



Orchestrating Intelligence for Decarbonization: AI-Enabled Carbon Reduction Strategies, Dynamic Capabilities, and Firm Performance

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Abstract

Although Artificial Intelligence (AI) has been advanced as a lever for corporate decarbonization, evidence on whether and how AI-enabled carbon reduction strategies (AICRS) translate into superior firm performance remains thin and theoretically under-specified. Integrating the natural-resource-based view with dynamic capabilities theory, we theorize AICRS as a strategic orchestration process through which firms combine AI assets with environmental routines to sense carbon risks, seize low-carbon opportunities, and reconfigure operating models. Using a panel of 1,842 large multinational listed firms from 14 industries over 2014-2024, we construct AICRS via transformer-based text classification of disclosures, triangulated with AI patents and validated against cloud-expenditure and green-AI job-posting microdata. Two-way fixed-effects, system-GMM, and staggered difference-in-differences estimators consistently show that AICRS improves financial performance (ROA, Tobin's Q) and carbon performance, with dynamic capabilities partially mediating and AI capability amplifying the effect. Supplier-facing (Scope 3) AICRS initially attenuates financial returns owing to coordination costs but converges to comparable returns over five years while delivering persistent Scope 3 abatement, and netting out the energy footprint of AI deployment yields attenuated but still significant carbon gains. We reframe decarbonization as an AI-mediated dynamic-capability problem, deliver a replicable operationalization of AICRS, and surface contingencies that reconcile conflicting evidence on the sustainability performance link.

Subject Areas

Business Management

Keywords

Artificial Intelligence, Carbon Reduction, Dynamic Capabilities, Firm Performance, Digital Transformation, Sustainability Strategy, Net Carbon Impact of AI

1. Introduction

Climate change constitutes the defining grand challenge of contemporary strategic management [1] [2]. The decarbonization imperative has intensified as investors price climate risk, regulators such as the EU Corporate Sustainability Reporting Directive (CSRD) and the U.S. SEC climate rule reshape the informational environment, and customers discriminate across carbon-differentiated products [3]-[5]; yet only a minority of firms with net-zero commitments are on a credible trajectory [6] [7]. Concurrently, AI has become a fundamental strategic asset [8]-[10] whose tools support granular emissions monitoring, energy-load forecasting, process optimization, and low-carbon design at scale [11] [12]. This convergence raises a basic question: under what conditions, and through which organizational mechanisms, do AI-enabled carbon-reduction strategies (AICRS) translate into superior financial and environmental performance?

The relevant literatures have advanced in parallel. The sustainability-strategy literature documents positive but contingent returns to environmental investments [13]-[16] but is agnostic about the digital means by which they are executed; the AI-capability literature documents the performance implications of AI investments [17]-[20] but rarely treats environmental performance as a strategic outcome; and where the streams intersect, treatments are conceptual, cross-sectional, or single-sector [21] [22]. Whether AI deployment for carbon reduction generates durable advantage, through which mechanisms, and under which boundary conditions, therefore remain open.

We address them by integrating the natural-resource-based view (NRBV; [23] [24]) with dynamic capabilities theory [25]-[27]. NRBV holds that environmental resources and routines yield sustained advantage when valuable, rare, inimitable, and non-substitutable; dynamic capabilities theory specifies how firms recombine resources through sensing, seizing, and transforming. We theorize AICRS not as a discrete technological artifact but as a strategic orchestration process in which AI assets are recombined with environmental routines to sense carbon risks with higher granularity and lower latency, seize abatement opportunities through AI-optimized operations, and transform business models toward low-carbon value propositions. We test the resulting hypotheses on a panel of 1842 large multinational listed firms from 14 industries over 2014-2024, using two-way fixed-effects, system-GMM [28] [29], and staggered difference-in-differences [30] estimators to address the unobserved heterogeneity, dynamic endogeneity, and staggered treatment timing that plague strategy-sustainability research [31] [32].

Five findings emerge. AICRS is positively associated with ROA and Tobin's Q and negatively with carbon intensity, with effects materializing after a two-year lag; dynamic capabilities partially mediate these relationships; AI capability amplifies them; financial returns are amplified under binding carbon pricing, whereas environmental returns are context-invariant; and supplier-facing (Scope 3) AICRS exhibits a temporal reversal in which short-run financial returns are attenuated by coordination costs but converge on Scope 1 - 2 returns within five years while delivering substantial Scope 3 abatement. Netting out the carbon footprint of AI deployment itself attenuates environmental gains by roughly one-fifth but leaves them significant: AICRS produces net, not merely gross, decarbonization.

We contribute in three ways. Theoretically, we extend NRBV into the AI era by specifying AICRS as a class of environmentally oriented dynamic capability whose microfoundations are orchestrational rather than purely technological or managerial [33], adjudicating between substitution, augmentation, and reconfiguration logics of AI's strategic role [20]. Empirically, we deliver a replicable operationalization of AICRS and a triangulated identification strategy that traces dynamic treatment effects. Managerially, the results reframe AI as an environmentally oriented strategic capability rather than a cost-efficiency tool and identify AI-enabled transitions and carbon pricing as strategic complements.

