

A Multi-Stage Nonlinear Relationship between Artificial Intelligence Development and Environmental Pollution

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1 A Multi-Stage Nonlinear Relationship between Artificial Intelligence
2 Development and Environmental Pollution

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Abstract: As China advances its green and low carbon transition, the influence of artificial intelligence (AI) development on environmental pollution remains a critical yet underexplored issue; nevertheless, evidence on stage dependent effects beyond the conventional inverted U Environmental Kuznets Curve (EKC) remains limited. Using provincial panel data from 2011 to 2022, this study constructs an Environmental Pollution Index (EPI) using the global entropy weight method (EWM), incorporating indicators of solid waste generation, chemical oxygen demand emissions, sulfur dioxide emissions, and carbon dioxide emissions. Kernel density estimation and Dagum Gini coefficient decomposition are employed to characterize distributional dynamics and identify the sources of regional disparities. After benchmarking seven machine learning models within a unified framework, the Generalized Additive Model (GAM) is selected as the optimal model due to its superior predictive performance and interpretability, and is then used to uncover nonlinear associations, turning points, and sign reversals. The GAM results reveal distinct multistage patterns: AI enterprises follow a segmented extended U-shaped curve, shifting from pollution aggravation to stable mitigation beyond a threshold; AI-Industry per capita GDP exhibits a W-shaped pattern; Industrial robot density declines overall with an inflection; AI patent grants display threshold effects with stronger mitigation at higher levels; R&D personal ratio in AI industry approximates a U-shaped curve, turning from positive to negative near a threshold before flattening; and AI technology innovation expenditure increases almost linearly with a stagewise shift from mitigation to aggravation. Public concern about environmental pollution follows an N-shaped curve, Environmental governance investment and Urbanization rate exhibit bimodal M-shaped patterns, and Marketization index shows a U-shaped relationship with mitigation concentrated in the middle range. Although EPI declines on average,

interprovincial disparities persist, and these multistage patterns refine EKC interpretations of scale and technique effects.

Keywords: Artificial Intelligence; Environment Pollution Index; Generalized Additive Model; Nonlinear Relationships; Environmental Kuznets Curve

1 Introduction

Against the backdrop of efforts to promote green and low carbon development, environmental pollution remains a salient practical constraint on sustainable economic and social development. As a typical form of comprehensive environmental stress, the pollution level is shaped jointly by industrial structure and technological progress, and it also adjusts systematically with changes in factor allocation and innovation activities (Liu et al., 2022). Meanwhile, artificial intelligence (AI), as a general purpose technology, is rapidly permeating firms' production and technological innovation processes. By influencing efficiency improvements, technology substitution, and factor allocation, it reshapes the mechanisms through which pollution is generated (Guo et al., 2025). Therefore, a more refined empirical identification and interpretation of the relationship between AI development and environmental pollution is warranted.

Existing research has produced multi perspective evidence on the relationship between artificial intelligence and environmental pollution. Zhou (2025) finds that AI development can improve urban air quality and highlights the channels through which government attention and public environmental concern operate. Ma et al. (2024) report that AI development can reduce water pollution, although the effects exhibit pronounced regional heterogeneity and strong context dependence. With respect to emission intensity and energy efficiency, evidence from Zhou et al. (2024) suggests

that AI can affect pollutant emissions by improving energy efficiency and advancing green technologies. In the area of carbon emissions, quasi natural experiment studies indicate that pilot AI related policies may reduce carbon emissions and generate synergistic benefits for pollution abatement (Zhang et al., 2025). At the micro level, firm level evidence shows that the adoption of AI may enhance corporate carbon abatement performance, operating through channels such as green innovation and information disclosure (Wang et al., 2025). Relatedly, AI has also been found to promote firms' green technology innovation, thereby providing a potential technological foundation for pollution improvement (Li and Chen, 2025). From the perspective of applications and governance, the potential of AI for environmental research and urban air pollution monitoring has attracted increasing attention, but it has also raised concerns about environmental justice, implying that technology deployment and pollution exposure may be unevenly distributed across regions (Krupnova et al., 2022). Methodologically, generalized additive models (GAM) have been widely used to characterize complex nonlinear relationships in environmental systems and provide a well established tool for accommodating potential changes in marginal effects (Ravindra et al., 2019). Research on threshold identification further demonstrates the advantage of this class of methods in estimating structural turning points (Benedetti et al., 2009). In addition, studies that integrate explainable machine learning with causal inference have been applied to uncover regional heterogeneity in the drivers of air quality, thereby reinforcing the methodological requirement for interpretability (Fu et al., 2025).

Nevertheless, several gaps remain in the existing literature. First, the quantification of environmental pollution has largely relied on single indicators, and the systematic application of comprehensive index systems in empirical analysis remains limited,

which constrains the measurement of overall pollution pressure and reduces cross regional comparability. Second, measures of AI development in prior studies often depend on a single proxy, making it difficult to capture the multidimensional nature of AI and thereby limiting the completeness of mechanism based interpretation. Third, disagreements regarding the direction of AI's impact on environmental pollution have not been adequately reconciled, and the nonlinear feature that marginal effects may vary with the level of development still lacks systematic identification. Fourth, relatively few studies transparently compare the performance of interpretable statistical models and multiple machine learning models within a unified data framework, leaving room to strengthen the basis for model selection and the robustness of empirical results.

In view of the limitations of prior research in pollution measurement systems, the representation of AI indicators, the transparency of model selection, and the identification of nonlinear effects, this study provides a systematic response within a unified empirical framework. It constructs a composite Environmental Pollution Index (EPI) using the entropy weight method and, on this basis, characterizes the dynamic features of pollution levels and regional disparities. AI development is represented through a multidimensional set of indicators capturing firm presence, industry performance, technological innovation, and factor inputs, thereby strengthening mechanism based interpretation. At the modeling stage, the study establishes a reproducible basis for model choice through the systematic benchmarking and screening of multiple machine learning algorithms. Building on the selected model, it then employs the generalized additive model to characterize nonlinear associations, identify intervals of changing marginal effects, and detect potential threshold features. The overall framework is illustrated in Figure 1.

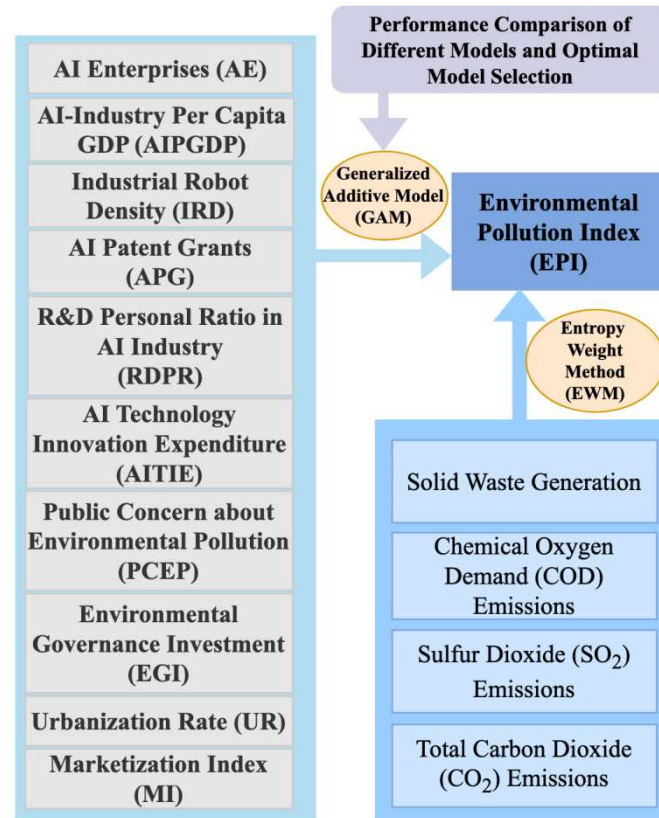


Figure 1. The Conceptual Framework

The remainder of the paper is organized as follows. Section 2 systematically reviews the literature on AI development and environmental pollution. Section 3 presents the research design and methodology, introduces the benchmarking and screening framework for machine learning models and, based on this framework, determines the optimal modeling strategy, and further describes the data sources and the construction of variables. Section 4 reports the empirical results. It first presents the temporal trends and regional disparities of environmental pollution levels, and then reports the estimation results from the generalized additive model, highlighting the nonlinear effects and marginal impacts. Section 5 discusses the main findings and derives policy implications. Section 6 concludes the study and provides policy recommendations.

2 Literature Review

2.1 Assessment of Environment Pollution

Existing empirical research on environmental pollution has primarily focused on major types of environmental stress, including air pollution (Zhan et al., 2017), water pollution (Wei et al., 2025), and solid waste pollution (Guo et al., 2024), and has developed relatively distinct measurement approaches and explanatory frameworks for each domain. In the air pollution literature, pollution levels exhibit pronounced spatial and temporal heterogeneity and are driven by a range of socioeconomic factors. Moreover, spatial dependence and transmission processes indicate that interregional linkages play an important role in comparative analysis and policy evaluation (Zhan et al., 2017; Du et al., 2021). Industrial structure and industrial activity affect air quality through multiple channels, closely tying pollution dynamics to economic structural adjustment (Liu et al., 2022). Research on water pollution emphasizes the importance of pollution assessment and source apportionment (Zhou and Li, 2022), and incorporates governance performance into efficiency evaluation frameworks to capture differences in regulatory effectiveness (Wei et al., 2025; Chen et al., 2022). Studies on solid waste further integrate the synergy between pollution abatement and carbon reduction into evaluation systems, offering a complementary perspective for quantifying comprehensive environmental stress (Guo et al., 2024). Related regional evidence also suggests substantial heterogeneity in the relationship between industrial structural evolution and pollution levels, reinforcing the central role of structural factors in explaining pollution outcomes (Sun et al., 2022).

Although substantial evidence has been accumulated on pollution types and the identification of their drivers, empirical studies still often rely on a single pollutant concentration or a single emission indicator to measure environmental pollution. As a result, assessments of overall pollution pressure are sensitive to indicator choice, and

the explanatory power of cross regional comparisons is correspondingly constrained (Zaharia, 2012). At the same time, the selection and construction of pollution indicator systems vary across studies and application contexts, and the systematic development and standardized use of comprehensive index systems remain relatively insufficient (Heravi et al., 2024), which to some extent weakens the comparability and consistency of empirical conclusions. Accordingly, there is a clear need to integrate multiple pollution components under a unified measurement protocol and develop comparable composite indicators, so as to more fully capture overall pollution pressure and provide a more robust measurement basis for subsequent empirical identification.

2.2 The Effects of Artificial Intelligence on Environmental Pollution

Existing studies have conducted empirical tests on whether AI development alters the level of environmental pollution (Kaied et al., 2025), covering multiple dimensions such as air pollution (Zhou, 2025), water pollution (Ma et al., 2024), and solid waste pollution (Liu et al., 2022). Related work has also extended the analytical focus to firm behavior, examining how AI adoption affects corporate emission reduction performance and green innovation (Wang et al., 2025; Li and Chen, 2025). In parallel, the potential of AI applications in environmental research and air pollution monitoring has been continuously discussed, and an environmental justice perspective has been introduced to assess the asymmetry between technology diffusion and pollution exposure (Guo et al., 2025; Krupnova et al., 2022).

