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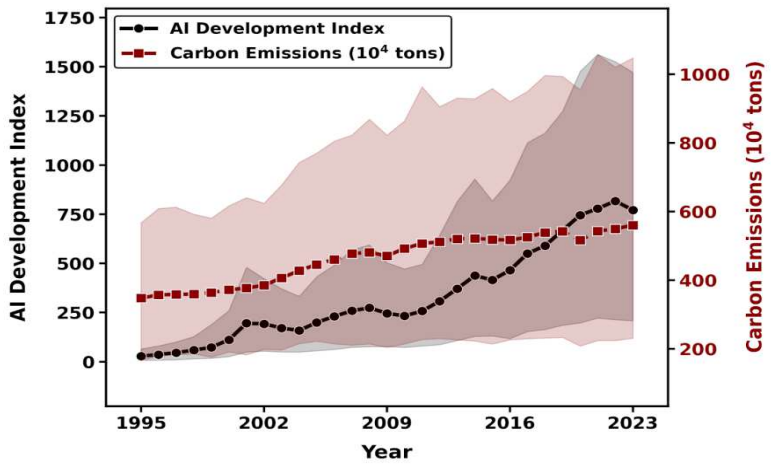
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Abstract:The impact of artificial intelligence on environmental quality has become a contentious issue in academic research. Clarifying the intrinsic relationship between the two is crucial for advancing global sustainable development. Employing a panel dataset of 61 countries worldwide from 1995 to 2023, this study systematically investigates the effects of artificial intelligence on per capita carbon emissions and ecological footprint. Empirical results demonstrate that artificial intelligence significantly increases both per capita carbon emissions and ecological footprint, thereby intensifying environmental pressure. Mechanism tests confirm that technological innovation and total-factor energy efficiency exert significant mediating effects in the process whereby AI influences the environment. Heterogeneity analysis indicates that the negative environmental effects of AI are primarily driven by general-purpose artificial intelligence, and such adverse impacts are more substantial in countries leading in AI development and upper-middle-income nations. Further research reveals that the environmental impact of AI exhibits nonlinearity subject to threshold constraints of technological innovation and total-factor energy efficiency. This study breaks through the conventional view that AI is inherently green, and uncovers the environmental costs behind its rapid expansion. The conclusions provide theoretical references for countries to formulate differentiated AI governance frameworks and green transition policies in line with their national conditions.

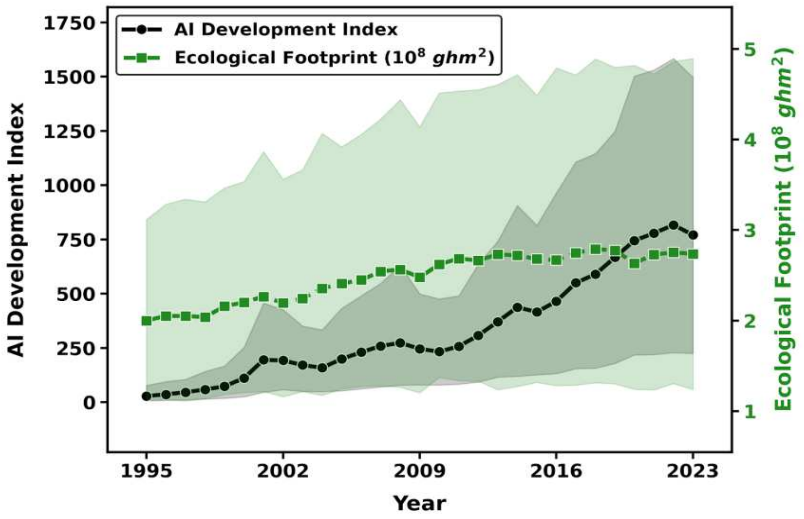
Keywords: Artificial Intelligence; Carbon Emissions; Ecological Footprint;Technological Innovation; Total-Factor Energy Efficiency

1.Introduction

Climate warming and natural resource depletion have emerged as severe existential challenges for humanity, with global environmental governance mired in a dilemma of "incremental game," leading to a substantial gap between actual emission mitigation outcomes and anticipated targets. As the core of the new round of technological revolution, artificial intelligence (AI) presents both opportunities and challenges for the environment. On the one hand, AI can optimize energy systems and monitor climate and ecological conditions (Ashraf et al., 2022; Zhou et al., 2025). On the other hand, the training and operation of large models entail high energy consumption and intensive resource use (Gaur et al., 2023; Alnafrah, 2025), with its expansion coinciding with mounting environmental pressure. Figures 1 and 2 respectively illustrate the synchronized upward trends between AI development and per capita carbon emissions as well as ecological footprint from 1995 to 2023, where shaded areas denote 95% confidence intervals that reflect cross-country heterogeneity.



Graph1 Evolution of AI and Carbon Emissions(1995-2023)



Graph2 Evolution of AI and Ecological Footprint(1995-2023)

The relationship between artificial intelligence and the environment has long been a focal topic in academic research. Early studies primarily concentrated on the applications of AI in specific fields such as energy management, carbon mitigation, and ecological monitoring (Jin et al., 2024; Aliane et al., 2025). In recent years, the literature has further extended the analysis of AI's impacts on carbon emissions and ecological footprint to the macro level, with existing cross-country empirical evidence generally supporting the environmental optimization effects of artificial intelligence (Wang et al., 2024). Several studies, by constructing AI development indices and investigating the deployment of industrial robots, have validated that AI advancement effectively curbs carbon emissions and reduces pollutant emission intensity (Li et al., 2022; Cao et al., 2025).Nevertheless, alongside the rapid expansion of artificial intelligence, growing concerns have arisen regarding its negative environmental externalities across the full life cycle, including intensive energy consumption, water resource usage, mineral depletion, and electronic waste generation (Dhar, 2020; Mhlanga, 2025). These studies reveal the potential adverse environmental impacts of AI in disaggregated sectors, yet insufficient attention and systematic investigation have been devoted to the negative environmental effects of AI at the macro level in the existing literature.The rebound effect and Jevons' Paradox provide a foundational framework for interpreting AI's environmental implications: efficiency gains induced by technological progress reduce marginal costs, triggering an explosive surge in

computing demand, which ultimately exacerbates environmental pressure (Hilty & Hercheui, 2010). Several scholars have conducted macro-level analyses from the perspective of negative effects. For instance, Zhang et al. (2025) argue that AI-driven efficiency improvements at the aggregate level may conversely lead to substantial increases in overall resource consumption.