2. Literature Review and Conceptual Framework

2.1. Sustainability Strategy and the Contingent Returns to Environmental Action

Meta-analytic syntheses document a positive but heterogeneous association between environmental and financial performance [13]-[16], rationalized by the Porter hypothesis [34] [35], stakeholder-based accounts [36] [37], and NRBV [23] [24], which grounds the premium in rare, causally ambiguous, path-dependent environmental routines. Three limitations persist: outcome measurement relies on composite ESG scores that are idiosyncratic across raters [38] [39]; the digital infrastructure mediating environmental action is black-boxed; and identification is often cross-sectional or short-panel, underexploiting the horizons over which environmental capabilities accrue value [40] [41]. Carbon-focused work using direct emissions data [6] [42] redresses the first problem but still treats carbon-reduction means as observationally equivalent.

2.2. AI, Digital Transformation, and Competitive Advantage

Early work positioned big-data analytics as a capability enabling superior decision-making and market sensing [43]-[45]. Recent treatments argue that AI differs qualitatively: prediction at scale reshapes the economics of decision-making [9]; self-improving systems compress learning cycles [20] [46]; and generative AI redefines the locus of creativity [47] [48]. AI capability is a bundle of technical, managerial, and cultural resources [17] [18] associated with superior operational

and innovation outcomes [19] [49]. Yet environmental outcomes remain peripheral here, and the generic AI-capability construct is too aggregated to predict where AI creates value. Following work on digital servitization [50] and platform ecosystems [51] that specifies the strategic problem to which digital means are applied, we specify decarbonization as that problem.

2.3. AI at the Service of Sustainability: An Emergent but Fragmented Literature

The nascent AI-sustainability literature comprises a conceptual strand theorizing AI as a lever for the sustainable development goals [21] [22] [52]; a technical-engineering strand demonstrating applications with documented abatement potential but limited engagement with corporate contingencies [11] [53]; and an empirical strand finding positive but contingent firm-level associations between AI adoption and environmental outcomes [54]–[56]. It is theoretically unmoored: few studies specify mechanisms or boundary conditions, ambiguity persists over whether AI substitutes for, complements, or reconfigures environmental routines [20], and measurement is fragmented across adoption dummies, patent counts, and ad hoc text counts.

2.4. Toward an Integrated Framework: NRBV Meets Dynamic Capabilities in the AI Era

NRBV [23] proposes that firms derive advantage from pollution prevention, product stewardship, and sustainable development, which Hart and Dowell [24] recast as dynamically evolving capabilities. Teece [25] [26] disaggregates dynamic capabilities into sensing, seizing, and transforming, and Helfat and Raubitschek [33] extend the taxonomy to ecosystem-level orchestration. We propose that AICRS constitutes a new class of environmentally oriented dynamic capability with three microfoundations. AI-enabled sensing satellite remote sensing, Internet-of-Things emission sensors, machine-learning-based Scope 3 inference, and natural-language scanning of regulatory texts raise the resolution and lower the latency of climate-relevant information [11] [53], allowing firms to internalize carbon costs before regulators or markets price them. AI-enabled seizing optimizes at the process, product, and network levels—reinforcement-learning process control, digital twins for low-carbon design, demand forecasting that reduces overproduction [9] and depends on complementary routines without which AI outputs remain inert [48] [57]. AI-enabled transforming reconfigures business models toward circular material-tracking platforms, emissions-indexed product-as-a-service offerings, and AI-curated Scope 3 governance, requiring path-dependent commitments that are difficult to imitate [26] [58]. This integration surfaces a latent ambiguity: whether AI substitutes for environmental capabilities (automation), augments them augmentation, or recombines them into novel capabilities (reconfiguration) [20]. We adopt the reconfiguration view: the value of AICRS lies in the orchestration through which it is embedded in routines, unfolds through learning, and depends on com-

plementary assets and the institutional environment.

2.5. The Multidimensionality of Firm Performance

Strategic management distinguishes accounting-, market-, and stakeholder-based performance [59], and the “accounting for carbon” stream adds direct environmental performance as a strategically meaningful outcome [42] [60]. Consistent with the NRBV premise that environmental resources generate both economic and ecological returns, we treat financial and carbon performance as parallel outcomes of AICRS. Three issues thus remain unsettled: the capability mechanism (reconfiguration versus substitution), the contingency structure (which moderators matter), and the temporal profile (short- versus long-run) of AICRS effects.

3. Hypotheses Development

We derive six hypotheses, summarized in **Figure 1**. H1 and H2 specify direct effects of AICRS on financial and carbon performance; H3 specifies mediation through dynamic capabilities; H4 specifies moderation of the direct paths by AI capability; H5 specifies asymmetric moderation of the indirect paths by regulatory stringency; and H6, shown in the lower panel of **Figure 1**, specifies the scope and temporal profile of AICRS effects on Scope 3 emissions and the associated financial returns.