In the field of air pollution, evidence suggests that AI development can improve urban air quality (Rautela et al., 2025), and government attention as well as Public Concern about Environmental Pollution have been used to explain the underlying channels (Zhou, 2025). By contrast, other research finds that AI development measured by

patents is positively associated with PM2.5 emissions, and this relationship appears to operate mainly through rising energy consumption and the expansion of industrial output (Ma et al., 2025). With respect to water pollution, Ma et al. (2024) report that AI development is associated with reduced water pollution, although the effect exhibits substantial regional heterogeneity and strong context dependence. In terms of emission intensity and energy efficiency, Zhou et al. (2024) indicate that AI can influence pollutant emissions by improving energy efficiency and advancing green technologies. Regarding carbon emissions, Zhang et al. (2025), using a quasi natural experiment based on policy pilots, find that AI related policies can reduce urban carbon emissions and generate synergistic benefits for pollution abatement. Firm level studies further suggest that corporate AI adoption can enhance carbon abatement performance through channels such as green innovation and information disclosure (Wang et al., 2025). Li and Chen (2025) also show that AI can promote firms' green technology innovation, thereby providing micro level foundations for pollution improvement. In the domain of waste management and resource circulation, reviews note that AI and machine learning can support sorting and identification, logistics scheduling, and process optimization, offering actionable technical pathways to reduce comprehensive environmental pressure (Rautela et al., 2025; Sugumaran et al., 2025). Further pathway oriented evidence also indicates systematic links between AI adoption and circular economy practices, implying that AI may indirectly affect pollution outcomes through improvements in resource use efficiency and process optimization (Ronaghi, 2023). At the same time, AI diffusion is often accompanied by industrial expansion and shifts in the structure of capital investment, which increases the likelihood that environmental effects will become more conditional across stages

of development and diverge in direction (Montanaro et al., 2024; Salimi and Sheikhzeinoddin, 2025).

Methodologically, much of the related literature identifies average effects within a linear regression framework (Zhou, 2025; Ma et al., 2025). It often combines spatial econometric approaches or network perspectives to address spatial dependence and cross regional transmission in pollution (Du et al., 2021; Liu et al., 2022), which makes empirical conclusions more readily summarized by linear specifications (Jin et al., 2024; Zhou, 2025; Zhang et al., 2025). To characterize regional heterogeneity, some studies also adopt methods such as geographically and temporally weighted regression (Chen et al., 2024) to describe spatiotemporal variation in pollution drivers. However, these approaches place greater emphasis on depicting spatial differences and are relatively limited in capturing how the marginal effects of technology related variables change across different development intervals.

In recent years, explainable machine learning has increasingly been applied in environmental research to uncover more complex nonlinear structures and potential thresholds; nevertheless, model selection criteria and reproducibility across algorithms still require support from more transparent benchmarking frameworks (Shi et al., 2025; Fu et al., 2025). By contrast, the GAM can represent nonlinear functional forms directly through smooth functions in studies of environmental systems, and it has demonstrated strong suitability in pollution related empirical research, providing an interpretable statistical tool for identifying interval specific effects (Pearce et al., 2011; Jiang et al., 2018).

In summary, existing research still leaves room for divergence in both stage dependent patterns and directional effects at the level of empirical findings, while methodologically it has largely relied on linear average effects and has been less

effective in revealing interval heterogeneity and turning point structures that may characterize technology related variables (Montanaro et al., 2024; Shi et al., 2025). At the same time, pollution studies are often organized around a single environmental medium, and there remains considerable scope to improve the unified measurement of comprehensive pollution pressure and the comparability of cross regional analysis (Wei et al., 2025; Guo et al., 2024). Building on these considerations, this study constructs a composite Environmental Pollution Index (EPI) and documents its temporal evolution and regional disparities. It further conducts model screening and, based on the selected optimal specification, applies the generalized additive model to uncover smooth nonlinear relationships and threshold features, thereby enhancing the transparency of model choice and the interpretability of empirical conclusions. This approach provides more robust evidence for identifying the net effect of AI development on environmental pollution and its stage dependent variation.

3 Research design

3.1 Methodology

3.1.1 Entropy Weighted Method

To objectively characterize provincial-level Environment pollution index (EPI) under a multidimensional indicator system, this study constructs a composite index using an improved global entropy weighted method (EWM), which helps reduce the potential bias associated with subjective weighting schemes. The EWM is an objective weighting approach grounded in information entropy and has been widely applied in multidimensional evaluations, such as assessing regional economic development (Huang et al., 2025), industrial competitiveness (Yuan & Zhao, 2026) and environment performance evaluation (Salimi & Sheikhzeinoddin, 2025).

The key computational procedures are as follows:

$$X=\{x_{ij}^t\}_{mT \times n} \quad (1)$$

In equation (1), m , n and T denote the number of provinces, the number of evaluation indicators, and the number of years, respectively. Let X be the initial global evaluation matrix, where x_{ij}^t represents the value of the j indicator for province i in year t . We then compute, for each indicator j and year t , the proportion represented by the observation of province i , and obtain the standardized matrix z , which is the dimensionless transformation of the original data matrix.

$$p_{ij}^t = \frac{z_{ij}^t}{\sum_{t=1}^T \sum_{i=1}^m z_{ij}^t} \quad (2)$$

In equation (2), p_{ij}^t reflects the relative weight of province i compared with other provinces for the j indicator in year t . On this basis, the information entropy of the j indicator, e_j is computed. Let $K = \frac{1}{\ln(mT)}$, Then:

$$e_j = -K \sum_{t=1}^T \sum_{i=1}^m p_{ij}^t \ln p_{ij}^t \quad (3)$$

The smaller the information entropy e_j of an indicator is, the greater its variation across provinces and over time and the richer the information it contains. On this basis, the information utility of the j indicator is obtained and its weight is determined as:

$$w_j = \frac{(1-e_j)}{\sum_{j=1}^n (1-e_j)} \quad (4)$$

In equation (4), w_j is the entropy-based weight of the j indicator and reflects its relative importance in the composite evaluation.

Finally, the standardized values of all indicators are aggregated using these weights to derive the composite environment pollution index (EPII) for province i in year t :

$$EPI_{it} = \sum_{j=1}^n w_j z_{ij}^t \quad (5)$$

In equation (5), EPI_{it} represents the comprehensive index of the provincial environment pollution level constructed in this study.

After constructing the composite index, Kernel Density Estimation (KDE) is employed to examine the temporal evolution of the dynamic distribution. The Dagum Gini coefficient and its decomposition are also applied to identify the sources of regional disparities in the spatial dimension. These methods are used to reveal the overall evolution pattern and regional gradient characteristics of environment pollution in China.

3.1.2 Model Selection

To obtain a more robust and reproducible modeling strategy within a unified data framework, this study conducts a systematic comparison of the goodness of fit and generalization performance of several widely used predictive models before proceeding to nonlinear effect identification, and then determines the baseline model for subsequent analysis accordingly. The candidate models include linear regression, Random Forest, Gradient Boosting, Support Vector Regression, K Nearest Neighbors, XG-Boost, and the Generalized Additive Model. Model performance is jointly evaluated using mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). These metrics collectively assess model performance from the perspectives of error magnitude, the robustness of prediction errors, and explanatory power.

The comparison results are reported in Table 1. The GAM performs best across all four evaluation metrics, with an MSE of 0.003, an RMSE of 0.058, an MAE of 0.044, and an R^2 of 0.826. By contrast, linear regression exhibits substantially weaker

explanatory power, with an R^2 of 0.424, and markedly larger prediction errors. Although ensemble learning models and kernel based methods outperform linear regression, their overall performance remains inferior to that of the generalized additive model. For example, XG-Boost achieves an R^2 of 0.740, while support vector regression yields an R^2 of 0.711. Based on these comparisons, this study adopts the generalized additive model as the core modeling tool for subsequent empirical analysis, as it offers superior fit and predictive accuracy while preserving interpretability, and provides a suitable methodological foundation for characterizing the nonlinear functional forms underlying the relationships among variables.

Table 1. Performance Comparison across Models and Selection of the Optimal Model

Models	MSE	RMSE	MAE	R2
GAM	0.003	0.058	0.044	0.826
Linear Regression	0.014	0.118	0.096	0.424
Random Forest	0.009	0.092	0.068	0.649
Gradient Boosting	0.008	0.087	0.062	0.691
Support Vector Regression	0.007	0.084	0.071	0.711
K Nearest Neighbors	0.008	0.087	0.065	0.689
XGBoost	0.006	0.079	0.058	0.740

3.1.3 Generalized Additive Model

To further characterize the potentially complex nonlinear relationships between AI development and environment pollution, this study employs GAM. Building on the conventional regression framework, GAM replaces linear coefficients with smooth functions, thereby retaining an additive structure and interpretability while allowing flexible estimation of nonlinear effects (Marra & Wood, 2011). Compared with linear models that require researchers to specify functional forms a priori, GAM allows the

data to inform the shape of the relationship, making it particularly suitable for analyzing the relationship between AI development and environment pollution that are jointly influenced by multiple factors and may involve thresholds or turning points.

Formally, a standard multiple linear regression model can be expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \quad (6)$$

where Y is the dependent variable, $X_1, \dots, X_p$ are the p explanatory variables, and $\beta_0, \beta_1, \dots, \beta_p$ are the parameters to be estimated. This specification implicitly assumes that the marginal effect of each explanatory variable on Y is constant, which makes it difficult to capture more general nonlinear patterns such as inverted-U relationships or diminishing marginal returns.

Building on this framework, the generalized additive model replaces the linear terms $\beta_j X_j$ with unknown smooth functions $S_j(X_j)$. In terms of conditional expectation, it can be written as

$$E(Y|X_1, \dots, X_p) = \beta_0 + S_1(X_1) + S_2(X_2) + \dots + S_p(X_p) \quad (7)$$

$S_j(\cdot)$ denotes the smooth function associated with the j -th explanatory variable, which is estimated in a data-driven manner using spline functions or related techniques. Each curve $S_j(\cdot)$ depicts how the marginal effect of X_j on Y changes over the range of X_j , thereby allowing nonlinear features to be identified.

In the empirical setting of this study, let $Y = EPI_{it}$ denote the composite EPI for province i in year t , and let x_{ij}^k represent the value of the k -th driving factor for province i in year t . The generalized additive model employed in this paper can then be written as:

$$EPI_{it} = \beta_0 + \sum_{k=1}^p S_k(x_{it}^k) \quad (8)$$

In Equation (8), β_0 is the constant term, and $S_k(\cdot)$ denotes the smooth function capturing the effect of AI development on environment pollution.

Estimation of Equation (8) is implemented in R using the mgcv package. The functional curves of $S_k(x_{it}^k)$ are then plotted to visually assess whether each explanatory variable exerts promoting or inhibiting effects across different value ranges. This procedure provides a basis for identifying effective input intervals of key factors and for designing differentiated policy interventions.

3.2 Variables and Data Sources

3.2.1 Dependent Variable

Given that environmental pollution is manifested simultaneously through solid waste pollution, water pollution, and air pollution, this study applies the entropy weight method to assign objective weights to the relevant indicators and constructs a province level composite EPI. Drawing on prior research on solid waste pollution (Guo et al., 2025), water pollution (Khan and Nasir, 2023), and air pollution (Kaied et al., 2025), a provincial comprehensive evaluation indicator system for environmental pollution is developed, as reported in Table 2.

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347
348

Table 2. Indicator System for the Composite Environmental Pollution Index

Primary indicator	Secondary indicator	Definition	Unit	Direction
Environmental Pollution Index (EPI)	Solid Waste Pollution	Solid Waste Generation	10,000 tons	Positive
	Water Pollution	Chemical Oxygen Demand	10,000	Positive

Primary indicator	Secondary indicator	Definition	Unit	Direction
		Emissions	tons	
	Air Pollution	Sulfur Dioxide Emissions	10,000 tons	Positive
		Total Carbon Dioxide Emissions	10,000 tons	Positive

350 Data Source: National Bureau of Statistics

351 3.2.2 Explanatory Variables

352 The core explanatory variables are used to characterize the level of provincial AI
353 development, including AI enterprises, AI-Industry per capita GDP, Industrial robot
354 density, AI patent grants, R&D personal ratio in AI industry, and AI technology
355 innovation expenditure). To control for other factors that may affect environmental
356 pollution, the analysis further includes Public concern about environmental pollution,
357 Environmental governance investment, Urbanization rate, and Marketization index as
358 explanatory variables. Detailed definitions, measurement procedures, supporting
359 references, and data sources for all variables are reported in Table 3.

