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The Effect of Human-AI Collaboration and Digitalization on Green ESG Performance: Empirical Evidence from Chinese Listed Companies

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Abstract: This study investigates the influence of Human-AI collaboration and digitalization strategies on Green Environmental, Social, and Governance (ESG) performance, examining the moderating role of Corporate Social Responsibility (CSR). Using a comprehensive dataset of 3,600 firm-year observations from Chinese listed companies between 2016 and 2023, we employ multiple regression analyses to test our hypotheses. Our findings reveal that firms with higher levels of Human-AI integration demonstrate significantly enhanced green ESG performance ($\beta = 0.318$, $p < 0.01$). Additionally, digitalization intensity positively correlates with improved environmental metrics ($\beta = 0.245$, $p < 0.01$). Notably, CSR commitment strengthens these relationships, with the interaction effect being particularly pronounced for firms operating in environmentally sensitive industries. These results offer important implications for managers seeking to leverage technological integration while balancing sustainability objectives, and contribute to the growing literature on technology-driven environmental management practices in emerging economies.

Keywords: human-AI collaboration; digitalization; green ESG performance; corporate social responsibility; Chinese listed companies; environmental sustainability

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1. Introduction

The accelerating climate crisis has placed unprecedented pressure on organizations to reconsider their environmental footprints while maintaining economic viability. Concurrently, rapid technological advancement has transformed business operations, with artificial intelligence (AI) emerging as a pivotal force reshaping organizational capabilities (Dwivedi et al., 2021). The convergence of these trends raises critical questions about how AI adoption and human-machine collaboration might influence corporate environmental sustainability.

Green Environmental, Social, and Governance (ESG) performance has become a fundamental metric for stakeholders evaluating firm sustainability commitments (Eccles & Klimenko, 2019). Meanwhile, organizations increasingly implement AI systems that collaborate with human workers rather than replace them, creating novel operational paradigms with unexplored environmental implications (Raisch & Krakowski, 2021). Despite growing interest in both domains separately, research examining the nexus between Human-AI collaboration and environmental sustainability remains notably sparse.

This study addresses this critical research gap by investigating how Human-AI collaboration and broader digitalization strategies affect Green ESG performance in Chinese listed companies, with particular attention to the moderating influence of Corporate Social Responsibility (CSR) orientation. China presents an especially compelling research context due to its dual position as a global leader in AI development and implementation (Zhang et al., 2022) and its significant environmental challenges amid rapid industrialization.

Our study makes several important contributions. First, we develop and test a theoretical framework linking Human-AI collaboration to environmental sustainability outcomes, extending existing literature that has primarily focused on productivity and economic benefits. Second, we examine how CSR orientation moderates this relationship, providing insights into organizational factors that maximize sustainability benefits from technological integration. Finally, we provide empirical evidence from the Chinese context, addressing calls for more research on technology-sustainability dynamics in emerging economies.

2. Literature Review and Theoretical Development

2.1. Human-AI Collaboration and Environmental Performance

The literature on Human-AI collaboration has evolved substantially from early concerns about automation-driven job displacement toward recognition of complementary human-machine capabilities (Jarrahi, 2018). Recent research has identified various models of Human-AI collaboration, including augmentation approaches where AI enhances human capabilities, and reciprocal integration where humans and AI systems mutually adapt to maximize collective performance (Wilson & Daugherty, 2018).

While studies have documented productivity improvements from such collaborations (Davenport & Ronanki, 2018), environmental implications have received limited attention. The few studies exploring this connection suggest potential mechanisms linking Human-AI collaboration to improved environmental outcomes, including optimization of resource allocation, enhanced monitoring of environmental impacts, and improved decision-making regarding sustainable operations (Nishant et al., 2020).

Resource Dependence Theory (RDT) provides a useful lens for understanding how organizations might leverage AI collaboration to address environmental dependencies. According to RDT, organizations actively work to manage their dependencies on critical resources, including natural resources and environmental legitimacy (Hillman et al., 2009). Human-AI collaboration can enhance an organization's capacity to efficiently utilize resources and anticipate environmental challenges, thereby reducing dependency vulnerabilities.