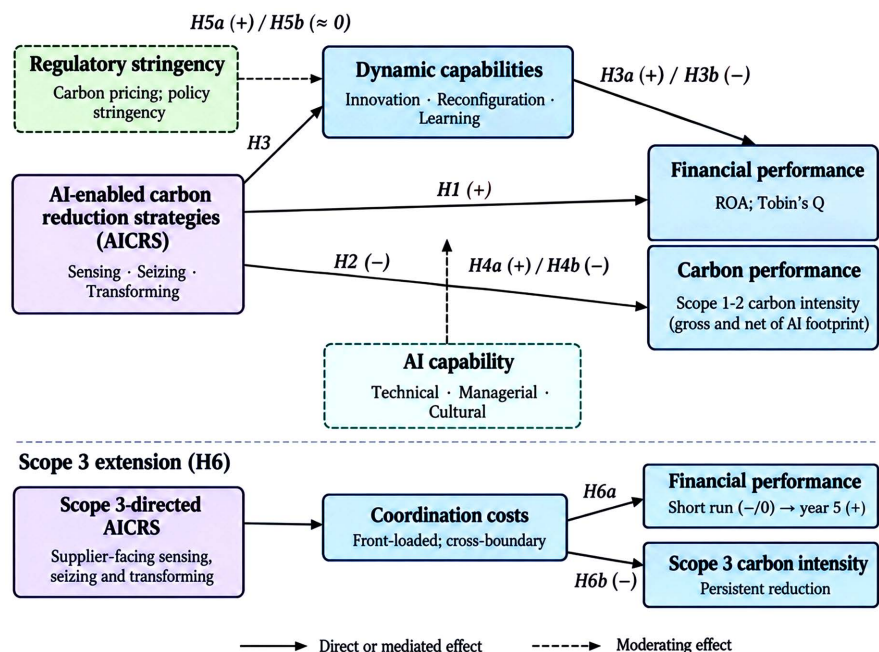


Figure 1. Conceptual model of AI-enabled carbon reduction strategies (AICRS), dynamic capabilities, and firm performance.

3.1. AICRS and Financial Performance

Three mechanisms link AICRS to financial outcomes. The innovation-offset mechanism [34] [35] implies that AI-optimized processes reduce energy, material, and

waste intensity: AI-based predictive maintenance reduces unplanned downtime by an order of magnitude [61], and machine-learning process control lowers energy intensity in heavy industry [53]. The signalling and cost-of-capital mechanism [4] [62] implies that credible AI-backed carbon disclosure lowers financing costs, as investors discriminate between verifiable abatement and ceremonial commitments [7]. The product-differentiation mechanism [63] implies that AICRS supports premium low-carbon positioning.

Hypothesis 1 (H1). AICRS is positively associated with financial performance (ROA and Tobin's Q).

3.2. AICRS and Carbon Performance

From an NRBV perspective, AICRS is a direct abatement capability: AI-enabled sensing provides the measurement foundation for credible reduction, AI-optimized operations lower emissions per unit of output, and AI-reconfigured business models reduce structural carbon intensity [11]. Under the reconfiguration logic, AICRS shifts the abatement-cost curve inward by rendering previously unavailable or prohibitively costly options feasible.

Hypothesis 2 (H2). AICRS is negatively associated with firm carbon intensity (Scope 1 + Scope 2 emissions per unit of revenue).

3.3. The Mediating Role of Dynamic Capabilities

NRBV holds that environmental capabilities yield performance through the accumulation of firm-specific, causally ambiguous routines here, the dynamic capabilities of sensing, seizing, and transforming. By upgrading these microfoundations, AICRS builds higher-order capabilities conferring adaptive gains beyond decarbonization: responsiveness to demand shocks, faster R&D cycles, and supply-chain resilience [26] [58]. Performance benefits should therefore be partially realized through improved dynamic capabilities.

Hypothesis 3 (H3). Dynamic capabilities mediate the relationship between AICRS and (a) financial performance and (b) carbon performance.

3.4. The Moderating Role of AI Capability

The reconfiguration view implies that AICRS is an orchestrated bundle of technical, managerial, and cultural practices [17] [33] whose value depends on the firm's broader AI capability—data infrastructure, machine-learning talent, algorithmic governance, and leadership commitment [48] [57]. Firms with limited AI capability lack the absorptive capacity to integrate AI outputs into operational decisions and the slack to reconfigure routines; firms with deep AI capability convert AICRS into performance more efficiently because complementary assets lower reconfiguration costs.

Hypothesis 4 (H4). AI capability positively moderates the effects of AICRS on (a) financial performance and (b) carbon performance, such that effects are stronger at higher levels of AI capability.

3.5. The Contingent Role of Regulatory Stringency (Moderated Mediation)

Regulatory stringency shapes the private returns to environmental capabilities [35] [64] [65]. Where carbon is priced through cap-and-trade, taxes, or binding standards, financial returns to abatement are enlarged because avoided emissions translate into saved compliance costs and monetizable allowance surpluses [3] [65]; where regulation is loose, returns depend on noisier and lagged reputational channels. The direct abatement effect of AICRS should be relatively unaffected, because technical abatement opportunities exist irrespective of whether they are priced. We therefore propose asymmetric moderated mediation:

Hypothesis 5a (H5a). The indirect effect of AICRS on financial performance via dynamic capabilities is stronger under higher regulatory stringency.

Hypothesis 5b (H5b). The indirect effect of AICRS on carbon performance via dynamic capabilities is relatively invariant across regulatory stringencies.

3.6. AICRS and Scope 3 Emissions: Coordination Costs and Temporal Reversal

H1 and H2 concern Scope 1 and Scope 2 emissions. For most large multinationals, however, Scope 3 emissions upstream inputs, downstream product use, and end-of-life account for 65% - 90% of the footprint [66]-[68] and are the primary target of mandatory regimes including the EU CSRD, California SB 253, and ISSB S2 [69]. Scope 3 abatement requires coordination across firm boundaries and depends on supplier data quality, supplier investment, and standardized emissions metrics [70] [71]; these coordination costs are front-loaded and appear as contemporaneous drags on financial indicators. Once supplier networks are reconfigured, however, shared data infrastructure, contractually enforced targets, and AI-enabled supplier monitoring produce durable, path-dependent rents. Following Flammer and Bansal [41], we expect Scope 3 AICRS effects to reverse sign in financial results over time while remaining directionally consistent in carbon performance.