Variables	Symbol	Variable Name	Definition	Measurement	Literature Sources	Data Sources
Explanatory	AE	AI Enterprises	Measures the scale of AI firm development	Year end number of AI firms in each region	Wang et al., 2025	Tianyancha
	AIPGDP	AI-Industry Per Capita GDP	Measures per capita development of the AI industry	AI industry value added / The permanent resident population	Ma et al., 2024	China Science and Technology Statistical Yearbook; China High-Technology Industry Statistical Yearbook
	IRD	Industrial Robot Density	Measures the extent of application of AI-related intelligent manufacturing equipment	$\ln ((\text{No. of industrial robots} / \text{Employment in the AI industry}))$	Ruiz-Vanoye et al., 2024; Zhang et al., 2024	International Federation of Robotics (IFR) China Labor Statistical Yearbook
	APG	AI Patent Grants	Measures the quality and implementability of AI patents	No. of granted AI patents / No. of AI patent applications	Luo et al., 2024	CNRDS

	RDPR	R&D Personnel Ratio in AI Industry	Measures the intensity of AI R&D human resources within AI industry employment	No. of AI R&D personnel / Employment in the AI industry	Jian et al., 2024	China Statistical Yearbook on Science and Technology; China High-Technology Industry Statistical Yearbook
	AITIE	AI Technological Innovation Expenditure	Measures the intensity of financial investment in AI-oriented technological upgrading by firms	ln (AI technological innovation exp enditure)	Montanaro et al., 2024; Huang & Wu, 2025	China Statistical Yearbook on Science and Technology; China Electronic Information Industry Statistical Yearbook
	PCEP	Public Concern about Environmental Pollution	Measures public attention to environmental pollution issues	Baidu haze search index as a proxy for public environmental concern	Wu et al., 2022; Zhou, 2025	Baidu
	EGI	Environmental Governance	Measures the intensity of local environmental governance inputs	Local fiscal spending on environmental governance / General	Zhao & Zhang, 2021	China Environment Statistical Yearbook

		Investment		public budget expenditure		
	UR	Urbanization Rate	Measures the spatial concentration of population and economic activity	Urban permanent resident population / Total permanent resident population	Li et al., 2023	China Statistical Yearbook
	MI	Marketization Index	Measures the degree of factor marketization and the quality of the regional business environment	Provincial marketization index following Fan et al. (2003)	Jin et al., 2024	China Market Index Database

4 Results

4.1 Measurement Results and Spatiotemporal Evolution of Environmental Pollution Index

4.1.1 Temporal Dynamics of the EPI

As illustrated in Figure 2, the annual provincial mean of the EPI exhibits a pronounced downward trend from 2011 to 2022. The EPI declines steadily from 0.361 in 2011 to 0.082 in 2022, indicating a substantial alleviation of overall pollution pressure over the sample period. Two notable drop points are observed along the temporal trajectory. In 2016, the EPI falls from 0.303 in 2015 to 0.182, corresponding to an annual growth rate of minus 0.399. In 2020, the EPI decreases further from 0.148 in 2019 to 0.085, with an annual growth rate of minus 0.428. Thereafter, the EPI stabilizes at a low level, reaching 0.082 in 2021 with a growth rate of minus 0.034, while the growth rate in 2022 is close to zero, suggesting that the marginal pace of pollution improvement slows in the later period.

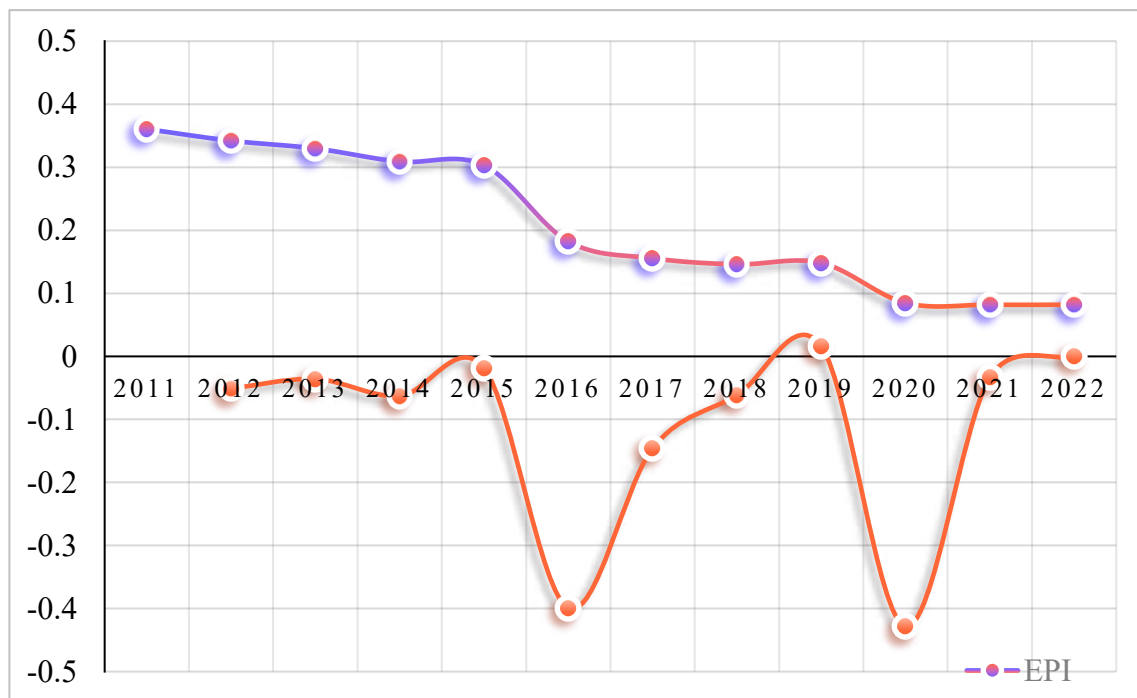
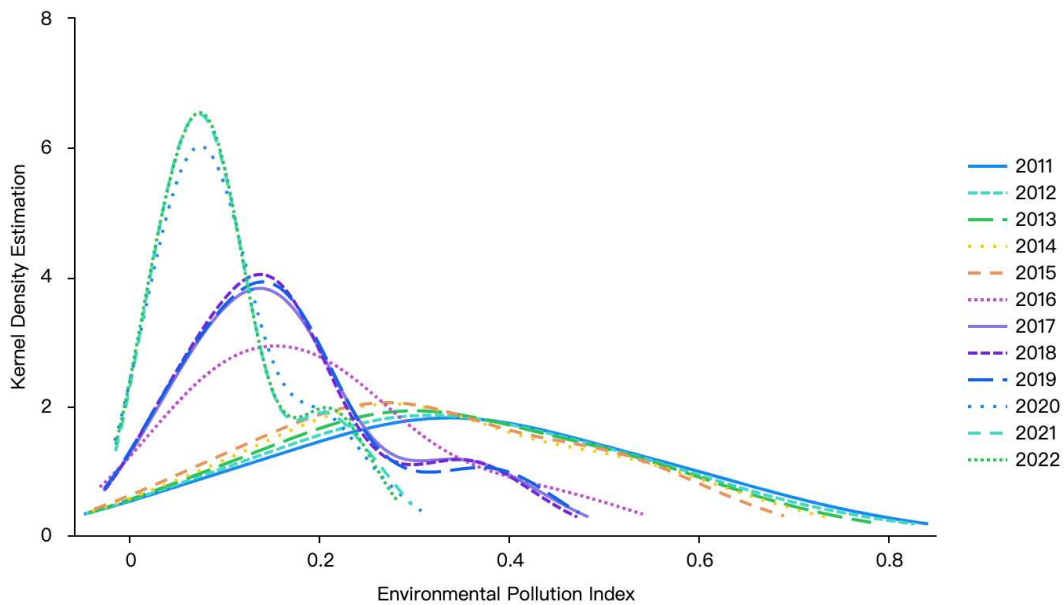


Figure 2. Annual Provincial Mean of the EPI and Its Growth Rate

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378 Building on the sustained decline in the overall level of pollution, it is further
379 necessary to assess whether the distributional shape of interprovincial pollution levels
380 adjusts in tandem. The kernel density results in Figure 3 show that the annual
381 distribution of EPI shifts toward lower values over time, indicating that the reduction
382 in pollution pressure is reflected not only in changes in the mean but also in a
383 downward movement of the distributional center. Consistent with the pronounced
384 downturns observed in 2016 and 2020, the density curves around these years exhibit a
385 more evident leftward shift, accompanied by a gradual contraction of the right tail.
386 This pattern suggests that the share of high pollution observations declines and the
387 influence of extreme values diminishes. At the same time, the density shapes retain
388 noticeable differences in peak characteristics and local shoulder features, implying
389 that interprovincial heterogeneity has not disappeared despite overall improvement
390 and partial convergence. Accordingly, it is necessary to further identify how this
391 heterogeneity manifests spatially and to trace its regional sources.



392

393 Figure 3. Evolution of the Kernel Density Distribution of the Provincial EPI

4.1.2 Spatial Evolution of the Composite EPI

Figure 4 depicts interprovincial disparities using the median EPI for each province over 2011 to 2022. Using the median helps attenuate the influence of extreme year specific fluctuations on the ranking and therefore better reflects a province's typical pollution pressure during the sample period. The results indicate pronounced interprovincial stratification, with a persistent gradient between provinces with high and low values. Jiangxi records the highest median EPI at 0.437. Shanxi and Liaoning follow with 0.382 and 0.377, and Hebei reaches 0.329, jointly forming the group of provinces with relatively high pollution pressure. By contrast, provinces at the lower end exhibit substantially weaker typical pollution pressure, with Anhui at 0.015, Beijing at 0.019, and Tianjin at 0.035. This ranking suggests that interprovincial differences in pollution are characterized by persistent structural features rather than being driven solely by fluctuations in a few individual years. To provide a more rigorous quantitative assessment of the disparities indicated in Figure 3, the Dagum Gini coefficient and its decomposition are further employed to measure both the intensity of inequality and the structure of its sources.

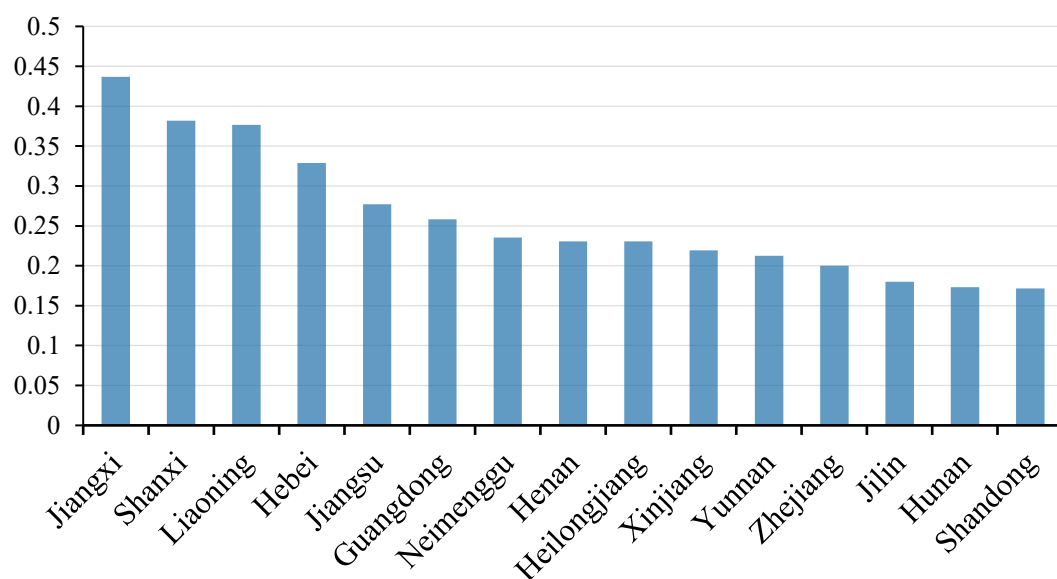


Figure 4. Provincial Medians of the EPI and Interprovincial Rankings

Table 4 reports the Dagum Gini coefficient of the EPI and its decomposition, which are used to identify the temporal evolution of overall disparities and the structure of their sources. For ease of interpretation, the Dagum Gini coefficient and the corresponding decomposition results reported in Table 4 are further visualized in Figure 5.