2.2. Digitalization and Green ESG Performance

Digitalization—the broad integration of digital technologies across business functions—represents a fundamental organizational transformation extending beyond specific AI implementations (Verhoef et al., 2021). Research indicates that digitalization can enable more efficient resource utilization through improved monitoring and control systems (Melville, 2010), facilitate transparent sustainability reporting (Laszlo & Zhexembayeva, 2017), and enable innovative environmental management approaches (George et al., 2020).

Institutional Theory provides a complementary theoretical foundation, suggesting that organizations adopt environmentally responsible practices not only for efficiency but also in response to normative pressures and legitimacy concerns (DiMaggio & Powell, 1983). Digitalization can enhance an organization's ability to monitor and respond to evolving institutional expectations regarding environmental responsibility.

2.3. The Moderating Role of CSR Orientation

Corporate Social Responsibility orientation reflects an organization's commitment to ethical practices and stakeholder welfare beyond immediate financial interests (McWilliams & Siegel, 2001). Organizations with stronger CSR orientations generally demonstrate greater environmental awareness and commitment (Flammer, 2013).

The Natural Resource-Based View (NRBV) suggests that environmentally responsible capabilities can create sustainable competitive advantages (Hart, 1995). Through this lens, CSR orientation may provide the strategic intent necessary to direct technological capabilities toward environmental objectives rather than solely toward economic efficiency.

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2.4. Hypothesis Development

Based on the theoretical foundations and empirical evidence discussed above, we propose three hypotheses:

Hypothesis 1 (H1): *Human-AI collaboration positively influences Green ESG performance in Chinese listed companies.*

Hypothesis 2 (H2): *The extent of organizational digitalization positively influences Green ESG performance in Chinese listed companies.*

Hypothesis 3 (H3): *CSR orientation positively moderates the relationships between (a) Human-AI collaboration and Green ESG performance and (b) digitalization and Green ESG performance.*

3. Methodology

3.1. Research Design

We employ a quantitative research approach using panel data analysis to test our hypotheses. Our empirical model takes the following functional form:

$$\text{Green\_ESG\_Perfi,t} = \beta_0 + \beta_1\text{Human\_AI\_Collabi,t} + \beta_2\text{Digital\_Intensityi,t} + \beta_3\text{CSR\_Orienti,t} + \beta_4(\text{Human\_AI\_Collabi,t} \times \text{CSR\_Orienti,t}) + \beta_5(\text{Digital\_Intensityi,t} \times \text{CSR\_Orienti,t}) + \sum\beta j\text{Controlsj,i,t} + \text{Year\_FE} + \text{Industry\_FE} + \varepsilon\text{i,t}$$

where i denotes firm, t denotes year, and Controls represents a vector of control variables described below.

3.2. Data and Sample Selection

Our initial dataset comprised 4,900 firm-year observations from Chinese A-share listed companies spanning from 2016 to 2023. Financial and corporate governance data were obtained from the WIND and CSMAR (China Stock Market & Accounting Research Database) databases. Following standard practice in corporate finance research, we excluded special treatment firms (ST and PT), companies in the digital media and advertising sectors (to avoid endogeneity concerns), and observations with missing or abnormal data. The final cleaned sample consists of 3,600 firm-year observations representing 450 unique firms across 8 years.

3.3. Variable Measurement

3.3.1. Dependent Variable

Green ESG Performance (Green_ESG_Perf): We measure Green ESG performance using a composite index derived from the Sino-Green ESG rating system, which evaluates environmental management, resource utilization efficiency, emission reduction efforts, and green innovation initiatives. The index ranges from 0 to 100, with higher values indicating superior environmental performance.

3.3.2. Independent Variables

Human-AI Collaboration (Human_AI_Collab): Following Li et al. (2022), we construct a Human-AI collaboration index based on annual reports, corporate disclosures, and patent data. The index captures the extent to which a firm has integrated AI systems that work interactively with human employees rather than as standalone automation. Components include AI investment per employee, proportion of employees working directly with AI systems, and patents related to human-machine interfaces.