Overall, while the academic community has extensively explored the potential of AI to improve resource efficiency, the environmental burden caused by its technological expansion at the macro level remains under-researched. Meanwhile, real-world data present a striking paradox: the exponential growth of AI coincides with synchronous increases in environmental pressure indicators. Accordingly, this paper aims to fill this theoretical gap. Using cross-country panel data covering 61 economies from 1995 to 2023, we reassess the impact of AI on environmental quality from the perspective of negative shocks. We not only examine the direct driving effects of AI on environmental indicators but also disentangle the underlying mediating mechanisms and capture the heterogeneous and nonlinear evolutionary patterns across different technological endowments and income levels.

Marginal Contributions:(1) This paper incorporates per capita carbon emissions and ecological footprint into a unified analytical framework to systematically investigate the environmental impacts of artificial intelligence. By examining the co-evolution between technological progress and environmental quality from a multi-dimensional perspective, we challenge the conventional belief that technological advancement necessarily improves the environment, offering a more critical research perspective. (2) We introduce technological innovation and total-factor energy efficiency as core mediating variables to analyze the transmission mechanism through which AI affects environmental quality, clarifying the logic of efficiency loss and transformation pathways in the conversion from technological dividends to environmental benefits.(3) Taking the aforementioned mediating variables as threshold factors, we comprehensively characterize the nonlinear impacts of artificial intelligence on environmental quality under heterogeneous technological endowments and energy efficiency levels.This study re-evaluates the ecological

implications of artificial intelligence from the perspective of environmental quality, providing new insights into its role in enabling the green transformation of society and supporting countries in formulating differentiated environmental governance strategies tailored to national conditions.

2.Theoretical Analysis and Hypotheses Development

2.1Direct Impact of Artificial Intelligence on the Environment

Scholarly discussions on the direct environmental impact of AI have centered on its life-cycle resource consumption and emissions, including energy use, greenhouse gas emissions, water consumption, and hardware-related waste. Specifically, the training of large-scale AI models represents a major source of environmental pressure. For instance, the carbon emissions from training a single Transformer model are equivalent to the lifetime emissions of five automobiles (Strubell et al., 2019). With the widespread deployment of AI, energy consumption during the inference stage has surpassed that of training, while carbon emissions from image generation far exceed those from text generation (Luccioni et al., 2024).Water consumption driven by AI is often overlooked. For example, the cooling and chip manufacturing processes for GPT-3 training alone consume approximately 700,000 liters of fresh water, and the water footprint under equivalent energy consumption can vary by up to 10 times across regions. Meanwhile, the heavy reliance of AI on rare earth elements, lithium, and other critical minerals exacerbates resource depletion and ecological degradation (Crawford et al., 2018). Based on the resource consumption and emission characteristics throughout the AI life cycle, we propose the following hypothesis:

Hypothesis 1. Artificial intelligence increases per capita carbon emissions and per capita ecological footprint.

2.2 Indirect Impact of Artificial Intelligence on the Environment

Conventional wisdom holds that artificial intelligence improves environmental quality through technological progress and enhanced energy efficiency. However, recent studies have challenged this view: although AI can improve energy efficiency

at the micro level, the accompanying rebound effect often intensifies overall environmental pressure (Sorrell, 2009).

Technological innovation can act both as an emissions-reduction tool and a source of additional environmental burden. While AI-driven algorithm optimization reduces single-operation energy consumption, the cost reductions from efficiency gains trigger an explosive expansion in AI application demand. The surging total computing demand ultimately offsets efficiency improvements (Bozkurt, 2025). Furthermore, rapid technological iteration shortens hardware replacement cycles. The production of high-performance chips is highly energy-intensive and polluting, and large volumes of electronic waste are difficult to recycle, further aggravating environmental pressure.

Although improved total-factor energy efficiency (TFEE) optimizes production systems, it also generates scale effects. By enhancing firm-level efficiency, AI enables enterprises to expand production at lower marginal costs. If output growth outpaces efficiency improvements, aggregate carbon emissions will rise—a pattern particularly evident in resource-intensive industries (Luccioni et al., 2025). In addition, AI development may divert resources from green research and development, deepen the digital divide, and reinforce carbon lock-in, thereby increasing the burden of environmental governance (Li et al., 2025). Accordingly, we propose the following hypotheses:

Hypothesis 2a. Artificial intelligence increases per capita carbon emissions and per capita ecological footprint through the channel of technological innovation.

Hypothesis 2b. Artificial intelligence increases per capita carbon emissions and per capita ecological footprint through the channel of total-factor energy efficiency.

2.3 Nonlinear Characteristics in the Environmental Impact of Artificial Intelligence

Building on the above indirect mechanisms, artificial intelligence may affect environmental quality through technological innovation (TECH) and total-factor energy efficiency (TFEE). However, as these mediating variables shift from

quantitative to qualitative change, the relationship between AI and environmental quality may evolve from linear to nonlinear.Taking technological innovation as an example, its level determines the energy-consumption profile of AI applications. At low levels of innovation, the negative energy-intensive effects of AI dominate. Once green patent applications and digital innovation capabilities cross a certain threshold, AI can significantly curb carbon emissions (Yuan et al., 2025).

TFEE acts not only as a mediator but also as a critical conditioning factor. Only when total-factor energy efficiency or environmental regulation intensity reaches a specific threshold can efficiency gains from AI offset the rebound effect. For instance, at high TFEE levels, AI reallocates production factors toward less polluting sectors, promotes industrial structure upgrading, and achieves decoupling between economic growth and environmental degradation (Zhang et al., 2025). We therefore propose the following hypothesis:

Hypothesis 3. The impacts of artificial intelligence on per capita carbon emissions and per capita ecological footprint exhibit significant nonlinear characteristics.

3. Methodology and Data

3.1 Model Specification

3.1.1 Baseline Model

To test Hypothesis 1, this paper establishes a two-way fixed-effects baseline model as follows:

$$CE_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Controls + \delta_i + \delta_t + \mu_{it} \quad (1)$$

$$EF_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Controls + \delta_i + \delta_t + \mu_{it} \quad (2)$$

In the equation,CE_{it} and EF_{it}denote per capita carbon emissions and per capita ecological footprint of country i in year t, respectively.AI_{it}represents the artificial intelligence development level of country i in year t.$Controls$denotes a set of control variables.δ_i and δ_t stand for country fixed effects and time fixed effects, respectively, and μ_{it} is the random error term.

