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Research Article

The Role of Artificial Intelligence in Facilitating Cross-Border Green Technology Transfer and Enhancing Sustainable Innovation in International Business: Evidence from Emerging Economies

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Abstract

Introduction: Cross-border green technology transfer remains uneven, with emerging economies often locked out of low-carbon production networks despite urgent climate needs. Artificial intelligence (AI) is increasingly positioned as a potential enabler that can lower information barriers, improve matching between technology suppliers and adopters, and accelerate the absorption of environmental knowledge.

Objective: This study examines how AI adoption influences cross-border green technology transfer and subsequent sustainable innovation performance among firms and industries in emerging economies, and identifies the conditions under which these effects are strongest.

Method: A mixed-methods design was employed. Quantitative analysis drew on a balanced panel of 1,842 firm-year observations from 18 emerging economies (2016–2023), combining patent assignment and licensing data, AI-related keyword frequencies in corporate disclosures, and secondary indicators of institutional quality and digital infrastructure. Fixed-effects, instrumental-variable, and mediation models were estimated. Complementary semi-structured interviews with 47 technology managers and policymakers provided process insights.

Results: Higher firm-level AI capability is positively associated with both the volume and quality of inbound green technology transfers. The relationship operates partly through improved cross-organizational collaboration and elevated R&D intensity. Institutional readiness (regulatory quality, cybersecurity, and ESG frameworks) and absorptive capacity significantly moderate the effects. Sustainable innovation outcomes, measured by green patenting, process eco-efficiency, and export of low-carbon products, rise following successful transfers, with stronger gains in middle-income economies that combine digital infrastructure with targeted industrial policy.

Conclusion: AI functions as a facilitator rather than an automatic substitute for institutional and capability-building efforts. Policy and managerial attention should focus on complementary investments in digital infrastructure, skills, and governance if emerging economies are to convert AI-enabled technology inflows into durable sustainable innovation advantages.

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Introduction

The global transition to lower-carbon economic systems depends heavily on the diffusion of green technologies such as renewable energy systems, energy-efficient processes, circular materials, and digital solutions that reduce environmental footprints. Yet the geography of these technologies remains highly concentrated. Recent evidence indicates that low-carbon technology trade and investment remain heavily concentrated among high-income economies and China, with most other emerging-market and developing economies participating only marginally and often as net importers [1]. Bandara et al. [1] document that developing countries are largely locked out of low-carbon technology trade, a pattern that risks entrenching a new form of technological inequality precisely when rapid, inclusive decarbonization is required.This pattern risks locking in a new form of technological inequality at precisely the moment when rapid, inclusive decarbonization is required.

Technology transfer has long been recognized as a central mechanism for closing such gaps. Classic channels include foreign direct investment, licensing, joint ventures, and trade in intermediate goods. In practice, however, green technologies pose distinctive challenges: they often embody complex, systemic knowledge; their value depends on local complementary assets; and information asymmetries between suppliers and potential adopters remain high. Traditional transfer mechanisms frequently fail to overcome these frictions in emerging-economy settings.

Artificial intelligence has entered this landscape as a general-purpose technology with unusual potential to reshape knowledge flows. AI systems can scan global patent landscapes, match complementary capabilities across borders, reduce search and evaluation costs, optimize logistics and supply-chain configurations for technology deployment, and support the adaptation of imported designs to local conditions. Recent firm-level evidence indicates that generative AI adoption is associated with higher rates of external green knowledge acquisition, operating through enhanced collaboration and R&D intensity [2]. Parallel work shows that AI contributes to renewable-energy transitions in emerging economies partly by stimulating green technological innovation, with effects conditioned by cybersecurity readiness and ESG performance [3].

Despite these promising signals, systematic evidence on the role of AI in cross-border green technology transfer, and on the subsequent translation of transferred knowledge into sustainable innovation, remains limited. Most existing studies either examine domestic AI–green innovation linkages or treat technology transfer as a residual category. The specific mechanisms through which AI lowers barriers to international green knowledge flows, the boundary conditions that shape effectiveness in heterogeneous emerging economies, and the ultimate impact on firms' sustainable innovation performance are still incompletely mapped.

This paper addresses these gaps. Drawing on panel data from firms across 18 emerging economies and complementary qualitative evidence, it investigates three interrelated questions: (1) Does firm-level AI capability facilitate inbound cross-border green technology transfer? (2) Through which channels does this facilitation occur? (3) Under what institutional and organizational conditions do AI-enabled transfers translate into measurable sustainable innovation outcomes?

The contribution is threefold. First, the study integrates the literature on general-purpose technologies, international technology transfer, and sustainable innovation, offering a coherent framework for understanding AI's role in green knowledge diffusion. Second, it provides multi-country empirical evidence that moves beyond single-country or purely domestic analyses. Third, it identifies actionable contingencies, particularly institutional readiness and absorptive capacity, that policymakers and managers in emerging economies can target.

