1. AI AND ESG – NEW QUALITY PRODUCTIVITY IN DIGITAL ECONOMY[1]

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Abstract

This research examines AI adoption's impact on corporate ESG performance using Lasso-based empirical analysis and data science methodologies. Results confirm AI significantly enhances ESG performance, albeit with regional and sub-dimensional variations. AI technology based on 3D Unmanned Aerial Vehicle (UAV) programming is used to optimize pro-ESG development via single- and multi-objective approaches. Path simulations using Ant Colony Optimization (ACO), A(Astar), and Rapidly-Exploring Random Tree (RRT) algorithms reveal regionally adaptive ESG patterns suited to hub-specific contexts, showing governance, efficiency, and demonstration effects. This study explores AI-driven sustainability, demonstrates interdisciplinary applications of 3D data and optimization technology in social computing science.*

Keywords: AI, ESG, New Quality Productivity, Lasso, AI Computational Optimization

JEL Classification: F23, M14, C61, O14

1. Introduction

While artificial intelligence (AI) and ESG philosophies thrive within the context of the digital economy, the potential role of AI in enhancing ESG performance presents a relatively complex picture. On one hand, AI, as a new quality productivity, holds significant potential to improve

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societal well-being by enhancing corporate ESG performance. AI-enabled practices can drive green-tech innovation, improve social information disclosure, and facilitate intelligent governance. On the other hand, AI adoption may introduce environmental challenges, such as data pollution and resource exploitation, as well as ethical risks related to privacy and employment displacement (Qin et al., 2024a; 2024b). Therefore, our study aims to explore AI's effects on overall and sub-dimensional ESG performance. Prior research has explored AI and digitalization's impact on ESG performance in modern enterprise practices as a rising issue, providing a general yet incomplete basis for further analysis (Donati et al., 2022; Chen et al., 2024; Liu et al., 2024). However, limited attention has been given to AI as both a transformative productivity and a data science tool, its broader applications remain underexplored. Additionally, most solutions are examined from a firm-level perspective, highlighting the need to explore regional collaboration and global optimization via advanced AI computation.

Our research fills this gap by examining firm-level AI adoption's impact on overall and sub-dimensional ESG performance, offering insights into pro-ESG initiatives through data science methodologies. Empirical analysis based on Least Absolute Shrinkage and Selection Operator (Lasso) is employed to examine the relationship between AI and ESG. Results show AI generally improves ESG performance, albeit with regional variations. Additionally, 3D UAV path programming is applied to optimize pro-ESG patterns. Multi-objective approaches centred on hub coordination are conducted for global analysis via AI computation. ACO, the A* (Astar) algorithm, and RRT are utilized to simulate implementation patterns and assess the effectiveness of pro-ESG initiatives across various policy contexts. The results indicate that multi-objective contexts generally involve more mid-level ESG interactions. Empirical evidence and optimization solution alignment highlight the research's implications for ESG externalities and regional synergy.

This paper makes three contributions: First, conceptually, we examine AI's role in enhancing ESG in the digital economy, highlighting its multifaceted potential as new quality productivity. Second, methodologically, we integrate empirical modelling with advanced data science techniques, strengthening the interdisciplinary application of 3D contextual technology within social computing science. By extending UAV path programming into 3D contexts that incorporate geographic distribution and ESG performance, we provide practical implications through path simulations. Third, we propose a referential paradigm that uses machine learning and optimization to develop high-dimensional solutions for complex problems beyond empirical limitations.

The subsequent structure is as follows: Section 2 establishes a theoretical foundation on the impact of AI on ESG, grounded in perspectives on industrial upgrading, contextual learning, and the new growth economy. Section 3 outlines the methodologies in empirical analysis and path optimization. Section 4 presents the results in detail. Finally, Section 5 concludes with key findings and managerial implications.

2. Literature Review

AI boosts industry upgrading, and resource efficiency to enhance resilience and greening. It also fosters synergy among economic agents, factors, and the environment, enabling self-organized ESG governance. AI's intelligence and embedded nature promise a mass knowledge economy, raising demand for AI-based ESG services. This demand stimulates social innovation for sustainability. This section outlines AI's ESG-enhancement via industrial upgrading, contextual learning, and new economic growth.

2.1 Artificial Intelligence Promotes Industrial Upgrading

Amid the fourth industrial revolution, the development of new quality productivity represented by AI has accelerated. AI fosters technological leaps and is considered a strategic technology leading the new round of technological revolution and industrial change (Kaiming, 2021; Zou and

Xiong, 2023), accelerates industrial upgrading across decision-making, resource allocation, productivity improvement, and innovation activities, and ultimately promotes corporate social responsibility and green transformation. Firstly, AI enables cognitive and creative tasks, facilitating ESG program development and decision-making. It enables businesses to swiftly identify high value-added and environmentally conscious market trends, thereby supporting industrial upgrading and the achievement of ESG goals. Specifically, AI enhances efficiency in complex R&D or decision processes. For managers, AI promotes earlier ESG integration and identifies more sustainable opportunities, mitigating the influence of personal biases and short-term executive decisions. For investors, AI improves ESG data access, thereby informing ESG investment strategies. Secondly, AI increases enterprise management and resource allocation efficiency. According to Wu et al. (2020), AI provides new methods of information management, significantly improves labor division efficiency, and expands the bounds of production possibilities. AI optimizes internal resources via algorithms, reducing waste and financial, administrative costs, thereby easing financial constraints. These cost reductions free funds for green R&D, driving industrial upgrading and advancing ESG goals. Broadstock et al. (2020) argue that employees are more motivated to improve production processes and develop new technologies in socially responsible companies. Thirdly, AI enhances enterprise automation and intelligence, liberating productivity and driving intelligent upgrades in traditional industries. For example, in healthcare, AI shortens R&D cycles and reduces costs. AI mobilizes big data to shift enterprises operations from labor- and capital-intensive to knowledge-intensive, which accelerates industrial upgrading. Additionally, AI's application in employee evaluation reduces personal subjective biases, promoting gender equity and social justice. This AI-driven automation contributes to both emission reduction and equity goals of enterprises, thereby improving overall ESG performance.

