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Artificial Intelligence, Green Innovation, and Firm Performance: Evidence from Emerging Economies

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Abstract

There are two types of artificial intelligence (AI) – sector-specific and technological – that can contribute to environmental innovation, but each one is context-dependent. Firm-level data are analyzed for firms in selected BRICS Plus countries. The country coverage is based on 2024 technology classifications, 2020-2024 averaged controls and 2015-2024 secondary performance panels. The design combines topic and category classification, averaged firm controls, and panel performance results. The difference in the probability of green-innovation classification was not statistically significant for broad AI classification. Large average differences are rejected by equivalence tests only at the broader pre-specified margin, and matching and weighting estimates are close to zero after improved observed covariate balance. The near-zero average masks important technological and sectoral variation. Industrial automation, as well as the Artificial Intelligence category, machine learning, predictive analytics and process automation, are positively associated with green innovation, whereas the latter is negatively associated after false-discovery-rate adjustment. One possible explanation for this is technological proximity to production: while the AI that relies more on technology than on software can have a more direct impact on energy, materials, process control, and maintenance, the AI that relies more on software has more general functionality and may be used more for commercial, financial, risk, and administrative purposes. The evidence of country interaction is not statistically significant, while the country-level inference is constrained by the common support, and the heterogeneity is more pronounced at the sectoral level. R&D proxies and intangible-capability proxies do not materially strengthen the association between AI-related technological orientation and green-innovation classification, even though AI-classified firms are more R&D-oriented. These findings support a conditional-deployment view: the environmental relevance of AI-related technological orientation depends on application domain, sectoral production architecture, and strategic orientation. Because classifications

are undated, the results should be read as conditional associations rather than causal adoption effects.

Keywords: AI-related technological orientation, green innovation, selected BRICS Plus countries, industrial automation, sectoral heterogeneity, R&D capability, equivalence testing.

1. Introduction

Artificial Intelligence (AI) and environmental innovation are generally considered as central drivers of industrial transformation in emerging economies. AI is increasingly recognized as a family of technologies that can transform prediction, search, experimentation, and organizational learning (Al Halbusi et al., 2025; Lin et al., 2024). Meanwhile, companies face increasing pressure to develop lower-carbon products, cleaner production processes, resource-efficient operations, and circular business models. The policy and managerial rationale for integrating these agendas is clear: AI-based systems can support monitoring, optimize energy and material flows, facilitate predictive maintenance, accelerate research and development (R&D), and improve complex environmental decision-making (Cheng et al., 2024; Lin et al., 2024; Zhu & Liang, 2026).

However, an environmental contribution from AI cannot be assumed. General-purpose technologies provide opportunities across diverse organizational activities, including marketing, finance, logistics, cybersecurity, customer analytics, and production control (Feng et al., 2024; Wu & Zhang, 2025). These uses may increase productivity without necessarily generating green innovation. Furthermore, AI development and deployment can be energy- and compute-intensive, complicating any assumption that AI is environmentally benign by design (Alzoubi & Mishra, 2024; Bolón-Canedo et al., 2024). The central question therefore concerns the conditional-deployment problem: whether AI-related technological orientation is directed toward environmental search, cleaner products, production redesign, and measurable resource-efficiency goals rather than digital capability in general.

Previous empirical research largely supports a positive relationship between AI use, digital transformation, and green innovation, particularly for listed companies in China (Cheng et al., 2024; Lin et al., 2024). Prior studies link AI and digital transformation to green patents, green innovation capability, green innovation efficiency, and manufacturing green-technology performance (Kaack et al., 2022; Ma et al., 2024). Recent research further reveals policy-contingent, nonlinear, and sectoral heterogeneity in this relationship (Wu & Zhang, 2025). The research gap is therefore not only whether AI matters for green innovation, but also which technological forms matter and under what conditions (Nasaj, 2026; Saeed & Bayong, 2026). Three issues remain underdeveloped: evidence beyond China, disaggregation of AI-related technological orientations, and formal treatment of near-zero or offsetting average relationships through equivalence testing, common-support diagnostics, and matching and weighting estimators (Bolón-Canedo et al., 2024; Lin et al., 2024)(Li et al., 2026).

This study addresses these questions across selected BRICS Plus countries: Brazil, China, Egypt, India, Indonesia, Russia, Saudi Arabia, South Africa, and the United Arab Emirates. These economies are heterogeneous in AI infrastructure, industrial maturity, and institutional conditions, so the paper does not treat them as institutionally homogeneous. They are analyzed within a common emerging-economy setting because they share rapid digitalization, industrial-upgrading pressure, and rising sustainability commitments, while the harmonized S&P taxonomy permits comparable firm-level measurement across countries. The pooled coefficient therefore concerns the firm-level average conditional association, not a country-average effect. The main empirical design is a cross-sectional structural analysis based on 2024 S&P Capital IQ Pro topic and category classifications and 2020-2024 averaged firm controls, while the secondary performance analysis uses 2015-2024 panels. Country fixed effects, country-sector support diagnostics, an equal-country-weighted sensitivity model, and country-specific estimates where support is adequate are used to assess whether the pooled result is dominated by China and India. We validate the core and broad AI classifications, decompose AI-related technological orientation into specific elements, and decompose green innovation into clean energy, cleantech, energy efficiency, environmental engineering, pollution control, circular domains, and low-carbon products. Throughout the manuscript, orientation-green linkage refers to the adjusted relationship between AI-related technological orientation and green-innovation classification.

The results indicate no consistent average link between broad AI classification and green-innovation classification. The estimated association is small and statistically indistinguishable from zero. This average, however, masks substantive heterogeneity. After false-discovery-rate correction, industrial automation has a positive association with green innovation (Ashraf et al., 2025(Feng et al., 2024; Lin et al., 2024), while the Artificial Intelligence, machine learning, predictive analytics, and process automation categories have negative associations. This is not a statement about reducing firms' greenness, but rather, such software tools can be used primarily to predict, price, assess risks, manage platforms, or optimize administration. The orientation-green linkage is stronger than the orientation-country linkage, and is not strengthened by observed R&D or by intangible-capability proxies, but rather by sectoral heterogeneity (Cheng et al., 2024; Greif et al., 2024; Kaack et al., 2022). Exploratory performance models also demonstrate that there is not necessarily complementarity between the current AI-related and the green classifications.

The study makes four contributions to the literature on AI, green innovation, and emerging-economy firm-performance. First, it examines green innovation in the broader context of AI rather than considering whether the technology in question is differently associated with green innovation. Second, it uses a harmonized S&P Capital IQ Pro taxonomy for the selected BRICS Plus countries, extending evidence beyond single-country samples. Third,

it provides false-discovery-rate control, common-support diagnostics, matching and weighting estimators, and equivalence testing as methods for treating the near-zero average as an inferential object. Fourth, it presents a conditional-deployment view, and the AI-related technological orientation has environmental relevance only when the technical form, the sectoral architecture, and the strategic orientation are aligned.

The paper proceeds as follows. Section 2 presents the literature review and formulation of hypotheses. Section 3 presents data, measures, and the empirical approach. Results of this study are presented in Section 4. The findings are discussed relative to previous studies in Section 5. Theoretical, managerial and policy implications are developed in Section 6. Section 7 discusses the limitations and future research directions.

2. Literature Review and Hypotheses Development

2.1 Environmental Sustainability, Digital Transformation, and Green Innovation

The increasing pressure from climate change, resource limitations, and environmental regulation has made environmental sustainability increasingly central to the agenda of policymakers and firms. The eco-innovation literature thus focuses on product, process and organizational innovations with the objective of lowering environmental impacts (Osei & Amoah, 2026; Wu et al., 2026). Pollution prevention, product stewardship and sustainable development are all conceptualized as capabilities that can be strategically valuable, as supported by the natural-resource-based view. Digital-transformation research introduces a technological pathway: digital systems can enhance the monitoring, production efficiency, energy management, and experimentation (Wang et al., 2024; Xu et al., 2026). However, this literature also presents the key conflict driving the present study. While digital capability contributes to the firm operational capability, it does not necessarily mean the direction of the firm's digital capability is toward green innovation, as the same infrastructure can be applied to different objectives, such as commercial or operational (Ashraf & Ghazali, 2026; Han et al., 2024; Xu et al., 2023). Theoretically, it is now a directional problem of capabilities, rather than possession.

2.2 AI as General-Purpose Innovation Technology

General-purpose technologies can be used in a broad range of downstream uses, and AI is similar in that it reduces the cost of prediction, search, experimentation, or knowledge recombination. Recent evidence also suggests that a strategic AI orientation can link to more general technological innovation, when managerial attention, skills, infrastructure, and governance are aligned with it (Greif et al., 2024; Qu et al., 2026), and that inventions using AI can combine knowledge from distinct technological fields. These mechanisms suggest a plausible positive pathway towards environmental innovation, as AI can facilitate equipment diagnosis, energy savings, cleaner design and scientific search (Wang & Zhong, 2024; Yao et al., 2025). However, the general nature of the concept of environmental AI also renders any automatic presumption of it less convincing (Al Halbusi et al., 2025; Yavuz et al., 2023). A company can be AI-oriented without being involved in

environmental innovation, such as using prediction, automation or analysis to generate sales, financial or customer management data, cybersecurity or other functions (Cheng et al., 2024; Xiao et al., 2026). In addition to consuming organizational resources, deployment of AI also requires computing resources and energy usage. The question that is relevant is therefore not whether there is an AI label, but whether the AI capability is being directed towards environmental search and implementation.