3.1.2 Mediating Effect Model

This study examines the mediating effects using the stepwise regression method. The mediating models capturing the impact of AI on carbon emissions and ecological footprint are specified as follows:

$$TECH_{i,t} = \delta_0 + \delta_1 AI_{i,t} + \delta_2 CONTROL_{i,t} + e_{it} \quad (3)$$

$$CE_{it} = \delta_3 + \delta_4 AI_{i,t} + \delta_5 TECH_{i,t} + \delta_6 CONTROL_{i,t} + e_{it} \quad (4)$$

$$TFEE_{i,t} = \omega_0 + \omega_1 AI_{i,t} + \omega_2 CONTROL_{i,t} + e_{it} \quad (5)$$

$$EF_{it} = \omega_3 + \omega_4 AI_{i,t} + \omega_5 TFP_{i,t} + \omega_6 CONTROL_{i,t} + e_{it} \quad (6)$$

In the equations,$TECH_{i,t}$denotes technological innovation of country i in year t,and $TFEE_{i,t}$ represents total-factor energy efficiency of country i in year t.$CONTROL_{i,t}$ denotes the control variables.

3.1.3 Panel Threshold Model

This paper employs the panel threshold model proposed by Hansen (1990) to examine the nonlinear relationship between artificial intelligence and environmental quality. The specification of the model is formulated as follows:

$$Y_{it} = \alpha_i + I(q_{it} \le \gamma) X_{it}\beta_1 + I(\gamma < q_{it}) X_{it}\beta_2 + \sum \delta_m Z_{it} + e_{it} \quad (7)$$

where$\delta_m$is independent of the threshold, and the indicator function is given by $I(\cdot)$:

$$I(q_{it} \le \eta) = \begin{cases} 1, & if\ q_{it} \le \gamma \\ 0, & if\ q_{it} > \gamma \end{cases} \quad ; \quad I(q_{it} > \eta) = \begin{cases} 0, & if\ q_{it} \le \gamma \\ 1, & if\ q_{it} > \gamma \end{cases} \quad (8)$$

Where$Y_{it}$is the dependent variable,$X_{it}$is the core explanatory variable subject to the threshold effect,Z_{it}denotes a vector of control variables,γrepresents the threshold parameter, and q_{it} indicates the threshold variable, which can be either $TECH_{i,t}$ or $TFEE_{i,t}$. The indicator function $I(q_{it} \le \gamma) = 1$ if $q_{it} \le \gamma$ and $I(q_{it} > \gamma) = 0$ otherwise.

3.2 Variable Selection

3.2.1 Core Explanatory Variables

Existing literature mainly measures the level of artificial intelligence (AI) technology through two approaches. The first is to employ inventory data of industrial

robots, which are primarily designed for physical tasks in specific sectors. The second is to utilize data on AI-related patents, treating AI as a general-purpose technological revolution to investigate its overall impact on the economic paradigm. Considering that AI technology is not confined to domain-specific applications, but tends to reshape socioeconomic structures as well as human production and lifestyles via technological progress, this study follows the research of Verendel V and uses the number of AI patent applications to measure the development level of AI.

Based on the World Intellectual Property Organization (WIPO) database, we manually collected the number of AI patent applications filed via the Patent Cooperation Treaty (PCT) by 61 countries. The specific procedures are as follows:(1) AI-related patent codes were identified in accordance with the International Patent Classification (IPC 2020.01);(2) Artificial intelligence was categorized into General Artificial Intelligence (GAI) and Applied Artificial Intelligence (AAI). Specifically, GAI covers the core algorithm layer and the perception-interaction layer, focusing on technical implementation and general capabilities, while AAI includes embodied intelligence and control as well as domain-specific applications, targeting practical scenarios and industry-specific problems;(3) Patent application counts for the 61 countries were retrieved from the WIPO database using the above patent codes, and further compiled separately for GAI and AAI.

3.2.2 Dependent Variables

Per capita carbon emissions (CE).Per capita carbon emissions serve as a key indicator reflecting a country's or region's climate responsibility and development stage. This variable is measured as the ratio of a country's annual total carbon dioxide emissions to its total population.

Per capita ecological footprint (EF).The ecological footprint represents the area of productive land and water required to produce the resources consumed and to assimilate the waste generated by human activities. As a measure of environmental pressure, its inherent forward-looking components render it more informative for evaluating environmental quality than carbon dioxide alone (Destek et al., 2019). Per

capita ecological footprint is estimated using a consumption-based accounting approach, with the unit of global hectares per capita (gha/person).

3.2.3 Mechanism Variables and Threshold Variables

In this study, technological innovation (TECH) and total-factor energy efficiency (TFEE) function as both mechanism variables and threshold variables.Technological innovation is measured by the number of patent applications across countries, with data obtained from the WIPO database.

Total-factor energy efficiency is a core metric for evaluating energy performance. It treats energy, capital, labor, and other factors as joint productive inputs, thereby providing a more comprehensive assessment of an economy's capacity for energy utilization. Following the methodology of Oh (2010), this paper measures total-factor energy efficiency using the Malmquist–Luenberger (ML) index based on the SBM model.Detailed descriptions of all variables are presented in Table 1.

Table 1

Indicators for Total-Factor Energy Efficiency

Variable Type	Variable Name	Unit	Data Source
Input Variables	Fixed Capital Stock (K)	Constant 2015 US dollars	World Bank (2024)
	Labor (L) Total	Total	
	Energy Consumption (E)	Constant 2017 PPP dollars per kilogram of oil equivalent	
Desirable Outputs	Gross Domestic Product (GDP)	Constant 2015 US dollars	
Undesirable Outputs	Carbon Dioxide Emissions (CO_2)	Million tons of carbon dioxide equivalent ($MtCO_2e$)	

3.2.4 Control Variables

To comprehensively and accurately assess the impact of artificial intelligence on environmental quality and avoid estimation bias caused by omitted variables, this

study selects the following control variables:(1) Population density (POP), measured as the number of people per unit of land area. Excessively high population density tends to exert pressure on environmental resources.(2) Inward foreign direct investment (IFDI), measured by net inflows of foreign investment in current US dollars. Pollution-intensive industries may relocate to regions with relatively lax environmental standards (Dong et al., 2024).(3) Industrial structure (IS), measured as the share of industrial value-added in GDP. Differences in industrial structure shape both the environmental effects of AI and industrial development patterns.(4) Urbanization (URB), measured as the share of urban population in the total population. Urbanization-driven expansion of infrastructure, energy consumption and logistics can significantly affect environmental outcomes (Li et al., 2023).(5) Trade openness (TRD), measured as the ratio of total trade volume to GDP. It facilitates cross-border exchanges of AI technologies and industrial upgrading, while also exerting indirect impacts on environmental conditions.