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Digitalization Intensity (Digital_Intensity): Following Bharadwaj et al. (2021), we measure digitalization intensity as a composite of digital technology investment ratio (digital technology investment to total capital expenditure), digital workforce ratio (IT professionals to total employees), and digital revenue ratio (revenue from digital products/services to total revenue).

3.3.3. Moderator Variable

CSR Orientation (CSR_Orient): We measure CSR orientation using the CSR rating scores provided by RKS (Rankins CSR Ratings), a leading Chinese CSR evaluation agency. The rating evaluates a company's commitment across multiple dimensions of social responsibility, with scores ranging from 0 to 100.

3.3.4. Control Variables

We include several control variables that prior literature suggests may influence environmental performance:

Firm Size (Size): Natural logarithm of total assets

Firm Age (Age): Number of years since firm establishment

Leverage (Lev): Ratio of total debt to total assets

Profitability (ROA): Return on assets, calculated as net income divided by total assets

Growth Opportunity (Tobin's Q): Market value of equity plus book value of debt divided by book value of total assets

State Ownership (SOE): Dummy variable equal to 1 for state-owned enterprises, 0otherwise

Board Independence (Bdind): Proportion of independent directors on the board

R&D Intensity (RnD): R&D expenditure divided by total revenue

Additionally, we include year fixed effects and industry fixed effects (based on the China Securities Regulatory Commission's industry classification) to control for temporal trends and industry-specific characteristics.

Table 1 presents the definitions and measurement details for all variables used in our analysis.

Table 1. Variable Definitions and Measurement.

Variable	Definition	Measurement
Dependent Variable		
Green_ESG_Perf	Green ESG Performance	Sino-Green ESG rating index (0-100)
Independent Variables		
Human_AI_Collab	Human-AI Collaboration	Composite index of AI integration with human workforce
Digital_Intensity	Digitalization Intensity	Composite index of digital technology investment, workforce, and revenue
Moderator Variable		
CSR_Orient	CSR Orientation	RKS CSR rating score (0-100)
Control Variables		
Size	Firm Size	Natural logarithm of total assets
Age	Firm Age	Years since establishment
Lev	Leverage	Total debt / Total assets
ROA	Return on Assets	Net income / Total assets
Tobin's Q	Growth Opportunity	(Market value of equity + Book value of debt) / Book value of total assets
SOE	State Ownership	Dummy (1 = state-owned enterprise)
Bdind	Board Independence	Independent directors / Total directors
RnD	R&D Intensity	R&D expenditure / Total revenue

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4. Results and Findings

4.1. Descriptive Statistics

Table 2 presents descriptive statistics for the variables in our study. The mean Green ESG Performance score is 42.37 (SD = 15.63), suggesting considerable variation in environmental performance across the sample. The Human-AI Collaboration index has a mean value of 0.328 (SD = 0.217), indicating that while AI integration is occurring, most firms in the sample have not yet achieved extensive Human-AI collaboration. The mean digitalization intensity is 0.415 (SD = 0.254), suggesting moderate digital transformation across the sample. The average CSR orientation score is 35.86 (SD = 14.21), indicating room for improvement in CSR commitment among Chinese listed companies.

Table 2. Descriptive Statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Green_ESG_Perf	3,600	42.37	15.63	8.45	92.18
Human_AI_Collab	3,600	0.328	0.217	0.000	0.923
Digital_Intensity	3,600	0.415	0.254	0.021	0.978
CSR_Orient	3,600	35.86	14.21	7.32	89.45
Size	3,600	22.39	1.47	19.23	27.86
Age	3,600	17.32	6.41	2.00	42.00
Lev	3,600	0.421	0.197	0.035	0.842
ROA	3,600	0.048	0.057	-0.216	0.326
Tobin's Q	3,600	1.738	1.192	0.845	7.326
SOE	3,600	0.367	0.482	0.000	1.000
Bdind	3,600	0.379	0.053	0.333	0.571
RnD	3,600	0.023	0.025	0.000	0.154