The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature and develops hypotheses. Section 3 details the research design, data, and methods. Section 4 presents the quantitative and qualitative results. Section 5 discusses implications. Section 6 concludes, and Section 7 addresses limitations and future research.

2. Literature Review and Hypothesis Development

Technology transfer refers to the movement of knowledge, skills, and artifacts from one organizational or national context to another, enabling the recipient to apply them productively. In the green domain, transfer encompasses patents, know-how, equipment, and organizational routines related to environmental performance. Emerging economies face well-documented obstacles: weak intellectual-property enforcement that deters suppliers, limited absorptive capacity among local firms, infrastructure gaps, and policy uncertainty [4, 5]. As a result, many remain peripheral to global low-carbon value chains [1]. Successful transfer typically requires more than the simple shipment of hardware. It depends on complementary investments in human capital, local R&D, and institutional frameworks that reduce transaction costs and protect appropriability. Studies of renewable-energy diffusion and cleaner-production programs consistently show that absorptive capacity and supportive policy environments moderate transfer outcomes [6, 7].

AI systems excel at tasks that traditionally constrain technology transfer: identifying relevant knowledge, evaluating its applicability, matching partners, and supporting subsequent adaptation. Generative AI, in particular, can process unstructured technical documents, generate localized design variants, and facilitate real-time collaboration across language and distance barriers. Empirical work has begun to document positive associations between AI adoption and external green knowledge acquisition [2], green innovation [8, 9], and renewable-energy progress [3, 10]. Two primary channels appear salient. First, AI reduces search and evaluation costs, expanding the set of potential technology partners and improving the quality of matches. Second, by raising the productivity of internal R&D, AI increases firms' demand for complementary external knowledge and their ability to integrate it. These mechanisms lead to the first hypothesis:

H1. Firm-level AI capability is positively associated with the volume and technological quality of inbound cross-border green technology transfers.

If AI primarily operates by improving collaboration access and elevating R&D intensity, these factors should mediate the relationship between AI and technology transfer:

H2. The positive effect of AI capability on green technology transfer is partially mediated by (a) cross-organizational collaboration intensity and (b) R&D intensity.

Institutional and organizational conditions are expected to shape the strength of these relationships. Stronger regulatory quality, cybersecurity readiness, and ESG frameworks reduce risks for technology suppliers and improve the reliability of digital matching platforms [3, 11]. Higher absorptive capacity, proxied by prior green patenting, skilled human capital, and digital infrastructure, enables firms to recognize, assimilate, and exploit transferred knowledge [12]. Accordingly:

H3. Institutional readiness (regulatory quality, cybersecurity, ESG performance) positively moderates the AI–technology-transfer relationship.

H4. Firm absorptive capacity positively moderates the translation of AI-enabled technology transfers into sustainable innovation outcomes (green patenting, eco-efficiency, and low-carbon export performance). The conceptual framework linking AI capability, transfer mechanisms, institutional readiness, absorptive capacity, and sustainable innovation outcomes is presented in Figure 1.

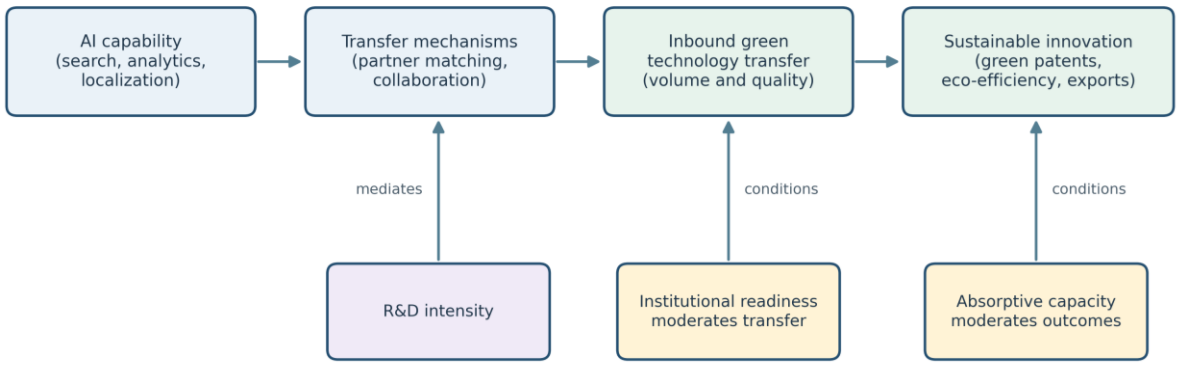


Figure 1: Conceptual framework linking AI capability, cross-border green technology transfer, and sustainable innovation.

