.000	1.020

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

As shown by the results of the correlation test in Table 1, the core independent variable—the level of artificial intelligence (AI) application—is significantly negatively correlated with the dependent variable—environmental cost pressure (ECP)—at the 1% significance level. This preliminarily confirms that the application of artificial intelligence

can effectively reduce enterprises' environmental cost pressure, which is consistent with the theoretical expectations of this paper and research hypothesis H1. At the same time, to further validate the scientific soundness of the dependent variable selection and avoid multicollinearity issues in the model, we employed the variance inflation factor (VIF) method to diagnose multicollinearity. The VIF values for all independent variables in this study range from 1.020 to 2.860. All VIF values are well below the critically accepted threshold of 10 in the academic community. Furthermore, the $1/VIF$ values for each independent variable are greater than 0.1, which further confirms the absence of multicollinearity among the variables.

4.2. Baseline Regression

Table 2 reports the baseline regression results regarding the impact of artificial intelligence on corporate environmental cost pressures. Column (1) presents the results of the basic regression without any control variables or fixed effects. The results show that the coefficient for artificial intelligence (AI) is significantly negative at the 1% level, preliminarily indicating that the application of AI can reduce firms' environmental cost pressures. Column (2) further incorporates all control variables to control for the interference of firm-specific characteristics; the AI coefficient is -0.302 , remaining significantly negative at the 1% level, which preliminarily demonstrates that the negative relationship between the two is robust. Column (3) introduces year-specific fixed effects on top of the control variables to mitigate the interference of annual macroeconomic and policy fluctuations. Here, the AI coefficient is -0.286 , with significance remaining unchanged, while the model's R^2 improves to 0.351, indicating enhanced explanatory power. Column (4) presents the final baseline regression model of this study, which simultaneously controls for firm-specific and year-specific fixed effects to minimize the issue of omitted variables. The results show that the AI coefficient is -0.253 , which is significantly negative at the 1% significance level. The above stepwise regression results indicate that, after controlling for firm-specific differences and time trends, the mitigating effect of artificial intelligence on firms' environmental cost pressures remains robust, thereby validating Hypothesis H1. From an economic perspective, a one-standard-deviation increase in the level of AI application reduces firms' environmental cost pressures by 11.3% relative to the sample mean, demonstrating clear economic significance. This result indicates that traditional corporate environmental governance models are extensive and inefficient in resource utilization, prone to generating ineffective governance costs and compliance risks, thereby increasing corporate environmental burdens. Leveraging technical advantages such as precise monitoring, intelligent scheduling, and process optimization, AI accurately identifies high-energy-consumption and high-pollution processes, optimizes production structures, reduces pollutant emissions and resource waste at the source, and lowers direct pollution control and energy consumption costs. By leveraging digital management and standardized information disclosure, these technologies reduce information asymmetry, thereby lowering hidden costs associated with corporate environmental violations, negative public sentiment, and financing constraints, ultimately effectively alleviating the overall environmental cost pressure on enterprises [51,52].

Table 2. Results of Benchmark Regression Analysis.

Variable	(1) ECP	(2) ECP	(3) ECP	(4) ECP
AI	-0.338^{***} (-8.126)	-0.302^{***} (-7.538)	-0.286^{***} (-7.025)	-0.253^{***} (-6.417)
Size		-0.125^{***} (-4.126)	-0.131^{***} (-4.352)	-0.142^{***} (-4.683)

Table 2. *Cont.*

Variable	(1) ECP	(2) ECP	(3) ECP	(4) ECP
Age		0.012 * (1.682)	0.014 * (1.795)	0.016 ** (1.986)
Lev		0.082 *** (2.965)	0.075 ** (2.638)	0.068 ** (2.412)
ROA		−0.085 ** (−2.213)	−0.092 ** (−2.385)	−0.103 *** (−2.657)
ERS		0.097 *** (3.416)	0.092 *** (3.185)	0.086 *** (2.947)
GovSub		−0.114 *** (−3.725)	−0.108 *** (−3.513)	−0.099 *** (−3.264)
Constant term	0.412 *** (10.258)	0.385 *** (9.687)	0.326 *** (8.952)	0.273 *** (8.125)
Firm fixed effects	NO	YES	NO	YES
Year fixed effects	NO	NO	YES	YES
N	13,684	13,684	13,684	13,684
R ²	0.224	0.305	0.351	0.412

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3. Robustness Tests

4.3.1. Parallel Trends Test

Since our core explanatory variable—the level of artificial intelligence (AI) application—is a continuous variable rather than a traditional policy-shock dummy variable, we conduct a parallel trends test in accordance with the mainstream paradigm of continuous variable event studies to accurately identify the dynamic time-series effects of AI on firms' environmental cost pressures. This test examines whether the dynamic marginal effects of the core explanatory variable exhibit pre-existing trend bias [53]. In terms of specific methodology, this paper defines the year in which a company's level of AI application first exceeds the annual industry median as the event period (Period 0). This approach allows for the precise identification of structural turning points in the deep adoption of AI by enterprises. The time window is set to $[-4, 3]$, covering the four periods prior to the deepening of technology adoption, the event period itself, and the three periods following it, thereby balancing temporal completeness with sample validity.

Based on the pre-trend results in Figure 1, prior to the deep application of AI, the dynamic coefficients for all periods failed to pass the significance test, with coefficient values approaching zero. This indicates that corporate environmental cost pressures do not exhibit a significant pre-existing trend, and there are no endogeneity issues such as reverse causality or pre-trend bias. Furthermore, the dampening effect of AI on corporate environmental cost pressures exhibits a clear lag. The coefficient for the current period is not significant, but a significant negative impact begins to emerge one period later and continues to strengthen over time. This confirms the validity of the parallel trends test.

4.3.2. Placebo Test

The results of the baseline regression confirm that artificial intelligence significantly alleviates environmental cost pressures on firms; however, these results may be subject to random sample fluctuations, spurious correlations, and omitted variable effects, posing a risk of spurious regression. To verify the validity and robustness of the core findings, this study conducts a random placebo test in accordance with mainstream research paradigms [54]. The specific steps are as follows: Based on the full sample of 13,684 annual firm-level observations, we randomly constructed dummy AI indicators according to the distribution characteristics of the true AI variable, substituted them for the core explanatory variable in the baseline model, and reran the regression. To avoid single-sample bias,

we repeated the random assignment and regression process 500 times. By analyzing the distribution characteristics of the coefficients and p -values from these 500 regressions, we tested whether the baseline regression results contained spurious associations. The test results are shown in Figure 2.