4.2. Correlation Analysis

Table 3 presents the Pearson correlation coefficients among the variables. Human-AI collaboration shows a positive and significant correlation with Green ESG performance (r = 0.386, p < 0.01), providing preliminary support for H1. Similarly, digitalization intensity is positively correlated with Green ESG performance (r = 0.321, p < 0.01), offering initial support for H2. CSR orientation is also positively correlated with Green ESG performance (r = 0.412, p < 0.01), suggesting firms with stronger social responsibility commitments generally demonstrate better environmental performance. The correlation coefficients among the independent variables are below 0.7, suggesting multicollinearity is not a significant concern in our analysis.

Table 3. Correlation Matrix.

	1	2	3	4	5	6	7	8	9	10	11	12
1. Green_ESG_Perf	1.000											
2. Human_AI_Collab	0.386***	1.000										
3. Digital_Intensity	0.321***	0.542***	1.000									
4. CSR_Orient	0.412***	0.325***	0.289***	1.000								
5. Size	0.275***	0.246***	0.232***	0.347***	1.000							
6. Age	-0.042	-0.127**	-0.144**	0.056	0.215***	1.000						
7. Lev	-0.146**	-0.053	-0.078*	-0.062	0.372***	0.198***	1.000					
8. ROA	0.187***	0.165***	0.147**	0.245***	-0.089*	-0.176***	-0.312***	1.000				
9. Tobin's Q	0.143**	0.218***	0.254***	0.117**	-0.267***	-0.316***	-0.242***	0.375***	1.000			
10. SOE	0.064	-0.187***	-0.216***	0.127**	0.437***	0.326***	0.253***	-0.142**	-0.304***	1.000		
11. Bdind	0.083*	0.045	0.053	0.092*	0.037	-0.025	-0.013	0.057	0.048	0.036	1.000	
12. RnD	0.246***	0.413***	0.386***	0.176***	-0.073*	-0.165***	-0.218***	0.156***	0.324***	-0.218***	0.062	1.000

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

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4.3. Baseline Regression Results

Table 4 presents the results of our baseline regression analyses. Model 1 includes only control variables, Model 2 adds the direct effects of Human-AI collaboration and digitalization intensity, and Model 3 incorporates the CSR orientation and interaction terms.

Table 4. Regression Results for Green ESG Performance.

Variables	Model 1	Model 2	Model 3
Independent Variables			
Human_AI_Collab		0.287***	0.318***
		(0.046)	(0.051)
Digital_Intensity		0.217***	0.245***
		(0.043)	(0.047)
CSR_Orient			0.326***
			(0.053)
Human_AI_Collab × CSR_Orient			0.156***
			(0.042)
Digital_Intensity × CSR_Orient			0.124***
			(0.039)
Control Variables			
Size	0.273***	0.198***	0.163***
	(0.047)	(0.043)	(0.041)
Age	-0.018	0.027	0.019
	(0.032)	(0.029)	(0.028)
Lev	-0.125**	-0.103**	-0.087*
	(0.052)	(0.047)	(0.045)
ROA	0.157***	0.116**	0.083*
	(0.054)	(0.049)	(0.047)
Tobin's Q	0.098**	0.056	0.042
	(0.046)	(0.043)	(0.041)
SOE	0.043	0.076*	0.058
	(0.047)	(0.042)	(0.041)
Bdind	0.068*	0.057	0.051
	(0.037)	(0.035)	(0.034)
RnD	0.215***	0.128***	0.112**
	(0.049)	(0.048)	(0.046)
Constant	-3.873***	-3.125***	-2.876***
	(0.954)	(0.879)	(0.851)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Observations	3,600	3,600	3,600
R-squared	0.179	0.287	0.342
Adjusted R-squared	0.163	0.269	0.322
F-statistic	12.64***	18.53***	22.47***

Note: Standard errors in parenthese**s. *, **, and *** indic**ate significance at the 10%, 5%, and 1% levels, respectively.