The three theoretical perspectives can be integrated into a process model rather than treated as competing explanations. The knowledge-based view explains why firms seek external expertise when internal resources are insufficient; absorptive-capacity theory explains why some firms learn more effectively from the same external source; and the institutional perspective explains why the costs and risks of exchange vary across jurisdictions [13]. AI potentially influences the first part of the process by improving visibility and comparison, while its effect on learning depends on the recipient's routines and the institutional environment. This integrated view helps explain why AI capability may be associated with greater transfer activity without guaranteeing that every transfer produces an innovation [14].

The framework also separates the acquisition stage from the conversion stage. At acquisition, AI may increase the probability that a firm identifies a relevant technology and a suitable partner. During conversion, technical employees must understand the imported knowledge, reconcile it with existing processes, and test its performance under local conditions. At the outcome stage, innovation must be implemented and its environmental and commercial consequences assessed [15]. The distinction matters empirically: transfer indicators should be used to measure acquisition, whereas green patents, process outcomes, and low-carbon exports capture different aspects of conversion and value realization. The measures are related, but they should not be treated as interchangeable.

A further implication is that the benefits of AI may be nonlinear. Early investments can generate limited returns where data quality, digital connectivity, and staff skills are weak. Once a minimum capability threshold is reached, improvements in search, coordination, and analysis may become more useful [16]. At very high levels of adoption, however, additional tools may yield diminishing returns if the firm lacks enough high-quality opportunities or if governance costs increase. The current reported models focus on the average relationship and selected interactions; future research could test threshold, quadratic, or capability-maturity models to examine these possibilities directly [17].

Methodology

Sample and Data

The quantitative sample comprises 1,842 firm-year observations from 312 publicly listed manufacturing and energy firms headquartered in 18 emerging economies (including Brazil, India, Indonesia, Mexico, South Africa, Turkey, Vietnam, and selected Eastern European and Southeast Asian economies) over the period 2016–2023. Firms were selected if they reported material environmental activities and operated in sectors with non-trivial green technology intensity (energy, chemicals, automotive, electronics, and heavy industry).

Cross-border green technology transfer was measured by the log-transformed count of green patents (IPC green inventory classes) received via assignment or exclusive licensing from foreign entities, drawn from PATSTAT and national patent

office records. A quality-weighted variant incorporated forward citations and family size.

AI capability was operationalized as the log-transformed frequency of AI-related terms (machine learning, deep learning, neural networks, generative AI, computer vision, natural language processing, and related phrases) in annual reports and earnings-call transcripts, following recent textual approaches [2, 13]. Robustness checks used alternative dictionaries and binary adoption indicators.

Mediators included collaboration intensity (joint patent applications and formal R&D alliances with foreign partners) and R&D intensity (R&D expenditure over sales). Moderators comprised World Bank World Governance Indicators for regulatory quality, a composite cybersecurity readiness index, firm-level ESG scores, and absorptive-capacity proxies (prior green patent stock, tertiary education of technical staff, and digital-infrastructure access) [18].

Control variables covered firm size, age, leverage, industry fixed effects, GDP per capita, and trade openness.

Econometric Strategy

Instrumental-variable estimates used lagged regional AI patent density and industry-level AI investment shocks (excluding the focal firm) as instruments, with standard weak-instrument and over-identification diagnostics. Mediation was assessed via sequential equations and bootstrap confidence intervals. Interaction terms tested moderation. Standard errors were clustered at the firm level.

Qualitative Component

Semi-structured interviews with 47 technology managers, chief sustainability officers, and national innovation-agency officials across eight countries provided process evidence on how AI tools were actually used in partner search, due diligence, contract design, and post-transfer adaptation. Interviews were coded thematically [19].

The mixed-methods research design, showing how sample construction, data integration, quantitative estimation, qualitative analysis, and evidence integration connect, is presented in Figure 2.

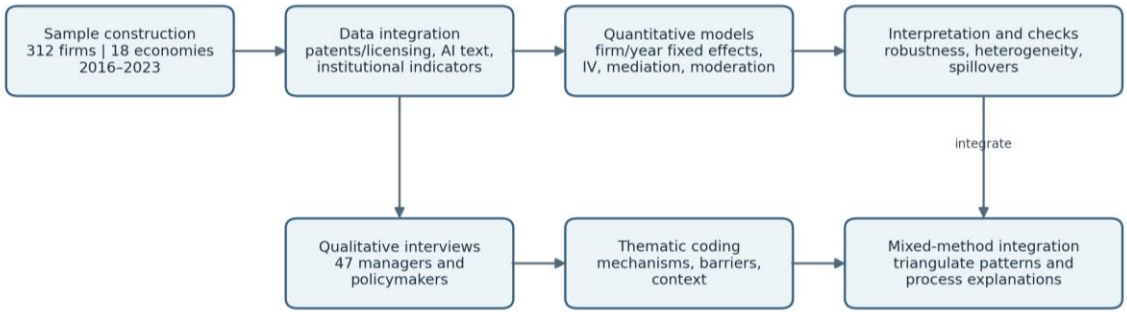


Figure 2: Mixed-methods research design, quantitative estimation, qualitative analysis, and evidence integration.