Hypothesis 6a (H6a). The financial-performance effect of Scope 3-directed AICRS is negative or null in the short run (one- to two-year horizon) but converges to the Scope 1 - 2 financial-performance effect over a five-year horizon.

Hypothesis 6b (H6b). Scope 3-directed AICRS is negatively and persistently associated with Scope 3 carbon intensity across both short- and long-run horizons.

4. Research Methodology

4.1. Research Design and Sample

We employ a longitudinal panel spanning 2014-2024, covering both the diffusion of deep-learning-era AI and the intensification of climate-disclosure regimes (TCFD 2017; EU Taxonomy 2020; SEC proposed climate rule 2022; EU CSRD 2023). The universe comprises all constituents of the MSCI World, S & P Global 1200, and FTSE All-World indices active during the period, excluding pure finan-

cial-holding companies (two-digit SIC 60 - 67). After requiring at least five consecutive observations, textual-disclosure coverage, and non-missing controls, the final sample comprises 1842 firms and 16,237 firm-year observations across 14 two-digit SIC sectors and 38 countries. This frame restricts inference to large multinational listed firms (median total assets above US\$6 billion): the orchestrational microfoundations we theorize presuppose slack and specialized human capital unevenly distributed below this frontier [57], and the disclosure obligations driving our identification bind principally to large listed firms. We therefore confine our claims to large multinational enterprises.

4.2. Data Sources and Variable Construction

Financial and carbon data. Financial variables are drawn from Compustat North America and Global, supplemented by WorldScope, and winsorized at the 1st and 99th percentiles within year-country cells. Scope 1 and 2 emissions are obtained, in order of preference, from CDP, Refinitiv/Trucost, and S & P Global Sustainable1; missing values are imputed from industry-region-year median growth rates, and firms with more than 40% imputed observations are dropped. Firm-reported Scope 3 data (CDP Categories 1 - 15) are used where available; aggregate-only Scope 3 is allocated between upstream and downstream categories using industry-specific EPA Supply Chain GHG Emissions Factor multipliers. Firms with fewer than three Scope 3-reporting years are retained only for Scope 1 - 2 models; the Scope 3 subsample covers 1247 firms and 11,309 firm-years.

Net carbon adjustment. Because AI systems consume electricity and embody hardware-manufacturing emissions, gross AICRS abatement overstates its net climate contribution [53] [72]. We estimate firm-year AI-attributable IT emissions by combining: 1) firm-reported IT and cloud expenditure (Compustat, annual reports, and Synergy Research's cloud-spend panel); 2) cloud-provider power usage effectiveness (PUE) and location-specific grid intensity from the International Energy Agency; and 3) an AI-intensity weight derived from the share of the firm's IT footprint classified as AI/ML workloads in job-posting and procurement text. These emissions are subtracted from gross abatement to yield a net carbon intensity measure; we report both gross and net coefficients.

AICRS measurement. AICRS is operationalized through a supervised transformer-based text-classification pipeline applied to 10-K, 20-F, annual-report, and sustainability-report corpora. We domain-adapt ClimateBERT [73] through continued pretraining on 1.2 million climate-related paragraphs; fine-tune the classifier on 5400 hand-coded paragraphs labelled by a typology distinguishing AI-enabled sensing, seizing, and transforming actions from generic AI and generic sustainability content (Krippendorff's $\alpha = 0.81$); aggregate paragraph-level probabilities to firm-year AICRS intensity normalized by document length; and triangulate with a patent-based measure from The Lens using OECD ENV-TECH (Y02) codes cross-tabulated with AI-related CPC codes (G06N, G06F 16, G06F 17, G06T 7). The two measures correlate at $r = 0.62$, and their first principal component (78% of variance) is the primary AICRS measure. Because disclosure-

based indicators may reflect voice-of-management bias, we add two operational microdata components: cloud-infrastructure expenditure (Compustat and annual-report technology-spend items, Synergy Research's hyperscaler-spend panel, and vendor-disclosed enterprise agreements with major cloud providers, with the AI share classified via workload metadata) and green-AI human capital (Revelio Labs and Lightcast postings co-occurring AI/ML skill terms with sustainability terms). These correlate with the disclosure-based measure at $r = 0.47$ and $r = 0.54$; their first principal component forms an operational AICRS index included alongside the disclosure-based measure in key specifications.

Dynamic capabilities and AI capability. Dynamic capabilities are a three-indicator latent construct comprising an innovation-intensity index (R&D intensity, patent grants, patent citations), a reconfiguration index (intangible investment, restructuring charges scaled negatively, business-segment reconfiguration), and a learning-orientation index derived from text analysis of management discussion using the validated dictionary of Bansal and DesJardine [40]; confirmatory factor analysis indicates acceptable fit (CFI = 0.94; TLI = 0.92; RMSEA = 0.061). AI capability follows Mikalef and Gupta [17]: technical (AI patents; AI-skilled workforce share from Revelio Labs/Burning Glass postings), managerial (executive AI roles; board AI expertise from BoardEx), and cultural (text-based indicators of AI-related organizational values) dimensions, standardized and equally weighted, with robustness to principal-component and factor-analytic weights.