2.2 Artificial Intelligence and Contextual Learning

Contextual learning enables cross-scenario skill application while enhancing societal adaptability. Brown et al. (1989) proposed that knowledge is inherently contextual, shaped by the activities, situations and cultures in which it is employed. Young (1993) urged complex authentic contexts for problem-hypothesis-solution skill development. Choi and Hannafin (1995) emphasize the roles of knowledge transmitters and collaboration in contextual learning. Contextual learning becomes vital for AI to comprehend human society. Hollister et al. (2019) note AI research aims to build computational systems that will ultimately equal and possibly surpass the intellectual and cognitive capabilities of humans. Advancements in big data enable AI to rapidly gather contextual information. Integrated via natural language processing and image analysis in "intelligent spaces," this supports model construction. Moreover, the interactivity emphasized in contextual learning aligns with the capabilities of generative AI, allowing for real-time human interaction. AI generates targeted solutions while influencing social values. Driven by ESG goals, AI leverages contextual continuous learning to generate sustainability-aligned solutions. As training iterations increase, AI improves its service capabilities through continuous contextual training and makes the applicable and serviceable contexts broader to enhance solution feasibility, creating a virtuous circle (Barakat et al., 2021). Thus, contextual learning is key for AI to align capabilities with societal needs. In China's takeaway industry, companies employ AI to intelligently match delivery personnel with orders based on distance, effectively reducing carbon emissions while simultaneously training AI within the delivery context—an embodiment of "learning by doing". Similar applications have emerged in online taxi services, express delivery logistics, and corporate procurement. In agricultural production, intelligent greenhouse systems utilize comprehensive analyses of yield and environmental data to regulate temperature, humidity, and light conditions, minimizing resource waste.

2.3 Artificial Intelligence and New Economic Growth

New economic growth theory reoriented development factors toward knowledge and human capital, prioritizing endogenous drivers. Romer (1986) posited knowledge as a critical production input whose accumulation creates positive externalities and increasing returns. Since ideas are non-competitive, they are usable simultaneously at near-zero marginal cost (Jones and Romer, 2010). Lucas (1988) highlighted human capital's dual role: internally boosting worker productivity and externally enhancing systemic productivity via knowledge spillovers, driving scale economies. However, complex social relations and exponential knowledge/data growth pose challenges. Jones (2009) highlighted "knowledge burden": limited human capacity to process expanding knowledge, constraining innovation. New tools are thus needed for efficient knowledge production. In the digital economy era, AI acts as "new human capital," integrating vast data and knowledge in real time. AI translates knowledge into data and uses deep learning for analysis, deduction, and innovation. Relying on the low-cost reproducibility of knowledge, AI fasters knowledge dissemination, and increases the frequency of knowledge production activities. Agrawal et al. (2018, 2019) propose that knowledge creation is the process of reorganization of existing knowledge. AI aids both discovering and organizing knowledge, enhancing production capacity. Traditionally, high-cost, long-cycle, high-risk R&D deterred enterprise participation. AI overcomes these barriers by accelerating R&D, lowering entry thresholds, and spurring innovation competition, thereby fostering knowledge-centric growth and diversifying innovative enterprises. Liu et al. (2020) found robotics boost innovation by faster knowledge spillovers, improving learning and absorptive capacity, and increasing R&D investment. Kakatkar et al. (2020) showed AI enhances innovation management by facilitating information feedback, which promotes corporate innovation. AI elevates knowledge as the core driver of digital-era growth.

AI-driven knowledge economy growth accelerates ESG progress. First, AI fosters innovation ecosystems: its interactivity engages small and medium-sized enterprises (SMEs), breaking "information silos" and innovation barriers. Large enterprises undertake more social responsibility and drive knowledge production across chains and industries, thus promoting SMEs' participation. Second, AI-enhanced knowledge production improves product quality and ESG fulfilment capacity. Third, AI rapidly disseminates green consumer knowledge, raising environmental awareness and spurring green innovation investment

3. Empirical Analysis Based on Lasso

3.1 Empirical Strategy

The Least Absolute Shrinkage and Selection Operator (Lasso) is employed to examine the impact of AI adoption on enterprise-level ESG performance within the digital economy, accounting for potential regional heterogeneity. A key challenge in this analysis lies in the selection of control variables, as the factors influencing corporate ESG strategies in the rapidly evolving digital era may also have significant relevance to AI-related transitions. Addressing endogeneity due to omitted explanatory variables, is critical to ensure the robustness of the empirical analysis. Given that research on AI and ESG remains relatively nascent, the lack of theoretical support presents challenges in model construction and variable selection.

To mitigate subjective bias in selecting variables, Lasso regression is used to construct the independent variable matrix. The Lasso method is well performed in predictor extraction, effectively mitigating overfitting by reducing multicollinearity and dimensionality (Tibshirani, 1996). Existing literature has supported our approach by commonly applying Lasso-based models to address firm-level complexities. These models focus on variables, ranging from operational profitability to growth potential, that influence firm strategies and are shaped by firm specialties (e.g., Coad and Srhoj, 2020; Li et al., 2021; Patel, 2024). In our study, we use Lasso to filter firm characteristics that significantly impact ESG initiatives and may correlate with AI adoption. Specifically, the core explanatory variable, AI, remains fixed, while other control variables and their interactions with AI are treated as alternatives. The study sample includes Chinese listed companies, excluding those classified as ST, *ST, or PT, over the period from 2007 to 2021. AI adoption is measured by the frequency of five specific terms related to AI and digital technologies in corporate annual reports: “AI technology”, “block-chain technology”, “cloud computing technology”, “big data technology”, and “data technology applications”. ESG performance is measured using overall and sub-scores from China Research Database Services (CNRDS).

In the Lasso framework, each alternative variable is assigned an identical penalty factor ranging from 0 to 1, diminishing the explanatory power of less relevant variables. As a result, variables with minimal influence have their coefficients reduced to zero and are excluded from the model, while influential variables retain significant coefficients despite the penalty. The estimated coefficients in the Lasso model are specified as follows:

$$\hat{\beta} = \arg\min_{\beta}\{\frac{1}{2n}\sum_{i=1}^{n}(y_i - X_i^{'}\beta)^2 + \lambda(\sum_{j=1}^{p}|\beta_j|)\}$$

Here, $\lambda\sum_{j=1}^{p}|\beta_j|$ represents the penalty term, and λ, which ranges from 0 to 1, mediates the degree of penalty. A smaller λ imposes a stronger penalty, resulting in more rigorous variable selection. Ten-fold Cross-validation (CV) is employed to select the optimal λ, based on the minimum out-of-sample mean squared error (MSE). In this study, two Lasso-based methodologies are employed for statistical inference. The first is Double Selection (DS) regression, which constructs the control variable matrix by taking the union of variables selected in two separate Lasso regressions: one using the dependent variable and the other using the core independent variable. This approach, validated by Monte Carlo simulations (Belloni et al., 2014), seeks to minimize the omission of key variables. The second method is Cross-fit Partialing Out (XPO), also known as Double Machine Learning (DML). XPO builds on the Partialing Out (PO) approach, which regresses the residuals of the dependent and independent variables obtained from the two Lasso processes (Chernozhukov et al., 2015a; 2015b). XPO may yield more accurate estimates by incorporating additional control variables through split-sample techniques (Chernozhukov et al., 2018). Both methods, with CV and Bayesian Information Criterion (BIC) criteria, are applied in each specific context for a comprehensive investigation.