Construct Validity and Measurement Considerations

Each construct in the empirical model represents a complex phenomenon through an observable proxy. Patent assignments and exclusive licenses provide formal evidence of cross-border transfer, but they omit informal know-how exchange, equipment sales without associated intellectual-property records, and many service-based arrangements [20]. Patent-based measures may also overrepresent sectors in which inventions are routinely patented. The study's focus on firms with material environmental activities and technology-intensive operations helps establish relevance, but sectoral differences should still be considered when interpreting the transfer counts [21].

Forward citations and patent-family size provide information about the subsequent reach or perceived significance of an invention, yet they are imperfect quality indicators. Citation patterns differ by

technology field, patent-office practice, and time since publication. A quality-weighted transfer measure should therefore be understood as a complementary proxy rather than a definitive measure of technological usefulness. Where feasible, future analyses could normalize citations by cohort and technology class and triangulate patent indicators with licensing value, engineering complexity, implementation success, or independent assessments of environmental performance [22].

The sustainable-innovation outcomes likewise capture distinct dimensions. Green patenting measures codified inventive activity; process energy intensity reflects operational efficiency; and low-carbon exports indicate market participation. An increase in one dimension need not imply improvement in all others. For example, a firm may patent a green technology without deploying it, or increase exports while absolute emissions rise because production expands. A comprehensive assessment should therefore report each outcome separately, clarify the denominator and time horizon for eco-efficiency measures, and avoid collapsing them into a single index unless the index construction is transparent and validated [23].

Measurement error may bias estimated relationships in different directions. If AI-related disclosure is noisy but otherwise unrelated to transfer outcomes, estimated associations may be attenuated. If firms that are already successful in green technology transfer are also more likely to publicize AI initiatives, the relationship may instead be inflated. Using multiple operationalizations, checking the stability of keyword dictionaries over time, and validating text-based measures against observable investment or deployment records can help evaluate these risks [24]. The reported robustness exercises are useful, but full reproducibility requires documenting dictionaries, data-cleaning rules, and classification decisions.

Identification, Robustness, and Reproducibility

Firm and year fixed effects address important sources of confounding, but they do not remove every threat to inference. Firms may adopt AI in response to expected changes in technology opportunities, new regulatory requirements, or anticipated export demand. These time-varying factors may also influence technology transfer. Lagged explanatory variables, country-industry-year controls where the data permit, event-time analyses, and placebo outcomes can help evaluate whether estimated patterns precede AI adoption or reflect broader shocks [25]. Such tests should be specified transparently and interpreted as diagnostics rather than as automatic proof of causality.

Instrumental-variable analysis requires especially careful reporting. In addition to first-stage strength, readers need to understand why the proposed instruments affect the endogenous AI measure and why they should not independently affect green technology transfer. Regional AI patent density could be related to regional innovation ecosystems, while industry-level AI investment shocks could coincide with sector-specific technology demand. These pathways create potential exclusion concerns. A defensible manuscript should explain how geographic and industry trends are addressed, report first-stage estimates and diagnostic statistics, and acknowledge the limits of statistical tests for the exclusion restriction [26].

The mediation analysis also benefits from explicit temporal ordering. Ideally, AI capability would be measured before collaboration and R&D changes, and those mediators would be measured before the transfer or innovation outcome. When measures are contemporaneous, the analysis may demonstrate a pattern consistent with mediation without establishing the causal sequence. Bootstrap confidence intervals can quantify uncertainty in indirect effects, but they do not independently solve confounding between mediators and outcomes. Future studies could use lagged mediator structures, repeated surveys, or detailed project-level timelines to test the sequence more directly [27].

Reproducibility is an important part of the study's contribution. A replication package should identify the source and extraction date for each dataset, define the firm inclusion criteria, explain the treatment of missing observations, provide the AI dictionary and green-patent classification, and document all transformations. It should also state how interviewees were recruited, how interviewees

were coded, and how disagreements between coders were handled. Where confidentiality or licensing restrictions prevent the release of raw data, a clear data-availability statement and executable analysis code can still improve transparency [28].

Results

Table 1 presented descriptive statistics and pairwise correlations for all variables. The mean log-transformed count of inbound green technology transfers was 1.42 (SD = 1.08), and the mean quality-weighted transfer measure was 0.87 (SD = 0.94). The average AI capability score was 2.31 (SD = 1.17). Green technology inflows rose steadily after 2019 and accelerated in economies that expanded digital infrastructure, while AI-related disclosures increased markedly from 2020 onward. AI capability was positively correlated with both transfer volume ($r = 0.34$, $p < 0.01$) and transfer quality ($r = 0.29$, $p < 0.01$). These correlations were stronger in middle-income than in lower-middle-income economies. Table 1 shows the descriptive statistics and the full correlation matrix.