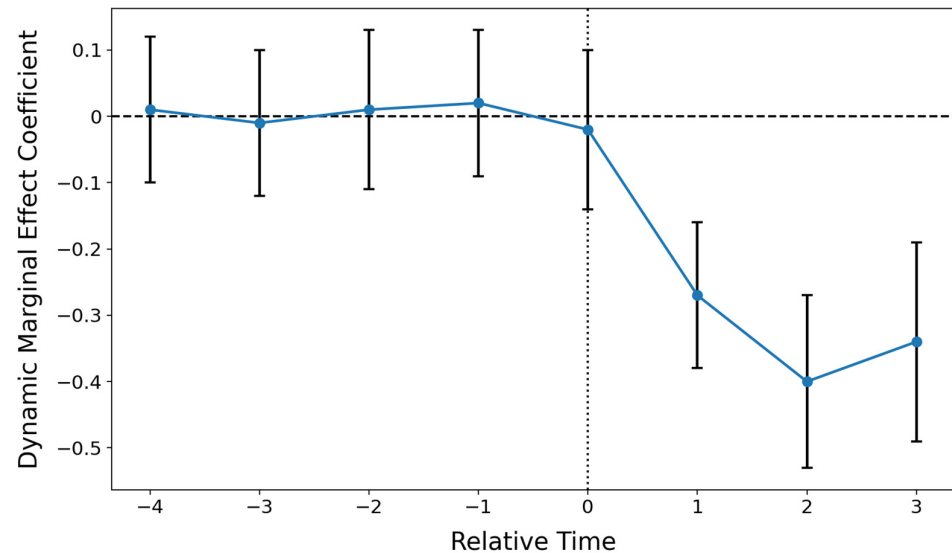


Figure 1. Results of the Parallel Trends Test.

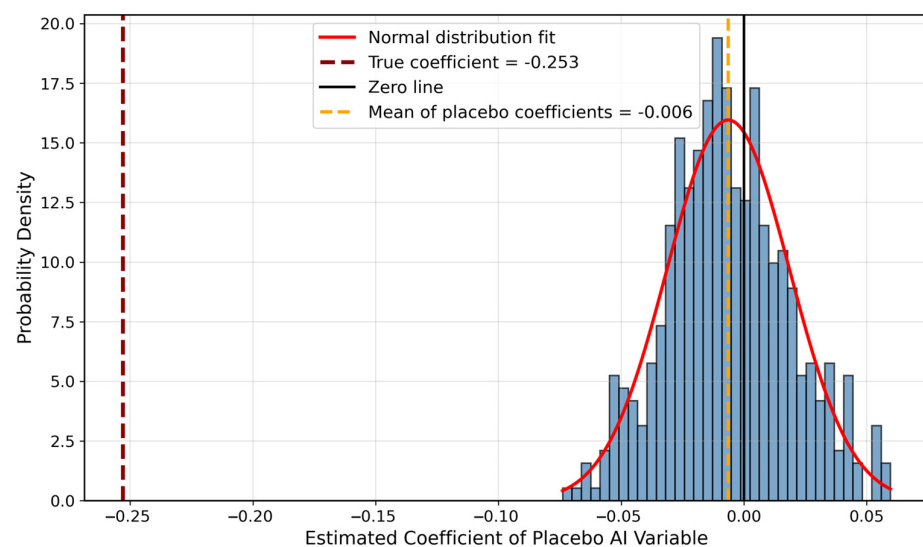


Figure 2. Distribution of Coefficients from the Placebo Test for Pseudo-AI Variables.

The results of the placebo test in Figure 2 show that when environmental cost pressure (ECP) is used as the dependent variable, the mean coefficient of the pseudo-AI variables obtained from 500 random regressions is -0.006 , which is close to 0 and far smaller than the true coefficient of -0.253 from the baseline regression. The 500 sets of pseudo-coefficients as a whole follow a normal distribution, concentrated around the value of 0. Statistical results indicate that 454 of the regressions had p -values greater than 0.1, rendering them non-significant at the 10% significance level, accounting for 90.8% of the total. Only a small number of random samples exhibited spurious significance. This result suggests that the core effect of AI in alleviating corporate environmental cost pressure is not attributable to random factors or omitted variables; rather, a genuine causal relationship exists between the two, and the conclusions of the baseline regression demonstrate robust validity.

4.4. Endogeneity Treatment

Although we have verified the significant mitigating effect of artificial intelligence on environmental cost pressures faced by enterprises, there remains a risk of endogeneity between the two: First, there is a bidirectional causal relationship—enterprises facing high environmental cost pressures are more motivated to undergo digital transformation and will proactively enhance their use of artificial intelligence; second, there is a risk of omitted variable bias, as the model cannot fully account for all micro- and macro-level influencing factors, which may lead to biased estimates. To accurately identify the net effect of these factors, this paper draws on mainstream research paradigms, selects dual-level instrumental variables at the industry and regional levels, and employs two-stage least squares (2SLS) to correct for endogeneity.

We selected two types of exogenous instrumental variables: first, an industry-level instrumental variable (IV1), measured by the average level of AI adoption among other firms in the same industry [55]; second, a regional-level instrumental variable (IV2), measured by the average level of AI adoption among other firms in the same region [56]. Both types of aggregate-level indicators are exogenous and can only indirectly affect environmental costs by influencing individual firms' AI levels; simultaneously, the AI-adoption environment at the industry and regional levels imposes significant constraints on firms' AI decisions, thereby satisfying the assumptions of instrument correlation and exclusion of restrictions.

The results of the first stage are shown in Table 3: the coefficient for IV1 is 0.692, indicating a significant peer spillover effect from industry-wide AI adoption; the coefficient for IV2 is -0.453 , suggesting that regional digital resources are limited; the expansion of AI adoption by leading firms within a region may generate a “siphoning effect,” displacing resources from other firms—that is, a competitive crowding-out effect. The overall F-value for Stage 1 is 145.68, far exceeding the critical value, thereby ruling out the issue of weak instrumental variables. The p -value for the Hansen J-test is 0.217, which fails to reject the null hypothesis of instrumental variable exogeneity, confirming the validity of the instrumental variable selection.

Table 3. Instrumental Variables Regression Results.

Variable	Phase 1 (AI)	Phase 1 (ECP)
Industry AI Average (IV1)	0.692 *** (11.876)	
Regional AI Average (IV2)	-0.453 *** (-10.653)	
AI		-0.262 *** (-6.958)
Size	-0.131 *** (-4.218)	-0.142 *** (-4.652)
Age	0.014 ** (1.998)	0.016 ** (2.012)
Lev	0.063 ** (2.321)	0.068 ** (2.405)
ROA	-0.095 *** (-2.472)	-0.103 *** (-2.635)
ERS	0.078 *** (2.863)	0.086 *** (2.931)
GovSub	0.106 *** (3.375)	-0.099 *** (-3.251)
Constant term	0.249 *** (7.714)	0.272 *** (8.216)
Firm fixed effects	YES	YES
Year fixed effects	YES	YES

Table 3. Cont.