Dependent variables and controls. Financial performance is measured by ROA (operating income before depreciation over lagged total assets) and Tobin's Q (market value of equity plus book liabilities over total assets). Carbon performance is the natural logarithm of (Scope 1 + Scope 2 tCO₂e) per US\$ million revenue; Scope 3 carbon intensity, computed analogously, is the dependent variable in the H6 tests; and net carbon intensity (Scope 1 + Scope 2 AI-attributable IT emissions) per revenue is the primary carbon outcome alongside the gross measure. Controls comprise firm size (ln total assets), leverage, capital intensity, R&D intensity, firm age, sector growth, country-year GDP growth, regulatory stringency (OECD Environmental Policy Stringency index), corporate tax rate, a binding-carbon-price dummy, ln(cloud and IT capital expenditure) scaled by revenue, and estimated AI-attributable IT emissions; the last two are retained in gross (but absorbed in net) carbon specifications.

4.3. Econometric Strategy

The baseline is a two-way fixed-effects (TWFE) model,

$$Y_{it} = \beta_0 + \beta_1 \cdot \text{AICRS}_{i,t-1} + \Gamma \cdot X_{i,t-1} + \alpha_i + \lambda_t + \varepsilon_{it}$$
, where Y_{it} is ROA, Tobin's Q, or log carbon intensity, AICRS is lagged one year to reduce simultaneity, X is a vector of controls, and α_i and λ_t absorb firm heterogeneity and common shocks; standard errors are clustered by firm. Because strictly exogenous covariates are unlikely with persistent dependent variables [31], we also estimate two-step system-GMM [28] [29] with a lagged dependent variable, using lagged levels ($t - 2$ through $t - 4$) as instruments for the differenced equation and lagged differences for the level

equation, with the instrument count collapsed [74]. To further address endogeneity, we exploit the staggered adoption of mandatory climate disclosure in seven jurisdictions (UK, phased 2013-2019; France 2015; China 2020; Japan 2022; Singapore 2022; EU CSRD 2023; New Zealand 2023) using the Callaway and Sant’Anna [30] estimator, robust to heterogeneous treatment effects [32] [75]; the identifying assumption is that mandatory disclosure raises the marginal private value of verifiable, AI-enabled abatement. Mediation is tested via the Baron and Kenny [76] framework with bootstrap-corrected confidence intervals [77] and a within-firm fixed-effects structural equation model [78]; moderated mediation via the index of moderated mediation [79] with 5000 bootstrap draws. Six robustness analyses alternative AICRS specifications; alternative performance measures (ROE, ROIC, Sharpe-adjusted returns); alternative estimators, including Lewbel [80] heteroskedasticity-based instruments; sector splits; event-study tests of parallel trends; and placebo pseudo-windows are reported.

5. Empirical Results

5.1. Descriptive Statistics and Correlations

Table 1 reports descriptive statistics. AICRS intensity is right-skewed, consistent with a diffusion pattern: the 75th percentile (0.042) is more than three times the median (0.013), and the top decile accounts for roughly 40% of aggregate AICRS mentions [81]. Pairwise correlations (untabulated) show that AICRS correlates positively with ROA ($r = 0.18$) and Tobin’s Q ($r = 0.22$) and negatively with log carbon intensity ($r = -0.24$), all $p < 0.01$; variance inflation factors (maximum 3.4) indicate no multicollinearity concerns.

Table 1. Descriptive statistics.

Variable	N	Mean	SD	Min	Median	Max
AICRS (composite)	16,237	0.027	0.038	0.000	0.013	0.412
ROA	16,237	0.113	0.094	-0.281	0.102	0.487
Tobin’s Q	16,237	1.842	1.216	0.512	1.471	8.903
Log carbon intensity	16,237	4.312	2.104	-1.823	4.267	9.842
Dynamic capabilities	16,237	0.000	1.000	-3.412	-0.088	4.217
AI capability (composite)	16,237	0.000	1.000	-2.106	-0.214	5.328
Regulatory stringency (EPS)	16,237	2.874	0.913	0.511	2.967	4.812
Firm size (ln assets)	16,237	9.417	1.823	4.192	9.384	14.721
Leverage	16,237	0.278	0.198	0.000	0.264	0.892
R&D intensity	16,237	0.034	0.061	0.000	0.008	0.412
Firm age (ln)	16,237	3.214	0.892	0.693	3.258	5.216

Notes: AICRS is the composite of text- and patent-based measures. Continuous variables are winsorized at the 1st and 99th percentiles within year-country cells; dynamic capabilities and AI capability are standardized composites. N = 16,237 firm-years, 1842 firms, 38 countries, 2014-2024.

5.2. Baseline Results: AICRS and Firm Performance

Table 2 reports the baseline TWFE results. The coefficient on AICRS is 0.028 ($p < 0.01$) for ROA, implying that a one-standard-deviation increase in AICRS raises ROA by 0.9 percentage points, an 8% improvement relative to the sample mean of 11.3%; Tobin's Q rises by 0.11 ($p < 0.01$) per standard deviation; and log carbon intensity falls by 0.076 ($p < 0.01$), a 7.3% reduction in emissions per unit of revenue. H1 and H2 are supported. System-GMM estimates (**Table 3**) are consistent: AR(2) p-values of 0.31, 0.24, and 0.19 and Hansen J p-values of 0.18, 0.22, and 0.29 support instrument validity, and AICRS retains its sign and significance with slightly attenuated magnitudes, as expected once dynamic endogeneity is addressed.