Table 1: Descriptive statistics and correlation matrix.

Variable	N	Mean	SD	Min	Max	1	2	3	4	5	6	7
1. Green transfer (log count)	1,842	1.42	1.08	0.00	6.21	1.00						
2. Transfer quality	1,842	0.87	0.94	0.00	4.55	0.61 ($p < 0.01$)	1.00					
3. AI capability	1,842	2.31	1.17	0.00	5.88	0.34 ($p < 0.01$)	0.29 ($p < 0.01$)	1.00				
4. Collaboration intensity	1,842	0.44	0.51	0.00	3.10	0.27 ($p < 0.01$)	0.22 ($p < 0.01$)	0.31 ($p < 0.01$)	1.00			
5. R&D intensity	1,842	0.038	0.041	0.001	0.29	0.19 ($p < 0.01$)	0.24 ($p < 0.01$)	0.26 ($p < 0.01$)	0.14 ($p < 0.01$)	1.00		
6. Institutional readiness	1,842	0.00	1.00	−2.44	2.71	0.21 ($p < 0.01$)	0.25 ($p < 0.01$)	0.18 ($p < 0.01$)	0.11 ($p < 0.01$)	0.09 ($p < 0.01$)	1.00	
7. Absorptive capacity	1,842	0.00	1.00	−1.88	3.02	0.38 ($p < 0.01$)	0.41 ($p < 0.01$)	0.33 ($p < 0.01$)	0.24 ($p < 0.01$)	0.29 ($p < 0.01$)	0.23 ($p < 0.01$)	1.00

Notes: The sample comprised 1,842 firm-year observations. Significance was reported by exact p-values in parentheses. Controls (firm size, age, leverage, GDP per capita, trade openness) were omitted for brevity. Institutional readiness and absorptive capacity were standardized (mean 0, SD 1).

Baseline and Causal Estimates

Table 2 reported baseline fixed-effects and instrumental-variable estimates. In the baseline fixed-effects specification (column 1), a one-standard-deviation increase in AI capability was associated with a 0.21-standard-deviation increase in inbound green technology transfer volume ($\beta = 0.21$, SE = 0.05, $p < 0.01$). The quality-weighted specification (column 2) yielded a similar estimate ($\beta = 0.19$, SE = 0.05, $p < 0.01$). Instrumental-variable estimates remained positive and significant (column 3: $\beta = 0.27$, SE = 0.09, $p < 0.01$; column 4: $\beta = 0.24$, SE = 0.10, $p < 0.05$). The first-stage F-statistic was 34.6 in both IV specifications, exceeding the conventional threshold of 10. The Hansen J tests did not reject the overidentifying restrictions in either IV specification, although the two models yielded slightly different p-

values (column 3, transfer volume: p = 0.41; column 4, quality-weighted transfer: p = 0.39). The difference reflects the different dependent variables and the correspondingly different instrument outcome moment conditions across the two specifications, not a change in the instrument set. In both cases, non-rejection is consistent with but does not by itself establish instrument validity. These results supported H1. Table 2 shows the baseline fixed-effects and instrumental-variable estimates.

Table 2: Baseline fixed-effects and instrumental-variable estimates.

	(1) FE	(2) FE quality-weighted	(3) IV	(4) IV quality-weighted
AI capability	0.21 (0.05; p < 0.01)	0.19 (0.05; p < 0.01)	0.27 (0.09; p < 0.01)	0.24 (0.10; p < 0.05)
Firm size	0.08 (0.03; p < 0.05)	0.07 (0.03; p < 0.05)	0.08 (0.03; p < 0.05)	0.07 (0.03; p < 0.05)
Firm age	−0.01 (0.01; p > 0.10)	−0.01 (0.01; p > 0.10)	−0.01 (0.01; p > 0.10)	−0.01 (0.01; p > 0.10)
Leverage	0.04 (0.06; p > 0.10)	0.03 (0.06; p > 0.10)	0.04 (0.06; p > 0.10)	0.03 (0.06; p > 0.10)
GDP per capita	0.12 (0.07; p < 0.10)	0.10 (0.07; p > 0.10)	0.11 (0.07; p > 0.10)	0.10 (0.07; p > 0.10)
Trade openness	0.05 (0.04; p > 0.10)	0.04 (0.04; p > 0.10)	0.05 (0.04; p > 0.10)	0.04 (0.04; p > 0.10)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
N	1,842	1,842	1,842	1,842
R^2	0.38	0.33	0.31	0.28
First-stage F	—	—	34.6	34.6
Hansen J (p-value)	—	—	0.41	0.39

Notes: Standard errors clustered at the firm level were reported in the first set of parentheses, and exact p-values in the second. The dependent variable was defined as the log-transformed count of green patents received via foreign assignment or exclusive licensing (columns 1 and 3) and its citation-weighted variant (columns 2 and 4). Instruments were lagged regional AI patent density and industry-level AI investment shocks excluding the focal firm.