2.3 Technology-Specific Deployment: Analytical AI Versus Operational Automation

The categories under the umbrella of AI have varying degrees of proximity to production. Based on the research of authors, the environmental significance of industrial automation can be manifested through mechanisms including waste reduction, process stability, energy optimization, predictive maintenance, and equipment modernization (Xu et al., 2024; Zhou et al., 2024). In contrast, the Artificial Intelligence category and machine learning, and predictive analytics are functionally general and can be applied in sales, finance, customer analytics, risk management and supply chain forecasting, just as they can be used in environmental management (Lyu et al., 2023; Ye et al., 2023). The difference should not be viewed as an antagonism between analytical AI and green orientation. Instead, it suggests that a technology label can refer to a highly diverse set of organizational uses (Rodriguez-Garcia et al., 2026). Recent findings of an inverted U-shaped relationship between CEO AI orientation and green innovation also indicate that the advantages of increased AI orientation may be accompanied by increased costs of resources and attention at higher levels of AI orientation (Chun & Hwang, 2025; Liang et al., 2025; Tao et al., 2024). The findings suggest that a technology-specific view on the conditional deployment of AI is needed instead of a general, undifferentiated AI effect.

2.4 Sectoral Conditions and Complementary Capabilities

The sectoral production architecture also plays a pivotal role in ensuring digital-green recombination. The complementarity theory suggests that the value of organizational practices depends on the presence and alignment of other practices. AI can be used more directly in manufacturing and product-oriented industries with machines, materials, energy systems, product design and process control, leading to further pathways to environmental outcomes (Li et al., 2024; Tao et al., 2024). AI may play a more pivotal role in business operations in information-driven industries, but less directly tied to environmental products or production processes (Han et al., 2024; Jin & Wang, 2025; Saeed & Bayong, 2026). Accordingly, sector can be considered a structural boundary condition instead of a nuisance control. The managerial argument of resource-orchestration aligns with this logic: firms need to assemble and coordinate technological, human, and organizational assets in pursuit of a particular goal before a general-purpose technology can turn into an environmentally valuable capability (Cheng et al., 2024; Feng et al., 2024; Zhu & Liang, 2026).

Dynamic-capabilities theory provides a related but distinct mechanism. R&D resources, knowledge-recombination routines, and intangible assets can help firms sense opportunities, seize them through investment, and reconfigure operations (Nasaj, 2026; Priya, 2026). Prior AI and green-innovation studies therefore emphasize R&D, human capital, and financing as potential enabling resources (Alemu, 2026; Bi, 2026; Hao et al., 2026). However, capability stock is not equivalent to capability orientation (Al Halbusi et al., 2025; Maug, 2026). Greater R&D can increase general innovation without increasing the share devoted to environmental problems. Complementarity, dynamic-capabilities, and resource-orchestration arguments imply that AI's environmental association should depend on where the technology is deployed and whether organizational resources are directed toward green objectives (Ma et al., 2024; Wu & Zhang, 2025).

2.5 Hypotheses of the Study

The theoretical mechanisms imply neither a universal positive effect nor a universal negative effect. AI can expand search, prediction, and operational control, but it can also be directed toward non-environmental uses and compete for limited organizational resources. We therefore formulate two-sided and conditional hypotheses that are anchored in dynamic capabilities, complementarity, and resource-orchestration reasoning. Robustness checks are treated as identification and validation checks in Section 3 rather than conceptual hypotheses.

- H1. Broad AI-related technological orientation is associated with green-innovation classification, although the direction is theoretically ambiguous.
- H2. The AI–green association varies across technologies, with more favorable associations expected for industrial automation than for general analytical AI.
- H3. The AI–green association varies across sectors, with less favorable associations expected in digitally intensive sectors.
- H4. AI classification is associated with innovation capabilities, which condition the AI–green association.
- H5. Joint AI-related and green classifications exhibit non-additive associations with firm performance.

3. Data and Empirical Strategy

3.1 Data Source, Coverage, and Unit of Analysis

Data were obtained from S&P Capital IQ Pro, the integrated market-intelligence platform of S&P Global Market Intelligence. The extraction combines standardized firm-level financials and operating attributes with S&P firm-level topic tags and category classifications. The primary green-innovation models are cross-sectional snapshot models: financial controls are averaged over 2020-2024, and topic/category strings are taken from the 2024 firm snapshot. Before complete-case restrictions, the resulting firm-level dataset contains 12,524 distinct firms.

The baseline sample requires a valid S&P topic classification and non-missing average log assets, leverage, return on assets (ROA), cash-to-assets, firm age, country, and sector. R&D-intensity analyses use firms reporting R&D intensity, while intangible-intensity analyses use firms with available intangible-intensity measures. The common-support comparability sample is defined by country-sector overlap between AI-classified and non-AI-classified firms. Panel observation counts vary by outcome availability. These panel counts refer to firm-year observations in secondary performance models rather than the baseline firm count.

The geographic extract covers Brazil, China, Egypt, India, Indonesia, Russia, Saudi Arabia, South Africa, and the United Arab Emirates. The BRICS Plus setting is analytically salient because emerging economies are simultaneously experiencing accelerated digitalization and growing sustainability pressure, but the countries are not assumed to be homogeneous. China and India account for most observations and provide the strongest empirical overlap between AI-classified and non-AI-classified firms. We therefore use country fixed effects, country-sector common-support rules, country-specific estimates where support is sufficient, and an equal-country-weighted sensitivity specification that gives each country the same total weight. The latter check directly tests whether the pooled broad-AI result is driven mechanically by the much larger Chinese and Indian samples.

Table 1: Sample Construction and Classification Frequencies

Panel / construct	Item	Firms / Observations	Share or Note
Panel A: Samples	Unique firms after 2020-2024 collapse	12,524	Firm-level analytic file
	Baseline complete-case sample	11,740	Primary cross-sectional models
	R&D intensity sample	6,071	R&D reporters
	Intangible intensity sample	9,518	Intangible reporters
	Country-sector common-support sample	9,142	77.87% of baseline
	Correlated random-effects ROA panel	92,652	11,942 firms
	Correlated random-effects labor-productivity panel	69,281	10,726 firms
	Correlated random-effects revenue-growth panel	92,059	11,834 firms
Panel B: AI Components	Artificial intelligence	213	1.76%
	Industrial automation	551	4.54%
	Machine learning	138	1.14%
	Predictive analytics	125	1.03%
	Process automation	182	1.50%
	Robotics/other automation	13	0.11%
Panel C: Green Domains	Circular domain	202	1.66%
	Clean energy	401	3.30%
	Cleantech	381	3.14%
	Energy efficiency	136	1.12%
	Environmental engineering	174	1.43%
	Low-carbon products	53	0.44%
	Pollution control	111	0.91%

Notes. The table documents the analytic sample and the frequency of the technology and green-innovation classifications used in the main analysis. Component shares are calculated among tagged firms. The common-support sample requires at least three AI-classified and three non-AI-classified firms in the same country-sector cell, so later comparability estimates are based on firms with observable overlap. Panel observation counts vary because performance outcomes have different missing-data patterns.

3.2 Measurement of AI and Green Innovation

S&P topic and category strings are converted into transparent binary classifications using exact term matching. Core AI classification equals one if a firm is tagged for artificial

intelligence, machine learning, or predictive analytics. Broad AI classification additionally includes industrial automation, process automation, and robotics/other automation. Core AI and broad AI are estimated in separate model families because core AI is nested within broad AI. We reconstruct these measures from the topic strings and verify consistency with the stored core and broad AI measures among tagged firms, thereby clarifying the content of each composite.

Green innovation is defined from S&P topics/categories covering clean energy, green technology, energy efficiency, environmental engineering, pollution control, circular/recycling domains, and low-carbon products (Dhayal et al., 2024; Song et al., 2024). The main dependent variable is a binary green-innovation classification. Because this is a classification rather than a count of patents or emissions outcomes, the estimand is an adjusted difference in the probability that a firm is classified within a green-innovation domain.

A central identification limitation follows from the source taxonomy. AI, green, and circular classifications are snapshots without adoption dates. In the empirical results, we therefore use AI-classified and reserve AI adoption for prior studies with temporally explicit measures. The design does not identify a before-after adoption effect, so all estimates should be interpreted as conditional associations.

3.3 Baseline Models and Controls

A linear probability model (LPM) of green-innovation classification on broad AI classification is used as a baseline specification. The coefficient is interpretable as an adjusted probability difference. The dependent variable is binary and functional-form risk is explicitly assessed (1,594 of 11,740 fitted LPM values outside [0,1] interval, so logit model with an average marginal effect is reported as a robustness check). The logit average marginal effect is close to the LPM estimate, which mitigates any concerns of a main conclusion being due to the linear probability functional form. To avoid overfitting due to low frequency in the subcategories, subcategories are estimated individually and not jointly; inferences are then evaluated using false-discovery-rate (FDR) adjustment. Only 13 firms are included in the Robotics/other automation category and so it is not treated as a stable ranked effect. Average log assets, leverage, ROA, cash-to-assets, firm age, and sector and country fixed effects are common to all primary firm-level models, with heteroskedasticity-robust standard errors for all regressions (Greif et al., 2024; Lin et al., 2024). Firm-level clustering is not applicable to the primary data set, but rather firm-clustered standard errors are used in the secondary repeated firm-year performance models. Core and broad AI are estimated separately in model families as core AI is a subset of broad AI.