Table 4. Gini Coefficient and Decomposition of EPI in China

Year	G	G_W			G_nb			G_z(%)		
		Eastern	Central	Western	Easter-Central	Eastern-Western	Central-Western	Within Region	Between Region	Transvariation
2011	0.298	0.404	0.185	0.192	0.343	0.362	0.199	31.551%	9.697%	58.752%
2012	0.300	0.404	0.181	0.201	0.346	0.360	0.202	31.771%	8.551%	59.678%
2013	0.299	0.403	0.188	0.202	0.345	0.356	0.204	31.934%	6.784%	61.282%
2014	0.302	0.403	0.185	0.205	0.348	0.364	0.200	31.770%	8.040%	60.190%
2015	0.302	0.402	0.175	0.216	0.345	0.364	0.205	31.781%	6.628%	61.591%
2016	0.357	0.445	0.226	0.272	0.379	0.427	0.271	32.001%	17.022%	50.977%
2017	0.356	0.448	0.220	0.256	0.392	0.428	0.254	31.703%	16.933%	51.363%
2018	0.354	0.439	0.229	0.270	0.386	0.419	0.263	31.953%	14.419%	53.627%
2019	0.357	0.438	0.237	0.285	0.384	0.419	0.275	32.156%	12.223%	55.621%
2020	0.369	0.438	0.240	0.280	0.409	0.431	0.270	31.979%	20.637%	47.384%
2021	0.373	0.433	0.269	0.275	0.418	0.432	0.278	31.836%	20.881%	47.283%
2022	0.371	0.431	0.287	0.263	0.419	0.425	0.281	31.772%	18.114%	50.115%

The overall Gini coefficient increases from 0.300 in 2012 to 0.371 in 2022, indicating a widening trend in interprovincial pollution disparities, with more pronounced upward movements after 2016 and again after 2020. The decomposition results show

that the contribution of within group inequality remains relatively stable across years, hovering around 31.7% to 32.2%. By contrast, the contribution of between group inequality rises substantially in the later period, increasing from roughly 6% to 8% during 2013 to 2015 to around 20% in 2020 and 2021. The contribution of the transvariation density term continues to account for the largest share, but it declines from about 60% in the early years to approximately 47% in 2020 and 2021. Taken together, these results indicate that interprovincial pollution disparities are not only substantial throughout the sample period, but their source structure also shifts over time. In this context, descriptions based solely on mean trends are insufficient to explain the drivers of pollution dynamics. It is therefore necessary to further test the pathways through which AI development affects pollution levels and the characteristics of marginal effects within an interpretable nonlinear modeling framework.

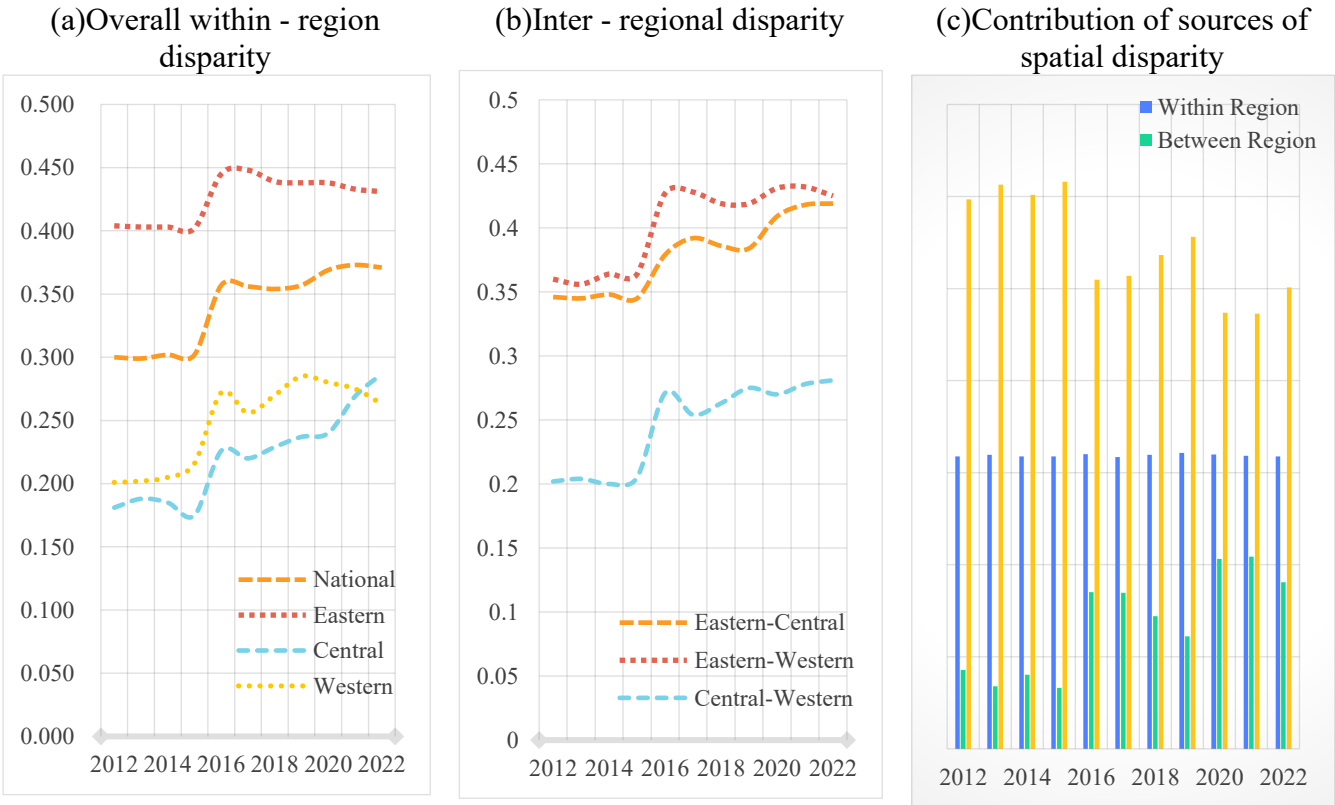


Figure 5. Gini Coefficient and Decomposition of EPI in China

4.2 Descriptive Statistics and Correlation Analysis

4.2.1 Descriptive Statistics

Table 5 reports the descriptive statistics for the main variables. As shown in Table 5, EPI exhibits pronounced interprovincial variation over the sample period. Its mean is 0.22, and the interquartile range spans from 0.09 to 0.33, indicating that most province year observations are concentrated in a relatively low to medium range. Meanwhile, the EPI ranges from a minimum of 0.01 to a maximum of 0.77, with a standard deviation of 0.17. This pattern suggests a long right tail and the presence of observations with relatively high pollution pressure, reflecting substantial dispersion in provincial pollution levels.

Table 5. Variables Descriptive Statistics

Variable	N	Q1	Mean	Q3	SD	Min	Max
EPI	360	0.09	0.22	0.33	0.17	0.01	0.77
AE	360	6.89	7.95	8.96	1.44	4.68	11.97
AIPGDP	360	7.64	8.47	9.33	1.24	4.32	10.76
IRD	360	7.50	8.53	9.74	1.53	4.71	12.31
APG	360	4.93	6.33	7.76	2.00	0.69	10.82
RDPR	360	14.27	23.35	29.15	12.47	1.06	66.28
AITIE	360	9.35	10.62	12.04	2.17	0.00	14.88
PCEP	360	79.88	105.80	131.63	38.23	17.77	215.38
EGI	360	112.37	253.14	336.96	184.40	9.99	952.48
UR	360	51.23	59.44	66.14	13.09	22.65	89.58
MI	360	6.77	8.15	9.63	1.95	3.36	12.86

4.2.2 Correlation Analysis

The correlation analysis provides an initial view of the network of associations between AI related indicators and the composite EPI. Figure 6 presents the correlation results between AI indicators and environmental pollution. The EPI is negatively correlated with most AI related measures, with correlation coefficients of minus 0.32 for AE and minus 0.27 for RDPR. The remaining AI indicators exhibit smaller magnitudes and are mostly weakly negative. By contrast, the EPI is positively correlated with EGI with a relatively large coefficient of 0.52, and it is also positively correlated with AITIE with a coefficient of 0.22, whereas its correlation with PCEP is weaker at 0.12.

However, correlation analysis captures only linear and relatively simple co movements between variables and is insufficient for uncovering more complex mechanisms. In practice, the relationship between AI development and environmental pollution is unlikely to follow a simple linear form and may instead embody nonlinear dynamics. To move beyond the limitations of linear correlation analysis and to more precisely identify and quantify the independent effect of AI development on environmental pollution, including its potential nonlinear influence, this study employs the GAM. A key advantage of the GAM is that it does not impose a fixed linear functional form between covariates and the outcome. Instead, it uses smooth functions that allow the data to reveal the underlying relationship, thereby providing a more flexible and empirically grounded characterization of the dynamic influence of AI development on environmental pollution.



Figure 6. Heatmap of the Correlation Coefficient Matrix

4.3 GAM Results

Table 6 reports the estimation results from the GAM. In this specification, the GAM uses effective degrees of freedom (EDF) to capture the complexity of each smooth term and thus to characterize the extent of nonlinearity in the relationship between the explanatory variables and environmental pollution. In general, an EDF close to 1 indicates an approximately linear association, whereas a larger EDF implies a more curved functional form and more pronounced nonlinear features. As shown in Table 6, the EDF values for most variables are significantly greater than 1, and the significance tests for the smooth terms pass conventional thresholds. These results suggest that AI related factors are broadly associated with environmental pollution in identifiable nonlinear ways, and that marginal effects may change systematically across different value ranges.

In terms of overall model performance, the GAM exhibits strong goodness of fit, with an R^2 of 0.826, indicating that it explains variation in the Environmental Pollution Index effectively without imposing a prespecified functional form. Overall, the results support the study's central argument that the relationship between AI development and environmental pollution cannot be adequately summarized by constant linear marginal effects. Adopting the GAM framework helps to more fully uncover stage dependent patterns and potential turning point features in the underlying associations.

Table 6. GAM Results

Variable	EDF	Ref.df	F	P
s(AE)	3.379	4.320	5.373	0.000253 ***
s(AIPGDP)	7.406	8.329	11.806	< 2e-16 ***
s(IRD)	1.005	1.010	4.637	0.031052 *
s(APG)	2.242	2.913	4.265	0.006027 **
s(RDPR)	3.523	4.410	12.483	< 2e-16 ***
s(AITIE)	1.001	1.001	52.722	< 2e-16 ***
s(PCEP)	4.732	5.863	5.302	4.7e-05 ***
s(EGI)	7.435	8.394	27.032	< 2e-16 ***
s(UR)	7.179	8.175	11.959	< 2e-16 ***
s(MI)	4.193	5.289	2.592	0.024175 *

4.4 Nonlinear Effects of AI Development on Environmental Pollution

4.4.1 Effect of AE on EPI

The smooth term in Figure 7(a) indicates a clear segmented and extended U-shaped nonlinear relationship between AE and EPI. When AE lies roughly between 5 and 8, the estimated s(AE) remains above zero but declines steadily, suggesting that at

relatively low levels of firm scale, an expansion in AE is weakly and positively associated with EPI, while this positive effect attenuates rapidly as AE increases. As AE approaches and then exceeds a turning point around 8, the curve crosses the zero line. When AE is approximately between 8 and 12, $s(AE)$ stays stably below zero and decreases slowly, indicating that once firm scale reaches a certain level, further growth in AE exerts a persistent mitigating effect on pollution, with a relatively stable negative marginal effect over the main range of the sample.