3.2 Benchmark Results

Variables with non-zero coefficients are included in the estimations, while those excluded by the penalty function are indicated with blank entries. However, since Lasso does not provide statistical significance, these results only offer a general overview of the influential factors.

More rigorous inferences will be provided through other Lasso-based methodologies. Models 1,3,5,7 are focused on the context of CV. Most alternative variables are retained in the full sample, regardless of whether the overall ESG score or its sub-dimensions are considered. This broad retention implies the complexity of factors influencing corporate ESG decisions across all dimensions. The detailed coefficient paths and CV plot for the Lasso regression in Model 1 are demonstrated in Figure 1, where 23 coefficients are selected. The smoothness of the CV plot curves around the optimal λ value (0.0024) further supports the robustness of these results.

In contrast, models 2,4,6,8 focus on the BIC context. It is observed that the number of selected variables under the BIC criterion is generally lower than under the CV criterion. This reduction occurs because BIC introduces a penalty term related to the number of model parameters, taking into account the sample size. When the sample size is large, BIC effectively prevents model complexity due to excessive accuracy, which is more restrictive than CV. For example, variables representing shareholding concentration (Top5, Top10) and audit status (Big4, Opinion) are excluded under the more stringent BIC criterion. Similarly, some critical financial indicators, such as ROA and Loss, are omitted in the environmental dimension as shown in model 4. It suggests that long-term operational risks, as indicated by the inclusion of the Leverage variable, exert a more significant influence on corporate pro-environment campaigns than short-term profitability. Figure 2 illustrates the coefficient paths and BIC plot for Lasso regression in Model 2, with the λ value (0.089) selected based on the minimum criterion under BIC, resulting in 17 screening variables.

Table 1. Lasso Regression for Variable Selection: Full Sample

	ESG		Environmental		Social		Governance	
	CV	BIC	CV	BIC	CV	BIC	CV	BIC
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
AI	0.0168	0.0146	-0.0175	-0.022	0.0697	0.0678	0.0516	0.05
Lev	-3.101	-2.127	-5.392	-3.828	-2.359	-1.934	6.5	5.842
ROA	7.372	5.028			3.244	1.641	9.608	6.671
ATO	0.371	0.179	0.707	0.429	-0.701	-0.562	-1.364	-1.249
CashFlow	6.925	7.113	2.389	1.575	6.003	5.876	7.798	6.919
FIXED	6.894	6.233	14.34	13.64	2.055	1.847	-2.512	-2.174
Loss	1.643	0.948	0.554		1.105	0.686	0.907	0.391
Top1	-1.42	-0.831					-3.708	-3.802
Top5	-7.307				-5.875		-9.086	
Top10	7.899		-0.724		10.56	4.403	18.97	9.338
BM	0.379	0.236	0.323	0.116	0.25	0.194	0.911	0.87
SOE	-1.135	-0.96	-2.155	-1.771	1.337	1.18	0.0525	
ListAge	0.909	0.623	0.398	0.27	0.555	0.476	1.643	1.476
FirmAge	5.164	5.322	6.282	6.389	7.093	7.087	2.723	2.708
INST	2.705	2.802	1.47	0.59	3.5	3.684	-0.61	
Mfee	-15.51	-14.23	-27.77	-26	-6.189	-4.802	2.099	0.619
Big4	0.0681		-1.388	-0.74	-0.873	-0.605	1.664	1.494
Opinion	0.573		-0.0604		0.986	0.635	-0.382	
Capital	1.32E-11	9.47E-12	5.37E-12		2.95E-11	2.72E-11	2.23E-11	1.92E-11
AI*Lev	0.118	0.0913	0.0625	0.0254	0.185	0.167	0.0206	
AI*ROA	-0.0707		-0.0379		-0.038		0.0293	
AI*Top10	-0.0304		-0.0223		-0.214	-0.189	0.0658	0.0559
AI*ListAge	-0.0529	-0.032	-0.0226		-0.133	-0.12	-0.0325	-0.0235
_cons	5.669	6.84	-6.359	-6.844	-4.934	-4.169	6.255	7.359
Obs.	13,980	13,980	13,980	13,980	13,980	13,980	13,980	13,980

Figure 1. Coefficient Paths and CV Plot for Lasso Linear Regression

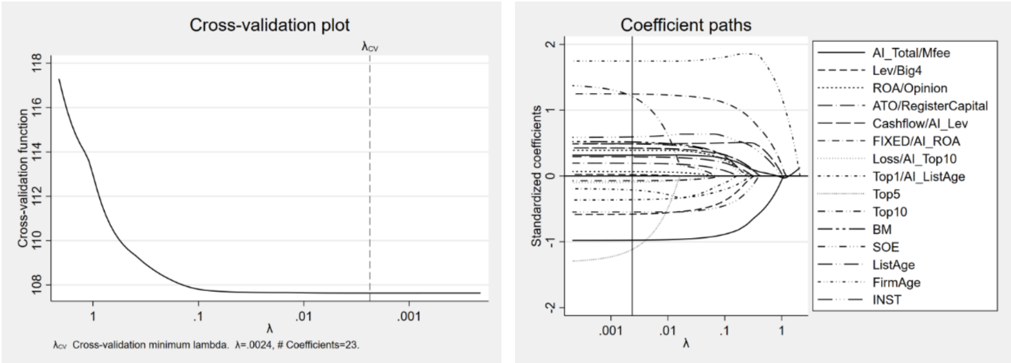
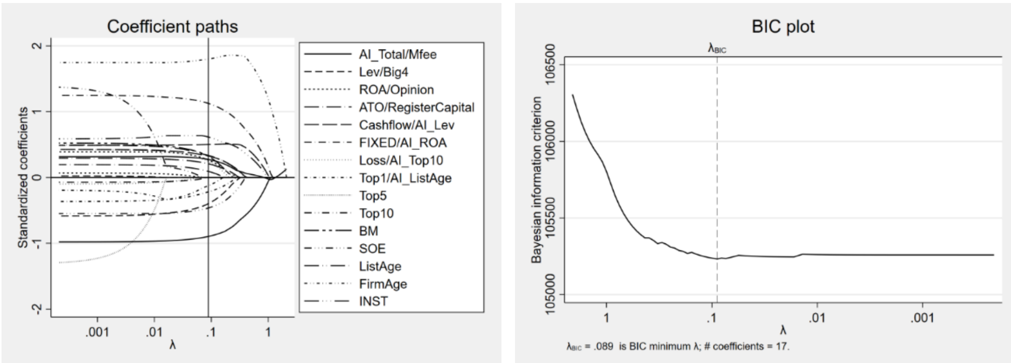


Figure 2. Coefficient Paths and BIC plot for Lasso Linear Regression



The statistical inferences based on Double Selection (DS) and Cross-fit Partialing Out (XPO) are presented in Table 2. The results indicate that AI adoption significantly improves corporate ESG performance, consistent with the findings of existing literature on mechanisms such as enhancing sustainable ESG potential and addressing practical ESG challenges (e.g., Sætra, 2021; Burnaev et al., 2023). These positive effects are particularly evident in the “S” (Social) and “G” (Governance) dimensions, likely due to the role of AI in fostering technological professionalism and balancing external and internal operational environments (e.g., Cui et al., 2022).