Variable	Phase 1 (AI)	Phase 1 (ECP)
N	13,684	13,684
R ²	0.365	0.401
Phase 1 F-statistic	145.68	
Kleibergen–Paap rk LM value		65.12 ***
Cragg–Donald Wald F-statistic		142.56
Hansen J p-value		0.217

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

Results from the second stage show that, after controlling for endogeneity, the coefficient for the core variable AI is -0.262 . The sign and significance of this coefficient are consistent with those in the baseline regression, indicating that the causal effect of artificial intelligence significantly reducing firms' environmental cost pressures is genuine and robust. The Kleibergen–Paap rk LM value is 65.12, rejecting the null hypothesis of insufficient model identification; the Cragg–Donald Wald F-value is 142.56, supporting the model's effective identification. In summary, the core conclusions of this paper are not subject to endogeneity bias.

4.5. Testing of Moderating Effects

To further clarify the boundary conditions under which artificial intelligence alleviates environmental cost pressures on firms and to test the moderating effect hypotheses H3 and H4 in this study, we examined the differential moderating roles of the internal contextual variable—firm green governance intentions—and the external institutional variable—regional digital regulatory environment—respectively [57]. Building upon the baseline regression model, we sequentially introduced interaction terms between the core explanatory variable and the two types of moderator variables to construct a dual-moderation model. We tested the boundary-enabling effects of internal and external factors in stages to avoid interference from variable interactions and ensure the accuracy of the test results. The baseline model for the moderation effects is as follows:

$$ECP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 Moderate_{i,t} + \beta_3 AI_{i,t} \times Moderate_{i,t} + \beta_4 Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

Here, $Moderate_{i,t}$ represents the moderating variable, referring to corporate green governance commitment (GGC) and the regional digital regulatory environment (DRE), respectively; the definitions of the remaining variables remain consistent with those in the baseline model described earlier. If the coefficient of an interaction term is significantly negative, it indicates that the corresponding moderating variable positively reinforces the cost-reduction and empowerment effects of artificial intelligence; conversely, it implies a negative constraint. The specific regression results are shown in Tables 4 and 5.

4.5.1. Moderating Effect of Corporate Green Governance Commitment

Columns (1) and (2) of Table 4 present the regression results for the moderating effect of corporate green governance commitment (GGC). Column (1) includes only the core explanatory variable, artificial intelligence (AI), and the moderator, green governance commitment (GGC). The results show that the coefficient for AI is significantly negative at the 1% level, and the coefficient for GGC is also significantly negative at the 1% level. This preliminarily indicates that both the application of artificial intelligence and enterprises' proactive green governance can effectively reduce corporate environmental cost pressures. In Column (2), after further including the interaction term $AI \times GGC$, the coefficient of the core explanatory variable AI remains significantly negative at the 1% level. The coefficient of the interaction term $AI \times GGC$ is -0.042 , which is significantly negative at the 1% level.

Furthermore, the model's R^2 value improves from 0.418 to 0.435, significantly enhancing the model's explanatory power, which preliminarily confirms the positive moderating effect of green governance willingness.

Table 4. Test Results for the Moderating Effect of Corporate Green Governance Intentions.

Variable	(1) ECP	(2) ECP	(3) Low GGC	(4) High GGC
AI	−0.249 *** (−6.378)	−0.218 *** (−5.824)	−0.182 *** (−4.253)	−0.276 *** (−6.892)
GGC	−0.085 *** (−3.264)	−0.072 *** (−2.915)		
AI × GGC		−0.042 *** (−3.528)		
Size	−0.145 *** (−4.711)	−0.138 *** (−4.591)	−0.125 *** (−4.116)	−0.152 *** (−4.893)
Age	0.014 ** (1.976)	0.015 ** (1.965)	0.013 * (1.725)	0.018 ** (2.053)
Lev	0.069 ** (2.431)	0.067 ** (2.395)	0.062 ** (2.215)	0.073 ** (2.563)
ROA	−0.104 *** (−2.641)	−0.101 *** (−2.638)	−0.095 ** (−2.416)	−0.108 *** (−2.783)
ERS	0.085 *** (2.897)	0.082 *** (2.872)	0.079 *** (2.651)	0.091 *** (3.025)
GovSub	−0.098 *** (−3.236)	−0.094 *** (−3.196)	−0.089 *** (−2.913)	−0.105 *** (−3.452)
Constant term	0.272 *** (8.144)	0.261 *** (7.985)	0.242 *** (7.536)	0.283 *** (8.352)
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	13,684	13,684	6842	6842
R^2	0.418	0.435	0.402	0.448

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Test Results for the Moderating Effect of the Regional Digital Regulatory Environment.

Variable	(1) ECP	(2) ECP	(3) Low DRE	(4) High DRE
AI	−0.251 *** (−6.389)	−0.225 *** (−5.916)	−0.195 *** (−4.637)	−0.268 *** (−6.725)
DRE	−0.063 *** (−2.873)	−0.058 ** (−2.516)		
AI × DRE		−0.035 *** (−3.164)		
Size	−0.141 *** (−4.652)	−0.139 *** (−4.615)	−0.129 *** (−4.235)	−0.148 *** (−4.786)
Age	0.016 ** (1.980)	0.015 ** (1.968)	0.014 * (1.768)	0.017 ** (2.012)
Lev	0.068 ** (2.408)	0.067 ** (2.392)	0.064 ** (2.281)	0.071 ** (2.496)
ROA	−0.102 *** (−2.649)	−0.100 *** (−2.625)	−0.097 ** (−2.485)	−0.106 *** (−2.726)
ERS	0.086 *** (2.913)	0.082 *** (2.889)	0.081 *** (2.712)	0.090 *** (3.056)
GovSub	−0.099 *** (−3.268)	−0.096 *** (−3.235)	−0.092 *** (−2.987)	−0.104 *** (−3.421)
Constant term	0.265 *** (8.053)	0.260 *** (7.962)	0.248 *** (7.689)	0.279 *** (8.264)
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	13,684	13,684	6842	6842
R^2	0.416	0.431	0.404	0.443

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

To visually verify the marginal differences in the moderation effect, we used the mean value of green governance willingness as the cutoff point to divide the sample into a low green governance willingness group and a high green governance willingness group for group-specific regression analysis. As shown in the results of columns (3) and (4), the coefficient of AI in the low GGC group is -0.182 , which is significant at the 1% level. The F-value from the further Chow test was 12.36, with a p -value of 0.000; the difference in coefficients between groups was statistically significant at the 1% level. This indicates that the stronger a company's willingness for green governance, the more pronounced the enabling effect of artificial intelligence in alleviating environmental cost pressures. The reason for this is that enterprises with high green governance willingness proactively integrate AI technology deeply into the entire process of production emissions reduction, energy consumption control, and environmental compliance. They actively invest resources in technical adaptation, system operation and maintenance, and talent development to maximize the cost-saving advantages of intelligent technology through precision management. In contrast, enterprises with weak green governance willingness tend to engage in passive compliance; their intelligent transformation remains superficial, with insufficient depth in technology implementation, making it difficult to fully leverage cost-saving effects [58,59]. These results fully validate research hypothesis H2.