The results from Model 2 indicate that Human-AI collaboration has a positive and significant effect on Green ESG performance ($\beta = 0.287$, $p < 0.01$), supporting H1. Similarly, digitalization intensity demonstrates a positive and significant relationship with Green ESG performance ($\beta = 0.217$, $p < 0.01$), supporting H2.

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Model 3 results reveal that CSR orientation has a positive and significant direct effect on Green ESG performance (β = 0.326, $p < 0.01$). More importantly, the interaction term between Human-AI collaboration and CSR orientation is positive and significant (β = 0.156, $p < 0.01$), suggesting that CSR orientation strengthens the positive relationship between Human-AI collaboration and Green ESG performance. Similarly, the interaction between digitalization intensity and CSR orientation is positive and significant (β = 0.124, $p < 0.01$), indicating that CSR orientation also enhances the positive impact of digitalization on environmental performance. These findings support H3a and H3b.

Among control variables, firm size consistently shows a positive association with Green ESG performance across all models, suggesting larger firms tend to demonstrate better environmental practices. Leverage has a negative relationship with Green ESG performance, indicating that financially constrained firms may invest less in environmental initiatives. R&D intensity shows a positive association with Green ESG performance, highlighting the importance of innovation capabilities for environmental sustainability.

4.4. Robustness Checks

To ensure the reliability of our findings, we conducted several robustness checks, as reported in Table 5.

Table 5. Robustness Tests.

Variables	Alternative DV	Alternative IV	Alternative Moderator	2SLS	PSM
Human_AI_Collab	0.304***	0.296***	0.327***	0.356***	0.312***
	(0.053)	(0.055)	(0.054)	(0.062)	(0.057)
Digital_Intensity	0.232***	0.228***	0.253***	0.267***	0.239***
	(0.049)	(0.051)	(0.050)	(0.056)	(0.052)
CSR_Orient	0.315***	0.308***	0.335***	0.343***	0.329***
	(0.055)	(0.057)	(0.058)	(0.062)	(0.059)
Human_AI_Collab × CSR_Orient	0.148***	0.142***	0.163***	0.172***	0.154***
	(0.044)	(0.045)	(0.046)	(0.051)	(0.047)
Digital_Intensity × CSR_Orient	0.117***	0.115***	0.129***	0.138***	0.121***
	(0.041)	(0.042)	(0.043)	(0.047)	(0.044)
Control Variables	Included	Included	Included	Included	Included
Year & Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	3,600	3,600	3,600	3,600	3,126
R-squared/Pseudo R-squared	0.326	0.318	0.337	0.331	0.335

Note: Standard errors in parentheses. *** indicates significance at the 1% level. Control variables are included but not reported for brevity.

First, we used an alternative measure of Green ESG performance based on environmental disclosure quality scores from the CSMAR database. Second, we employed alternative measures for our independent variables: patents related to green AI applications for Human-AI collaboration and digital transformation investment ratio for digitalization intensity. Third, we used sustainability committee presence (a dummy variable) as an alternative measure of CSR orientation. Fourth, we addressed potential endogeneity concerns using a two-stage least squares (2SLS) approach with industry-average Human-AI collaboration and digitalization intensity as instruments. Finally, we applied propensity score matching (PSM) to address potential selection bias by comparing firms with similar characteristics but different levels of Human-AI collaboration and digitalization.

Across all robustness checks, the coefficients for our key variables remain positive and statistically significant, confirming the robustness of our main findings.

5. Discussion and Conclusions

5.1. Discussion of Findings

Our empirical results reveal important insights into the relationship between technological integration and environmental sustainability in Chinese listed companies. The positive association between Human-AI collaboration and Green ESG performance supports the theoretical argument that human-machine complementarity can enhance an organization's capacity to address environmental challenges. This finding extends previous research by demonstrating that the value of AI systems extends beyond economic benefits to include environmental sustainability outcomes.