However, AI adoption exhibits significant negative effects on environmental performance. Although this finding aligns with the UNCTAD Digital Economy Report 2024, which highlights the environmental pressures associated with digitalization and AI-based activities, it appears counterintuitive, particularly given existing literature. Two recent studies specifically investigate the impact of AI applications on the environmental performance of Chinese enterprises, both concluding that AI positively influences environmental outcomes (Cheng et al., 2024; Shang et al., 2024b). The discrepancy between their findings and ours primarily arises from differences in variable measurement. For AI adoption, the two studies employ robot-related indicators, which capture operational efficiency improvements, whereas our use of keywords in annual reports reflects firms’ AI investment decisions. These investments often divert resources from current green capital but may generate long-term positive impacts. For environmental performance, the two studies focus on pollution emissions, while our “E” indicator adopts a broader framework, encompassing aspects such as the circular economy, green office practices, and environmental certifications. Pollution reductions may occur in the short term, but robust green practices require longer timelines to materialize.

Table 2. Further Analysis in Statistical Inference: Full Sample

Model	Selection	Variables	ESG Performance			
			ESG	E	S	G
Double Selection (DS)	CV	AI	0.0167***	-0.0167***	0.0697***	0.0517***
			(3.76)	(-3.37)	(9.54)	(7.98)
		Obs.	13,980	13,980	13,980	13,980
	BIC	AI	0.0167***	-0.0167***	0.0697***	0.0517***
			(3.76)	(-3.37)	(9.54)	(7.98)
		Obs.	13,980	13,980	13,980	13,980
Cross-fit Partialing Out (XPO)	CV	AI	0.0160***	-0.0168***	0.0693***	0.0520***
			(2.92)	(-2.73)	(8.76)	(7.54)
		Obs.	13,980	13,980	13,980	13,980
	BIC	AI	0.0170***	-0.0164***	0.0695***	0.0514***
			(3.00)	(-2.84)	(9.23)	(6.77)
		Obs.	13,980	13,980	13,980	13,980

*Note: Control variables are not reported for brevity. Robust z-statistics are reported in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

Our findings underscore a potential lag between AI advancements and the implementation of pro-environmental practices. While long-standing corporate social responsibility (CSR) initiatives have facilitated relatively standardized management practices that align with AI-driven governance, the integration of environmental considerations into corporate governance and ESG frameworks remains inadequate. The insights and mechanisms proposed in the two studies provide valuable implications for improving AI implementation in corporate practices, particularly the role of robot-driven efficiency—such as total factor productivity improvements, equipment investment, and input optimization—in advancing internal sustainability.

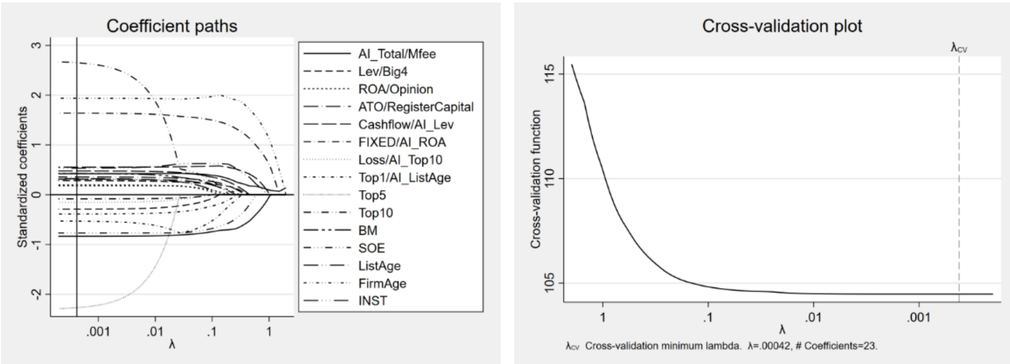
Overall, while AI offers substantial benefits to ESG, particularly in social and governance domains, its potential in addressing environmental challenges has yet to be fully realized. The findings highlight the need for greater emphasis on integrating environmental strategies into AI-driven corporate governance to achieve more balanced ESG outcomes.

3.3 Heterogeneity Analysis

In this section, we further examine the regional heterogeneity of AI's impact on ESG by categorizing the sample into Eastern, Central, and Western regions. Table 3 presents the results of variable selection, with Models 9–12 focusing on enterprises in the Eastern region, 13–16 on the Central region, and 17–20 on the Western region. Table 4 displays the Lasso regression results for the regional heterogeneity analysis.

For the Eastern region, the optimal lambda value ($\lambda = 0.00042$) under the cross-validation (CV) criterion is significantly lower than that for the full sample ($\lambda = 0.0024$); however, both regressions select the same number of variables (23). This finding suggests that numerous indicators in eastern firms exert a strong influence, even when moderated by smaller penalty factors. This aligns with the characteristics of the Eastern region, which features a higher concentration of advanced manufacturing and high-tech firms in competitive markets. Such conditions necessitate the inclusion of a broader range of variables to accurately isolate the impact of AI on ESG performance. The coefficient paths and CV plot for Model 9 are shown in Figure 3. As demonstrated in Table 4, the statistical inferences for the eastern region align with those for the full sample, regardless of whether Double Selection (DS) or Cross-fit Partialing Out (XPO) is applied. The Eastern region's abundant resources—including knowledge spillovers, market mechanisms, infrastructure, human capital, and access to finance—equip companies with greater access to information and technological reserves for AI-driven transformation, thereby enhancing their capacity to engage in ESG activities and sustainable investments. Moreover, due to industrial agglomeration and the uneven distribution of resources, firms in the Eastern region constitute a significant portion of the total sample. Consequently, the overall estimates from the benchmark regression predominantly reflect conditions specific to the Eastern region.