3.3 Data Sources

This study examines a panel of 61 countries over the period 1992–2023. Data are obtained from the World Bank, the World Intellectual Property Organization (WIPO), and the International Federation of Robotics (IFR).The selected countries account for more than 90% of global AI patent applications, carbon emissions and ecological footprint, indicating strong representativeness of the sample. Meanwhile, the sample covers both developed and developing countries at different stages of economic development across six global geographical regions, rather than being restricted to a specific group of economies, which effectively enhances the robustness and generalizability of the empirical findings.Detailed variable definitions, data sources and descriptive statistics are presented in Table 2 and Table 3, respectively.

Table 2

Variable Definitions and Data Sources

Variable	Definition	Source

Artificial Intelligence (AI)	Number of artificial intelligence patent applications (units)	WIPO Database
Per Capita Carbon Emissions (CE)	Ratio of total CO_2 emissions to total population (tons/person/year)	World Bank
Per Capita Ecological Footprint (EF)	Estimated using the consumption-based approach (gha/person)	World Bank
Technological Innovation (TECH)	Total number of patent applications across countries (units)	WIPO Database
Total-Factor Energy Efficiency (TFEE)	GML index	World Bank
Population Density (POP)	Population per unit of land area (hundred persons/km²)	World Bank
Inward Foreign Direct Investment (IFDI)	Net inflows of foreign direct investment (current US dollars)	World Bank
Industrial Structure (IS)	Share of industrial value-added in GDP (%)	World Bank
Urbanization (URB)	Share of urban population in total population (%)	World Bank
Trade Openness (TRD)	Ratio of total trade volume to GDP (%)	World Bank

Table 3

Descriptive Statistics of Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
EF	1769	1.337	0.780	-1.122	3.777
CE	1769	1.634	0.927	-1.922	3.360
AI	1769	2.456	2.473	0.000	9.447
TECH	1769	7.577	2.508	0.000	14.333
TFEE	1769	1.073	0.152	0.093	2.462
POP	1769	4.254	1.227	0.981	7.185
IFDI	1769	22.411	1.986	0.000	27.322
IS	1769	3.283	0.282	2.210	4.222
TRD	1769	4.278	0.547	2.750	5.977
URB	1769	4.308	0.299	2.327	4.605

4 Empirical Results

4.1 Baseline Regression Results

Table 4 reports the estimation results of the baseline model (1), in which a structured analysis is conducted according to variable composition. Columns (1) and

(2) examine the impact of artificial intelligence on per capita carbon emissions and per capita ecological footprint, respectively, while Columns (3) and (4) present extended analyses with the inclusion of control variables.The regression results indicate that, in the absence of control variables, artificial intelligence exerts a significantly positive effect on both per capita carbon emissions and ecological footprint at the 1% level. After controlling for the additional covariates, the estimated coefficients remain significantly positive at the 1% level. These findings suggest that the advancement of artificial intelligence increases per capita carbon emissions and ecological footprint, thereby affecting global environmental quality, which provides empirical support for Hypothesis 1.

Table 4

Baseline Regression Results

Variabl	(1) CE	(2) EF	(3) CE	(4) EF
AI	0.0483***	0.0312***	0.0528***	0.0352***
	(6.50)	(5.21)	(8.62)	(6.24)
cons	1.457***	1.185***	-4.979***	-2.574***
	(52.17)	(52.65)	(-17.24)	(-9.68)
Control variable	NO	NO	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	1769	1769	1769	1769
R2	0.107	0.138	0.414	0.262

t statistics in parentheses，* p < 0.1, ** p < .05, *** p < .01

4.2 Robustness Checks

To ensure the reliability of the baseline regression estimates, this study follows existing literature and performs robustness checks using four approaches, as detailed below:

(1) Replacing the dependent variables. We employ total carbon emissions (TCE) and total ecological footprint (TEF) as alternative indicators to per capita carbon emissions and per capita ecological footprint, both of which are widely used measures of regional carbon emission intensity and resource consumption. As shown in

Columns (1)–(2) of Table 5, the coefficient of AI remains significantly positive after replacing the dependent variables.

(2) Replacing the explanatory variable. We use the number of robots installed per capita (RP) to substitute for the core explanatory variable AI. As a major practical application carrier of artificial intelligence, the penetration rate of industrial robots directly reflects the application level of AI technologies. The regression results in Columns (3)–(4) of Table 5 demonstrate that the coefficient of RP is significantly positive, confirming the robustness of the baseline findings.

(3) Excluding pandemic-affected years. To rule out disturbances caused by special conditions during the COVID-19 pandemic, we re-estimate the model after excluding observations from 2020 to 2022. Columns (5)–(6) of Table 5 indicate that the coefficient of AI remains significantly positive, further strengthening the reliability of the conclusions.

(4) Excluding missing values of AI development. To address the issue of partial missing values in the AI development indicator, we re-run regressions using a balanced sample with no missing observations. Columns (7)–(8) of Table 5 show that the coefficient of AI is significantly positive at the 1% level, implying that non-random missingness of the explanatory variable does not cause substantial bias to the empirical results.

Table 5

Results of Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variabl	Replacing Dependent Variables		Replacing Explanatory Variable		Excluding Pandemic Years		Excluding Missing AI Observations	
	TEF	TCE	EF	CE	EF	CE	EF	CE
AI	0.0467***	0.0297***	0.00577***	0.0101***	0.0328***	0.0490***	0.0652***	0.0908***
	(2.79)	(5.00)	(3.18)	(5.07)	(5.56)	(7.51)	(8.73)	(10.61)
cons	12.76***	-4.956***	-2.400***	-4.689***	-2.826***	-4.664***	-0.111	-2.402***
	(16.13)	(-17.66)	(-8.88)	(-15.88)	(-9.90)	(-14.78)	(-0.31)	(-5.82)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1769	1769	1769	1769	1586	1586	1201	1201
R^2	0.121	0.624	0.250	0.397	0.282	0.381	0.216	0.342

t statistics in parentheses， * p < 0.1, ** p < .05, *** p < .01

4.3 Endogeneity Tests

To address potential endogeneity issues arising from bidirectional causality in the baseline regression, this study constructs two instrumental variables and employs the two-stage least squares (2SLS) method for estimation, as detailed below:

(1) IV1: One-period lag of AI (AI_Lag1).The rationale for selecting this instrumental variable is as follows. First, the lagged value of a variable is highly correlated with its contemporaneous value, thereby satisfying the relevance condition. Second, historical values precede the contemporaneous error term, which satisfies the exogeneity assumption.