4.5.2. Moderating Effects of the Regional Digital Regulatory Environment

Columns (1) and (2) of Table 5 present the regression results for the moderating effects of the regional digital regulatory environment (DRE). Column (1) includes only the core explanatory variable AI and the moderator DRE. The results show that the coefficients for both AI and DRE are significantly negative at the 1% level, indicating that a well-developed regional digital regulatory environment can independently alleviate enterprises' environmental cost pressures while complementing the cost-reduction effects of artificial intelligence. Column (2) introduces the interaction term $AI \times DRE$. The coefficient of the interaction term is -0.035 , which is significantly negative at the 1% level. The sign and significance of the core explanatory variable AI remain stable, and the model's R^2 significantly improves, proving that the positive moderating effect of the regional digital regulatory environment is significant.

To further verify marginal differences, we conducted group-specific regressions, dividing the data into low-regulation and high-regulation groups based on the mean of the digital regulatory environment. In Column (3) (the low DRE group), the coefficient of AI is -0.195 , which is significant at the 1% level; in Column (4) (the high DRE group), the coefficient of AI is -0.268 , Significant at the 1% level; the F-value from the Chow test was 10.41, with a p -value of 0.000, indicating that the differences in coefficients between groups were statistically significant at the 1% level. This indicates that a sound regional digital regulatory environment can significantly amplify the green cost-reduction effects of artificial intelligence. From a mechanistic perspective, well-developed regional digital infrastructure, standardized digital environmental regulatory systems, and unified environmental data accounting standards can effectively lower the barriers and trial-and-error costs associated with enterprises' intelligent green transformation. These factors help avoid issues such as chaotic technology adaptation, missing governance standards, and resource misallocation, thereby providing robust institutional support for the implementation of AI technologies and enabling enterprises to fully unleash their potential for cost reduction and efficiency improvement [60,61]. These results validate research hypothesis H3.

4.6. Testing for Mediation Effects

To test the mediation mechanisms underlying Hypotheses H4 and H5 in this study and to clarify the core transmission channels through which artificial intelligence alleviates environmental cost pressures on firms, we focus on testing the validity of two key mediation channels: green technological innovation and the optimization of factor allocation. We conducted stepwise regression tests, with the model specified as follows:

$$Mediator_{i,t} = \varphi_0 + \varphi_1 AI_{i,t} + \varphi_2 Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

$$ECP_{i,t} = \gamma_0 + \gamma_1 AI_{i,t} + \gamma_2 Mediator_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (4)$$

Here, $Mediator_{i,t}$ represents the mediating variable, referring to green technological innovation (GTI) and the optimization of factor allocation (FAC), respectively. The logic of the mediation analysis is to test whether the regression coefficient of the core explanatory variable AI on the mediating variable M is significant. Additionally, by simultaneously including AI and the mediating variable M, the joint effect of both on ECP is examined, and the presence of a mediation effect is determined based on the significance and magnitude of the coefficients. The specific regression results are shown in Tables 6 and 7.

Table 6. Test Results for the Mediating Effect of Green Technology Innovation.

Variable	(1) GTI (Mediating Variable)	(2) ECP (Mediation Test)
AI	0.316 *** (8.235)	−0.168 *** (−5.126)
Size		−0.269 *** (−7.538)
Age	0.152 *** (5.136)	−0.121 *** (−4.215)
Lev	−0.012 * (−1.735)	0.014 ** (1.963)
ROA	−0.059 ** (−2.286)	0.061 ** (2.325)
ERS	0.092 *** (3.025)	0.084 *** (2.786)
GovSub	0.118 *** (3.652)	−0.093 *** (−3.068)
Constant term	−0.195 *** (−6.853)	0.225 *** (7.632)
Firm fixed effects	YES	YES
Year fixed effects	YES	YES
N	13,684	13,684
R ²	0.395	0.452

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Quantification Results of the Mediating Effect in the Green Technology Innovation Bootstrap Analysis.

Effect Type	Effect Size	Standard Error	Bootstrap 95% Confidence Interval (Lower Bound)	Bootstrap 95% Confidence Interval (Upper Bound)	Proportion of Mediated Effect (%)
Total Effect	−0.253 ***	0.039	−0.330	−0.176	
Direct Effect	−0.168 ***	0.033	−0.233	−0.103	
Mediated Effect	−0.0850 ***	0.0117	−0.1072	−0.0614	33.60

Note: *** indicate significance at the 1% levels, respectively.

4.6.1. Testing the Mediating Effect of Green Technology Innovation

Stepwise regression was conducted using green technology innovation (GTI) as the mediating variable, with the results shown in Table 6. Column (1) presents the regression results of AI on the mediating variable GTI. It can be seen that the coefficient of AI is 0.316, which is statistically significant at the 1% level and positive, indicating that the application of artificial intelligence can significantly drive green technology innovation in enterprises. Leveraging technological advantages such as big data simulation, algorithmic modeling, and intelligent iteration, AI significantly reduces the trial-and-error costs and development cycles associated with corporate green technology R&D. It facilitates the iterative upgrading of core green technologies—including clean production, energy conservation, and pollution control—thereby effectively empowering corporate green technological innovation, consistent with theoretical expectations [62].

Column (2) presents the mediation regression results incorporating both AI and GTI. The results show that the GTI coefficient is significantly negative at the 1% level, indicating that green technology innovation can effectively alleviate enterprises' environmental cost pressures; simultaneously, the AI coefficient remains significantly negative, but its absolute value has decreased compared to the baseline regression, suggesting that green technology innovation exerts a partial mediating effect. This result indicates that artificial intelligence not only directly alleviates enterprises' environmental cost pressures but also, by driving green technology innovation, optimizes enterprises' production and emissions structures at the source, reduces reliance on end-of-pipe pollution control, and lowers long-term green retrofitting costs, thereby indirectly achieving a reduction in environmental costs [63]. Hypothesis H4 is thus confirmed.