3.4 Heterogeneity and Capability Tests

The heterogeneity analysis is an interaction between broad AI and three binary moderators: pollution intensive (Energy, Industrials, Materials, and Utilities); digital intensive (Information Technology and Communication Services); and above median (log of assets) firm size. Additional models examine the interaction of AI and standardized R&D intensity, and standardized intangible intensity. The joint AI-by-country and AI-by-sector tests are complemented by subgroup regressions only if there are 20 or more AI-classified and 20 or more non-AI-classified firms. Innovation capability is measured using three outcomes: reporting of R&D intensity, standardized R&D intensity of the reporters and standardized intangible intensity. Logit average marginal effects are used for the R&D reporting. We estimate an inverse-probability-of-R&D-reporting weighted sensitivity model of reporting using baseline firm characteristics, country and sector because R&D intensity is observed for 6,071 of the 11,740 baseline firms. The 1st and 99th percentiles of the weights are trimmed to reduce the effect of extreme weights. No conventional Heckman correction is performed because the focal green-innovation outcome is dichotomous and the data at hand do not offer a defensible exclusion restriction for R&D reporting. For this sensitivity check, we consider the observed selection into the subsample of firms reporting R&D, but do not rule out unobserved selection.

3.5 Matching, Weighting, and Common Support

To test whether the baseline result reflects the observable selection process we require country-sector cells with sufficient AI-classified and non-AI-classified firms. In this common-support sample, the main comparisons panel includes contrasts labeled with ATET, using Mahalanobis nearest-neighbour matching with exact country and sector matching, propensity-score matching, inverse-probability weighting, and IPW regression adjustment. Another version of the AIW, where the available implementation reports the ATE rather than ATET, is estimated separately in a different-estimand robustness check as a separate panel. Propensity scores are estimated using the baseline covariates and country and sector indicators. Overlap is visually reviewed and standardized mean differences (SMDs) are used to provide a measure of balance, with values near zero suggesting a better observed balance (Hripcsak et al., 2025; Wan et al., 2024). While these are covariate-adjusted comparisons and not treatment causal estimators, they remain noncausal estimators due to unobserved confounding, the fact that the broad AI category is not monolithic in its content, and the lack of date information for when the content was adopted.

3.6 Firm-Performance Models

We examine whether joint AI-related-orientation and green-innovation classifications are associated with firm performance using two complementary designs. First, 2020-2024 firm-mean models relate the AI-by-green interaction to average ROA, log labor productivity, and revenue growth. Second, annual 2015-2024 panel models use correlated random effects (CRE) specifications that include both time-varying controls and their firm

means, together with year, country, and sector indicators and firm-clustered standard errors for repeated firm-year outcomes (Kumar & Shukla, 2026; Wooldridge, 2019).

The performance analysis is secondary. Because AI and green classifications are static snapshots, these models estimate conditional performance differences associated with firm type; they do not imply that AI or green innovation caused changes in revenue growth, productivity, or profitability. The performance analysis should therefore be interpreted as comparing historical performance profiles of firms with different current technological orientations rather than estimating performance effects of AI-related transformation.

3.7 Analysis Protocol, Equivalence Testing, and Multiplicity Control

The written protocol was created prior to the review of the associated coefficients and was used for the supplementary analyses. The protocol was used to establish the order of measurement validation, heterogeneity, capability, matching and weighting, circularity, performance and equivalence analyses. However, the protocol was not preregistered, so it did not eliminate flexibility in choosing from these specifications. A set of two one-sided equivalence tests (TOST) with pre-specified margins of ±0.02 (in probability units) and ±0.03 (in probability units) are performed and the 80% minimum detectable effect (Lakens, 2017) is calculated for the baseline broad-AI estimate. These margins are reported transparently rather than described in the generic terms ‘small,' because the overall prevalence of green-innovation is around 7.9%. The narrowest margin, ±0.02, is the more stringent test while the wider margin, ±0.03, is interpreted only as indicating average differences of about three percentage points or more. The confidence interval and substantive scale of the outcome are complementary to equivalence testing.

4. Results

4.1 No Consistent Average Green-Innovation Premium for Broad AI Classification

The baseline broad-AI coefficient suggests a small difference in probability of being classified as green-innovation. The associated confidence interval includes zero, but the estimate does not suggest a general positive green-innovation premium for the pooled sample based on broad AI-related technological orientation. The logit specification yields an average marginal effect of 0.00423 (SE = 0.00836, p = 0.613; 95% CI: [-0.01216, 0.02061]), which closely matches the LPM result despite out-of-range fitted values. Results differ for specific AI measures. The negative association between Core AI classification and green innovation is statistically significant, while AI share is not statistically significant. The negative relationships between Core AI classification and green innovation and between continuous AI score and green innovation are statistically significant. This sensitivity suggests that the broad indicator includes technologies that have varying environmental linkages.

Table 2: AI Definitions and Component-Level Associations with Green Innovation

AI measure	N	Effect	SE	P	FDR q	95% CI
Core AI Classification	11740	-0.05133	0.00783	<0.001	<0.001	[-0.06669, -0.03598]
Broad AI Classification	11740	0.00616	0.01071	0.565	0.565	[-0.01483, 0.02714]
AI Score	11740	-0.00785	0.00479	0.102	0.136	[-0.01724, 0.00155]
AI Share	11740	-0.08333	0.01708	<0.001	<0.001	[-0.11681, -0.04984]
Artificial Intelligence	11740	-0.06044	0.00795	<0.001	<0.001	[-0.07603, -0.04486]
Machine Learning	11740	-0.05219	0.00989	<0.001	<0.001	[-0.07158, -0.03280]
Predictive Analytics	11740	-0.04399	0.00948	<0.001	<0.001	[-0.06257, -0.02541]
Industrial Automation	11740	0.04213	0.01552	0.0067	0.0067	[0.01171, 0.07255]
Process Automation	11740	-0.04382	0.01429	0.0022	0.0026	[-0.07182, -0.01581]
Robotics/Other Automation	11740	-0.09727	0.01547	<0.001	<0.001	[-0.12760, -0.06695]

Notes. Entries report adjusted probability differences from linear probability models with robust standard errors, firm controls, country fixed effects, and sector fixed effects. FDR q-values are Benjamini-Hochberg adjustments within the AI-definition or AI-component family. The contrast between broad AI and the individual components shows why the pooled estimate should not be interpreted as a uniform AI effect. Robotics/other automation is very sparse (13 firms) and should be treated only as a descriptive signal.

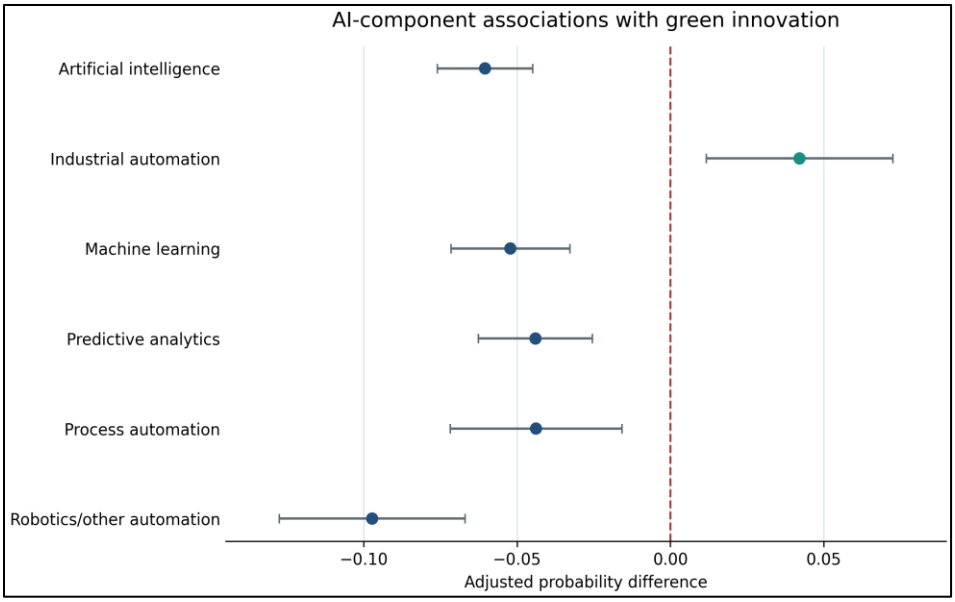

Figure 1: AI-Component Associations with Green Innovation (Industrial automation is the only component with a positive adjusted association; the remaining estimated components are negative)

Figure 1 presents the component decomposition. Industrial automation is positively associated with green classification, whereas the Artificial Intelligence category, machine learning, predictive analytics, and process automation are negative after FDR adjustment. These opposing component associations are consistent with the near-zero estimate obtained when the categories are combined. The robotics/other automation estimate is not interpreted substantively because the category is very sparse. This caution also reduces the risk of overinterpreting sparse-category estimates.

4.2 Broad AI Classification - Selectively Associated with Green Domains

The green-domain decomposition yields a selective rather than pervasive pattern. Broad AI classification is negatively associated with the circular domain, while environmental engineering is negative before but not after FDR adjustment. Clean energy, cleantech, energy efficiency, pollution control, and low-carbon products are statistically indistinguishable from zero. The broad AI measure therefore does not map uniformly onto environmental technology domains.

Table 3: Broad AI Classification and Specific Green-Innovation Domains

Green domain	N	Effect	SE	P	FDR q	95% CI
Circular Domain	11740	-0.01202	0.00291	<0.001	<0.001	[-0.01771, -0.00632]
Environmental Engineering	11740	-0.00952	0.00416	0.022	0.077	[-0.01767, -0.00137]
Energy Efficiency	11740	0.00589	0.00531	0.267	0.495	[-0.00451, 0.01629]
Pollution Control	11740	0.00495	0.00461	0.283	0.495	[-0.00409, 0.01399]
Low-Carbon Products	11740	-0.00112	0.00142	0.428	0.525	[-0.00390, 0.00165]
Cleantech	11740	0.00570	0.00755	0.450	0.525	[-0.00909, 0.02050]
Clean Energy	11740	0.00331	0.00749	0.658	0.658	[-0.01137, 0.01800]

Notes. Each row estimates a separate green-domain model using the same baseline controls and country and sector fixed effects. FDR q-values are calculated within the green-domain family. These estimates show whether broad AI classification maps onto particular environmental domains rather than the overall green-innovation composite.