(2) IV2: AI_Bartik.This study constructs the Bartik instrumental variable using the shift-share approach. Specifically, it is generated by combining each country's AI patent share in 1995 with the global growth trend of AI patents from 1995 to 2023. The justification is that the base-year patent share is closely related to the current level of AI development, while the global technological trend represents an exogenous shock. Moreover, the pre-determined base-year share is not affected by contemporaneous economic conditions.

Table 6 reports the estimation results using the two sets of instrumental variables. The first-stage and second-stage results are both significantly positive. In addition, the underidentification test and weak instrument test are both satisfied. These findings confirm that, after accounting for endogeneity, the positive impact of AI on carbon emissions and ecological footprint remains robust.

Table 6

Results of Endogeneity Tests

VARIABLES	IV1-2SLS			IV2-2SLS		
	First-stage	stage II		First-stage	stage II	
	(1)	(2)	(3)	(4)	(5)	(6)
	AI	EF	CE	AI	EF	CE
AI_Lag1	0.671***					
	(38.13)					
AI_Bartik				0.044***		
				(26.51)		
AI		0.018**	0.030***		0.038***	0.080***
		(2.08)	(3.25)		(3.67)	(7.15)
Observations	1,708	1,708	1,708	1,769	1,769	1,769
Number of Country	61	61	61	61	61	61
R-squared	0.613	0.254	0.400		0.262	0.407
Underidentification test		780.594***			495.86***	
Weak identification test		1454.144			684.38	
		(16,38)			(16.38)	

t statistics in parentheses， * p < 0.1, ** p < .05, *** p < .01

4.4 Mechanism Analysis

To verify Hypothesis 2a and Hypothesis 2b, this paper takes technological innovation (TECH) and total factor energy efficiency (TFEE) as mediating variables, and adopts the stepwise regression method to empirically examine the mediating effects of artificial intelligence (AI) on per capita carbon emissions and ecological footprint.Columns (1) to (3) in Table 7 report the regression results with technological innovation (TECH) as the mediating variable. Column (1) indicates that artificial intelligence exerts a significantly positive impact on technological innovation at the 1% statistical level. After incorporating both artificial intelligence and technological innovation into the regression model, the results in Columns (2) and (3) demonstrate that artificial intelligence still shows a significant positive correlation with per capita carbon emissions and ecological footprint at the 1% level, while the regression coefficients decline compared with those in the benchmark regression. The above empirical evidence confirms the existence of a partial mediating effect.Similarly, Columns (4) to (6) of Table 7 present the regression results taking total factor energy efficiency (TFEE) as the mediating variable. It is found that TFEE also plays a partial

mediating role in the nexus between artificial intelligence, carbon emissions and ecological footprint.In summary, both Hypothesis 2a and Hypothesis 2b are fully verified. The research conclusions are consistent with the theoretical mechanism analysis and existing literature findings. This suggests that artificial intelligence not only imposes direct environmental impacts throughout its life cycle, but also induces rebound effects via technological innovation and total factor energy efficiency, thereby indirectly exacerbating regional environmental pressure.

Table 7

Results of Mediation Effect Test

VARIABLES	(1) TECH	(2) CE	(3) EF	(4) TFEE	(5) CE	(6) EF
TECH		0.0140***	0.0136***			
		(3.29)	(3.45)			
TFEE					0.125***	0.0912***
					(3.43)	(2.70)
AI	0.185***	0.0502***	0.0327***	0.0350***	0.0484***	0.0320***
	(5.28)	(8.15)	(5.77)	(8.59)	(7.76)	(5.57)
_cons	-3.821**	-4.925***	-2.522***	0.475**	-5.038***	-2.617***
	(-2.31)	(-17.07)	(-9.50)	(2.47)	(-17.47)	(-9.84)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1769	1769	1769	1769	1769	1769
R2	0.110	0.418	0.268	0.157	0.418	0.266

t statistics in parentheses * p < .1, ** p < .05, *** p < .01

4.5 Heterogeneity Analysis

4.5.1 Heterogeneity of Artificial Intelligence Types

Based on the benchmark regression model of this study, this section further explores the structural differences in the environmental effects of artificial intelligence (AI).As reported in Table 8, General Artificial Intelligence (GAI) exerts a significantly positive impact on per capita carbon emissions and ecological footprint at the 1% statistical level, whereas the effect of Applied Artificial Intelligence (AAI)

is statistically insignificant.This empirical evidence indicates that the adverse environmental impacts of AI are primarily driven by the development of general artificial intelligence. The underlying mechanism can be explained as follows: AAI focuses on micro-level operational optimization and presents prominent energy efficiency with low parameter computational load. In contrast, GAI follows the development paradigm of pursuing intelligence through scale expansion. The exponential expansion of model parameters leads to substantial energy consumption during model training and inference stages. Furthermore, the continuous expansion of global computing power infrastructure further intensifies resource depletion and ecological pressure, ultimately deteriorating regional environmental quality.