Furthermore, using the bias-corrected Bootstrap sampling method, the proportion of the mediating effect for this path was quantified through 500 repeated samples. The specific results are shown in Table 7, which clearly presents the specific values and significance levels of the total effect, direct effect, and mediating effect, further validating the robustness of the partial mediating effect.

As shown in Table 7, the mediation effect of green technology innovation is -0.0850 , the total effect is -0.253 , and the mediation effect accounts for 33.60% of the total effect. Furthermore, the 95% Bootstrap confidence interval $[-0.1072, -0.0614]$ does not include 0, indicating that the mediating effect along this path is significant and robust. These results suggest that artificial intelligence, by accelerating green technological innovation, optimizes firms' production and emissions structures and reduces long-term environmental remediation expenditures, thereby effectively alleviating environmental cost pressures. Hypothesis H4 is thus fully supported.

4.6.2. Testing the Mediating Effect of Optimized Allocation of Production Factors

To verify the mediating role of optimized allocation of production factors, stepwise regression was conducted using factor allocation efficiency (FAC) as the mediating variable. The results are shown in Table 8. Column (1) examines the effect of AI on the mediating variable FAC. The results show that the AI coefficient is 0.283, which is significantly positive at the 1% level, demonstrating that artificial intelligence can significantly optimize the efficiency of a firm's allocation of production factors. Under traditional production models, enterprises commonly face issues such as misallocation of factors like labor, equipment, and energy, as well as resource idleness and redundant energy consumption. Artificial intelligence, however, can precisely match the supply of production factors with operational demand through real-time data analysis and dynamic intelligent scheduling. This effectively addresses pain points such as waste of factor resources and allocation imbalances, thereby enhancing overall production and operational efficiency [64].

Table 8. Test Results for the Mediating Effect of Production Factor Allocation Optimization.

Variable	(1) FAC (Mediating Variable)	(2) ECP (Mediation Test)
AI	0.283 *** (7.652)	−0.189 *** (−5.438)
Size		−0.224 *** (−6.895)
Age	0.136 *** (4.892)	−0.125 *** (−4.362)
Lev	−0.010 (−1.625)	0.015 ** (1.971)
ROA	−0.055 ** (−2.193)	0.063 ** (2.348)
ERS	0.086 *** (2.876)	0.083 *** (2.824)
GovSub	0.109 *** (3.487)	−0.095 *** (−3.135)
Constant term	−0.178 *** (−5.898)	0.222 *** (8.012)
Firm fixed effects	YES	YES
Year fixed effects	YES	YES
N	13,684	13,684
R ²	0.382	0.445

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

Column (2) simultaneously includes the core explanatory variable AI and the mediating variable FAC. The results show that the FAC coefficient is significantly negative at the 1% level, indicating that improved factor allocation efficiency can effectively reduce enterprises' inefficient production and environmental governance expenditures, thereby alleviating environmental cost pressures. At the same time, the AI coefficient is significantly negative and its absolute value is lower than that in the baseline regression, confirming that the optimization of production factor allocation also exerts a partial mediating effect. This suggests that artificial intelligence can reduce excessive energy consumption and inefficient environmental governance costs caused by resource misallocation by optimizing the allocation structure of production factors such as energy, labor, and equipment, thereby indirectly alleviating enterprises' environmental cost pressures from the perspective of production and operational efficiency [65]. Hypothesis H5 is thus supported.

Furthermore, using the bias-corrected Bootstrap sampling method, we quantified the proportion of the mediating effect for this path through 500 repeated samples. The specific results are shown in Table 9, which clearly presents the specific values and significance levels of the total effect, direct effect, and mediating effect, further validating the robustness of the partial mediating effect.

Table 9. Quantification Results of Mediating Effects via Bootstrap for the Optimization of Factor Allocation.

Effect Type	Effect Size	Standard Error	Bootstrap 95% Confidence Interval (Lower Bound)	Bootstrap 95% Confidence Interval (Upper Bound)	Proportion of Mediated Effect (%)
Total Effect	−0.253 ***	0.039	−0.330	−0.176	
Direct Effect	−0.189 ***	0.035	−0.258	−0.120	
Mediated Effect	−0.0634 ***	0.0109	−0.0841	−0.0406	25.06

Note: *** indicate significance at the 1% levels, respectively.

4.7. Testing for Spatial Spillover Effects

Against the backdrop of industrial agglomeration and regional economic integration, the green production behaviors of individual firms do not exist in isolation; neighboring firms often exhibit interactive characteristics such as technology exchange, resource sharing, and industrial linkages. As a general-purpose digital technology, the green empowerment effects of artificial intelligence are no longer confined to individual firms. Instead, they can generate cross-entity transmission effects through channels such as regional industrial chains, technology diffusion, and governance demonstrations, allowing the green cost-saving benefits of local firms' intelligent transformation to radiate to surrounding market entities. Ignoring these spatial interdependencies would make it difficult to comprehensively and accurately identify the full impact of AI in alleviating enterprises' environmental cost pressures, and could also lead to model specification errors and biased empirical conclusions. Therefore, we first use the global Moran's I index to test the spatial autocorrelation characteristics of enterprises' environmental cost pressures and AI application levels during the sample period, to determine whether there is a significant spatial clustering pattern between the two, thereby providing a preliminary basis for the subsequent construction of spatial econometric models and spillover effect analysis [66].

Moran's I index is a core indicator in academia for identifying the spatial dependence of variables and discerning spatial clustering characteristics, with a value range of $[-1, 1]$. A significantly positive index indicates that the variable exhibits positive spatial correlation characterized by high-high clustering or low-low clustering; a significantly negative index indicates high-low dispersion, reflecting spatial competition; and an index approaching 0 indicates that the spatial distribution of the variable is random and lacks spatial correlation [67]. This paper matches firms' registered locations to spatial units, focusing on the premise that geographic proximity serves as the fundamental channel for technology diffusion and industrial synergy. Personnel mobility, knowledge spillovers, and supply chain linkages are more pronounced among neighboring firms, while green technology spillovers and the transmission of environmental costs diminish with increasing geographic distance. This study calculates the global Moran's I index for the core variables from 2018 to 2024. The specific test results are shown in Table 10.

Table 10. Results of Spatial Autocorrelation Tests for Core Variables.