4.3 Strong Sector Heterogeneity – Weak Country Heterogeneity

The joint AI-by-country test is suggestive but not statistically conclusive. Under the minimum-support rule, only China and India support country-specific regressions, and both estimates are close to zero. National differences therefore do not explain the principal heterogeneity observed in this sample.

Sector heterogeneity is much stronger. The joint AI-by-sector test is highly significant. Consumer Discretionary exhibits a positive association, while Information Technology exhibits a negative association. The interaction for digital-intensive sectors is also negative, whereas interactions for pollution-intensive sectors and large firms are not significant. The evidence therefore points toward sectoral production architecture, rather than firm size or broad pollution intensity, as the primary observable boundary condition.

Table 4: Heterogeneity in the Orientation-Green inkage

Moderator / Sub-group	N	Effect	SE	P	FDR q	95% CI
AI x Digital-Intensive Sector	11740	-0.06194	0.01921	0.0013	0.0038	[-0.09960, -0.02427]
AI x Pollution-Intensive Sector	11740	0.03163	0.02371	0.182	0.252	[-0.01485, 0.07811]
AI x Large Firm	11740	0.02177	0.01902	0.252	0.252	[-0.01552, 0.05906]
Digital-Intensive = 1	1729	-0.02646	0.01118	0.018	0.108	[-0.04838, -0.00453]
Digital-Intensive = 0	10011	0.02877	0.01593	0.071	0.213	[-0.00247, 0.06000]
Pollution-Intensive = 1	4763	0.01677	0.02140	0.433	0.744	[-0.02518, 0.05872]
Pollution-Intensive = 0	6977	0.00009	0.01041	0.993	0.993	[-0.02031, 0.02049]
Large Firm = 1	5870	0.01049	0.01541	0.496	0.744	[-0.01971, 0.04069]
Large Firm = 0	5870	-0.00055	0.01399	0.968	0.993	[-0.02799, 0.02688]
China	5617	0.00305	0.01333	0.819	0.843	[-0.02307, 0.02918]
India	4129	-0.00409	0.02069	0.843	0.843	[-0.04466, 0.03648]
Consumer Discretionary	1795	0.08864	0.03360	0.0084	0.042	[0.02273, 0.15455]
Information Technology	1278	-0.03056	0.01308	0.0196	0.049	[-0.05622, -0.00490]
Financials	1089	-0.00528	0.00323	0.102	0.171	[-0.01162, 0.00106]
Communication Services	451	0.00041	0.00069	0.553	0.692	[-0.00094, 0.00176]
Industrials	2451	0.00115	0.02236	0.959	0.959	[-0.04270, 0.04500]

Notes. Interaction rows test whether the broad AI-green association differs by sectoral or firm characteristics; subgroup rows report within-group estimates only where minimum support is satisfied. Joint tests indicate weak country heterogeneity ($p=0.0843$) but strong sector heterogeneity ($p<0.001$). Estimates are adjusted probability differences and should be interpreted as conditional associations, not causal treatment effects.

4.4 AI-Classified Firms more R&D-Oriented - Capability not Strengthening the Orientation-Green Linkage

AI-classified firms are more likely to report R&D intensity and, among reporters, are associated with higher R&D intensity, whereas they are unrelated to standardized intangible intensity. These patterns are consistent with a stronger general innovation orientation, particularly toward R&D; the near-zero orientation-green estimate is not readily explained by lower observed R&D intensity among AI-classified firms. The moderation evidence does not show that the observed capability proxies strengthen the environmental alignment of AI-related technological orientation. The AI-by-R&D interaction is negative and marginal in the raw test but not after FDR adjustment. The AI-by-intangibles interaction is essentially zero. Conditional on R&D reporters, standardized R&D intensity itself is slightly negatively associated with green classification. Thus, more general R&D is not synonymous with more environmentally directed innovation in this sample.

Table 5: Innovation-Capability Outcomes and Moderation

Outcome / Focal Term	N	Effect	SE	P	FDR q	95% CI
AI Classification and R&D Reporting (AME)	11740	0.06785	0.01163	<0.001	<0.001	[0.04506, 0.09064]
AI Classification and Standardized R&D	6071	0.17607	0.03736	<0.001	<0.001	[0.10283, 0.24930]
AI Classification and Standardized Intangibles	9518	0.00160	0.03388	0.962	0.962	[-0.06481, 0.06802]
AI in Green Model including R&D	6071	-0.00447	0.01263	0.724	0.724	[-0.02922, 0.02029]
R&D Association with Green Innovation	6071	-0.00613	0.00273	0.0249	0.0497	[-0.01149, -0.00078]
AI x Standardized R&D	6071	-0.01140	0.00589	0.0531	0.106	[-0.02294, 0.00015]
AI x Standardized Intangibles	9518	-0.00050	0.01072	0.963	0.963	[-0.02152, 0.02052]

Notes. The R&D-reporting coefficient is an average marginal effect from a logit model; all other entries are linear-model coefficients. Interaction q-values are adjusted within the capability-moderation family. The table separates capability possession from environmental direction: AI-classified firms are more R&D-oriented, but R&D and intangible intensity do not make the AI-green linkage more positive.

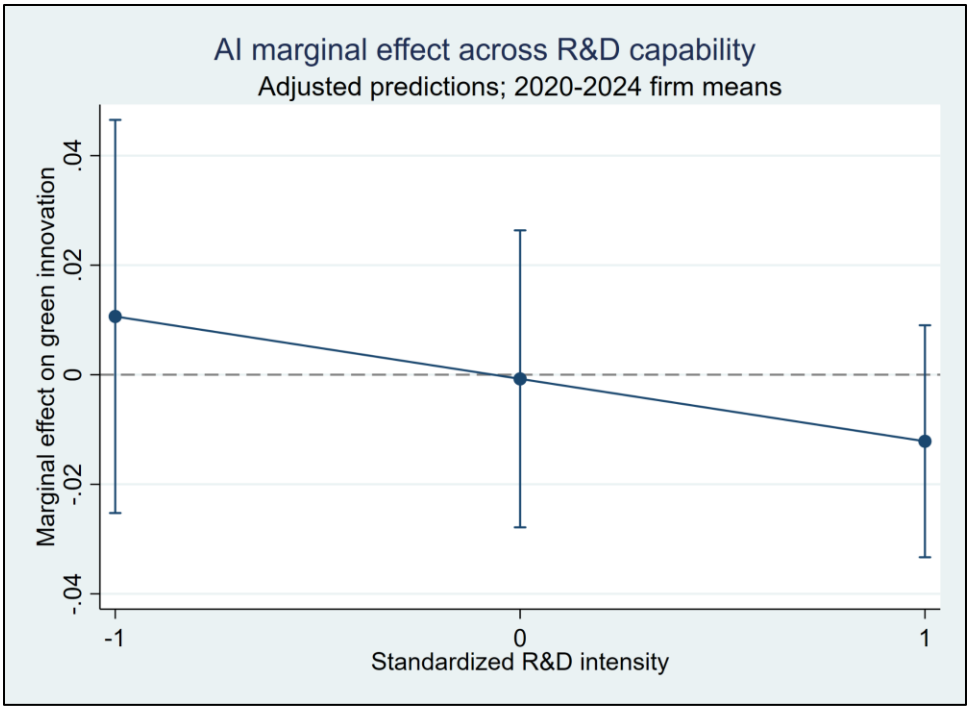

Figure 2: Marginal Effect of AI Classification Across Standardized R&D Intensity

The marginal-effects pattern in Figure 2 declines across the observed R&D-intensity range, but none of the estimates is statistically distinguishable from zero. The figure is therefore consistent with, at most, weak evidence that greater R&D intensity attenuates rather than amplifies the orientation-green linkage.

Because R&D reporting is selective, we also re-estimated the R&D moderation model using inverse-probability-of-reporting weights based on baseline observables. In this sensitivity model, the AI main association is -0.01541 (SE = 0.01363, p = 0.258) and the AI-by-R&D interaction is 0.00463 (SE = 0.00942, p = 0.623). The interaction changes sign relative to the unweighted reporter-only estimate but remains statistically indistinguishable from zero. The stable substantive conclusion is therefore that observed R&D intensity does not reliably strengthen the orientation-green linkage; the exact moderation coefficient is sensitive to how R&D-reporting selection is handled.

Figure 3 shows virtually no moderation by intangible intensity. The estimated AI difference remains close to zero across the observed capability range, with wide intervals spanning zero.