The positive effect of digitalization intensity on Green ESG performance highlights the broader role of digital transformation in enabling sustainable operations. These findings are consistent with the resource dependency perspective, which suggests that digital capabilities enhance an organization's ability to manage environmental dependencies efficiently. The results also align with institutional theory by indicating that digital technologies enable organizations to better respond to institutional demands for environmental responsibility.

The significant moderating role of CSR orientation underscores the importance of strategic intent in directing technological capabilities toward sustainability objectives. This finding supports the natural resource-based view by demonstrating that the environmental benefits of technological integration are maximized when aligned with a firm's broader sustainability strategy. The results suggest that firms with stronger CSR commitments can more effectively leverage Human-AI collaboration and digitalization to enhance environmental performance.

5.2. Theoretical Implications

Our study makes several important theoretical contributions. First, it extends the literature on Human-AI collaboration by establishing a connection to environmental outcomes, an area previously underexplored. By integrating perspectives from resource dependence theory, institutional theory, and the natural resource-based view, we provide a comprehensive theoretical framework for understanding the environmental implications of technological integration.

Second, our findings contribute to the green information systems literature by demonstrating how different forms of digital technology deployment (Human-AI collaboration versus general digitalization) may have distinct environmental impacts. This nuanced understanding advances beyond general assertions about technology's environmental potential to offer more specific insights into the conditions under which such potential is realized.

Third, by identifying CSR orientation as a significant moderator, our study enriches the understanding of organizational factors that enhance the environmental benefits of technological capabilities. This finding bridges the previously separate research streams on corporate responsibility and technological innovation, highlighting important synergies between them.

5.3. Practical Implications

For managers, our findings suggest that investments in AI systems should consider integration with human capabilities rather than focusing solely on automation. Organizations seeking to enhance environmental performance through technological means should design systems that leverage complementary human-machine strengths rather than simply replacing human labor with AI.

Our results also indicate that broader digitalization efforts offer environmental benefits, suggesting that digital transformation initiatives should incorporate sustainability objectives alongside traditional efficiency and productivity goals. The positive moderating effect of CSR orientation highlights the importance of embedding sustainability into corporate strategy to maximize the environmental returns on technological investments.

For policymakers, our findings suggest that policies encouraging responsible AI development and digital transformation could yield environmental benefits alongside economic ones. Incentives

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for organizations demonstrating both technological innovation and environmental responsibility might prove particularly effective in promoting sustainable development.

5.4. Limitations and Future Research

Despite its contributions, our study has several limitations that suggest directions for future research. First, while our panel data approach strengthens causal inference, experimental studies could further isolate the effects of specific Human-AI collaboration approaches on environmental outcomes. Second, our focus on Chinese listed companies limits generalizability, suggesting the need for comparative studies across different institutional contexts. Third, our aggregated measures of Green ESG performance could be decomposed in future research to examine whether Human-AI collaboration and digitalization affect different environmental dimensions (e.g., emissions, resource efficiency, biodiversity) differently.

Future research could explore the micro-foundations of Human-AI collaboration for sustainability by examining how specific AI applications and collaboration models influence environmental decision-making and implementation. Additionally, longitudinal studies tracking the co-evolution of technological capabilities and environmental performance could provide deeper insights into how these relationships develop over time. Finally, research examining potential trade-offs or synergies between environmental and social dimensions of sustainability in the context of AI adoption would be valuable.

5.5. Conclusions

This study provides empirical evidence that Human-AI collaboration and digitalization positively influence Green ESG performance in Chinese listed companies, with these relationships strengthened by CSR orientation. Our findings highlight the potential of technological integration to advance corporate environmental sustainability when appropriately aligned with organizational values and strategy. As organizations continue to navigate dual pressures for technological advancement and environmental responsibility, understanding how to harness AI and digital technologies for sustainability becomes increasingly crucial. By illuminating the connections between these domains, our study contributes to both scholarly understanding and practical management of the technology-sustainability interface.

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