This segmented pattern is consistent with the environmental economics view of the tradeoff between scale effects and technique effects. Specifically, the expansion of economic activity may raise emissions through scale effects, whereas technological progress and managerial improvement may reduce emissions through technique effects. In the context of expanding AI firm scale, when AE remain in a lower range, the entry of AI firms and the extensive expansion of the industry are more likely to increase demand for computing power and data infrastructure. Energy consumption and related production activities rise accordingly, so that pollution pressure is difficult to alleviate in net terms and may even increase. As AE increases and surpasses the threshold around 8, agglomeration forces and network externalities strengthen, and the application of algorithms and data factors deepens in both production and governance. Faster technology diffusion improves resource allocation and process management efficiency, which lowers energy intensity and emission intensity. As a result, the net effect of expanding AE shifts toward pollution mitigation. The transition from a positive to a negative effect around the threshold, together with a sustained negative influence at higher levels, reflects a structural transformation in environmental outcomes as the AI industry evolves from extensive expansion toward an efficiency driven stage.

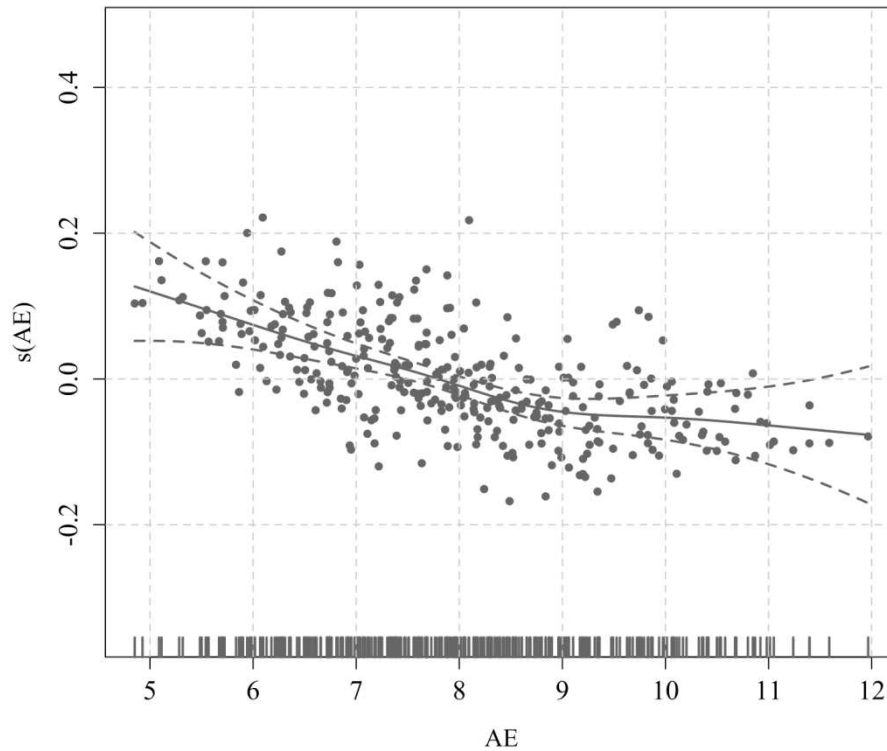


Figure 7(a). The effect of AE on EPI

4.4.2 The effect of AIPGDP on EPI

Figure 7(b) shows a pronounced W-shaped relationship between AIPGDP and EPI, indicating dynamics that are more complex than the classic U-shaped Environmental Kuznets Curve (EKC). From an EKC perspective, the pattern can also be interpreted as an inverted M-shaped configuration. The smooth term $s(\text{AIPGDP})$ exhibits a relatively high effective degrees of freedom and is statistically significant at conventional levels ($p < 0.01$), indicating a complex nonlinear structure. The presence of two clear troughs and two peaks suggests that the effect of AIPGDP on environmental pollution is not monotonic, but instead involves repeated stagewise reversals and structural adjustment.

Three key turning points are identified. The first occurs around AIPGDP equal to 6.5, where the curve shifts from near zero to negative and continues to decline, implying that in the early development stage, higher per capita output is more likely driven by

efficiency gains and improved factor allocation, which reduces emission intensity per unit of output and thus temporarily alleviates pollution pressure. The second turning point appears around AIPGDP equal to 8.5, where the curve switches from negative to positive and rises to a local peak, suggesting that as the industry enters a medium development stage, the increase in energy consumption induced by industrial expansion and rising computing demand may temporarily dominate and offset efficiency gains, leading to a rebound in pollution pressure. The final turning point occurs around AIPGDP equal to 9.5, where the curve turns negative again and declines toward the second trough, reflecting a stage in which technology diffusion and managerial capability are more fully realized, promoting process optimization and energy efficiency improvement and thereby reducing pollution pressure once more. Beyond this range, the curve rises again at higher levels, indicating that marginal abatement gains may weaken at the upper end while expansionary pressures may re intensify. This W-shaped trajectory extends the conventional EKC narrative by showing that the interaction between environmental pollution and AIPGDP growth operates through multiple transition stages rather than a single turning point.

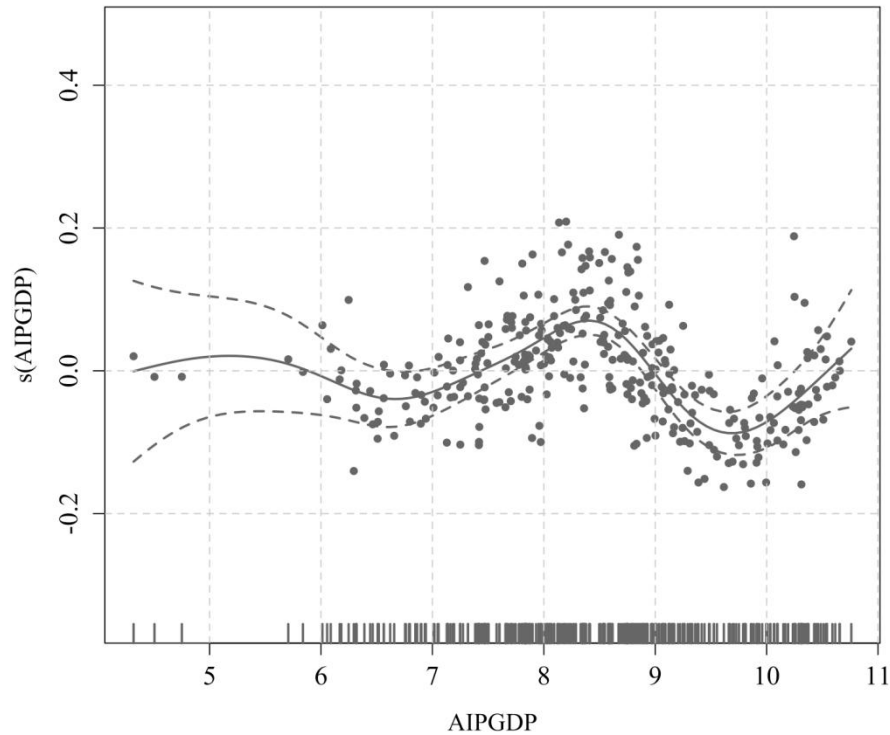


Figure 7(b). The effect of AIPGDP on EPI

4.4.3 The effect of IRD on EPI

The smooth term in Figure 7(c) indicates that the association between IRD and EPI is close to linear overall and follows a gradual downward trend. When IRD is roughly between 5 and 9, the estimated $s(\text{IRD})$ lies around the zero line and is slightly positive, suggesting that at low to moderate levels of robot density, its relationship with EPI is weak and does not imply a clear mitigating effect. As IRD continues to increase and approaches about 9, the curve crosses the zero line. When IRD is approximately between 9 and 12, $s(\text{IRD})$ remains consistently negative and continues to decline, indicating that once robot density reaches a certain level, its marginal effect shifts toward pollution mitigation, and the negative effect strengthens as density increases. Overall, the result is better characterized as a directional switch around a single turning point rather than a complex nonlinear pattern with multiple turning points. When IRD remains below roughly 9, automation is still at a stage of limited diffusion. Adjustments in production organization and process design are relatively modest,

which makes it difficult to meaningfully alter energy use and emission structures in the short run. Accordingly, increases in IRD are not associated with a pronounced pollution mitigation effect in this range. As IRD rises further and exceeds the threshold around 9, automation and intelligent upgrading are more likely to generate substitution and complementarity in key production stages, facilitating process optimization and more fine grained control. These changes reduce material waste and energy intensity and enhance the stability and consistency of emission management, so that the net effect of higher IRD increasingly manifests as pollution suppression.

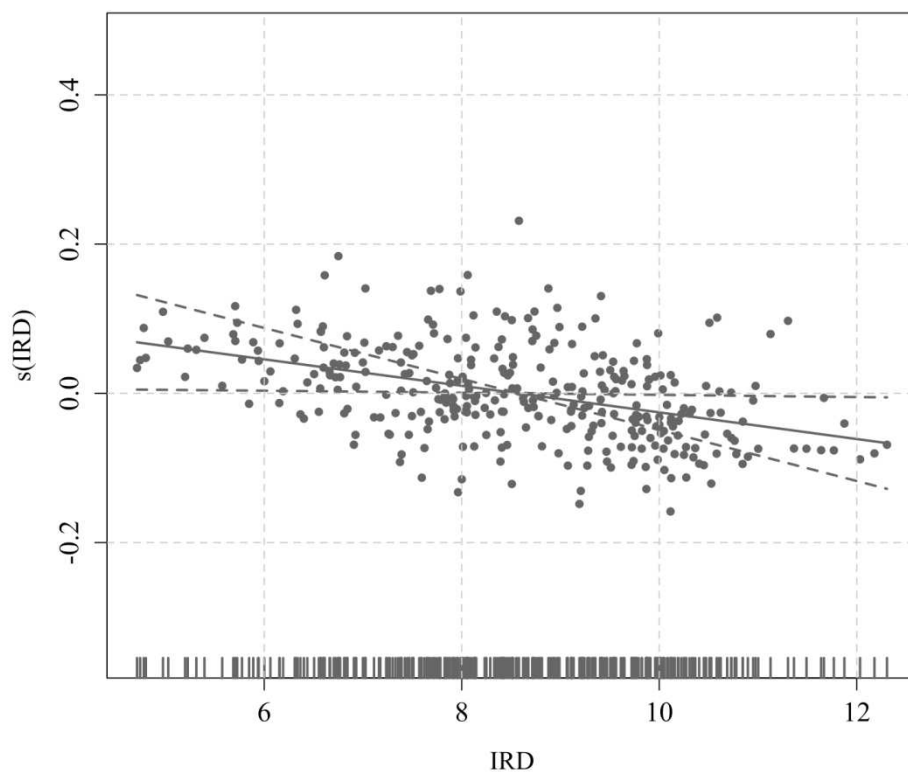


Figure 7(c). The effect of IRD on EPI

4.4.4 The effect of APG on EPI

The smooth term in Figure 7(d) suggests that the relationship between APG and EPI is approximately linear overall, with a clear downward trend. When APG is roughly between 0 and 6, the estimated $s(\text{APG})$ lies mostly above the zero line and declines slowly, indicating that at low to moderate levels of patent grants, increases in APG are

weakly and positively associated with EPI, or alternatively that a mitigating effect has not yet become apparent. As APG approaches and exceeds about 6, the curve crosses the zero line. When APG is approximately between 6 and 11, $s(\text{APG})$ remains stably below zero and continues to decrease, implying that once patent grants reach a certain level, their marginal effect shifts toward pollution mitigation, and the negative effect strengthens as APG increases further.