Table 2. AICRS and firm performance: Two-way fixed effects.

Variable	(1) ROA	(2) Tobin's Q	(3) ln Carbon intensity
AICRS ($t-1$)	0.028*** (0.007)	0.110*** (0.031)	-0.076*** (0.018)
Firm size (ln assets)	0.019*** (0.004)	0.142*** (0.024)	0.037** (0.016)
Leverage	-0.088*** (0.013)	-0.412*** (0.062)	0.051 (0.041)
R&D intensity	0.156** (0.072)	1.982*** (0.312)	-0.218* (0.118)
Firm age (ln)	-0.004 (0.003)	-0.091** (0.042)	-0.028 (0.023)
Regulatory stringency	0.006 (0.007)	0.078* (0.045)	-0.134*** (0.031)
Firm FE/Year FE	Yes/Yes	Yes/Yes	Yes/Yes
Observations	16,237	16,237	16,237
R-squared (within)	0.184	0.271	0.398

Notes: AICRS and all controls are lagged one year. Standard errors clustered at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3. AICRS and firm performance: System-GMM.

Variable	(1) ROA	(2) Tobin's Q	(3) ln Carbon intensity
Lagged DV	0.482*** (0.038)	0.612*** (0.047)	0.734*** (0.029)
AICRS ($t-1$)	0.021*** (0.006)	0.087*** (0.028)	-0.061*** (0.017)
Firm size (ln assets)	0.014*** (0.004)	0.108*** (0.026)	0.029* (0.017)
Leverage	-0.067*** (0.015)	-0.332*** (0.071)	0.042 (0.044)
R&D intensity	0.128* (0.076)	1.641*** (0.334)	-0.183 (0.129)
Year FE	Yes	Yes	Yes
Observations	14,395	14,395	14,395
AR(2) p-value	0.31	0.24	0.19
Hansen J p-value	0.18	0.22	0.29
Instrument count	34	34	36

Notes: Two-step system-GMM (Blundell and Bond [29]) with Windmeijer-corrected standard errors in parentheses; instruments collapsed following Roodman [74]. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3. The Mediating Role of Dynamic Capabilities

Table 4 reports tests of H3. AICRS is positively associated with dynamic capabilities ($\beta = 0.142$, $p < 0.01$). Once dynamic capabilities are included as a mediator, the direct coefficient on AICRS decreases by roughly 34% for ROA and 28% for Tobin's Q, with bootstrapped indirect effects of 0.010 (95% CI: 0.006 - 0.014) for ROA, 0.031 (95% CI: 0.018 - 0.045) for Tobin's Q, and -0.018 (95% CI: -0.028 to -0.009) for carbon intensity. Partial mediation is therefore supported for all three outcomes, consistent with H3a and H3b.

Table 4. Mediation by dynamic capabilities.

	ROA	Tobin's Q	ln Carbon intensity
Total effect of AICRS	0.028*** (0.007)	0.110*** (0.031)	-0.076^{***} (0.018)
Direct effect of AICRS	0.018** (0.008)	0.079** (0.033)	-0.058^{***} (0.019)
Indirect effect via DC	0.010*** [0.006, 0.014]	0.031*** [0.018, 0.045]	-0.018^{***} [-0.028 , -0.009]
Proportion mediated	35.7%	28.2%	23.7%
Sobel z	4.12	3.87	-3.56
Observations	16,237	16,237	16,237

Notes: Total, direct, and indirect effects estimated within a firm-fixed-effects structural equation model; standard errors in parentheses. Bias-corrected 95% bootstrap confidence intervals (5,000 replications; Hayes [77]) in brackets. DC = dynamic capabilities. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.4. Moderation by AI Capability

Table 5 reports the moderation tests. The interaction AICRS $\times$ AI capability is positive and significant for ROA (0.014, $p < 0.01$) and Tobin's Q (0.046, $p < 0.01$), and negative and significant for log carbon intensity (-0.029 , $p < 0.01$). Simple-slope analysis shows that, at one standard deviation above the mean of AI capability, the marginal effect of AICRS on ROA is roughly 2.3 times that at one standard deviation below the mean. H4a and H4b are supported.

Table 5. Moderation by AI capability.

Variable	(1) ROA	(2) Tobin's Q	(3) ln Carbon intensity
AICRS ($t-1$)	0.026*** (0.007)	0.104*** (0.030)	-0.071^{***} (0.018)
AI capability	0.021*** (0.005)	0.139*** (0.028)	-0.049^{**} (0.021)
AICRS $\times$ AI capability	0.014*** (0.004)	0.046*** (0.013)	-0.029^{***} (0.009)
Marginal effect at low AI (-1 SD)	0.012*	0.058*	-0.042^{**}
Marginal effect at mean AI	0.026***	0.104***	-0.071^{***}
Marginal effect at high AI ($+1$ SD)	0.040***	0.150***	-0.100^{***}

Continued

Controls + Firm/Year FE	Yes	Yes	Yes
Observations	16,237	16,237	16,237
R-squared (within)	0.201	0.294	0.418