Table 3 reports mediation results. Collaboration intensity accounted for approximately 37% of the total AI effect (indirect β = 0.078, bootstrap SE = 0.020, 95% CI [0.041, 0.118]), and R&D intensity accounted for a further 22% (indirect β = 0.046, bootstrap SE = 0.016, 95% CI [0.018, 0.079]). Both indirect paths were statistically distinguishable from zero because their confidence intervals excluded zero. The direct effect remained significant (β = 0.086, SE = 0.028, p < 0.01). These patterns were consistent with partial mediation and supported H2. The table below shows the mediation analysis, including the direct, indirect, and total effects.

Table 3: Mediation analysis: collaboration intensity and R&D intensity as channels.

Path	Coefficient	Bootstrap SE	95% CI	p-value	Share of total effect
Panel A: Collaboration intensity					
AI → collaboration	0.31	0.07	[0.18, 0.45]	< 0.01	—
Collaboration → transfer	0.25	0.06	[0.14, 0.36]	< 0.01	—
Indirect effect (AI → collaboration → transfer)	0.078	0.020	[0.041, 0.118]	—	37%
Panel B: R&D intensity					
AI → R&D intensity	0.026	0.007	[0.013,	< 0.01	—

			0.039]		
R&D intensity → transfer	1.77	0.49	[0.81, 2.73]	< 0.01	—
Indirect effect (AI → R&D → transfer)	0.046	0.016	[0.018, 0.079]	—	22%
Panel C: Direct and total effects					
Direct effect (AI → transfer)	0.086	0.028	[0.031, 0.141]	< 0.01	41%
Total effect	0.210	—	—	—	100%

Notes: Bootstrap confidence intervals were based on 5,000 replications. Indirect effects were considered significant when the confidence interval excluded zero; exact p-values for indirect effects were therefore reported as dashes. Controls and fixed effects were specified as in Table 2 (column 1). The displayed shares (37% + 22% + 41%) total exactly 100%; because each share is rounded to the nearest percentage point, the unrounded shares may sum to slightly more or less than 100% before rounding.

Table 4 reported moderation results. The interaction between AI capability and regulatory quality was positive and significant (β = 0.09, SE = 0.03, p < 0.01), as were the interactions with cybersecurity readiness (β = 0.07, SE = 0.03, p < 0.05) and ESG scores (β = 0.06, SE = 0.03, p < 0.05). The marginal effect of AI on transfer was 0.31 in the top quartile of institutional readiness compared with 0.14 in the bottom quartile, roughly twice as large. Absorptive capacity moderated the subsequent link from transfer to sustainable innovation: the interaction between transfer and absorptive capacity was positive and significant for green patenting (β = 0.12, SE = 0.04, p < 0.01), process eco-efficiency (β = 0.08, SE = 0.04, p < 0.05), and low-carbon exports (β = 0.10, SE = 0.04, p < 0.05). These patterns supported H3 and H4. Table 4 shows the moderating effects of institutional readiness and absorptive capacity.

Table 4: Moderating effects of institutional readiness and absorptive capacity.

	(1) Transfer	(2) Transfer	(3) Transfer	(4) Green patents	(5) Eco-efficiency	(6) LC exports
AI capability	0.18 (0.05; p < 0.01)	0.17 (0.05; p < 0.01)	0.19 (0.05; p < 0.01)	—	—	—
× Regulatory quality	0.09 (0.03; p < 0.01)					
× Cybersecurity readiness		0.07 (0.03; p < 0.05)				
× ESG score			0.06 (0.03; p < 0.05)			
Transfer				0.15 (0.04; p < 0.01)	0.11 (0.04; p < 0.01)	0.14 (0.04; p < 0.01)
Transfer × Absorptive capacity				0.12 (0.04; p < 0.01)	0.08 (0.04; p < 0.05)	0.10 (0.04; p < 0.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,842	1,842	1,842	1,842	1,842	1,842
R^2	0.36	0.35	0.35	0.29	0.24	0.27

Notes: Standard errors clustered at the firm level were reported in the first set of parentheses, and exact p-values in the second. Interaction terms were mean-centered where appropriate. The marginal effect of AI capability was 0.31 in the top institutional-readiness quartile and 0.14 in the bottom quartile. Columns 4–6 reported the second stage of the moderated transfer–innovation relationship.