In the lower grant range of about 0 to 6, patent activity more likely reflects innovation inputs and the research and production processes accompanying industrial expansion, which may not translate into immediate reductions in emission intensity in the short run. Consequently, the pollution improvement effect is limited. As the grant level rises beyond the threshold around 6, a larger share of implementable technological outcomes enters diffusion and application stages, promoting process optimization, energy efficiency improvement, and stronger pollution control capacity. Accordingly, the net effect of higher APG increasingly manifests as pollution suppression.

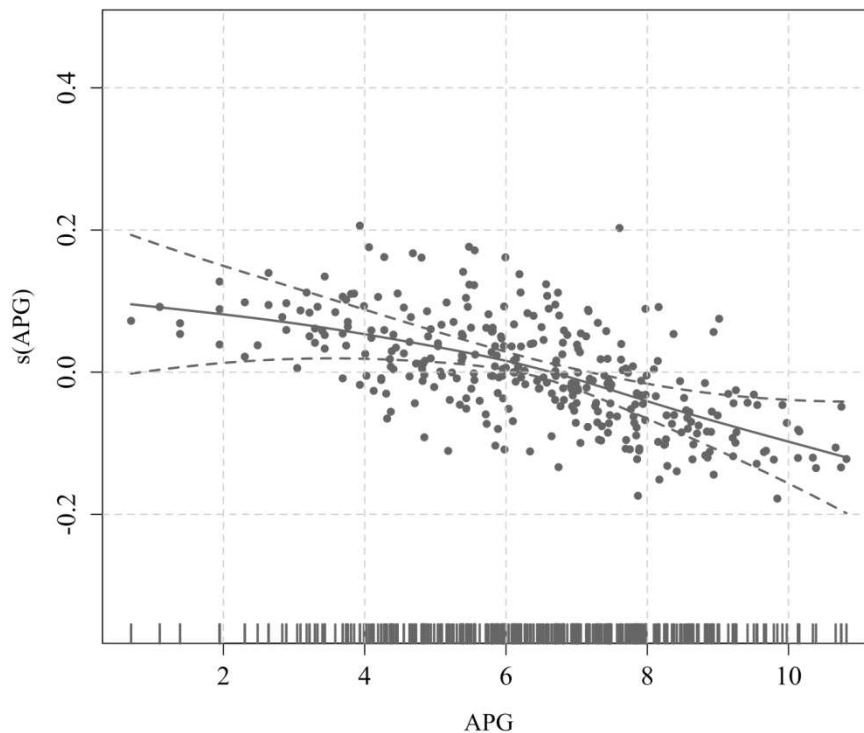


Figure 7(d). The effect of APG on EPI

4.4.5 The effect of RDPR on EPI

The smooth term in Figure 7(e) indicates an approximately U-shaped nonlinear relationship between RDPR and EPI, with a clear turning point around 20%. When RDPR ranges from roughly 0% to 20%, the estimated $s(\text{RDPR})$ remains above the zero line but declines rapidly, suggesting that at relatively low levels of R&D personnel intensity, increases in RDPR are weakly and positively associated with EPI, while this positive association attenuates markedly as RDPR rises. As RDPR approaches and exceeds about 20%, the curve crosses the zero line and enters the negative region. When RDPR is approximately between 20% and 60%, $s(\text{RDPR})$ remains negative, but its rate of decline gradually slows, indicating that higher RDPR is associated with pollution mitigation at more advanced levels, although the marginal pace of improvement weakens and progressively stabilizes. Overall, the curve primarily reflects a sign reversal around the threshold and a flatter pattern over the higher range.

When RDPR remains in the low range of about 0% to 20%, an increase in the R&D personnel share typically corresponds first to an expansion of research activity and related supporting inputs, while the associated technological outputs have not yet been sufficiently integrated into production processes and pollution control practices. In the short run, it is therefore difficult to generate substantive improvements in emission intensity, which helps explain why improvements in EPI are limited and may even appear as a weak positive association. As RDPR rises and surpasses the threshold around 20%, the scale of R&D teams and their organizational capacity are more likely to support sustained technological iteration and implementation, enabling digital upgrading, process optimization, and energy efficiency management to diffuse more broadly. This reduces pollution intensity per unit of output and shifts the relationship

into the negative range. At higher RDPR levels, the curve becomes flatter, indicating that the marginal environmental returns to additional R&D inputs may gradually diminish, and that pollution improvement increasingly reflects stable accumulation rather than continued acceleration.

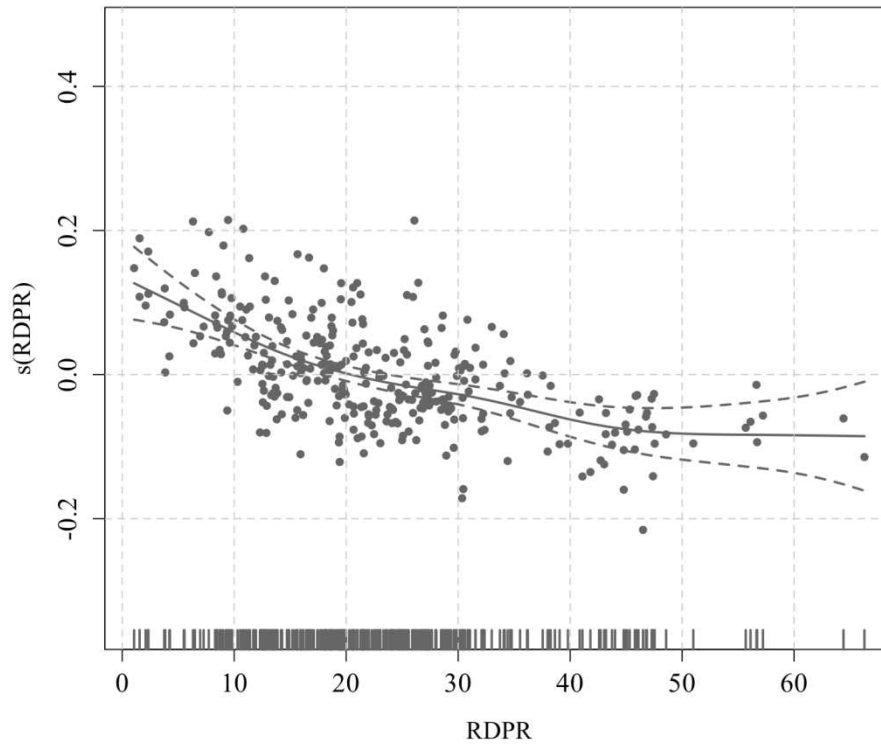


Figure 7(e). The effect of RDPR on EPI

4.4.6 The effect of AITIE on EPI

As shown in Figure 7(f), AITIE exhibits an approximately linear increasing relationship with EPI, with a clear transition from negative to positive around AITIE equal to about 11. When AITIE ranges from roughly 0 to 11, the estimated $s(\text{AITIE})$ lies mostly below the zero line but rises steadily as expenditure increases, indicating that the mitigating effect weakens gradually and approaches zero. Once AITIE exceeds about 11, the curve crosses the zero line and continues to increase, remaining positive over approximately 11 to 15. This pattern suggests that at higher investment levels, greater technological transformation expenditure is positively associated with EPI, with a more pronounced marginal impact.

In the lower investment stage of about 0 to 11, technological transformation is more likely to reflect localized equipment upgrading and process improvements, which typically enhance process control and energy efficiency and thereby provide some relief from pollution pressure. When investment intensity rises beyond roughly 11, technological transformation is more likely to coincide with capacity expansion or high intensity input accumulation. The resulting strengthening of production activity increases energy consumption and emissions, so that scale expansion effects increasingly dominate in net terms, leading pollution pressure to rise as AITIE increases.

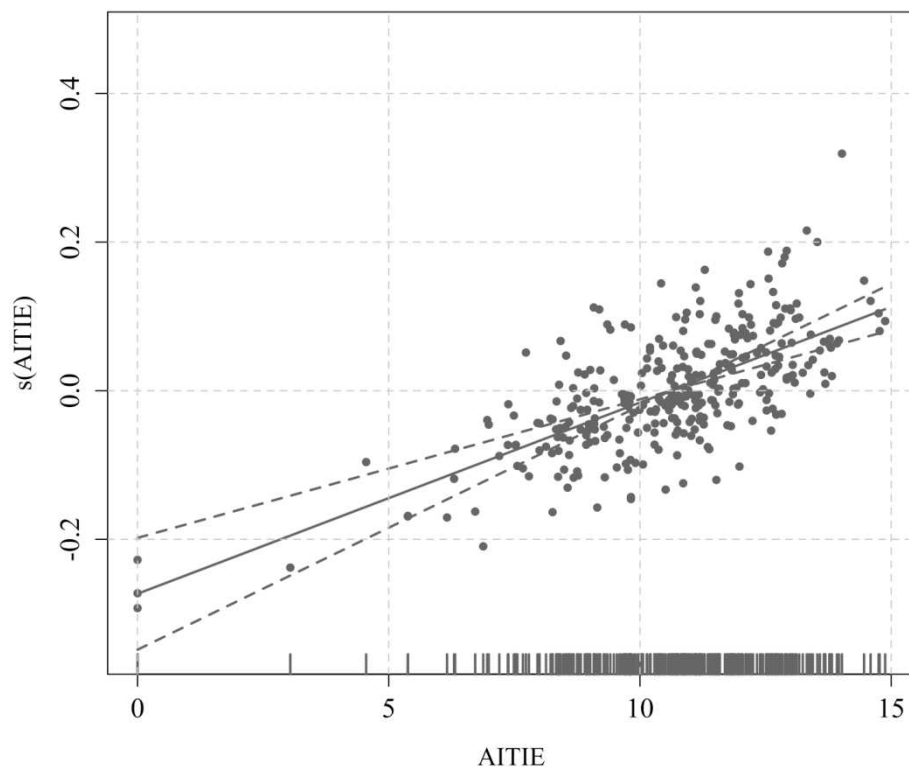


Figure 7(f). The effect of AITIE on EPI

4.4.7 The effect of PCEP on EPI

The smooth term in Figure 7(g) indicates a typical N shaped nonlinear relationship between PCEP and EPI. When PCEP is roughly between 0 and 80, the estimated $s(\text{PCEP})$ rises rapidly from negative values and approaches the zero line, suggesting

that higher public concern is associated with an increase in EPI. As PCEP enters the range of approximately 80 to 110, the curve shifts from rising to a modest decline and fluctuates around zero, indicating that the association weakens substantially and becomes less stable in direction. When PCEP increases further to about 110 to 200, the curve turns upward again and remains positive, implying that at high levels of public concern, the positive association between public attention and pollution pressure strengthens and becomes more pronounced.

This pattern can be understood by jointly considering the informational content embodied in public concern and the time lag in governance responses. At low levels of attention, rising pollution exposure or unexpected pollution events are more likely to trigger online searches and the diffusion of public sentiment. In this case, increases in PCEP primarily serve as an outcome signal of rising pollution pressure, which yields an upward and positive association. When attention reaches a moderate level, information diffusion and social monitoring are more likely to induce local governments to strengthen enforcement and increase governance inputs, which may partially offset pollution pressure in the short run and thereby generate the observed weakening and decline in the relationship over the range of about 80 to 110. At high levels of attention, sustained and intensive concern often coincides with more frequent pollution shocks or broader exposure. The marginal mitigating effect of governance measures becomes insufficient to fully counteract the upward pressure, leading the relationship to re enter a positive regime over the range of about 110 to 200.