Table 8

Regression Results of Different Types of Artificial Intelligence

VARIABLES	(1) EF	(2) CE	(3) EF	(4) CE
GAI	0.0173***	0.0287***		
	(3.10)	(4.70)		
AAI			-0.00258	0.00882
			(-0.46)	(1.42)
cons	-2.563***	-4.970***	-2.504***	-4.917***
	(-9.54)	(-16.93)	(-9.29)	(-16.64)
Control variable	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	1769	1769	1769	1769
R^2	0.250	0.396	0.245	0.389

t statistics in parentheses * p < .1, ** p < .05, *** p < .01

4.5.2 Heterogeneity of Income Level

This study adopts a regression model incorporating interaction terms to examine the heterogeneous environmental impacts of artificial intelligence (AI) across economies with different income levels. Referring to the 2024 income classification criteria released by the World Bank, the 61 sample countries are divided into three

groups: lower-middle income countries (LMC), upper-middle income countries (UMC), and high-income countries (HIC). Correspondingly, interaction terms between AI and income group dummy variables are constructed for empirical estimation.As shown in Table 9, the regression coefficients of AI and the interaction terms LMC×AI and UMC×AI are all significantly positive, suggesting that AI exerts a positive effect on per capita carbon emissions and ecological footprint across all three income groups. In terms of the absolute value of impact coefficients, the magnitude follows a hierarchical order: upper-middle income countries > high-income countries > lower-middle income countries.Specifically, high-income countries suffer from a high stock of environmental load yet witness a slowing growth rate of environmental pressure. For upper-middle income countries, simultaneous industrialization progress and international pollution transfer bring about the most prominent ecological pressure. By contrast, restricted by the digital divide, the development of artificial intelligence in lower-middle income countries remains relatively laggard, thereby resulting in a weaker environmental impact of AI.

Table 9

Estimation Results of Income Level Heterogeneity

VARIABLES	(1) EF	(2) CE
AI	0.0205***	0.0171**
	(2.8697)	(2.2407)
UMC×AI	0.0552***	0.1078***
	(4.2613)	(7.7759)
LMC×AI	0.0170*	0.0513***
	(1.9004)	(5.3512)
cons	-2.1905***	-4.2071***
	(-7.8460)	(-14.0855)
Control variable	Yes	Yes
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	1,769	1,769
R2	0.271	0.438

t-statistics in parentheses*** p<0.01, ** p<0.05, * p<0.1

4.5.3 Heterogeneity of AI Development Level

To further investigate the heterogeneous environmental impacts caused by disparities in artificial intelligence (AI) development, the full sample is divided into a high-AI development group (HAI) and a low-AI development group (LAI), taking the mean value of the AI development index as the grouping threshold.The heterogeneity estimation results in Table 10 indicate that AI yields a significantly positive effect on per capita carbon emissions and ecological footprint for both groups at the 1% statistical level. Moreover, the regression coefficient of the HAI group is markedly larger than that of the LAI group. This finding demonstrates that the adverse environmental externalities of AI become more prominent with the continuous improvement of AI development level.Such empirical evidence verifies the existence of the Jevons Paradox in the digital era. Although AI algorithm optimization contributes to productivity and energy efficiency improvement, the efficiency dividend further induces industrial scale expansion and a surging demand for computing power. The resulting scale effect eventually offsets the energy-saving benefits brought by technological progress, leading to a rise in carbon emissions and resource consumption.

Table 10

Estimation Results of AI Development Level Heterogeneity

VARIABLES	(1) EF(HAI)	(2) EF(LAI)	(3) CE(HAI)	(4) CE(LAI)
AI	0.105***	0.0457***	0.152***	0.0540***
	(14.32)	(5.39)	(16.91)	(6.40)
cons	0.514	-3.147***	-1.322***	-5.876***
	(1.60)	(-8.08)	(-3.38)	(-15.17)
Control variable	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
N	725	1044	725	1044
R2	0.457	0.341	0.558	0.521

t statistics in parentheses * p < .1, ** p < .05, *** p < .01

4.6 Regression Results of Panel Threshold Model

To verify Hypothesis 3, this study adopts the panel threshold model to examine the threshold effects of artificial intelligence on carbon emissions and ecological footprint, taking the two mediating variables as threshold variables respectively.Following the threshold regression approach proposed by Hansen Bruce (1999), this paper conducts 300 iterations of Bootstrap sampling to identify the threshold effect and estimate threshold characteristics of AI on per capita carbon emissions and ecological footprint. As presented in Table 11, when technological innovation (TECH) is set as the threshold variable, AI exhibits a double-threshold effect on both carbon emissions and ecological footprint, which is significant at the 1% statistical level. When total factor energy efficiency (TFEE) serves as the threshold variable, a single-threshold effect exists in the AI-carbon emission nexus, while a double-threshold effect is observed in the AI-ecological footprint nexus.Overall, the empirical outcomes confirm that the impact of AI on per capita carbon emissions and ecological footprint presents an obvious nonlinear characteristic. The above threshold estimation results fully validate the establishment of Hypothesis 3.

Table 11

Test Results of Threshold Effects

Threshold Variable	Explained Variable	Threshold Type	F-statistic	BS Times	Threshold Estimate	95% Confidence Interval
TECH	CE	Single Threshold	39.743***	300	6.637	(4.407,9.072)
		Double Threshold	27.452***	300	9.072	(8.746,9.128)
	EF	Single Threshold	66.953***	300	6.943	(6.613,7.144)
		Double Threshold	25.676***	300	9.072	(8.948,9.264)
TFEE	CE	Single Threshold	39.76***	300	0.982	(0.964,1.001)
		Double Threshold	13.856	300	Insignificant	
	EF	Single Threshold	54.954***	300	1.041	(1.031,1.054)
		Double	12.970***	300	1.176	(0.995,1.200)

Threshold Variable	Explained Variable	Threshold Type	F-statistic	BS Times	Threshold Estimate	95% Confidence Interval
		Threshold				

Figures 3–4 and Figures 5–6 respectively present the threshold graphs of artificial intelligence on carbon emissions and ecological footprint. The figures plot the confidence intervals of the likelihood ratio statistics for threshold tests, with the red dashed line representing the critical value. It can be observed that both the first and second threshold values are significantly lower than the red critical line, indicating that the estimation of the above threshold effects is statistically reasonable and reliable.