Year	AI Moran's I Index	AI <i>p</i> -Value	ECP Moran's I Index	ECP <i>p</i> -Value
2018	0.185	0.003	0.201	0.002
2019	0.196	0.002	0.215	0.001
2020	0.208	0.001	0.228	0.001
2021	0.219	0.000	0.241	0.000
2022	0.232	0.000	0.255	0.000
2023	0.245	0.000	0.268	0.000
2024	0.258	0.000	0.282	0.000

As shown by the results in Table 10, during the sample observation period from 2018 to 2024, the Moran's I index for both the level of artificial intelligence application and enterprises' environmental cost pressures remained consistently positive, with *p*-values for each year being statistically significant at the 1% level. This result clearly demonstrates that the level of intelligent transformation and environmental cost pressures among China's listed companies are not randomly distributed in space, but rather exhibit significant positive spatial clustering characteristics. Specifically, enterprises with a higher degree of intelligent transformation tend to cluster spatially, and surrounding enterprises often also possess a high level of AI application; similarly, enterprises with relatively high environmental cost pressures exhibit regional clustering, forming distinct high-pressure

clusters. From the perspective of temporal dynamics, the Moran's I indices for the two core variables show an overall trend of steady annual increase. This indicates that, alongside the development of the digital economy and the improvement of green governance systems, the interconnections among enterprises—including technological linkages, industrial synergy, and environmental governance—continue to strengthen. The spatial agglomeration of the core variables is deepening, further validating the necessity and rationality of conducting an analysis of spatial spillover effects.

To further isolate spatial correlation effects and accurately identify the local and cross-regional spillover impacts of artificial intelligence on enterprises' environmental cost pressures, this paper constructs a two-way fixed-effects spatial Durbin model (SDM) and, following the classical research paradigm, employs a partial differential decomposition method to break down the overall effect into direct, indirect, and total effects. The direct effect captures the net impact of AI adoption by local firms on local environmental cost pressures; the indirect effect—that is, the spatial spillover effect—represents the radiating and driving impact of local firms' digital transformation on the environmental cost pressures of firms in neighboring regions [68]. Finally, the results of the effect decomposition are used to test the study's spatial spillover hypothesis H6. The detailed decomposition results are shown in Table 11.

Table 11. Results of Spatial Effect Decomposition.

Variable	Direct Effect	Indirect Effect	Total Effect
AI	−0.238 *** (−5.666)	−0.046 * (−1.916)	−0.284 *** (−6.311)
Size	−0.133 *** (−3.410)	−0.037 * (−1.947)	−0.170 *** (−4.146)
Age	0.014 ** (2.333)	0.007 (1.400)	0.021 ** (3.000)
Lev	0.065 ** (2.407)	0.021 (1.235)	0.086 ** (3.071)
ROA	−0.101 *** (−2.729)	−0.024 (−1.600)	−0.125 *** (−3.289)
ERS	0.079 *** (2.713)	0.018 (1.285)	0.097 *** (3.265)
GovSub	−0.094 *** (−3.102)	−0.029 * (−1.864)	−0.123 *** (−3.857)
Firm fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
N	13,684	13,684	13,684
R ²	0.712	0.686	0.735

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Analysis of the decomposition results reveals that the direct, indirect, and total effects of the core explanatory variable—artificial intelligence (AI)—are all significantly negative. This fully confirms that AI's role in alleviating environmental cost pressures on enterprises exhibits dual characteristics of both local empowerment and regional synergy, thereby validating Research Hypothesis H6 of this paper. Regarding the direct effect, the coefficient for AI is −0.238, which is significantly negative at the 1% level. This indicates that enterprises' digital transformation can effectively reduce their own environmental cost pressures, which is highly consistent with the conclusions of the baseline regression analysis discussed earlier. By empowering enterprises to innovate in green technologies and optimize the allocation of internal production factors, AI improves the structure of production-related emissions and energy consumption from both source and process dimensions, reduces ineffective environmental governance expenditures, and achieves precise reductions in

local environmental costs. It serves as the core endogenous driving force for enterprises to reduce costs through green initiatives.

From the perspective of spatial spillovers, the coefficient of the indirect effect of AI is -0.046 , which was marginally significant at the 10% level ($p < 0.1$), indicating preliminary positive signs that the digital transformation of local enterprises helps alleviate environmental cost pressures on enterprises in neighboring regions. The underlying transmission logic is primarily realized through two pathways: First, the spillover of green technologies and governance expertise. After local enterprises achieve green production and efficient pollution control through AI, they establish a mature model for intelligent green transformation. Enterprises in neighboring regions within the same or related industries can rapidly replicate this low-cost, high-efficiency green governance model through learning by example, technology introduction, and talent mobility, thereby reducing their own costs for green technology R&D and trial-and-error in pollution control, and consequently alleviating environmental cost pressures; second, regional industrial synergy and collaboration. Upstream and downstream enterprises in the industrial chain maintain close production ties. The intelligent green transformation of local core enterprises compels surrounding supporting enterprises to undertake green upgrades simultaneously. Through collaborative pollution control, resource sharing, and joint energy management across the industrial chain, they overcome the governance bottlenecks of individual enterprises, drive improvements in overall regional environmental governance efficiency, and achieve cluster-based cost reduction.

In terms of contribution to the effect, the total effect coefficient of artificial intelligence is -0.284 , with the direct effect accounting for as much as 83.8% and the indirect effect accounting for 16.2%. This result indicates that artificial intelligence alleviates enterprises' environmental cost pressures primarily through internal empowerment, supplemented by regional spillover effects. The core cost-reduction benefits of intelligent transformation are concentrated within the enterprises' own production and governance systems, while modest spillover effects can be achieved through industrial linkage and technology diffusion [69].

5. Further Analysis

The baseline regression in the preceding section verified that AI exerts a significant overall mitigating effect on enterprises' environmental cost pressures, reflecting the average effect across the entire sample. However, differences in regional resource endowments, industry pollution characteristics, and enterprise scale lead to structural variations in the green empowerment effects of AI. Based on this, this paper conducts heterogeneous regression tests across three dimensions—regional location, industry type, and enterprise scale—to further clarify the patterns and applicability boundaries of AI's differentiated role in alleviating enterprises' environmental cost pressures, thereby providing empirical evidence for promoting green digital transformation through tailored, context-specific approaches [70].

5.1. Regional Location Heterogeneity

There are significant east–west gradients in China regarding the level of regional digital infrastructure, the intensity of environmental regulations, and industrial innovation resources. Consequently, the effectiveness of AI in mitigating enterprises' environmental cost pressures may vary across regions. To address this, this paper divides the sample enterprises into three groups—Eastern, Central, and Western regions—based on their registered locations for group-specific analysis. The specific regression results are shown in Table 12.

Table 12. Regression Results for Regional Location Heterogeneity.