Figure 3. Coefficient Paths and CV Plot for Lasso Linear Regression in Eastern Regions



In the central region, the Lasso model identifies a substantial number of variables, even under less stringent penalty constraints compared to the baseline and Eastern region, with 17 variables selected (λ = 0.078), as illustrated in Figure 4. Statistical inferences suggest that AI adoption exerts significant negative effects on ESG performance in this region. Unlike the Eastern region, which benefits from a well-established industrial base, and the Western region, which receives substantial policy support, the Central region has experienced a deceleration in growth. As a result, the focus on economic stimulation through AI transformation may lead enterprises in the Central region to deprioritize ESG objectives. Specifically, AI-driven technological practices appear to undermine corporate governance, contributing to the observed negative effects. The Central region, characterized by its distinct geographic location, resource base, and growth potential, possesses notable advantages from late-stage development. However, due to a relatively underdeveloped management system linked to a weaker economy, enterprises in this region struggle to effectively integrate, utilize, and optimize available resources. Advancements in AI may exacerbate these managerial challenges, undermining sustainable performance through immature governance mechanisms.

For western enterprises, it is noteworthy that the optimal λ (0.038) in Model 17 is over an order of magnitude larger than that in the full sample context (0.0024). The coefficient paths and the CV plot for Lasso linear regression in Model 17 are depicted in Figure 5. Additionally, only four variables are retained under the stringent BIC criterion in Model 28: Cash Flow, List Age, INST, and Registered Capital. These variables, with positive coefficients, effectively characterize firms and development conditions in the Western region. Cash flow remains critical across regions, as it supports balancing liquidity-driven operations with sustainability-oriented investments. Furthermore, a longer listing period and higher registered capital reflect a significant commitment in the Western region and a complex investor relationship, both of which necessitate robust ESG performance.

Figure 4. Coefficient Paths and CV Plot for Lasso Linear Regression in Central Regions

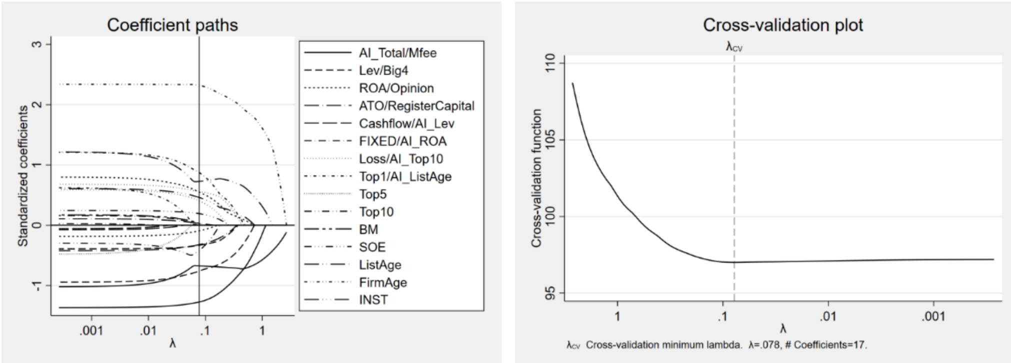
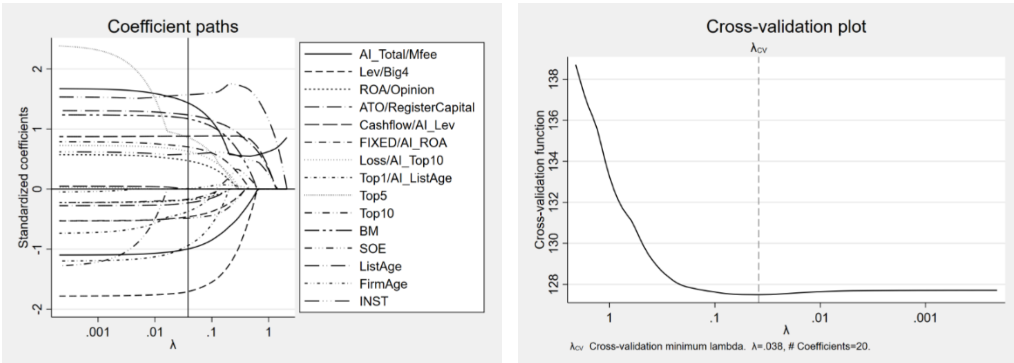


Figure 5. Coefficient Paths and CV Plot for Lasso Linear Regression in Western Regions



The Lasso-based statistical inferences, presented in Table 4, reveal strong positive effects of AI on environmental performance, a finding that contradicts the baseline regression results. This discrepancy likely arises from the fact that AI transformations in the Western region, supported by preferential policies, are initially designed to alleviate the stringent energy consumption targets and higher electricity costs faced by firms in the east. As transferees of computational resources that might otherwise contribute to environmental pressures, western enterprises are more inclined to invest in sustainable development (Su et al., 2025). Moreover, AI transitions in the Western region are found to have significant positive effects on corporate social responsibility, driven by the high social marginal benefits generated through AI-enabled improvements in efficiency and employment, especially during the early stages of AI adoption, where most western firms currently stand. However, the effects of AI on the overall ESG score are significant only at the 90% confidence level in the DS model and lose significance in the XPO estimation. Furthermore, the potential of AI to enhance corporate governance—observed in the full and eastern samples—is not evident in the Western region. This suggests that weak governance structures may offset AI's positive contributions to the environmental and social dimensions. The most plausible explanation is the lack of advanced management practices in western businesses, coupled with reduced market competition that diminishes the incentive for companies to improve management capabilities in AI technologies. State-owned enterprises (SOEs) and a few dominant industry players also fail to effectively disseminate governance best practices or leverage policy preferences. This is reflected in the omission of the ownership structure variable, SOE, in all BIC-based estimations (as shown in Table 5), particularly in both CV and BIC models for governance performance, indicating that institutional support does not play a key role in driving governance improvements.

As anticipated, the number of selected variables is lower under the more stringent BIC criterion across all regions. Nevertheless, most corporate characteristics—including size, age, financial status, audit condition, and ownership structure—remain included in the estimations. The regression results under the BIC criterion are highly similar to those under the CV criteria, as shown in Table 5 and Table 6. Detailed discussions on these findings are omitted here.