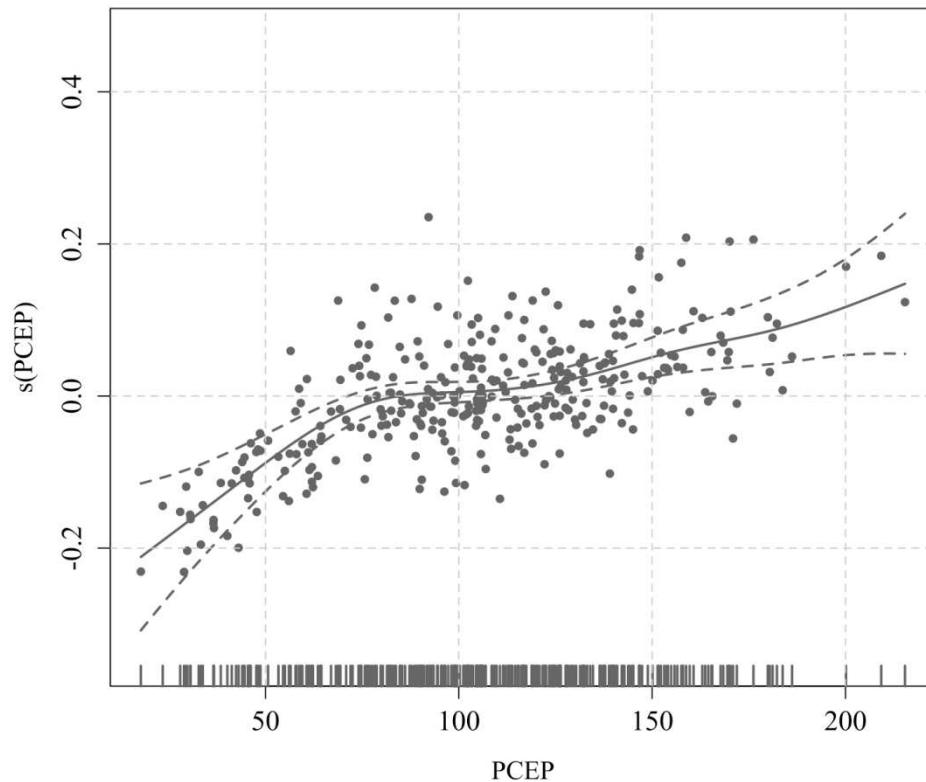


Figure 7(g). The effect of PCEP on EPI

4.4.8 The effect of EGI on EPI

The smooth term in Figure 7(h) indicates an extended M-shaped nonlinear relationship between EGI and EPI, with the second peak markedly higher than the first. When EGI is roughly between 0 and 300, the estimated $s(\text{EGI})$ rises overall and forms the first local peak around 300. As EGI increases further to approximately 300 to 500, the curve does not exhibit a substantial decline; instead, it continues to trend upward with fluctuations, suggesting that the positive association between EGI and EPI continues to accumulate over this interval. When EGI enters the range of about 500 to 800, the curve rises more rapidly and reaches a second peak around 800, with a magnitude clearly exceeding the first peak. Once EGI surpasses roughly 800, the curve begins to decline, indicating that at very high investment levels, the positive association weakens at the margin and turns downward.

The two peak structure, with a higher second peak, aligns with the tendency for governance investment and pollution pressure to co move across different intensity ranges. At low to moderate levels of EGI, spending increases often occur as pollution problems become more salient, and fiscal escalation in governance investment tends to respond to rising pollution pressure. Accordingly, the curve rises overall and forms a stagewise peak around 300. As investment expands further, governance tasks and project intensity typically increase in parallel, and provinces facing heavier pollution burdens are more likely to sustain increases in governance spending. As a result, EGI and EPI continue to move together over the range of approximately 300 to 800, culminating in a higher peak around 800. At very high investment levels, governance capacity, infrastructure, and regulatory intensity are more likely to approach critical thresholds, allowing more stable abatement outcomes to materialize in some provinces. Pollution pressure then becomes less prone to further escalation, and the curve correspondingly declines beyond roughly 800.

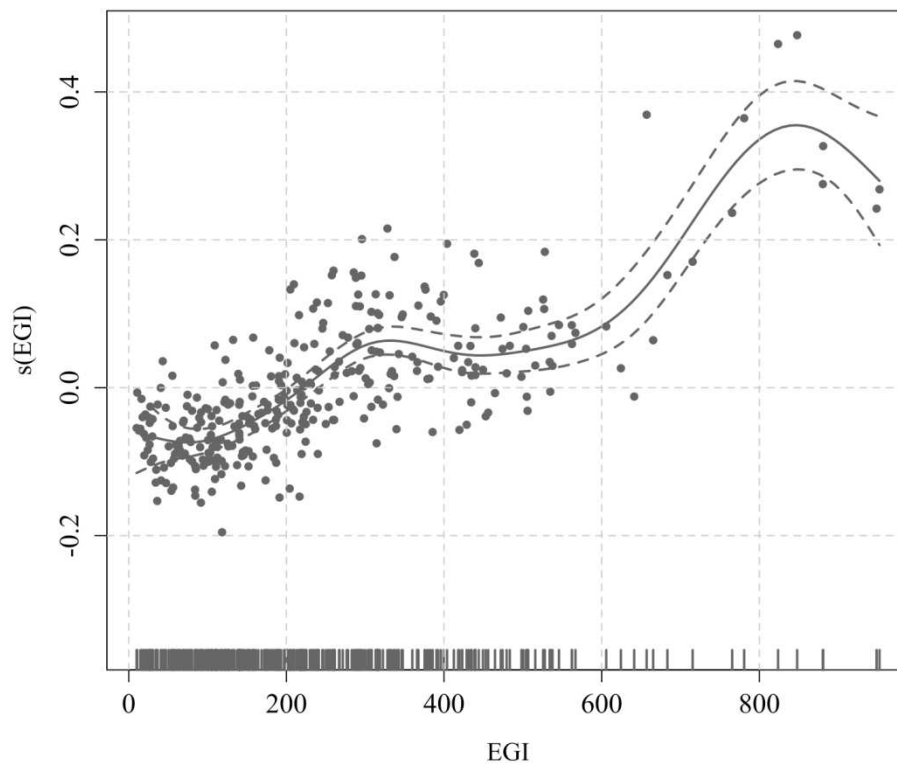


Figure 7(h). The effect of EGI on EPI

4.4.9 The effect of UR on EPI

Figure 7(i) indicates a pronounced M-shaped nonlinear relationship between UR and EPI, with two peaks located around 40 and 65. When UR is approximately between 25 and 40, the estimated $s(UR)$ is positive and increasing, implying that rising urbanization is associated with higher pollution pressure, and it reaches a local high point around 40. As UR moves into the range of roughly 45 to 60, $s(UR)$ becomes negative and remains below the zero line, suggesting that further urbanization in this interval is associated with pollution mitigation. When UR increases beyond about 60, $s(UR)$ returns to positive values and forms a second peak around 65, indicating that at high levels of urbanization the net effect shifts back toward pollution aggravation, although the magnitude is relatively moderate and subsequently becomes flatter.

At low levels of urbanization, rapid concentration of population and industrial activity tends to coincide with expanding energy consumption, transport demand, and construction activity. Emission growth may then outpace the carrying capacity of environmental infrastructure, thereby intensifying pollution pressure. As urbanization reaches a medium level, public services and environmental infrastructure become more complete. Broader coverage of centralized energy supply, wastewater treatment, and solid waste disposal, together with more compact spatial organization and stronger management capacity, reduces emission intensity per unit of activity, allowing the mitigating effect to emerge more clearly. As urbanization advances further, urban scale expansion and high density consumption can contribute to traffic congestion, higher building energy use, and a rebound in service sector emissions, creating new environmental burdens in some areas. Under these conditions, UR is more likely to exhibit a renewed pollution increasing effect in the upper range.

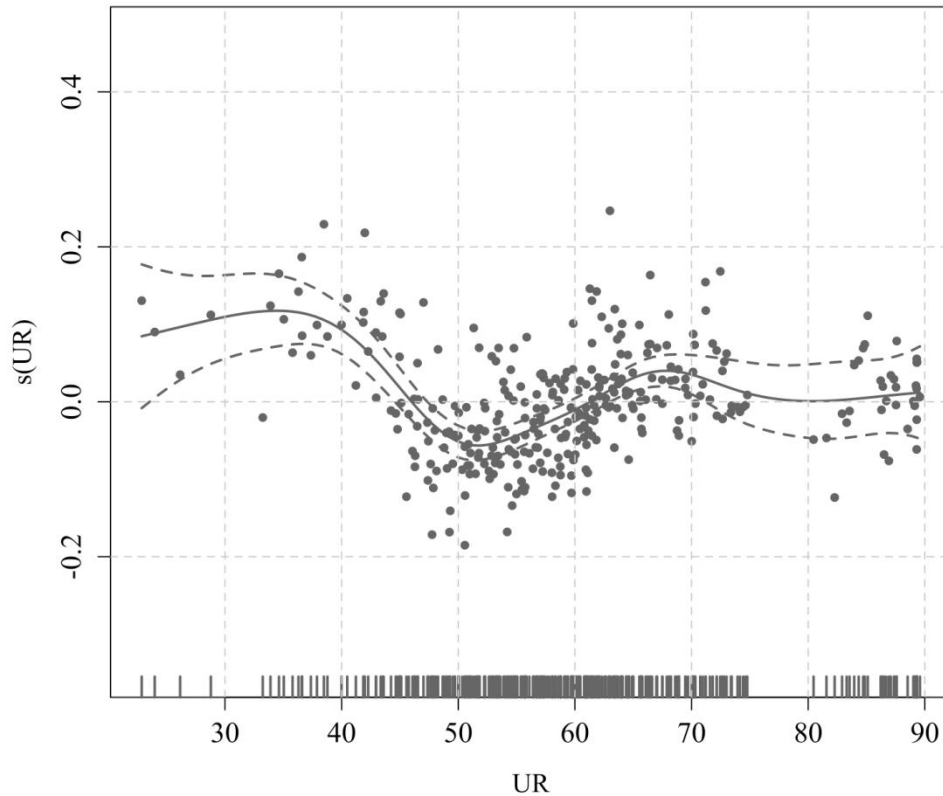


Figure 7(i). The effect of UR on EPI

4.4.10 The Effect of MI on EPI

Figure 7(j) shows a U-shaped nonlinear relationship between MI and EPI, with a transition from decline to increase around MI equal to about 8. When MI is approximately between 3 and 8, the estimated $s(MI)$ decreases as MI rises and shifts from positive to negative, indicating that as marketization moves from a low level toward a medium level, its net effect changes from pollution aggravation to pollution mitigation. When MI enters the range of roughly 8 to 12, $s(MI)$ turns upward and gradually returns toward the zero line, suggesting that at higher levels of marketization the mitigating effect weakens and may become weakly positive. In terms of effect signs, the curve lies largely below zero over the interval of about 6 to 10, implying pollution suppression, whereas both the lower and the upper ranges are more likely to display a positive association.

When marketization remains in a lower range of roughly 0 to 6, resource allocation efficiency and environmental constraint mechanisms tend to be relatively weak. Firm expansion and factor agglomeration are therefore more likely to rely on energy intensive inputs, raising pollution pressure. As marketization improves to a medium level of about 6 to 10, competition and allocative efficiency strengthen, facilitating the exit of inefficient capacity and encouraging technological upgrading. Pollution control investment and emission management also become more standardized, so that the net effect of higher marketization shifts toward pollution mitigation. At higher marketization levels of about 10 to 12, expansion in the scale of production and consumption, faster cross regional factor mobility, and greater intensity of service and transport activities may generate additional emissions. The curve therefore rises in the upper range, reflecting a weakening of the mitigating effect and a potential shift toward a weakly positive association.