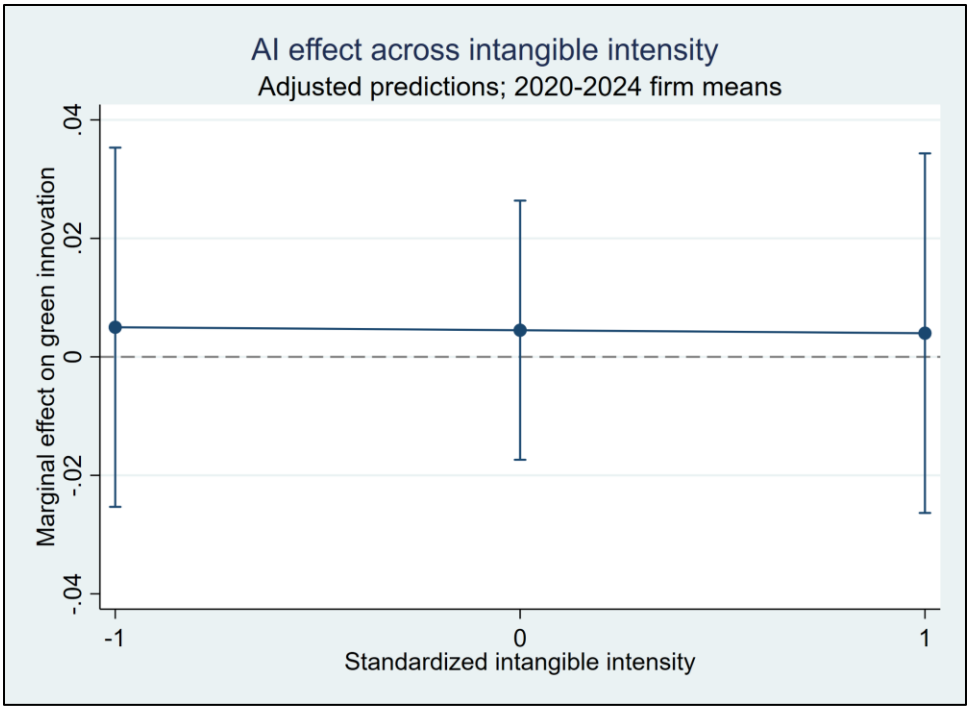

Figure 3. Marginal Effect of AI Classification Across Standardized Intangible Intensity

4.5 Matching, weighting, and balance reinforce the near-zero average association

The common-support restriction retains most of the baseline sample. Exact country-sector nearest-neighbour matching yields a nominally positive ATET, but the estimate does not survive matching-and-weighting-family FDR adjustment. Propensity-score matching, inverse-probability weighting, and IPW regression adjustment produce ATET-labeled contrasts that are statistically indistinguishable from zero. The augmented IPW estimate targets the ATE rather than the ATET in the available implementation and is therefore reported separately as a different-estimand sensitivity check; it is also close to zero. Observed balance improves sharply under weighting. Before weighting, several continuous covariates show meaningful imbalance; after weighting, the reported standardized mean differences are close to zero. The broad conclusion is therefore not driven by one matching or weighting routine, although these procedures address observed rather than unobserved selection.

Table 6: Matching, Weighting, and Observed Covariate Balance

Estimator	Estimand	N	Effect	SE	p	FDR q
Exact Country-Sector NN	ATET	9142	0.02824	0.01389	0.042	0.210
Propensity-Score Matching	ATET	9142	-0.01294	0.01543	0.402	0.832
Inverse-Probability Weighting	ATET	9142	-0.00227	0.01071	0.832	0.832
IPW Regression Adjustment	ATET	9142	-0.00286	0.01072	0.789	0.832
Panel B. Continuous-covariate standardized mean differences						
Covariate			**Before Weighting**		**After Weighting**	
Average Log Assets			0.2602		-0.0065	
Average Leverage			-0.2909		-0.0029	
Average ROA			0.0005		0.0174	
Average Cash			0.3183		-0.0307	
Firm Age			-0.1909		0.0081	

Notes. NN = nearest neighbour; IPW = inverse-probability weighting; IPWRA = IPW regression adjustment. Panel A reports ATET-labeled covariate-adjusted contrasts on the common-support sample so that the main matching/weighting estimates share the same target population. The AIPW estimator available in the analysis reports an ATE and is therefore shown separately in Appendix Table B14 rather than mixed with the ATET panel. Panel B shows standardized mean differences before and after weighting. These estimators address observed selection only; they do not resolve unobserved confounding or the absence of dated AI adoption information.

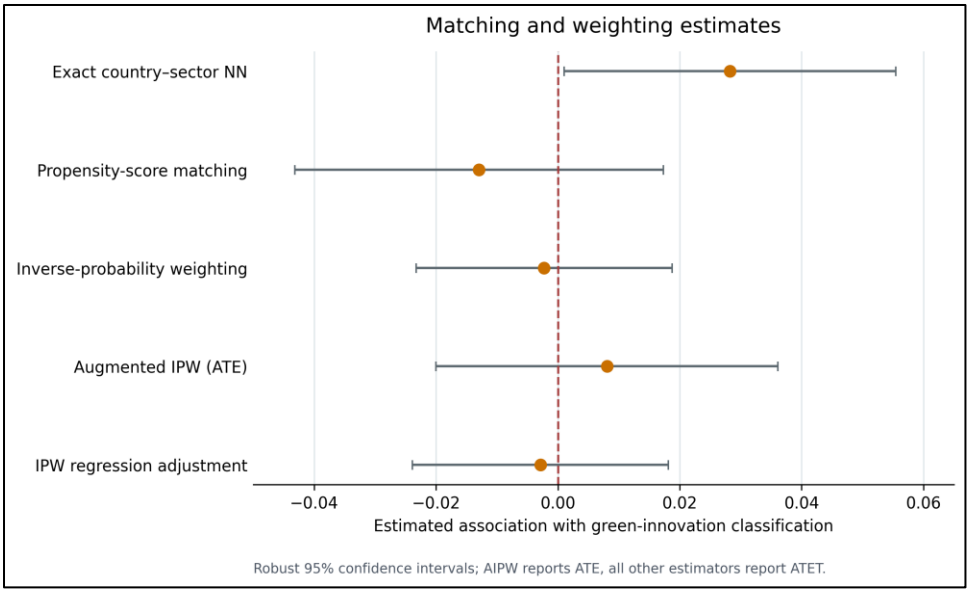

Figure 4: Matching and Weighting Estimates of Orientation-Green Linkage

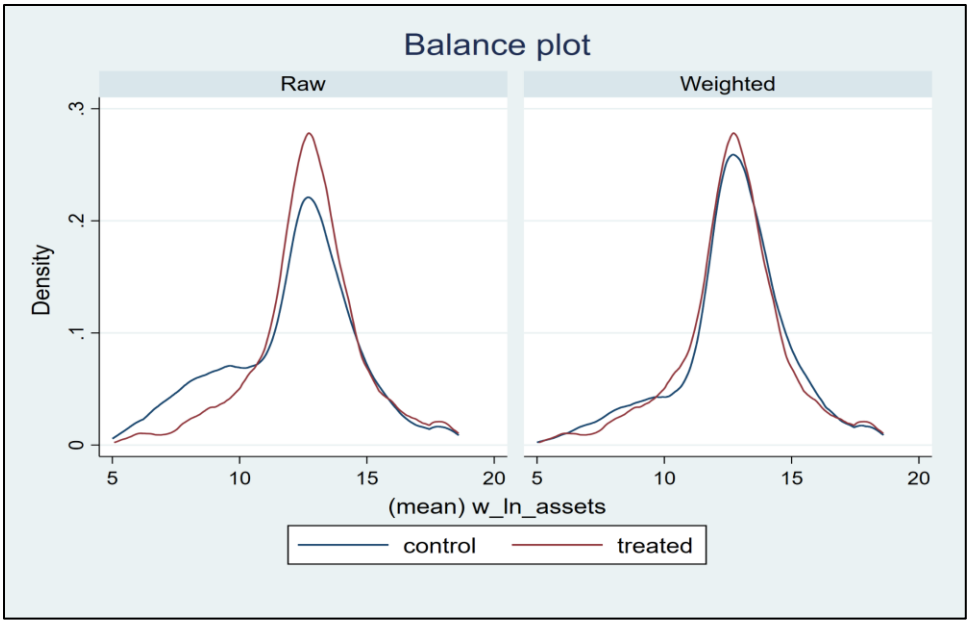

Figure 5: Distributional Balance in Log Assets (before and after weighting)

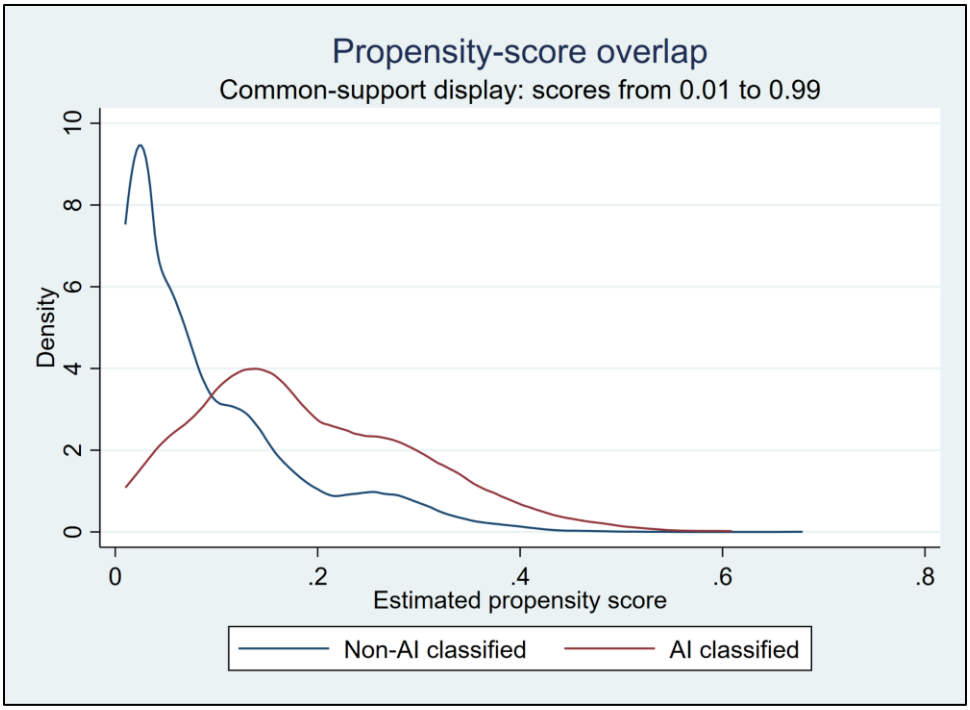

Figure 6: Propensity-Score Overlap (among AI-classified and non-AI-classified firms)

The overlap plot illustrates that the propensity score is systematically associated with the observed characteristics of the firms: non-AI-classified firms are at the lower end of the propensity score distribution, while AI-classified firms are concentrated at the higher end. So the support restriction is of a substantial nature. It also spells out where the comparisons with general AI have clear overlap and where they are weak. Concurrently, weighting provides substantial balance on the reported covariates and the collapse of the IPW, AIPW and IPWRA estimates to zero is an informative robustness finding.