Notes: AICRS and AI capability are mean-centred before interaction; marginal effects of AICRS are evaluated at the mean of AI capability and at ± 1 SD. Controls and fixed effects as in **Table 2**. Standard errors clustered at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.5. Moderated Mediation by Regulatory Stringency

The conditional indirect effects of AICRS via dynamic capabilities at low, mean, and high regulatory stringency, together with the index of moderated mediation, are presented in **Table 6**. The index is positive and significant for ROA (0.008, 95% CI: 0.003 - 0.013) and Tobin's Q (0.022, 95% CI: 0.011 - 0.033), indicating that the indirect effect of AICRS on financial performance is amplified in high-regulation environments; H5a is supported. For carbon intensity, the index is -0.005 and not statistically distinguishable from zero (95% CI: -0.012 to 0.002), consistent with H5b: direct abatement returns are comparatively context-invariant.

Table 6. Moderated mediation by regulatory stringency.

Conditional indirect effect of AICRS via DC	ROA	Tobin's Q	ln Carbon intensity
Low regulatory stringency (-1 SD)	0.005* [0.001, 0.009]	0.015** [0.004, 0.026]	-0.020^{***} [-0.031 , -0.008]
Mean regulatory stringency	0.010*** [0.006, 0.014]	0.031*** [0.018, 0.045]	-0.018^{***} [-0.028 , -0.009]
High regulatory stringency ($+1$ SD)	0.016*** [0.010, 0.022]	0.051*** [0.030, 0.072]	-0.017^{**} [-0.029 , -0.006]
Index of moderated mediation	0.008*** [0.003, 0.013]	0.022*** [0.011, 0.033]	-0.005 [-0.012 , 0.002]

Notes: Conditional indirect effects of AICRS on the three dependent variables, transmitted through dynamic capabilities (DC) and moderated by country-year regulatory stringency (OECD Environmental Policy Stringency index). Bootstrap 95% confidence intervals (5000 replications) in brackets. Index of moderated mediation from Hayes [79]. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.6. Staggered Difference-in-Differences and Dynamic Treatment Effects

Event-study plots (untabulated; available on request) show pre-treatment coefficients indistinguishable from zero, supporting parallel trends. Post-treatment effects compound gradually: a firm one standard deviation above the median AICRS earns a 1.6-percentage-point ROA premium by year 3 post-treatment relative to

untreated firms, and its carbon-intensity reduction premium reaches 11.2%, consistent with the learning-based reconfiguration view (Section 2.4).

5.7. Scope 3 Temporal Reversal and the Net Carbon Impact of AI

Tests of H6 use the 1247-firm Scope 3 panel. H6a is supported: Scope 3-directed AICRS carries a negative and significant ROA coefficient in the first post-treatment year ($\beta = -0.018$, $p < 0.05$), consistent with supplier-coordination costs; the coefficient is indistinguishable from zero by year 3 ($\beta = -0.004$, n.s.) and turns positive and significant by year 5 ($\beta = 0.019$, $p < 0.05$), converging on the Scope 1 - 2 effect. The Tobin's Q dynamic is similar but weaker. H6b is also supported: Scope 3-directed AICRS is negatively and persistently associated with Scope 3 carbon intensity ($\beta = -0.051$, $p < 0.01$ at year 1; $\beta = -0.089$, $p < 0.01$ at year 5), an 8.6% Scope 3 reduction per standard deviation of AICRS by year 5. Because Scope 3 represents roughly 78% of total emissions for the median sample firm [82], AICRS emerges as the dominant lever through which AI shapes the corporate carbon footprint.

Turning to the net carbon adjustment, reported AI-attributable IT emissions rise from under 0.5% of firm carbon intensity at the start of the window to a median 4.3% by 2024, still a small fraction for most sectors [83]. Re-estimating H2 with net carbon intensity yields an AICRS coefficient of -0.061 ($p < 0.01$), compared with the gross estimate of -0.076 in Table 2: an attenuation of roughly 20% that retains significance. Attenuation is largest in information- and software-intensive sectors and smallest in heavy industry. AICRS thus delivers net decarbonization, although where AI compute dominates the firm's footprint the net gain is modest, and under accelerated compute scaling it could invert.

5.8. Robustness

Results survive all six robustness exercises. Lewbel [80] IV estimates lie within 10% of the baseline, strengthening the causal interpretation; sector splits show larger but qualitatively consistent effects in carbon-intensive sectors (utilities, materials, energy), indicating that AICRS is not exclusively a software-sector phenomenon; patent-only and text-only AICRS measures yield coefficients that are directionally identical and within one standard error of the baseline; and placebo tests on pre-treatment pseudo-windows produce coefficients indistinguishable from zero.

6. Discussion

Our findings advance four propositions. First, the reconfiguration logic dominates the substitution logic. Had AI merely substituted for environmental capability, the direct effect of AICRS should have dissipated once we conditioned on dynamic capabilities and AI capability; instead, AICRS retained a direct effect while also operating through dynamic capabilities, consistent with a higher-order capability that orchestrates pre-existing routines. To the debate over whether AI automates or augments strategic work [20] [46], the environmental domain an-

swers “it recombines”—but only where firms possess the complementary AI capability to integrate AI outputs into decisions [48] [84].