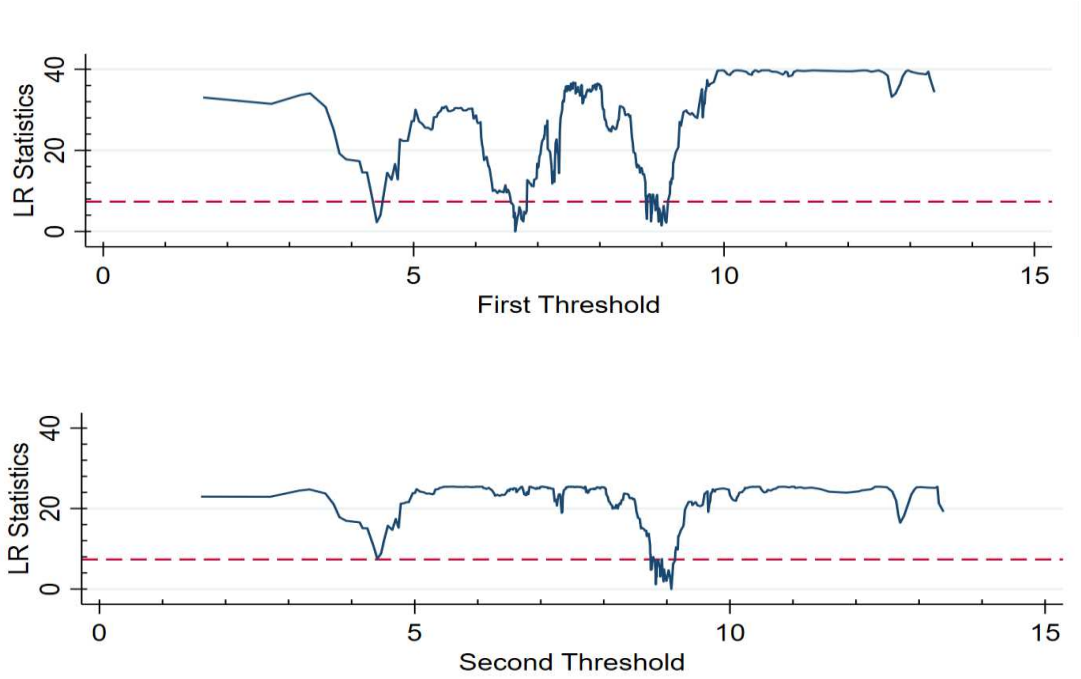
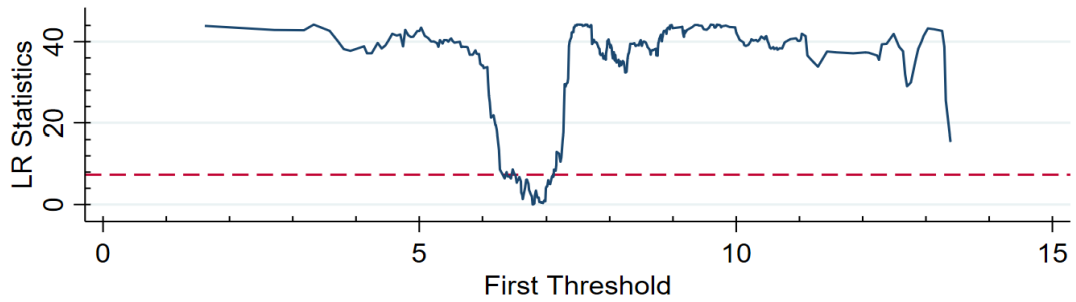


Figure 3 Likelihood Ratio Plot of TECH Threshold Test (CE)



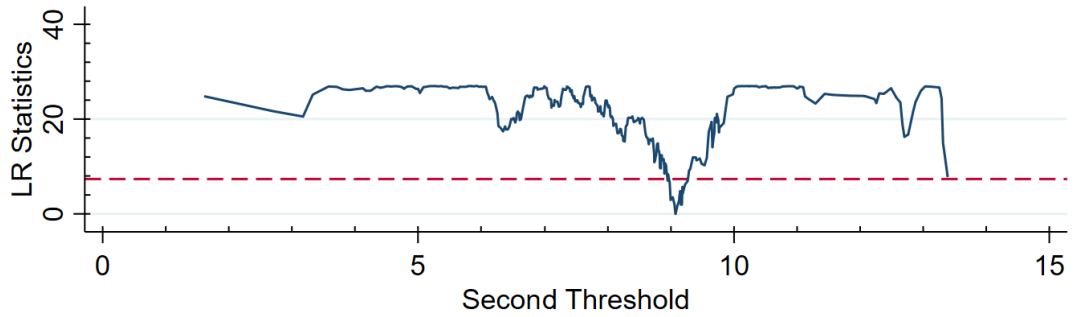


Figure 4 Likelihood Ratio Plot of TECH Threshold Test (EF)

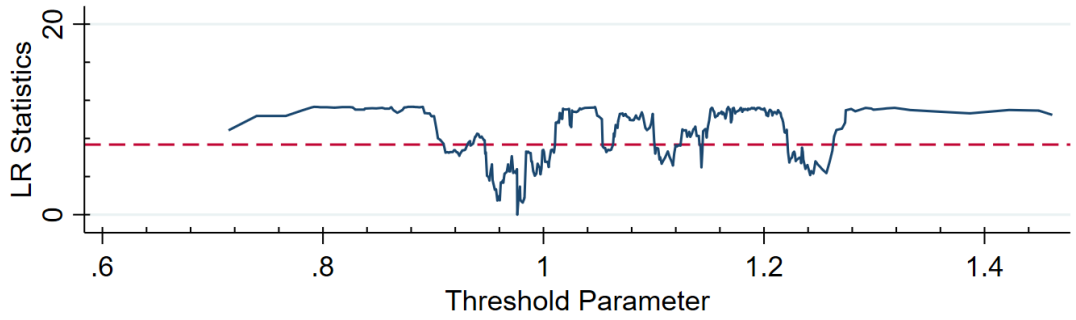


Figure 5 Likelihood Ratio Plot of TFEE Threshold Test (CE)