We also estimated the baseline LPM with weights which lead each of the nine countries to contribute equally to the total weighting of the baseline LPM. The broad-AI coefficient remains statistically indistinguishable from zero (0.02366, SE = 0.02770, p = 0.393; 95% CI [-0.03063, 0.07795]). This point estimate is less precise than the unweighted result since the smaller national samples are given more weight, but it does not provide an indication of an underlying pooled association. This sensitivity check confirms the conclusion that the headline near-zero result is not entirely mechanical in nature, as a result of the Chinese and Indian sample shares.

4.6 Mixed Exploratory Performance Associations (do not indicate automatic complementarity between AI-related and green orientations)

The firm-mean models yield few indications of improved profitability or labor productivity of the jointly AI- and green-classified firms. AI-by-green interaction is negative for average revenue growth, but it is not FDR adjusted, and the interactions between AI and average ROA and AI and log of labor productivity are not statistically significant.

The models give a more complex curve of revenue growth on the panel. Annual revenue growth for AI classification and green classification are both positive, but the effect of the two classifications on one another is negative. But the negative correlation is not necessarily a conclusive indicator that co-classification firms grow less. The fitted joint contrast is 2.81725 + 2.48284 - 5.43039 = -0.13030, and a post-estimation linear combination is statistically insignificant (SE = 1.20566, p = 0.914; 95% CI [-2.49334, 2.23274]). The evidence therefore does not lead to the conclusion of a joint growth penalty, but does not rule out non-additivity of the two primary associations. The plausible competing transformation costs have not yet been proven to be causal explanations and should be considered instead.

Regarding labor productivity, AI classification is negatively associated, green classification is positively associated, and the interaction is close to zero. AI is immaterial and neither is the interaction for ROA. The variations across the outcomes provide a warning not to have a single performance narrative and should be considered exploratory conditional associations.

Table 7: Joint AI-Related and Green Classifications and Firm Performance

Panel / Outcome	Focal term	Obs.	Firms	Effect	SE	P	FDR q
A: 2020-2024 mean	Revenue Growth: AI x Green	11537		-3.3140	1.67831	0.048	0.145
	Log Labor Productivity: AI x Green	10406		-0.0333	0.08237	0.686	0.953
	ROA: AI x Green	11740		-0.0488	0.83044	0.953	0.953
B: CRE 2015-2024	Revenue Growth: AI	92059	11834	2.81725	0.62650	<0.001	<0.001
	Revenue Growth: Green	92059	11834	2.48284	0.63490	<0.001	
	Revenue Growth: AI x Green	92059	11834	-5.4304	1.44205	<0.001	<0.001
	Revenue Growth: Joint AI + Green Contrast	92059	11834	-0.1303	1.20566	0.914	
	Log Labor Productivity: AI	69281	10726	-0.1476	0.03289	<0.001	<0.001
	Log Labor Productivity: Green	69281	10726	0.12709	0.03893	0.001	
	Log Labor Productivity: AI x Green	69281	10726	-0.0114	0.07846	0.885	0.957
	ROA: AI	92652	11942	-0.3401	0.25145	0.176	0.264
	ROA: Green	92652	11942	-0.0410	0.20913	0.845	—
	ROA: AI x Green	92652	11942	-0.0292	0.53610	0.957	0.957

Notes. Panel A uses 2020-2024 firm means. Panel B reports correlated-random-effects (Mundlak) models for 2015-2024 with year, country, sector indicators, time-varying controls, firm means of controls, and firm-clustered standard errors. The revenue-growth joint contrast is the post-estimation linear combination AI + green + AI×green; it is not statistically different from zero. FDR q-values are reported for focal AI and interaction terms where posted; a dash indicates that no family-level q-value was posted for that contrast or green main effect. Static classifications mean the estimates describe performance profiles, not causal performance effects.

4.7 Equivalence Testing Bounds: The Average Association At The Wider Margin

The equivalence results narrow the interpretation but does not demonstrate a zero effect. At the ±0.02 margin, TOST does not establish equivalence ($p = 0.098$), because the 90% confidence interval [-0.01145, 0.02377] extends beyond the positive boundary. At the wider ±0.03 margin, equivalence is supported ($p = 0.013$). Thus, the data rule out average broad-AI differences of approximately three percentage points or larger in either direction under this specification, but they do not rule out differences as large as two percentage points. Because baseline green-innovation prevalence is about 7.9%, a three-percentage-point margin is economically meaningful; the result is therefore best described as bounding very large average associations rather than proving a negligible relationship.

Table 8: Equivalence Tests and Statistical Power for the Baseline Broad-AI Estimate

Equivalence Margin	N	Estimate	SE	90% CI	TOST p	Equivalent?	80% MDE
+/-0.02	11740	0.00616	0.01071	[-0.01145, 0.02377]	0.09799	No	0.02999
+/-0.03	11740	0.00616	0.01071	[-0.01145, 0.02377]	0.01297	Yes	0.02999

Notes. TOST = two one-sided tests. The 90% confidence interval corresponds to two one-sided 5% tests. The ±0.02 margin does not establish equivalence, whereas the wider ±0.03 margin does. Baseline green-innovation prevalence is approximately 7.9%, so ±0.03 should not be described as economically trivial; it bounds average differences of roughly three percentage points or more. The 80% MDE is calculated from the baseline robust standard error.

5. Discussion of Findings

The main result is a tightly bounded average association between broad AI classification and green innovation, with substantial heterogeneity beneath the average. This pattern challenges the technology-determinist proposition that AI is inherently green (Greif et al., 2024). It is more aligned with a conditional-deployment view: environmental alignment varies with the technological form represented, the sector in which the technology is embedded, and the organizational goals to which it is deployed (Chun & Hwang, 2025). This perspective sharpens the natural-resource-based view of digital technologies because perceived advanced-technology orientation does not necessarily represent an environmentally valuable organizational capability. Technology integration is more likely to have environmental value when it changes routines involving materials, energy use, products, clean production, or compliance-related processes.

Initially, the baseline null appears counterintuitive relative to research that finds positive AI-green relationships in Chinese listed companies (Lin et al., 2024). Recent innovation-management evidence also shows that strategic AI orientation can increase technological innovation when AI is embedded in managerial attention, skills, and organizational infrastructure (Tseng & Lin, 2024; Yavuz et al., 2023), while patent evidence indicates that AI can facilitate novel knowledge recombination (Qu et al., 2026). These positive mechanisms are compatible with the present results because our outcome is specifically green classification rather than innovation in general. At the same time, Hao et al. (2026) document an inverted-U relationship between CEO AI orientation and green innovation, highlighting benefits at lower levels and resource constraints at higher levels. This literature collectively reinforces the "as-is" stance of AI potentially increasing innovative capacity, but any resulting increase in innovative capacity is not necessarily green, depending on the AI's deployment domain, the organizational resources, and direction. The S&P Capital IQ Pro measure only measures the existence of a company's classification in a select set of technology fields related to AI at one particular moment, it does not measure a dated adoption event or the intensity of usage. The present cross-country taxonomy is thus an identification of conditional orientation differences, not dynamic adoption effects.

There, the only positive FDR-robust association is with Industrial automation, an area where AI is playing a major role. One possibility is that it is near physical metamorphosis. Many green-process innovations can be found in industrial-automation classifications that are closely related to machines, process control, energy consumption, throughput, defects and material flow (Tseng & Lin, 2024; Yavuz et al., 2023). The sector evidence corroborates this interpretation: Digital sectors might find their main use for AI in software, data, customer analysis or the delivery of services, whereas product and production sectors might be more closely linked to redesigning physical products. This is consistent with previous research which has demonstrated the potential of digital investment and Industry 4.0 to contribute to environmental performance through production efficiency and green innovation. On the other hand, negative analytical-AI coefficients could be a result of companies employing machine learning, predictive analytics, and process automation in other prediction-related fields outside of environment, such as marketing or financial optimization or platform operations.

The second theoretical distinction is drawn from the R&D results. AI-classified companies are more R&D oriented, but the linkage between the orientation and R&D is not reinforced. Innovation capacity, in general, is not the same as green innovation capacity. This distinction is important since much of the AI green innovation literature views the boost in R&D as a means by which AI can benefit green innovation. In this sample, the AI classification is associated with R&D orientation, but not systematically oriented towards green domains, with additional R&D. In future theory, capability acquisition should be separated from capability orientation, and the environmental search routines, green R&D requirements, environmental data infrastructure, and incentive systems should be explored that facilitate or steer AI-based sustainability search processes.

The covariate-adjusted comparability analysis enhances observed comparability. The reported CMEs near zero with weighting as well as the IPW, AIPW, and IPWRA estimates are near zero. This convergence reduces the likelihood that the baseline null is simply the result of the observable difference in size, leverage, profitability, cash holdings, age, country or sector. But matching and weighting won't solve the primary temporal problem: AI classification is not a "mute of the past" metric. Methods can't eliminate unobserved sources of bias such as management quality, environmental strategy, ownership, and regulatory exposure.