Second, the coupling of financial and environmental performance is not incidental. The dynamic-capabilities channel that drives financial returns also drives carbon returns, implying that AICRS, under the conditions we identify, dissolves rather than imposes a sustainability-profitability trade-off, reframing a long-standing debate [36] [85] [86] by locating win-win conditions in the quality of AI-enabled orchestration. The asymmetry we document regulation amplifies financial but not carbon returns suggests, however, that the win-win is partly institutionally constructed: carbon pricing converts latent environmental value into priced financial value.

Third, the results reconcile mixed findings in the AI-sustainability literature by locating heterogeneity in firm- and country-level moderators: the gap in marginal returns between top- and bottom-decile AI-capability firms is sufficient to account for most between-study variance [21] [54] [55], so meta-analytic syntheses should explicitly model capability heterogeneity.

Fourth, the Scope 3 temporal reversal (H6) deserves emphasis. The short-run financial drag and five-year reversal are consistent with Flammer and Bansal’s [41] long-horizon premium but ground the mechanism in inter-organizational coordination rather than intra-firm learning: shared data infrastructure, contractually enforced targets, and AI-enabled supplier monitoring constitute a coordination architecture whose rents accrue only after the coordination has been paid for. Because Scope 3 commonly accounts for 65% - 90% of a multinational’s footprint [66], scholarship focusing exclusively on Scope 1 - 2 will underestimate both the climate stakes and the horizons over which AI-enabled decarbonization rewards firms. Relatedly, net carbon gains are roughly one-fifth lower than gross gains but remain meaningful [87], a time- and sector-indexed statement, since at projected compute scales the balance could tip [88]. The net carbon impact of AI is thus a moving target whose sign depends on the relative growth rates of AI-enabled abatement and AI-induced compute demand [53] [72].

Two further points warrant note. Reliance on disclosure corpora introduces voice-of-management bias, which our staggered design, patent triangulation, and operational microdata mitigate but do not eliminate [39]. And the results support an emerging view that dynamic capabilities are domain-specific and technology-mediated [33] [58], such that capturing this mediation is necessary to resolve conflicting evidence on the environmental-performance link.

7. Implications

7.1. Managerial Implications

For managers of large multinationals, AI investments dedicated to decarbonization should be evaluated as strategic capability-building rather than cost-efficiency projects. This implies cross-functional “green-AI” teams linking sustainability officers, data scientists, and operations leaders; dual-purpose KPIs reward-

ing both abatement and operational performance; and board-level AI governance integrating ESG and technology oversight. Firms with limited AI capability should build foundational AI maturity before layering environmental applications on top, or risk delivering neither financial nor environmental returns. Managers should budget for the short-run financial drag of supplier-facing AICRS, aligning incentives to a three- to five-year horizon, and govern the IT-side carbon footprint of AI deployment as a monitored metric, because abatement claims that do not net out AI's own compute emissions will be increasingly less credible to auditors, regulators, and investors. For SMEs and private firms, outside our sampling frame, these implications are testable conjectures.

7.2. Policy Implications

Carbon pricing not only internalizes externalities but catalyzes private AI investment in abatement by raising the marginal value of AICRS. Because top-decile AI-capability firms gain disproportionately from carbon-pricing reforms, flanking policies shared AI infrastructure, SME green-AI support schemes will be needed to broaden the benefits. Finally, mandatory climate-disclosure regimes appear to catalyze capability-building beyond their informational value, a channel that policy design should consciously exploit.

8. Limitations and Future Research

Several limitations bound our claims. First, none of our measurement components directly observes the operational incorporation of AI into abatement decisions; ethnographic, survey, or process-mining work would complement our architecture. Second, our frame is restricted to large multinational listed firms; we expect the direction of the AICRS effect to carry over to SMEs, private firms, and emerging-market incumbents, but the magnitude and the AI-capability moderation may differ, and comparative panels are a priority. Third, the dynamic-capabilities construct remains contested, and alternative operationalizations may yield different mediation magnitudes. Fourth, employee-, customer-, and community-level outcomes deserve study [2]. Fifth, the net carbon adjustment rests on approximations cloud expenditure is a noisy proxy for compute intensity, grid-intensity data vary in quality, and we do not internalize hardware-manufacturing emissions embedded in chip fabrication and data-centre construction and we model neither rebound (Jevons-paradox) effects nor algorithmic greenwashing. Sixth, the Scope 3 panel is smaller than the Scope 1 - 2 panel and may be biased toward better-resourced reporters, a gap that the Corporate Sustainability Due Diligence Directive should progressively close.

Three research directions follow: qualitative and experimental work opening the black box of orchestration; the heterogeneity of dynamic-capability microfoundations across AI generations (generative, agentic, quantum-assisted); and the interaction between AICRS and supplier-network architecture as Scope 3 reporting becomes universal, since coordination-based rents may increasingly determine

who wins the low-carbon transition.

Author Contributions

Conceptualization, D.M.P.J.; methodology, D.M.P.J.; software, D.M.P.J.; validation, D.M.P.J. and R.J.X.; formal analysis, D.M.P.J.; investigation, D.M.P.J.; resources, D.M.P.J. and R.J.X.; data curation, D.M.P.J.; writing—original draft preparation, D.M.P.J.; writing—review and editing, D.M.P.J. and R.J.X.; visualization, D.M.P.J.; supervision, R.J.X.; project administration, D.M.P.J.; funding acquisition, D.M.P.J. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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