Variable	(1) Eastern Region	(2) Central Region	(3) Western Region
AI	−0.286 *** (−5.321)	−0.102 (−1.562)	−0.087 (−1.243)
Size	−0.135 *** (−4.286)	−0.094 ** (−2.485)	−0.082 * (−1.894)
Age	0.012 ** (2.159)	0.010 * (1.780)	0.009 (1.423)
Lev	0.062 *** (3.026)	0.051 ** (2.243)	0.045 * (1.832)
ROA	−0.105 *** (−3.878)	−0.072 ** (−2.330)	−0.065 * (−1.794)
ERS	0.092 *** (3.125)	0.076 ** (2.513)	0.068 ** (2.198)
GovSub	−0.108 *** (−3.542)	−0.085 *** (−2.763)	−0.072 ** (−2.315)
Constant term	3.125 *** (6.878)	2.468 *** (5.129)	1.985 *** (3.660)
Firm fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
N	6248	4126	3310
R ²	0.725	0.684	0.612

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

As shown by the regression results in Table 12, the mitigating effect of artificial intelligence on enterprises' environmental cost pressures exhibits significant regional heterogeneity. Specifically, the AI coefficient for the eastern region is −0.286, indicating a statistically significant negative correlation at the 1% level, which suggests that artificial intelligence can significantly reduce environmental cost pressures for enterprises in the eastern region. Although the AI coefficients for the central and western regions were negative, they did not pass the significance test, indicating that the empowering effect was not significant. The reasons for this lie in the fact that the eastern region boasts well-developed digital infrastructure, a concentration of digital talent, a strong atmosphere of green innovation, and a high level of maturity in corporate digital transformation. This enables the region to fully leverage the technical advantages of AI in production optimization, energy consumption control, and targeted pollution control, thereby effectively reducing environmental governance costs. At the same time, stricter environmental regulations in the eastern region compel enterprises to rely on intelligent technologies to pursue green upgrades, further enhancing cost-reduction effects. In contrast, the central and western regions lag behind in digital economic development, suffer from a scarcity of technical resources and high-end talent, and face insufficient investment in intelligent transformation and shallow application levels. Coupled with weaker environmental regulatory constraints and insufficient motivation for green transformation, these factors prevent the full realization of AI's potential to reduce costs through green initiatives.

5.2. Heterogeneity of Industry Attributes

Pollution emission intensity, remediation pressures, and the scope for green transformation vary significantly across different industries. To further identify industry-specific differences in the impact of AI empowerment, this study categorizes the sample into two groups—heavy-polluting industries and non-heavy-polluting industries—based on the industry classification standards of the Ministry of Ecology and Environment. The regression results are shown in Table 13.

Table 13. Regression Results on Industry Attribute Heterogeneity.

Variable	(1) Heavy-Polluting Industries	(2) Non-Heavy-Polluting Industries
AI	−0.312 *** (−6.153)	−0.118 * (−1.924)
Size	−0.142 *** (−4.536)	−0.096 ** (−2.515)
Age	0.015 *** (2.678)	0.009 (1.549)
Lev	0.071 *** (3.263)	0.048 ** (2.062)
ROA	−0.113 *** (−4.122)	−0.075 ** (−2.432)
ERS	0.098 *** (3.325)	0.073 ** (2.451)
GovSub	−0.112 *** (−3.687)	−0.086 *** (−2.813)
Constant term	3.426 *** (7.257)	2.158 *** (4.838)
Firm fixed effects	YES	YES
Year fixed effects	YES	YES
N	5872	7812
R ²	0.741	0.635

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

As shown in Table 13, the AI coefficient for heavily polluting industries is −0.312, which is significantly negative at the 1% level, indicating a highly pronounced cost-reduction effect; in contrast, the AI coefficient for non-heavily polluting industries is significant only at the 10% level, the F-value from the Chow test was 10.87, with a *p*-value of 0.000; the difference in coefficients between groups was statistically significant at the 1% level. This suggests that the role of artificial intelligence in alleviating environmental cost pressures is more significant and effective in heavily polluting industries. The reason lies in the fact that heavily polluting industries involve multiple emission stages, high energy intensity, and substantial environmental remediation investments, resulting in persistently high costs for traditional end-of-pipe treatment and significant room for cost reduction and optimization. Artificial intelligence can comprehensively improve the production and emission patterns of heavily polluting enterprises through technical means such as intelligent monitoring, precise emission reduction, process optimization, and energy consumption scheduling, thereby reducing redundant treatment costs at the source. In contrast, non-heavily polluting industries have low pollution levels and minimal environmental compliance pressures, with a low baseline for treatment costs; consequently, the marginal benefits of intelligent optimization are limited, resulting in relatively weak empowerment effects.

5.3. Heterogeneity in Enterprise Scale

Enterprises of different scales exhibit hierarchical differences in financial strength, technological reserves, governance systems, and transformation capabilities. To verify the differences in the impact of AI empowerment across these entities, this study uses the annual median total assets as a cutoff point to divide the sample into two groups: large and medium-sized enterprises, and small and micro-enterprises. The results of the group-specific regression are shown in Table 14.

Table 14. Regression Results for Firm Size Heterogeneity.

Variable	(1) Large and Medium-Sized Enterprises	(2) Small and Micro Enterprises
AI	−0.297 *** (−5.842)	−0.105 * (−1.893)
Size	−0.151 *** (−4.766)	−0.083 ** (−2.344)
Age	0.013 ** (2.387)	0.010 (1.622)
Lev	0.068 *** (3.143)	0.046 * (1.912)
ROA	−0.109 *** (−3.962)	−0.068 ** (−2.143)
ERS	0.095 *** (3.215)	0.071 ** (2.326)
GovSub	−0.107 *** (−3.512)	−0.082 *** (−2.685)
Constant term	3.287 *** (6.942)	2.014 *** (4.363)
Firm fixed effects	YES	YES
Year fixed effects	YES	YES
N	6842	6842
R ²	0.733	0.628

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

As shown in Table 14, the AI coefficient for large and medium-sized enterprises is −0.297, which is highly significant at the 1% level, indicating a notable cost-reduction effect; in contrast, the AI coefficient for small and micro-enterprises is significant only at the 10% level. The F-value from the further Chow test was 9.97, with a *p*-value of 0.000; the difference in coefficients between groups was statistically significant at the 1% level. This indicates that the effectiveness of artificial intelligence in alleviating enterprises' environmental cost pressures exhibits significant heterogeneity across enterprise sizes, with superior enabling effects observed in large and medium-sized enterprises. From a practical perspective, large and medium-sized enterprises possess ample financial reserves, well-established digital talent systems, and standardized production governance frameworks. These enterprises have the foundational conditions to undertake intelligent transformation, enabling the deep integration of AI with green production, pollution control and emissions reduction, and energy consumption management, thereby fully unleashing the cost-saving and efficiency-enhancing value of digital technologies. In contrast, small and micro-enterprises generally face tight capital constraints, a shortage of digital talent, and weak governance systems. Their capacity to invest in intelligent transformation is limited, and most remain at the level of superficial digital applications, making it difficult to achieve systematic green cost-reduction effects. Consequently, the enabling role of AI is significantly weakened.