The absence of mechanical additivity between the already available AI-related and green classifications is also reflected in the performance of the panel. The interaction between revenue growth is negative but the estimated joint contrast is -0.13030 which is not statistically different from zero ($p = 0.914$). It is thus not a matter of a "simple sum" for firms classified as both in the two groups, it is not a matter of data showing an absolute growth penalty. The negative interaction term is still possible due to resource competition, simultaneous transformations on the resources, organizational change or a lag between

resource investment and payoff, but is not discernable with static classifications, particularly in resource scarce BRICS Plus environments. Additionally, there is no corresponding interaction pattern for ROA and labor productivity, further highlighting the fact that implications for performance of the two variables are outcome-specific.

5.1 Conclusion and Policy Implications

Across the selected BRICS Plus countries, broad AI classification is not associated with a consistent average green-innovation premium. Matching and weighting estimates remain close to zero, the logit and equal-country-weighted sensitivity checks converge on the same conclusion, and equivalence testing rules out large average associations only at the wider ±0.03 margin. The overall pattern is heterogeneous: industrial automation is positively related to green innovation, several analytical AI categories are negatively related, sectoral heterogeneity is pronounced, and R&D capability does not reliably strengthen the orientation-green linkage. Country interaction evidence is not statistically conclusive, but national comparisons are limited because adequate common support is concentrated in China and India. AI-related technological orientation should therefore be viewed as a conditional enabling capability rather than a standalone green-transition mechanism.

5.2 Theoretical Implications

The theoretical contribution moves the manuscript from an average-effect framing to a contingency and resource-orchestration framing. Dynamic-capabilities reasoning explains how AI can expand sensing, search, and reconfiguration capacity, while complementarity theory explains why the value of that capacity depends on alignment with sectoral production systems and other organizational practices. Resource orchestration adds a directional mechanism: firms must structure and deploy technological, human, and R&D resources around environmental objectives before a general-purpose AI capability becomes a green capability. This framing is consistent with the contrast between operationally embedded industrial automation and functionally general analytical AI categories. The R&D evidence further separates capability stock from capability orientation, and the sector results identify production architecture as an observable boundary condition.

5.3 Managerial Implications

The managerial implication is that AI investments are not automatically sustainability investments. AI-related initiatives have greater potential to create environmental gains when they focus on specific process outcomes such as energy efficiency, material yield, defect reduction, predictive maintenance, resource scheduling, or low-carbon product redesign. Companies should manage sustainability-oriented AI initiatives with clear environmental goals, accountable ownership, measurable indicators, regular review, and direct links to product or process redesign. Higher innovation spending will not necessarily increase a firm's green-innovation profile if investments are not environmentally targeted.

5.4 Policy Implications

The policy implication is that public support for AI-related technologies should not automatically be treated as green-transition policy. Automation, digital control, and analytics are more defensible when framed as sector- and application-specific programs when linked to measurable efficiency, emissions, resource-use, or environmental-innovation outcomes. For China and India, where the data provide the strongest firm-level common support, policy can emphasize verifiable cleaner manufacturing and energy-efficient automation. For the UAE and Saudi Arabia, AI programs can be tied to resource-efficiency and diversification objectives; for Brazil, South Africa, Indonesia, Egypt, and Russia, priorities include data infrastructure, sector-specific pilots, and environmental-output reporting. These latter country suggestions are policy interpretations rather than country-specific causal estimates because several national samples lack sufficient common support. Across all countries, program evaluation should distinguish general digital adoption from demonstrated environmental outcomes.

5.5 Limitations and Future Research

First, the S&P AI, green, and circular indicators are undated topic and category snapshots. Because the design cannot determine whether AI-related orientation came before green innovation, causal interpretation is unwarranted. Future research should combine dated AI adoption measures with subsequent green patents, environmental R&D, process efficiency, or emissions outcomes. Second, technological orientation is not the same as innovation output intensity. Green-classified firms may differ substantially in patent quality, investment scale, or realized environmental impact. Construct validity could be strengthened through triangulation with patent citations, capital expenditure, environmental performance, and emissions.

Third, common support varies across countries. China and India provide the most informative country-specific comparisons, while some economies have no country-sector cells satisfying the minimum support rule. The multi-country contribution therefore lies chiefly in a common taxonomy and pooled institutional coverage than in equally precise national effects. Fourth, several AI components are sparse, particularly robotics/other automation. Sparse categories can produce unstable point estimates even when standard errors appear small, so those results should be treated as descriptive signals rather than definitive rankings.

Fifth, the circular-orientation analysis contains a part-whole overlap because circularity is part of the broader green construct. We therefore report those estimates in the Online Appendix and do not interpret them as mediation or structural pathways. Future specifications should build a non-circular green index before analyzing circular complementarity. Finally, matching and weighting address observed selection only. Stronger causal designs could use staggered AI adoption, plant-level robot penetration,

occupational exposure shocks, exogenous changes in digital infrastructure, or policy discontinuities. Such designs would allow the conditional-deployment view to be tested dynamically rather than cross-sectionally.

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Declaration of AI Use

AI-assisted tools were used only for language refinement, grammar correction, sentence restructuring, and improving readability during manuscript preparation. They were not used to collect data, execute the statistical analyses, generate numerical results, or make substantive scientific judgments about the findings. All analyses, citations, interpretations, and conclusions were checked and approved by the authors.

Data Availability

The data will be made available from the corresponding author upon reasonable request.

Declaration of Conflict of Interest

The authors declare no financial competing interests relevant to this study.

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Appendix: Supplementary Results

This appendix reports the full set of focal estimates for the analyses described in the article. Coefficients for controls and fixed effects are omitted unless substantively necessary. All estimates use the S&P Capital IQ Pro extraction described in Section 3. Appendix A reports common-support comparability evidence; Appendix B reports robustness, capability, heterogeneity, and performance estimates; Appendix C defines constructs; Appendix D reports the circular-orientation diagnostic.

Appendix A: Common-Support Comparability Evidence

Table A1: Common Country-Sector Comparability Support by Country

Country	Baseline firms	Supported firms	Supported share
Brazil	327	49	14.98%
China	5617	5480	97.56%
Egypt	194	0	0.00%
India	4129	3287	79.61%

Country	Baseline firms	Supported firms	Supported share
Indonesia	757	257	33.95%
Russia	170	0	0.00%
Saudi Arabia	232	38	16.38%
South Africa	183	31	16.94%
United Arab Emirates	131	0	0.00%
Total	11740	9142	77.87%

Notes. Support requires at least three AI-classified and three non-AI-classified firms within the same country-sector cell. The comparability sample therefore identifies the portion of the BRICS+ extract where observed overlap exists, with China and India providing most supported observations. Countries with zero supported firms are retained in descriptive coverage but cannot anchor country-specific common-support estimates.

Appendix B: Robustness, capability, heterogeneity, and performance estimates

Table B1: Capability Outcomes

Model / Effect	Subgroup	N	Estimate	SE	P	FDR q
AI and R&D Reporting AME	Baseline	11740	0.06785	0.01163	<0.001	<0.001
AI and Standardized R&D	R&D reporters	6071	0.17607	0.03736	<0.001	<0.001
AI and Standardized Intangibles	Intangible reporters	9518	0.00160	0.03388	0.962	0.962

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. The table is intended to document mechanism-relevant capability patterns rather than stand-alone causal effects.

Table B2: Capability-Adjusted Green Models

Model / effect	Subgroup	N	Estimate	SE	P	FDR q
R&D Association with Green	R&D reporters	6071	-0.00613	0.00273	0.0249	0.0497
Green Model Including R&D: AI	R&D reporters	6071	-0.00447	0.01263	0.724	0.724

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. These models test whether R&D adjustment changes the AI-green association among R&D-reporting firms.

Table B3: Binary Moderator Interactions

Model / effect	Subgroup	N	Estimate	SE	P	FDR q
AI x digital-intensive	Interaction	11740	-0.06194	0.01921	0.0013	0.0038
AI x pollution-intensive	Interaction	11740	0.03163	0.02371	0.182	0.252
AI x large firm	Interaction	11740	0.02177	0.01902	0.252	0.252

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. Interaction terms evaluate whether the broad AI-green association differs by digital intensity, pollution intensity, or firm size.

Table B4: Binary Subgroup Estimates

Model / effect	Subgroup	N	Estimate	SE	P	FDR q
AI Within Digital-Intensive	digital=1	1729	-0.02646	0.01118	0.018	0.108
AI Within Digital-Intensive	digital=0	10011	0.02877	0.01593	0.071	0.213
AI Within Pollution-Intensive	pollution=1	4763	0.01677	0.02140	0.433	0.744
AI Within Large Firm	large=1	5870	0.01049	0.01541	0.496	0.744
AI Within Large Firm	large=0	5870	-0.00055	0.01399	0.968	0.993
AI Within Pollution-Intensive	pollution=0	6977	0.00009	0.01041	0.993	0.993

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. Subgroup estimates are descriptive checks and should be read alongside the interaction tests.

Table B5: Country-Specific AI Estimates

Model / effect	Subgroup	N	Estimate	SE	p	FDR q
Country-specific AI effect	China	5617	0.00305	0.01333	0.819	0.843
Country-specific AI effect	India	4129	-0.00409	0.02069	0.843	0.843

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. Country-specific estimates are shown only where support is sufficient, which limits direct national comparisons.

Table B6: Sector-Specific AI Estimates

Model / effect	Subgroup	N	Estimate	SE	P	FDR q
Sector-specific AI effect	Consumer Discretionary	1795	0.08864	0.03360	0.0084	0.0421
Sector-specific AI effect	Information Technology	1278	-0.03056	0.01308	0.0196	0.0490
Sector-specific AI effect	Financials	1089	-0.00528	0.00323	0.102	0.171
Sector-specific AI effect	Communicati on Services	451	0.00041	0.00069	0.553	0.692
Sector-specific AI effect	Industrials	2451	0.00115	0.02236	0.959	0.959

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. These estimates illustrate sectoral boundary conditions and should not be interpreted as a complete ranking of sectors.