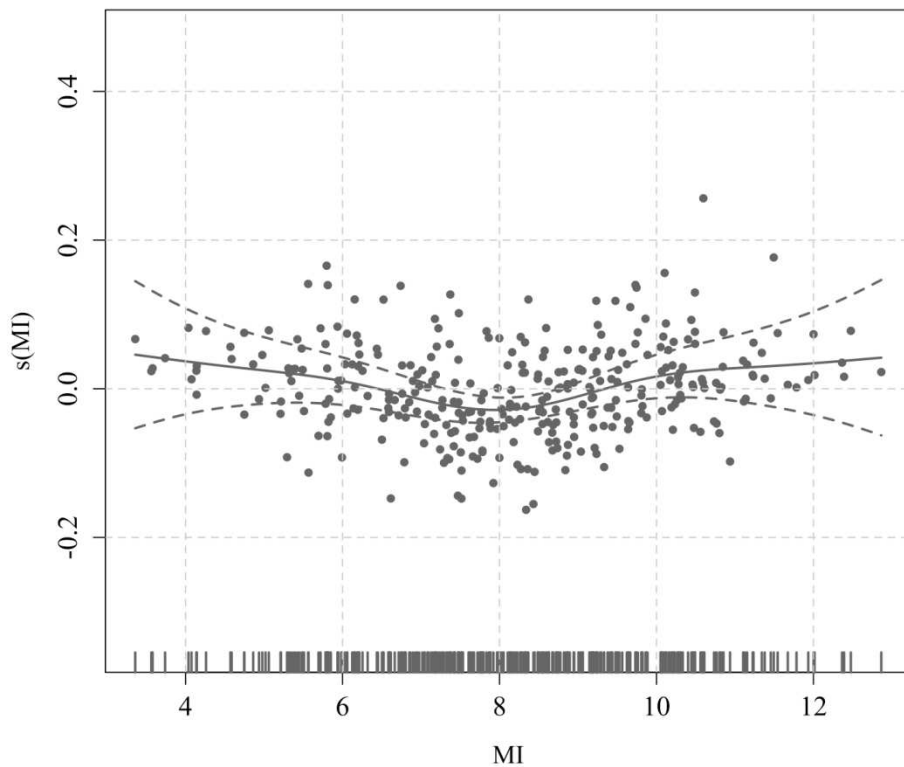


Figure 7(j). The effect of MI on EPI

5 Discussion

Based on a systematic analysis of Chinese provincial panel data from 2011 to 2022, the study demonstrates that the relationship between AI development and environmental pollution is characterized by pronounced and heterogeneous nonlinearities. The evidence advances understanding beyond traditional linear specifications and the simple inverted U-shaped Environmental Kuznets Curve.

Regarding the spatiotemporal heterogeneity of environmental pollution, the analysis indicates that pollution levels decline overall during the sample period, while regional disparities remain pronounced, implying that pollution improvement does not translate into synchronized spatial convergence. The finding is consistent with Du et al. (2021), who emphasize spatial dependence and cross regional linkages in pollution dynamics, and with Liu et al. (2022), who argue that industrial patterns and structural adjustment shape regional differences in pollution. The results also extend Sun et al. (2022) by showing that pollution disparities are reflected not only in level gaps but also in the persistence of the mechanisms through which inequality is generated. In addition, by constructing a composite index that integrates multiple pollution components, the study provides a measurement approach that is better suited for cross regional comparison and long run tracking. Such an approach complements the discussion in Zaharia (2012) and Heravi et al. (2024) that single indicators are insufficient to capture overall pollution pressure and limit comparability across studies.

In identifying driving mechanisms, the analysis underscores that methodological choice is pivotal to the reliability of empirical conclusions. The generalized additive model is not imposed a priori. Instead, the study benchmarks multiple model classes

within a unified data framework, including linear regression, random forest, gradient boosting, support vector regression, K nearest neighbors, and XGBoost, and selects the GAM as the preferred specification based on overall fit and predictive performance. This procedure provides a reproducible basis for model selection and supports subsequent nonlinear interpretation. The approach is consistent with Ravindra et al. (2019), who argue that the GAM can balance interpretability and nonlinear fitting capacity in environmental applications, and with Fu et al. (2025), who emphasize that interpretable modeling helps uncover complex structures in environmental drivers. Moreover, clear turning points and sign reversals are identified for multiple covariates, complementing Benedetti et al. (2009) by illustrating that thresholds and structural turning points can be more robustly detected within a nonlinear framework. Substantively, the screening and estimation results converge on a shared implication: the environmental effects of AI are unlikely to be well summarized by constant linear marginal effects. Instead, they appear to reflect stagewise shifts in the relative dominance of expansion effects and efficiency effects, providing a unified perspective for reconciling mixed findings in the existing literature (Ma et al., 2024; Ma et al., 2025).

The complex nonlinear relationship between AI development and environmental pollution constitutes the central finding of the study. AI enterprises exhibit a threshold type turning point structure. Effects are weak and decline gradually at lower levels, and shift to a more stable pollution mitigating pattern once the threshold is crossed. The evidence is consistent with Wang et al. (2025), who show that firm level digital technology adoption can improve emission reduction performance, and it further suggests that such improvements are more likely to materialize in a stable manner after scale has been formed. AI-Industry per capita GDP displays a W-shaped

relationship with pollution, indicating repeated stagewise reversals during the development process. The implied dynamics go beyond the classic single turning point EKC trajectory and complement the argument of Terrell (2021) and Zhang and Wang (2025) that development environment linkages may follow multi stage and complex paths. Industrial robot density follows an almost linear downward trend with a sign reversal from positive to negative, supporting Zhou et al. (2024) in that intelligent manufacturing can raise energy efficiency and influence emissions. AI patent grants also decline in an approximately linear manner and shift from positive to negative, complementing the discussion in Luo et al. (2024) and Dong et al. (2023) on the linkage between innovation output and economic performance, while further indicating that the environmental returns to innovation are more likely to emerge once implementability and diffusion conditions improve. R&D personal ratio in AI industry shows an approximately U-shaped curve and turns to a mitigating and then stabilizing pattern after a threshold, corroborating Jian et al. (2024) on the importance of R&D inputs while emphasizing that environmental implications are conditional on development stages. AI technology innovation expenditure is nearly linear increasing and shifts from negative to positive, extending Montanaro et al. (2024) by suggesting that investment expansion may coincide with higher energy use and emissions in certain stages. Public concern about environmental pollution follows an N-shaped pattern, supporting and extending Zhou (2025) by showing that the linkage between public concern and environmental outcomes is distinctly nonlinear. Environmental governance investment exhibits a bimodal M-shaped pattern, with a more pronounced peak at higher investment levels and a decline in the very high range, reinforcing Chen et al. (2022) in that governance inputs and governance outcomes are not linked through a monotonic linear relationship. Urbanization rate also shows a bimodal

M-shaped pattern with mitigation in the middle range, consistent with Li et al. (2023) on stage dependent coupling between urbanization and ecological conditions. Marketization index follows a U-shaped pattern with mitigation concentrated in the middle range, aligning with Jin et al. (2024) on the role of institutional environment in shaping economic behavior and performance while further indicating that environmental effects are interval dependent. Overall, the evidence challenges approaches that treat the environmental effects of AI related and institutional variables as constant and linear, because multiple curves display sign reversals and multi turning point structures, making average linear coefficients unable to represent the true marginal effects in key intervals (Benedetti et al., 2009; Ravindra et al., 2019).

The study has several limitations. Future research could benefit from incorporating more advanced machine learning approaches (Rautela et al., 2025; Sugumaran et al., 2025) to capture more complex interaction effects. Greater granularity in pollution measurement and in the representation of explanatory variables, together with improved monitoring and higher quality data integration, would also strengthen external validity and the policy interpretability of empirical findings (Krupnova et al., 2022; Kaied et al., 2025).

Overall, the analysis documents persistent spatial disparities and structural differentiation in the evolution of environmental pollution, applies a model screening procedure to select the generalized additive model in order to enhance the reliability of nonlinear identification, and confirms that AI related factors are associated with diverse nonlinear patterns, including threshold type turning points and W-shaped, N-shaped, M-shaped, and U-shaped curves. These results enrich the EKC related literature in the context of environmental pollution and move beyond the simple

inverted U paradigm, aligning with recent evidence on more complex development environment pathways (Terrell, 2021). The findings support the view that, at certain stages, AI can mitigate pollution through efficiency gains and green innovation (Wang et al., 2025; Zhou et al., 2024; Li and Chen, 2025). At the same time, the results provide additional evidence that AI may increase pollution pressure when expansion effects dominate, and they situate such outcomes within an interval based interpretive framework (Ma et al., 2025; Ma et al., 2024). Linear specifications that summarize the environmental consequences of AI and the effects of institutional variables as constant are therefore challenged, because thresholds and multi turning point structures emerge as key empirical facts for reconciling divergent findings and deriving policy implications (Ravindra et al., 2019; Benedetti et al., 2009; Fu et al., 2025).

Policy design and pollution governance in the context of AI development should move beyond linear thinking and adopt a refined regulatory framework grounded in thresholds and interval specific effects. Policy makers should account for possible sign reversals across value ranges and for heterogeneity in regional development conditions, and should align constraints on industrial expansion, incentives for technology diffusion, and investments in governance capacity in a stagewise manner. Such an approach would enable more precise reductions in overall pollution pressure and improve the effectiveness of environmental policy.

6 Conclusions

Using provincial panel data from 2011 to 2022, the study constructs a composite Environmental pollution index that integrates solid waste, water pollution, and air pollution components, and systematically examines the relationship between AI

development and environmental pollution within a unified empirical framework. The analysis first benchmarks and screens multiple machine learning models to determine a preferred modeling strategy. Building on this comparison, the generalized additive model is employed to characterize nonlinear associations and identify potential turning points, thereby enhancing the transparency of model choice and the reproducibility of results.

Three main conclusions emerge. First, overall pollution pressure declines during the sample period, while interprovincial disparities remain pronounced, implying that pollution improvement does not lead to synchronized spatial convergence. Such a pattern provides an essential empirical backdrop for understanding pollution dynamics in the context of digital transformation. Second, the model screening results indicate that the generalized additive model, which captures smooth nonlinearities while retaining interpretability, outperforms a range of alternative models in both fit and predictive accuracy. The evidence suggests that the relationship between AI development and pollution is better identified and interpreted within a nonlinear framework. Third, the GAM estimates reveal that AI related factors exhibit pronounced interval dependence and frequent sign reversals in their effects on pollution, manifested as threshold type turning points and diverse curve shapes, including W shaped, N shaped, bimodal M shaped, and U shaped patterns. Overall, some variables display more stable pollution mitigating effects after crossing specific thresholds, whereas others show multistage fluctuations and repeated reversals. These findings indicate that the environmental effects of AI cannot be summarized by constant linear marginal effects, and that net impacts depend on development stages and institutional conditions.

The policy implications are that pollution governance in the context of AI development should shift from a single linear mindset toward interval based and stagewise policy design. Policymaking should identify effective value ranges and potential thresholds for key drivers, avoid underestimating pollution risks when expansion related pressures dominate, and strengthen innovation diffusion, green upgrading, and governance capacity building when efficiency and technique effects become more salient. Regulatory policy mixes should also be tailored to regional conditions, thereby improving the precision and effectiveness of pollution abatement and enhancing overall policy efficiency.

Declarations

All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors

Author Contributions Statement

Feiyang Zhao collected and organized the data and drafted the initial manuscript. Mingxia Qi and Chaojie Ma jointly revised and polished the manuscript and performed final checks of the content. All authors read and approved the final version of the manuscript.

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