Table 3. Lasso Regression for Regional Heterogeneity Analysis: CV Criteria

CV Criteria	Eastern Region				Central Region				Western Region			
	ESG	E	S	G	ESG	E	S	G	ESG	E	S	G
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
AI	0.0192	-0.0167	0.0654	0.0529	-0.0926	-0.0582	-0.0347	-0.0703	0.103	0.13	0.246	0.0892
Lev	-1.52	-2.864	-1.929	6.511	-4.395	-4.028	-0.716	3.555	-9.033	-13.17	-12.21	3.749
ROA	3.485	0.438	-3.387	2.599	10.43		11.72	11.77	8.462		3.725	13.42
ATO	0.598	0.85	-0.164	-1.264	0.0581	0.725	-0.985	-0.698	-0.491	-0.235	-3.611	-1.931
CashFlow	7.765	1.679	4.12	6.613		-1.004	1.636	5.262	12.78	14.2	16.59	15.95
FIXED	9.239	17.97	3.359	-4.129		2.395	-0.537	0.0588	3.796	9.051	1.503	1.059
Loss	1.24	0.103	0.539	0.212	1.508	1.094	1.668	0.338	2.232		1.457	2.195
Top1	-3.488	-3.115	-4.133	-4.109	5.837	8.42	8.301		-2.633	2.656	5.227	-7.903
Top5	-14.5		-12.95	-9.546					6.491		2.125	
Top10	16.96	1.264	21.4	19.41	-2.771	-5.647		9.698				9.548
BM	0.304	0.0198	0.0496	1.115	0.0221	0.145	0.166	0.738	0.952	1.861	0.852	-0.176
SOE	-1.561	-3.038	1.417		0.426	0.0634	1.953		-1.064	-0.102	-0.511	
ListAge	0.572	-0.0944	1.125	1.538	1.466	2.337		1.878	3.391	1.261	1.07	4.154
FirmAge	5.602	6.994	6.105	1.98	7.178	5.353	9.953	4.905	0.0239	2.007	4.49	0.958
INST	2.35	2.299	1.924	-0.287	2.206	-0.188	7.681	-0.328	2.973		4.839	0.187
Mfee	-12.95	-22.83	-8.659	-0.164	-21.51	-43.66	3.188	12.12	-16.3	-20.69	-12.6	-0.0097
Big4	0.898	-1.138	0.237	2.197	-1.376		-5.214	-1.369	-2.623	-2.292	-1.075	
Opinion	1.66	0.342	1.355	0.51	-0.945	3.076		-5.197	-1.371	-7.845	0.254	
Capital	1.31E-11	5.48E-12	2.97E-11	2.08E-11	-8.87E-11		-1.25E-10		6.82E-10	1.70E-10	9.03E-10	6.97E-10
AI*Lev	0.111	0.0516	0.16	0.0103		-0.103	0.0448	0.211		0.37	-0.254	-0.292
AI*ROA	-0.0703	-0.0708	0.031	0.0641		0.899	-0.285		-0.236	-0.126	-0.579	-0.0168
AI*Top10	-0.043	-0.0196	-0.21	0.0663	0.543	0.0679	0.168	0.59		0.0976	-0.278	-0.0179
AI*ListAge	-0.0504		-0.134	-0.0403		-0.101	-0.0777	0.168	-0.144	-0.397	-0.276	
_cons	2.215	-9.897	-4.225	8.519	3.848	-8.098	-12.82	2.916	16.07	13.06	6.312	6.306
Obs.	9,075	9,075	9,075	9,075	3,075	3,075	3,075	3,075	1,830	1,830	1,830	1,830

Table 4. Regional Heterogeneity Analysis in Statistical Inference: CV Criteria

	Model	Variables	ESG Performance			
			ESG	E	S	G
Eastern Region	Double Selection (DS)	AI	0.0192***	-0.0166***	0.0654***	0.0529***
			(4.11)	(-3.25)	(8.89)	(7.82)
	Cross-fit Partialing Out (XPO)	AI	0.0195***	-0.0164***	0.0622***	0.0523***
			(3.20)	(-2.61)	(7.55)	(6.99)
		Obs.	9,075	9,075	9,075	9,075
Central Region	Double Selection (DS)	AI	-0.1404***	-0.0400	0.0031	-0.1067**
			(-4.02)	(-0.54)	(0.07)	(-2.48)
	Cross-fit Partialing Out (XPO)	AI	-0.1351***	-0.0465	0.0191	-0.1043**
			(-3.35)	(-0.60)	(0.28)	(-2.53)
		Obs.	3,075	3,075	3,075	3,075
Western Region	Double Selection (DS)	AI	0.1177*	0.1780***	0.2516***	-0.0139
			(1.90)	(2.88)	(4.50)	(-0.28)
	Cross-fit Partialing Out (XPO)	AI	0.0995	0.1790***	0.2052***	0.0115
			(1.45)	(2.92)	(3.04)	(0.19)
		Obs.	1,830	1,830	1,830	1,830

*Note: Control variables are not reported for brevity. Robust z-statistics are reported in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

Table 5. Lasso Regression for Regional Heterogeneity: BIC Criteria

BIC Criteria	Eastern Region			Central Region				Western Region			
	E	S	G	ESG	E	S	G	ESG	E	S	G
	Model 21	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31
AI	-0.0167	0.0633	0.052	-0.095	-0.108	-0.0484	-0.0242	0.0415	0.096	0.184	0.0906
Lev	-1.954	-0.798	6.079	-3.72			2.419		-11.96	-7.907	2.363
ROA			1.496	6.341			7.437				9.647
ATO	0.6		-1.095			-0.226	-0.587			-2.922	-1.663
CashFlow	1.284	2.947	5.716				4.922	9.498	13.44	15.18	15.79
FIXED	17.25	3.179	-3.828						8.389		0.675
Loss		0.303		0.611							1.616
Top1	-1.121	-3.904	-4.206	3.434	1.354	4.865			1.872	2.952	-6.087
Top5										2.095	
Top10		7.871	9.568				7.844				7.799
BM			1.101				0.711		1.736	0.5	
SOE	-2.8	1.157		0.204		1.038					
ListAge		0.97	1.378	1.559	2.842		0.709	3.135	1.699	1.915	3.819
FirmAge	6.452	6.138	1.968	6.745	3.472	9.151	5.038		1.817	3.931	0.925
INST	1.499	2.215		1.41		6.929		2.226		4.22	0.421
Mfee	-20.8	-6.259		-18.84	-36.04		10.12		-18.14	-5.488	
Big4	-0.498	0.0629	2.071	-1.047		-3.154	-0.833		-1.663		
Opinion		0.669					-4.414		-7.097		
Capital		2.74E-11	1.83E-11	-5.76E-11		-1.68E-11		3.26E-10	1.13E-10	8.05E-10	6.39E-10

BIC Criteria	Eastern Region			Central Region				Western Region			
	E	S	G	ESG	E	S	G	ESG	E	S	G
	Model 21	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31
AI*Lev	0.0231	0.13					0.118		0.303		-0.286
AI*ROA			0.024								
AI*Top10		-0.161	0.062	0.457			0.354		0.0491	-0.203	
AI*ListAge		-0.117	-0.0341						-0.315	-0.136	
_cons	-8.256	-3.27	10.06	3.491	-2.573	-8.569	6.549	14.79	11.46	4.899	8.191
Obs.	9,075	9,075	9,075	3,075	3,075	3,075	3,075	1,830	1,830	1,830	1,830

Note: The optimal λ value and corresponding coefficient paths are not obtained in the overall ESG context of the eastern region, as the Lasso regression model for the eastern region does not converge under the more stringent BIC criterion.