6. Conclusions

Based on panel data from Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2018 to 2024, this study systematically examines the impact, transmission mechanisms, boundary conditions, and spatial characteristics of artificial intelligence on corporate environmental cost pressures. The findings reveal that artificial intelligence can significantly alleviate corporate environmental cost pressures, a conclusion supported by robustness tests. Mechanism analysis indicates that artificial intelligence effectively reduces corporate environmental costs by driving green technological innovation and optimizing the allocation of production factors; willingness to engage in green governance

and the regional digital regulatory environment can positively reinforce the cost-reduction and enabling effects of AI. Heterogeneity results show that the cost-mitigating effect of AI is more pronounced in the eastern region, among large and medium-sized enterprises, and in heavily polluting industries. At the same time, AI exhibits a clear positive spatial spillover effect, which can further drive a coordinated decline in environmental costs among regional enterprises and facilitate regional green and coordinated development. Based on this, we propose the following optimization pathways.

Enterprises should pursue a differentiated, low-cost path toward smart and green transformation based on their own scale, industry characteristics, and pollution discharge profiles, while fully leveraging the cost-saving and efficiency-enhancing benefits of artificial intelligence and digital technologies. Large and medium-sized enterprises, with their advantages in technology, capital, and resources, should take the lead in researching and developing green and smart technologies, build an integrated digital environmental protection system covering the entire process—from production and energy consumption to pollution discharge and treatment—and improve treatment efficiency while reducing overall environmental protection costs through technological upgrades. Small and micro-enterprises, which do not require heavy capital investment, can rely on public digital platforms to undertake a streamlined transition. By utilizing shared tools for environmental monitoring, green production, and compliance management, they can optimize production processes and refine energy consumption controls, thereby effectively reducing transition costs and avoiding risks such as inadequate technological adaptation and excessive investment. Enterprises must incorporate smart and green transformation into their long-term development strategies, improve internal environmental protection and digital management systems, routinely advance technological innovation and management upgrades, continuously unleash the benefits of digital and green empowerment, and achieve synergistic improvements in economic, environmental, and social benefits.

The government should implement differentiated support and complementary governance policies to precisely assist enterprises in their smart and green transformation. For small and micro enterprises in central and western regions, as well as those with weaker risk-resilience and transformation capabilities, the government should alleviate their financial pressures through fiscal subsidies, tax incentives, and credit support for transformation. It should also coordinate the establishment of public digital platforms to integrate and share resources such as green technologies, governance experience, and compliance standards, thereby addressing the transformation challenges faced by small and medium-sized enterprises due to technological shortages and lack of experience. Efforts should be made to promote the balanced development of regional digital infrastructure, address shortcomings in facilities at the grassroots industrial park level, and improve mechanisms for digital environmental supervision, information disclosure, and green credit systems. Compliance approval processes should be streamlined, administrative costs reduced, and the institutional transaction and compliance burdens on enterprises effectively alleviated. Furthermore, the government can leverage industrial parks and clusters to promote the coordinated transformation of upstream and downstream enterprises, establish platforms for sharing industry-specific technologies and best practices, accelerate the diffusion of advanced green and smart technologies, and activate synergies between industrial chains and regional development.

This sample covers only A-share listed companies and lacks data on small, medium, and micro enterprises, limiting the generalizability of the conclusions; It does not break down AI technology types and does not explore their dynamic threshold effects or optimal investment intensity. In the future, the sample scope could be expanded, analysis of technological heterogeneity enriched, and dynamic threshold models introduced to further

investigate the optimal range and long-term evolutionary characteristics of AI's green empowerment, thereby providing more precise empirical support for corporate digital transformation and regional green governance.

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Appendix A

Table A1. Descriptive Statistics for Variables.

Variable Name	Variable Symbol	N	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
Environmental Cost Pressure	ECP	13,684	0.326	0.185	0.021	0.987	0.923	3.876
Level of AI Adoption	AI	13,684	0.281	0.162	0.000	0.962	0.875	3.621
Company Size	Size	13,684	13.021	1.205	10.812	16.534	0.689	3.357
Years in Business	Age	13,684	10.125	3.986	4	21	0.352	2.756
Debt-to-Equity Ratio	Lev	13,684	0.389	0.187	0.048	0.862	0.296	2.289
Return on Total Assets	ROA	13,684	0.052	0.063	−0.205	0.214	−0.812	6.721
Strength of Environmental Regulation	ERS	13,684	0.458	0.173	0.086	0.912	0.412	2.965
Government Subsidies	GovSub	13,684	0.036	0.042	0.000	0.218	1.568	5.234

Table A2. Comprehensive Evaluation Index System for Enterprise Environmental Cost Pressure (ECP).

Level 1 Dimensions	Secondary Indicators	Definition and Calculation Method of Indicators
Explicit Environmental Costs	Expenditures on Pollution Control	The enterprise's annual direct expenditures on end-of-pipe treatment and purification of various pollutants, such as wastewater, exhaust gases, and solid waste, standardized using the natural logarithm of the raw data
	Depreciation of Environmental Protection Equipment	The enterprise's annual cumulative depreciation of environmental protection equipment and energy-saving and carbon-reduction facilities, reflecting the enterprise's fixed environmental protection investment costs; the final indicator is obtained after standardization
	Energy Procurement Costs	The enterprise's total annual expenditure on the procurement of various energy sources—such as coal, electricity, and oil and gas—during production and operations, reflecting the energy consumption cost burden at the production end; this is standardized using the natural logarithm
	Solid Waste Disposal Costs	The enterprise's annual expenditure on the collection, harmless disposal, and resource recovery of industrial solid waste and hazardous waste; after standardization, this is incorporated into the indicator system

Table A2. Cont.

Level 1 Dimensions	Secondary Indicators	Definition and Calculation Method of Indicators
Implicit Environmental Costs	Compliance Risk Costs	The enterprise's annual compliance-related losses—including environmental fines, remediation costs, and late payment penalties—resulting from environmental violations and illegal activities; this is standardized using the natural logarithm
	Losses from Environmental Public Opinion	Using the disclosure date of a negative environmental incident as the base date, and selecting $[-120, -11]$ as the estimation period and $[-10, 10]$ as the event window in accordance with mainstream standards, we calculate the cumulative excess return (CAR) and take its absolute value to represent the reputational loss resulting from public sentiment
	Costs of Green Financing Constraints	Implicit financing costs faced by the enterprise due to poor environmental performance, such as financing premiums and restrictions on credit scale, are comprehensively estimated by combining green bond spreads and credit interest rate fluctuations

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