Table B7: AI-Component Models

Model / effect	Subgroup	N	Estimate	SE	p	FDR q
Green Innovation on AI-Related Technological Orientation	All firms	11740	-0.06044	0.00795	<0.001	<0.001
Green Innovation on Robotics / Other Automation	All firms	11740	-0.09727	0.01547	<0.001	<0.001
Green Innovation on Machine Learning	All firms	11740	-0.05219	0.00989	<0.001	<0.001
Green Innovation on Predictive Analytics	All firms	11740	-0.04399	0.00948	<0.001	<0.001
Green Innovation on Process Automation	All firms	11740	-0.04382	0.01429	0.0022	0.0026
Green Innovation on Industrial Automation	All firms	11740	0.04213	0.01552	0.0067	0.0067

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. The component models decompose the broad AI classification and show that the average association masks opposing technology-specific patterns.

Table B8: Alternative AI-Definition Models

Model / effect	Subgroup	N	Estimate	SE	P	FDR q
Green innovation on core AI	All firms	11740	-0.05133	0.00783	<0.001	<0.001
Green innovation on AI share	All firms	11740	-0.08333	0.01708	<0.001	<0.001
Green innovation on AI score	All firms	11740	-0.00785	0.00479	0.102	0.136
Green innovation on broad AI	All firms	11740	0.00616	0.01071	0.565	0.565

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. Alternative AI definitions are reported to show how inference changes when the technology construct is narrowed or made continuous.

Table B9: Green-Domain Models

Model / effect	Subgroup	N	Estimate	SE	p	FDR q
Circular Domain on Broad AI	All firms	11740	-0.01202	0.00291	<0.001	<0.001
Environmental Engineering on Broad AI	All firms	11740	-0.00952	0.00416	0.022	0.077
Energy Efficiency on Broad AI	All firms	11740	0.00589	0.00531	0.267	0.495
Pollution Control on Broad AI	All firms	11740	0.00495	0.00461	0.283	0.495
Low-Carbon Products on Broad AI	All firms	11740	-0.00112	0.00142	0.428	0.525
Cleantech on Broad AI	All firms	11740	0.00570	0.00755	0.450	0.525
Clean Energy on Broad AI	All firms	11740	0.00331	0.00749	0.658	0.658

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. Domain models evaluate whether broad AI classification is associated with specific green classifications rather than the overall composite alone.

Table B10: Capability-Moderation Interactions

Model / Effect	Subgroup	N	Estimate	SE	P	FDR q
AI x Standardized R&D	R&D reporters	6071	-0.01140	0.00589	0.0531	0.106
AI x Standardized Intangibles	Intangible reporters	9518	-0.00050	0.01072	0.963	0.963

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. Interaction terms test whether R&D or intangible intensity strengthens the AI-green linkage.

Table B11: 2020-2024 Firm-Mean Performance Models

Model / Effect	Subgroup	N	Estimate	SE	P	FDR q
AI x green: revenue growth	2020-2024 mean	11537	-3.31403	1.67831	0.0483	0.145
AI x green: log labor productivity	2020-2024 mean	10406	-0.03334	0.08237	0.686	0.953
AI x green: ROA	2020-2024 mean	11740	-0.04882	0.83044	0.953	0.953

Notes. Focal coefficient rows are drawn from the analysis protocol. Estimates include the corresponding controls and fixed effects described in the main text, omitted here for readability. Family-level FDR q-values are reported where posted. The models use 2020-2024 firm means and should be interpreted as cross-sectional performance associations.

Table B12: 2015-2024 Correlated-Random-Effects Performance Models

Model / effect	Subgroup	N	Estimate	SE	p	FDR q
AI: Revenue Growth	2015-2024 panel	92059	2.81725	0.62650	<0.001	<0.001
AI: Log Labor Productivity	2015-2024 panel	69281	-0.14759	0.03289	<0.001	<0.001
AI x Green: Revenue Growth	2015-2024 panel	92059	-5.43039	1.44205	<0.001	<0.001
AI: ROA	2015-2024 panel	92652	-0.34006	0.25145	0.176	0.264
AI x Green: Log Labor Productivity	2015-2024 panel	69281	-0.01138	0.07846	0.885	0.957
AI x Green: ROA	2015-2024 panel	92652	-0.02920	0.53610	0.957	0.957

Notes. Focal coefficient rows are drawn from the analysis protocol. CRE = correlated random effects. Models include year, country, sector indicators, time-varying controls, firm means of controls, and firm-clustered standard errors. Family-level FDR q-values are reported where posted. Static classifications preclude causal claims about performance changes.

Table B13: Matching and Weighting Estimators

Model / effect	Subgroup	N	Estimate	SE	p	FDR q
Exact-Stratum Nearest Neighbor	Country-sector exact	9142	0.02824	0.01389	0.0420	0.210
Propensity-Score Matching	Baseline	9142	-0.01294	0.01543	0.402	0.832
Augmented IPW	Country-sector support	9142	0.00805	0.01432	0.574	0.832
IPW Regression Adjustment	Baseline	9142	-0.00286	0.01072	0.789	0.832
Inverse-Probability Weighting	Baseline	9142	-0.00227	0.01071	0.832	0.832

Notes. Focal coefficient rows are drawn from the analysis protocol. Family-level FDR q-values are reported where posted. Controls and fixed-effect coefficients are omitted for readability. The table compares common-support matching and weighting estimates to assess whether the near-zero average association is robust to observable selection adjustment.

Table B14: Additional Sensitivity Analyses

Sensitivity Check	N	Effect	SE	P	95% CI	Interpretation
Equal-country-weighted LPM	11,740	0.02366	0.02770	0.393	[-0.03063, 0.07795]	Broad-AI conclusion remains nonsignificant when each country receives equal total weight.
Logit average marginal effect	11,740	0.00423	0.00836	0.613	[-0.01216, 0.02061]	Near-zero result is robust to nonlinear binary-outcome functional form.
AIPW (ATE; different estimand)	9,142	0.00805	0.01432	0.574	[-0.02001, 0.03611]	Different-estimand check remains close to zero; reported separately from ATET models.
R&D-reporting-weighted AI main effect	6,071	-0.01541	0.01363	0.258	[-0.04212, 0.01131]	Observed-selection weighting does not reveal a

						significant AI difference among R&D reporters.
R&D-reporting-weighted AI × R&D	6,071	0.00463	0.00942	0.623	[-0.01384, 0.02309]	R&D does not reliably strengthen the orientation-green linkage after reporting-selection weighting.
CRE revenue-growth joint AI + green contrast	92,059	-0.13030	1.20566	0.914	[-2.49334, 2.23274]	Negative interaction does not imply a statistically significant absolute joint growth penalty.

Notes. All numerical entries are verified from Stata results. Equal-country weights assign each country the same total influence. The R&D-reporting sensitivity uses stabilized inverse-probability-of-reporting weights based on baseline observables, trimmed at the 1st and 99th percentiles because untrimmed weights are highly skewed. AIPW reports the ATE and is intentionally separated from the ATET panel. These are associative sensitivity checks, not causal estimates.

Appendix C. Construct definitions and exact topic/category reconstruction

Core AI classification is the row maximum of artificial intelligence, machine learning, and predictive analytics. Broad AI classification additionally includes industrial automation, process automation, and robotics/other automation. The reconstructed measures match the stored core and broad AI indicators exactly among tagged firms. The green construct is reconstructed from the exact S&P topic and category logic summarized below.

Table C1: Component Construction from S&P Topic/Category Strings

Component	Exact topic/category logic
Artificial intelligence	Artificial Intelligence topic/category
Machine learning	Machine learning topic/category
Predictive analytics	Predictive analytics topic/category
Industrial automation	Industrial automation topic/category
Process automation	Process automation topic
Robotics/other automation	Robotics; robotic process automation; business process automation; data center automation; warehouse automation categories
Clean energy	Clean energy or renewable energy

Component	Exact topic/category logic
Cleantech	Cleantech, climatetech, or Greentech
Energy efficiency	Energy efficiency
Environmental engineering	Environmental engineering
Pollution control	Pollution control
Circular domain	Bio-based and renewable materials; disposal and recycling; recycling; waste management
Low-carbon products	Green consumer goods; sustainable aviation fuel; green steel; renewable ammonia; CCUS/CCS; green building; carbon capture

Notes. The table summarizes the exact keyword and category logic implemented in the Stata analysis. Matching was case-normalized and delimiter-aware to reduce partial-string errors. The taxonomy is used for transparent reconstruction of the AI-related and green-innovation classifications rather than to infer adoption timing.

Appendix D. Circular-Orientation Diagnostic and Part-Whole Limitation

Circular orientation is one component of the broader green-innovation classification. Models that include both variables therefore contain a mechanical part–whole relationship and are unsuitable for mediation or structural interpretation. They are reported for transparency because they were included in the analysis protocol.

Table D1: Exploratory Circular-Orientation Models

Model / focal term	N	Effect	SE	p	FDR q	95% CI
Circular orientation on AI	11740	-0.01202	0.00291	<0.001	<0.001	[-0.01771, -0.00632]
AI controlling for green	11740	-0.01332	0.00330	<0.001	<0.001	[-0.01978, -0.00686]
Green controlling for AI	11740	0.21160	0.01369	<0.001	<0.001	[0.18477, 0.23843]
AI x green interaction	11740	-0.18315	0.02776	<0.001	<0.001	[-0.23757, -0.12874]

Notes. Because circular orientation is nested within the overall green-innovation construct, the green coefficient and AI x green interaction are mechanically contaminated by construct overlap. A future analysis should rebuild a non-circular green indicator before testing its relationship with circular orientation.