Table 6.Regional Heterogeneity Analysis in Statistical Inference: BIC Criteria

	Model	Variables	ESG Performance			
			ESG	E	S	G
Eastern Region	Double Selection (DS)	AI	0.0192***	-0.0164***	0.0665***	0.0535***
			(4.11)	(-3.23)	(8.94)	(7.91)
	Cross-fit Partialing Out (XPO)	AI	0.0199***	-0.0164***	0.0655***	0.0523***
			(2.99)	(-2.66)	(7.84)	(6.91)
		Obs.	9,075	9,075	9,075	9,075
Central Region	Double Selection (DS)	AI	-0.1405***	-0.0381	0.0051	-0.1067**
			(-4.04)	(-0.53)	(0.11)	(-2.48)
	Cross-fit Partialing Out (XPO)	AI	-0.1326***	-0.0416	0.0094	-0.0991**
			(-3.75)	(-0.53)	(0.16)	(-2.16)
		Obs.	3,075	3,075	3,075	3,075
Western Region	Double Selection (DS)	AI	0.1099*	0.1792***	0.2538***	-0.0138
			(1.80)	(2.90)	(4.56)	(-0.28)
	Cross-fit Partialing Out (XPO)	AI	0.0972	0.1997***	0.2162***	0.0027
			(1.43)	(3.18)	(3.54)	(0.05)
		Obs.	1,830	1,830	1,830	1,830

*Note: Control variables are not reported for brevity. Robust z-statistics are reported in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

The reasons for substantial regional differences in AI advancement and corresponding ESG performance are twofold. First, resource efficiency (Shang et al., 2024a). The abundant natural resources in western regions enable these areas to capitalize on AI's efficiency-enhancing potential, resulting in positive environmental benefits during the early stages of technological transition. In contrast, eastern regions experience opposite effects due to resource constraints. Second, policy coordination (Huang et al., 2024). Divergent pilot initiatives and their demonstration effects drive multi-dimensional differences in regional AI development—

innovation-oriented in the east, steady growth in the center, and foundational advancements in the west. These distinct objectives further refine AI technology service scenarios across regions. Particularly, our findings partially diverge from existing literature suggesting that AI adoption improves firms' ESG scores in central regions (Chen et al., 2024; Huang et al., 2024). This discrepancy may be from methodological differences. While the Lasso-based approach used in our study accounts for context-specific variable matrices, traditional two-way fixed effects (TWFE) rely on consistent controls across models. This distinction provides valuable insights for tailoring context-specific business strategies.

4. 3D UAV Path Programming by AI Technology

4.1 Methodology

3D Unmanned Aerial Vehicles (UAV) path programming within the Mobile Ad Hoc Network (MANET) is further introduced for pro-ESG path optimization. This method targets planning an optimal and collision-free path for UAV in complexities of high-dimensional environments and real-time dynamics (e.g., Gómez Arnaldo, 2024). Yang et al. (2014) provide a comprehensive overview of a large number of capable algorithms successfully implemented in 3D UAV contexts, with subsequent studies contributing to this field through algorithm improvements and innovations (Carvajal-Rodriguez, 2023; Du, 2023; Wang et al., 2024). With rising societal demand and given its simulation-based advantages, 3D UAV path planning has been widely used in scientific research for practical support, benefiting from the progress of AI technology (e.g., Cai et al., 2019; Zammit and van Kampen, 2023).

In this analysis, we employ the 3D UAV path to model potential development trends and cross-regional governance patterns of ESG, aiming to enhance substitutability through corporate synergies, which require efficient coverage across the extensive West-East geographical span. Specifically, virtual buildings are constructed to represent ESG performance, with their heights corresponding to corporate ESG scores. The top 100 companies by overall ESG scores are selected for the analysis. The X-axis denotes longitude, the Y-axis latitude, and the Z-axis corporate ESG performance, with all data standardized for visualization. These virtual buildings serve as obstacles that the UAV must navigate around or over, simulating the challenges posed by regions with higher corporate ESG standards. Such regions often impose stricter sustainability demands and governance requirements, complicating the application of "low-altitude" policies that benefit latecomers. Hence, the primary objective of this 3D path programming is to identify the optimal UAV flight path, minimizing distance while avoiding horizontal geographic dispersion and vertical obstacles. This approach models optimal pro-ESG development within cross-regional governance frameworks.

Specifically, multi-objective programming approach is utilized to explore the positive externalities of ESG. On one hand, AI technology facilitates the diffusion of ESG externalities by enhancing industrial chain governance, creating an organic connection between vertical and horizontal knowledge spillovers (Yang et al., 2024). On the other hand, AI-driven contexts innovatively provide incentives for ESG initiatives through more inclusive approaches, offsetting the additional social costs incurred by enterprises due to the externalities of their pro-sustainability efforts (Cornell and Shapiro, 2021; Jia and Guang, 2024). The multi-objective programming seeks to balance path efficiency with broader regional coverage tailored to ESG considerations. Three AI algorithms are applied for comparison in multiple objective scenarios:

(1) Ant Colony Optimization (ACO): This algorithm optimizes path selection by simulating pheromone-based ant behavior, making it effective for global optimization in complex and dynamic environments, albeit with higher computational complexity.

(2) A* Algorithm (Astar): Astar is a highly efficient direct search method for finding the shortest paths in static road networks. It utilizes heuristic information to guide the search toward the destination, thereby reducing the need to traverse the entire map and saving computational power and time.

(3) Rapidly-Exploring Random Tree (RRT): This random sample-based algorithm rapidly explores path space by generating spatial tree structures. It is particularly suited for real-time or high-dimensional contexts, making it highly applicable to the challenges addressed in this study.

4.2 Simulation Results

3D UAV programming is employed for ESG path optimization across geographic regions through AI computation. Multi-objective programming is applied to balance overall path efficiency with region-specific ESG construction needs. Four key sites—start, end, and two intermediate UAV stops—are strategically positioned across major geographic and economic hubs. The UAV is tasked with covering all four sites within the most efficient 3D path.