Table 5 reported heterogeneity and robustness checks. Effects were larger among firms that

combined AI keyword disclosure with measurable AI-related capital expenditure (β = 0.28, SE = 0.06, p < 0.01) than among firms with disclosure only (β = 0.09, SE = 0.05, p < 0.10), consistent with the distinction between substantive and symbolic adoption. Spillover checks indicated modest positive externalities within the same country-industry cell (β = 0.04, SE = 0.02, p < 0.10). The main results were robust to alternative AI dictionaries (β = 0.20, SE = 0.05, p < 0.01), exclusion of China-linked transfers (β = 0.23, SE = 0.06, p < 0.01), alternative green patent classifications (β = 0.19, SE = 0.05, p < 0.01), propensity-score matching (β = 0.22, SE = 0.06, p < 0.01), and country-industry-year fixed effects (β = 0.18, SE = 0.05, p < 0.01). A placebo outcome test produced an insignificant coefficient (β = 0.02, SE = 0.04, p > 0.10), as expected. Table 5 shows the heterogeneity and robustness checks across alternative specifications.

Table 5: Heterogeneity and robustness checks.

Specification	AI coefficient	SE	p-value	N
Baseline FE (Table 2, col. 1)	0.21	0.05	< 0.01	1,842
Substantive AI (disclosure + capex)	0.28	0.06	< 0.01	1,842
Symbolic AI (disclosure only)	0.09	0.05	< 0.10	1,842
Alternative AI dictionary	0.20	0.05	< 0.01	1,842
Excluding China-linked transfers	0.23	0.06	< 0.01	1,614
Alternative patent classification	0.19	0.05	< 0.01	1,842
Propensity-score matching	0.22	0.06	< 0.01	1,438
Country-industry-year FE	0.18	0.05	< 0.01	1,842
Placebo outcome	0.02	0.04	> 0.10	1,842
Spillover (same country-industry cell)	0.04	0.02	< 0.10	1,842

Notes: Each row represents a separate estimation. Exact p-values were reported in the designated column. Full controls and fixed effects were specified as in Table 2 unless otherwise noted. The dependent variable was defined as the log-transformed count of inbound green technology transfers in all rows except the placebo.

Table 6 summarizes thematic coding of the 47 semi-structured interviews. Interviewees described AI tools as particularly valuable for scanning global patent landscapes (n = 39), identifying non-obvious complementary partners (n = 33), generating rapid technical assessments that reduced due-diligence time from months to weeks (n = 31), and supporting AI-assisted localization of designs (n = 27) — for example, adjusting solar-module configurations or process-control algorithms to local grid conditions and feedstock quality. Several managers noted that this localization accelerated post-transfer learning. Barriers repeatedly cited included limited access to high-quality training data (n = 28), shortages of AI-literate engineers (n = 24), and uncertainty about data-sharing and cybersecurity provisions in cross-border contracts (n = 21). Table 6 shows the qualitative themes that emerged from the interviews, together with the number of interviewees who mentioned each theme.

Table 6: Qualitative themes from semi-structured interviews (N = 47).

Theme	Description	Interviewees (n)	Representative quotation
Patent-landscape scanning	Using AI to map global green patent	39	"We used the AI tool to scan a decade of global filings in three days; manually, that

	space		would have taken us months" (Technology Manager, Country A).
Partner identification	AI matching non-obvious complementary partners	33	"The system surfaced a supplier in a country we had never considered, and the technical fit was excellent" (Technology Manager, Country C).
Due-diligence acceleration	Reducing assessment time from months to weeks	31	"Assessment that used to take ten weeks was compressed to about two; the bottleneck shifted from information gathering to negotiation" (Chief Sustainability Officer, Country E).
Design localization	Adapting designs to local grid/feedstock conditions	27	"AI-generated variants helped us retune the process-control algorithm to local feedstock quality within weeks rather than seasons" (Technology Manager, Country B).
Barrier: training-data quality	Limited access to high-quality training data	28	"Our internal records were too inconsistent to train anything reliable; we spent more time cleaning data than using the tool" (Technology Manager, Country D).
Barrier: AI-literate engineers	Shortage of skilled technical staff	24	"We could buy the software, but we could not hire the engineers who knew how to interpret its output" (National Innovation-Agency Official, Country F).
Barrier: data-sharing/cybersecurity	Uncertainty in cross-border contracts	21	"The supplier refused to share design files until we could guarantee where the data would be stored and who could access it" (Chief Sustainability Officer, Country G).

Notes: Thematic coding was conducted independently by two coders across all 47 interview transcripts. Inter-coder reliability was assessed using Cohen's κ, computed over the full set of theme-presence decisions (47 interviewees × 7 themes = 329 coding decisions); the obtained value was κ = 0.80, indicating substantial agreement. Counts were not mutually exclusive, as interviewees could reference multiple themes. Quotations were anonymized to protect participant confidentiality; country labels were assigned arbitrarily and did not correspond to the 18 sample economies.