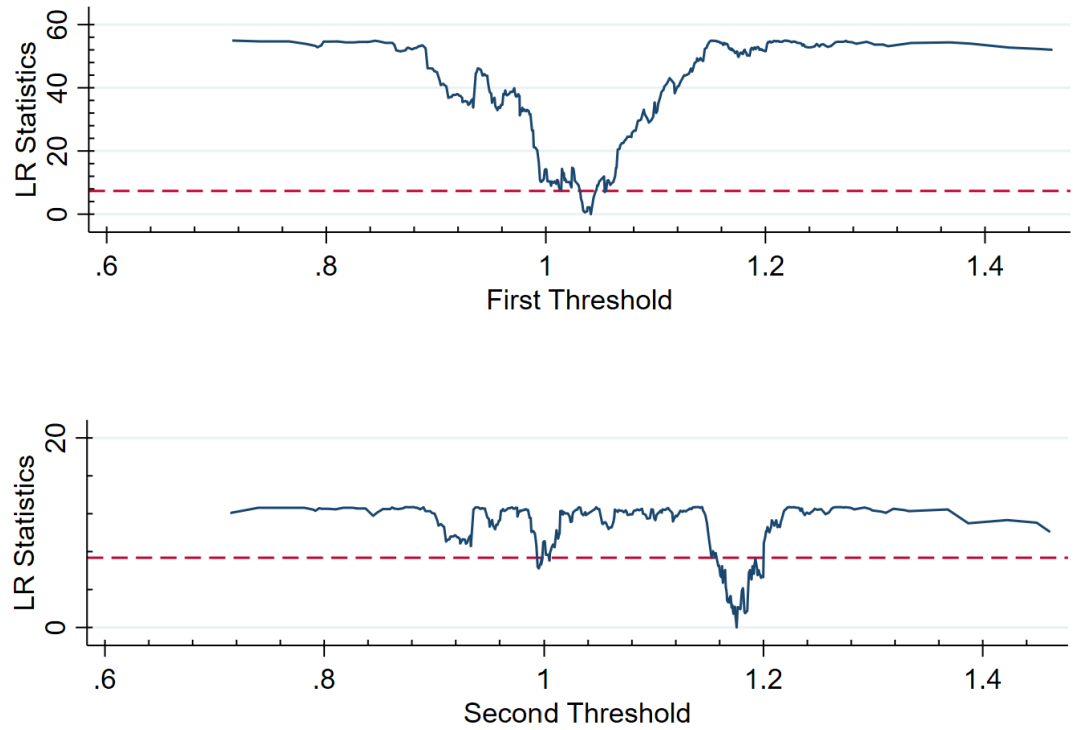


Figure 6 Likelihood Ratio Plot of TFEE Threshold Test (EF)

Table 12 reports the threshold estimation results of artificial intelligence on carbon emissions and ecological footprint. When technological innovation (TECH) is taken as the threshold variable, AI presents a driving characteristic of double thresholds, and the corresponding influence coefficient gradually weakens after crossing the two threshold points. Taking total factor energy efficiency (TFEE) as the threshold variable, the impact of AI on carbon emissions tends to converge at the threshold value of 0.982, while its impact on ecological footprint begins to decline at 1.041. Although the coefficient rises slightly after the second threshold, the overall trend remains downward. These findings demonstrate that technological maturity and economic foundation serve as the core determinants for releasing the environmental dividend of artificial intelligence.

Table 12

Nonlinear Effects of Artificial Intelligence on Carbon Emissions and Ecological Footprint

	TECH		TFEE	
VARIABLES	CE	EF	CE	EF
	(1)	(2)	(3)	(4)
C.AI_0	0.1811***	0.1137***	0.144***	0.0958***
	(10.86)	(13.35)	(12.21)	(12.15)
C.AI_1	0.0927***	0.0602***	0.0768***	0.0447***
	(14.96)	(10.30)	(14.94)	(9.15)
C.AI_2	0.0572***	0 .0288 ***		0 .0528***
	(9.50)	(5.23)		(11.07)
Single threshold	6.637***	6.943***	0.982***	1.041***
Double threshold	9.072***	9.072***		1.176***
cons	-5.669 ***	-3.223***	-5.328***	-2.948***
	(20.26)	(-12.64)	(-19.12)	(-11.58)
Control variable	YES	YES	YES	YES
Country fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	1769	1769	1769	1769
R2	0.396	0.252	0.387	0.236

t statistics in parentheses， * p < 0.1, ** p < .05, *** p < .01

5 Conclusions and Policy Implications

5.1 Conclusions

From the perspective of global sustainable development, this study systematically investigates the linear and nonlinear impacts of artificial intelligence (AI) on environmental quality. Taking per capita carbon emissions and ecological footprint as two core environmental indicators, this paper employs panel data covering 61 countries from 1995 to 2023 to identify the influencing paths and threshold characteristics of AI on environmental quality. The main conclusions are summarized as follows:

(1) AI significantly exacerbates environmental pressure. The empirical results reveal that the expansion of AI remarkably increases per capita carbon emissions and ecological footprint, resulting in obvious negative environmental spillover effects. Such findings remain valid after addressing endogeneity concerns and conducting a series of robustness tests. Mediating effect analysis further indicates that technological innovation and total factor energy efficiency exert partial mediating effects in the impact mechanism of AI on environmental performance.

(2) The adverse environmental impacts of AI present significant heterogeneous characteristics. In terms of AI technology type, the increased environmental burden is mainly driven by general artificial intelligence, while applied artificial intelligence shows no pronounced environmental effect. From the perspective of national income and AI development level, the adverse environmental impacts follow a hierarchical pattern: upper-middle income countries > high-income countries > lower-middle income countries. Moreover, the negative environmental effect is more prominent in countries with advanced AI development, which verifies the existence of the rebound effect in the digital economy.

(3) The environmental impacts of AI exhibit evident nonlinear threshold characteristics. When technological innovation (TECH) and total factor energy efficiency (TFEE) cross their respective threshold values, the overall adverse environmental impacts of AI show a marginal diminishing trend.

5.2 Policy Implications

Based on the above empirical conclusions, this paper puts forward the following

three policy implications:

(1) Implement classified governance for general AI to control resource rebound effects. Strict energy efficiency access standards should be established for the training of large-scale general AI models. Environmental external costs can be internalized via carbon taxation and green power quota policies, guiding the transformation of AI development from scale-oriented computing power to efficiency-oriented computing power. Meanwhile, it is essential to support the application of applied artificial intelligence in intelligent scheduling, precision agriculture and other scenarios to offset rising resource consumption.

(2) Promote breakthroughs in technological and energy efficiency thresholds to release environmental dividends. Special funds for "AI & green technology integration" should be set up to accelerate technological innovation and energy efficiency improvement. Relevant policies can help high-income countries consolidate the convergence trend of adverse environmental effects, assist countries at the initial stage of AI development in avoiding polarization risks after crossing threshold constraints, and facilitate the marginal diminishing transition of AI's environmental impacts.

(3) Establish a global cross-border coordination mechanism to address the dilemma of low-income countries. A transnational system of technology transfer and environmental compensation needs to be constructed. High-income countries are encouraged to provide low-energy-consumption algorithms and computing power support, so as to help low-income countries improve green infrastructure construction. This can prevent low-income economies from falling into the carbon emission reduction trap, and ultimately achieve coordinated development between artificial intelligence advancement and environmental protection.

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