Figure 6. Multi-Objective 3D UAV Path Optimization by AI Technology

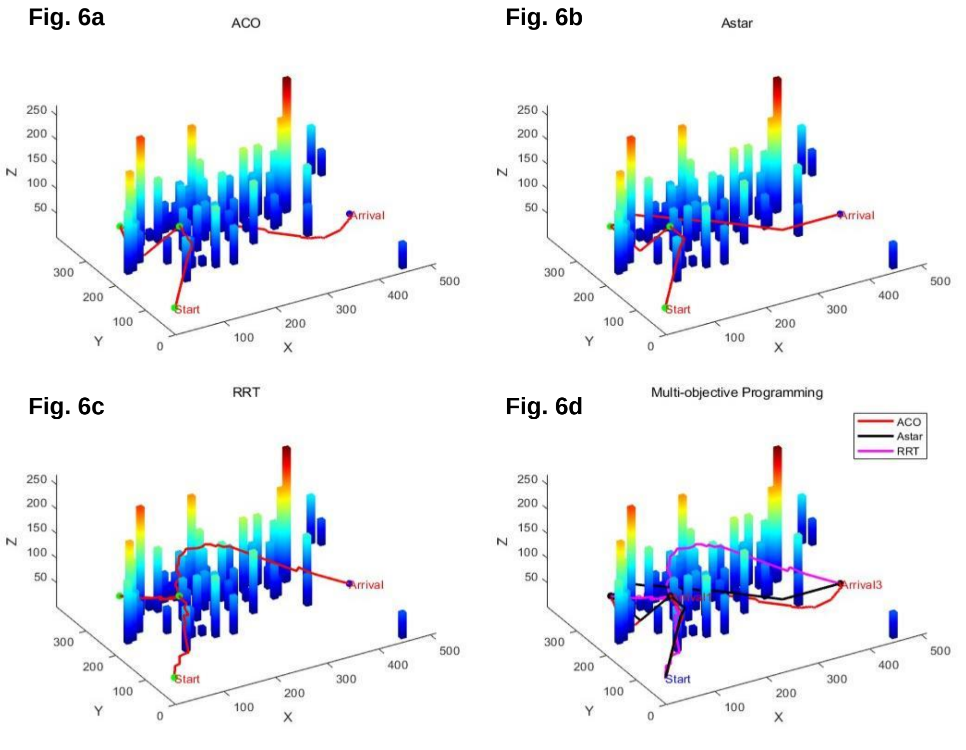


Figure 6a presents the path optimized by ACO. The UAV still follows a low-altitude flight pattern, navigating through numerous low-floor ESG entities, but with increased efficiency through moderate climbing. This ACO-derived path underscores the importance of integrating firm-specific initiatives into broader efficiency assessments in cross-regional synergies. However, multilateral coordination within key sites may challenge absolute inclusion at the specific level, necessitating a certain ESG altitude to address cross-regional governance. Figure 6b shows the path optimized by Astar algorithm. The UAV follows a similarly straight-line path as in the single-objective context, highlighting the need for straightforward efficiency in promoting ESG implementation while accounting for heterogeneous hubs. This pattern ensures more thorough mid-altitude interactions, thereby enhancing the diffusion of positive ESG externalities. Figure 6c presents the path generated by RRT. The UAV adopts a general high-altitude strategy but sacrifices some vertical height—and potentially efficiency—compared to the single-objective context, to facilitate communication and synergies with lower and medium ESG zones. This outcome emphasizes the need to balance specificity, efficiency, and innovation, advocating for tech-inclusive ESG scenarios that parallel flagship-driven AI advancements.

Figure 6d provides a comparative analysis of the solutions generated by the three algorithms. The analysis reveals that higher-altitude flights, indicative of broader governance strategies, tend to cluster in the West, while lower-altitude paths, representing targeted initiatives, are more prevalent in the East. Although this finding might seem counterintuitive—since less developed regions are often thought to require more targeted support—it aligns with our empirical evidence on ESG sub-dimensions. Eastern companies, despite being more advanced, face significant environmental pressures, which require context-specific operational measures. In contrast, Central and Western regions, though exhibiting green potential, have yet to achieve robust overall ESG performance, necessitating more harmonized governance at a higher level. Consequently, the advanced Eastern region and the emerging Central and Western regions can develop a complementary synergy for ESG enhancement, leveraging their geographic and industrial strengths.

5. Conclusion

This paper investigates the impact of AI adoption on corporate ESG performance within the digital economy, focusing on the potential role of new quality productivity in promoting sustainable development. We combine Lasso-based empirical analysis with 3D UAV path planning—AI-based technology—to form a comprehensive methodological framework within social computing science. The empirical findings indicate that AI significantly enhances ESG performance, though with regional and sub-dimensional variations. Path simulations reveal diverse ESG harmonization patterns based on broad geographic spans, tailored to situational ESG construction in selected key hubs. The conclusions underscore the importance of fostering comprehensive sustainability through AI advancements, alongside the growth of new quality productivity. Overall, this study further examines the heated issue of AI-ESG, deepening the understanding of AI as a powerful development tool that empowers both practical applications and research methodologies.

Our findings offer clear managerial and policy implications based on both empirical and simulation results. For corporate management, AI-driven strategies should be adopted proactively but tailored to specific contexts to enhance ESG performance. In the eastern region, enterprises are recommended to balance a wide range of latent factors in response to high-tech concentration and intense market competition. Numerous indicators significantly influence ESG outcomes with AI adoption in consideration, shaping firms' strategic practices through the region's complex business environment. Central region companies should prioritize mitigating firm-specific uncertainties related to governance capabilities, as this serves as the only region where ESG performance risks being lower due to inefficient management. Western companies, meanwhile, should cautiously balance financial flexibility and market commitment when leveraging AI to enhance ESG performance, as both cash flow and listing period play critical roles in influencing ESG outcomes but fail to create synergistic benefits.

For policy initiatives, the government's primary goal should be to disseminate the positive externalities of advanced ESG performance through regional collaboration. The government can facilitate this by providing industrial communication platforms and connecting AI opportunities with company portals, thereby promoting knowledge sharing and mutual experience learning. These initiatives would encourage geographically dispersed firms to jointly create social benefits through coordinated resource deployment. Specifically, local governments in less developed western regions should offer fiscal support for establishing AI training hubs, enabling the transfer of computing resources. The central government should be responsible for constructing and coordinating computing channels and networks to facilitate the flow of computing power, thereby improving the national AI efficiency. The development of robust national computing hubs will contribute to enhancing overall ESG performance and sustainability.

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