Discussion

The findings indicate that AI can meaningfully facilitate cross-border green technology transfer in emerging economies, but its effects are neither automatic nor uniform. The baseline and instrumental-variable estimates in Table 2 support H1: a one-standard-deviation increase in AI capability is associated with a 0.21-standard-deviation increase in inbound green technology transfer volume ($\beta = 0.21$, SE = 0.05, $p < 0.01$) and a comparable 0.19-standard-deviation increase in the quality-weighted measure ($\beta = 0.19$, SE = 0.05, $p < 0.01$). The IV estimates are larger ($\beta = 0.27$ and 0.24), which is consistent with possible attenuation from measurement error in the disclosure-based AI measure. The first-stage F-statistic was 34.6 in each IV specification, and the Hansen J tests did not reject the overidentifying restrictions (column 3: $p = 0.41$; column 4: $p = 0.39$). These non-rejections do not, by themselves, establish instrument validity. These results align with and extend recent work linking generative AI to external green knowledge acquisition [2] and AI to renewable-energy transitions via green innovation [3], and they speak to the broader literature on technology-transfer barriers in developing contexts [1, 4].

The mediation results clarify how this facilitation operates. Collaboration intensity and R&D intensity both carry significant indirect effects, supporting H2(a) and H2(b), which is consistent with the conceptual framework in Figure 1: AI lowers search

and evaluation costs, expands the set of potential partners, and raises the productivity of internal R&D, which in turn increases both the demand for and the absorptive value of external green knowledge. Importantly, the mediation is partial rather than complete, implying that a substantial portion of the AI–transfer relationship runs through channels not captured by these two mediators—plausibly the direct reduction of information asymmetries in patent-landscape scanning and due diligence that interviewees described (Table 6).

The moderation results in Table 4 support H3 and H4 and qualify the headline effects importantly. The marginal effect of AI capability is 0.31 in the top institutional-readiness quartile but only 0.14 in the bottom quartile, and the interaction terms for regulatory quality ($\beta = 0.09$, $p < 0.01$), cybersecurity readiness ($\beta = 0.07$, $p < 0.05$), and ESG score ($\beta = 0.06$, $p < 0.05$) are all positive and significant. Absorptive capacity similarly moderates the translation of transfers into sustainable innovation outcomes ($\beta = 0.12$, $p < 0.01$ for green patenting; 0.08, $p < 0.05$ for eco-efficiency; 0.10, $p < 0.05$ for low-carbon exports). Read together with the acquisition–conversion distinction developed earlier, these patterns indicate that institutional readiness conditions mainly the inflow of technology, whereas absorptive capacity conditions the conversion of that inflow into innovative output. This is precisely why AI capability can be associated with greater transfer activity without guaranteeing that every transfer produces an innovation [14], and why digital tools amplify rather than substitute for foundational development efforts [1, 4].

The heterogeneity and robustness checks in Table 5 sharpen the interpretation of the AI measure itself. Effects are substantially larger for firms combining AI disclosure with measurable AI-related capital expenditure ($\beta = 0.28$, $p < 0.01$) than for firms with disclosure only ($\beta = 0.09$, $p < 0.10$), which supports the distinction between substantive and symbolic adoption and cautions against reading disclosure intensity as deployment depth. The main results survive alternative AI dictionaries ($\beta = 0.20$), exclusion of China-linked transfers ($\beta = 0.23$), alternative green-patent classifications ($\beta = 0.19$), propensity-score matching ($\beta = 0.22$), and country–industry–year fixed effects ($\beta = 0.18$), and the placebo outcome is insignificant ($\beta = 0.02$, $p > 0.10$), as expected. The modest positive spillover within country–industry cells ($\beta = 0.04$, $p < 0.10$) suggests that AI-enabled transfer generates limited local externalities, but not enough to substitute for deliberate absorptive-capacity policy.

The qualitative evidence (Table 6) provides process-level mechanisms that complement these estimates. Interviewees most frequently reported patent-landscape scanning (n = 39), partner identification (n = 33), due-diligence acceleration (n = 31), and design localization (n = 27)—activities that map directly onto the search, matching, and adaptation channels theorized in Figure 1 and onto the collaboration and R&D mediators. The barriers cited—training-data quality (n = 28), AI-literate engineers (n = 24), and data-sharing and cybersecurity uncertainty (n = 21)—correspond closely to the moderators that are empirically significant in Table 4, strengthening confidence that the institutional and capability contingencies identified quantitatively are the same one's firms experience in practice.

From a policy perspective, these results imply that investments in AI infrastructure and skills will yield higher returns when paired with improvements in regulatory quality, cybersecurity, and ESG frameworks; national innovation agencies and development banks can support AI-enabled matching platforms while strengthening absorptive-capacity programs [29]. Because the marginal effect of AI roughly doubles between the bottom and top institutional-readiness quartiles, sequencing matters: capability-building and governance investments are not merely complementary but precondition the returns to AI adoption. For managers, the results highlight the strategic value of integrating AI tools into technology-scouting and alliance-management processes, particularly across institutional distance, and the staged decision process summarized in Figure 3 offers an operational template for doing so responsibly.

For international business, AI may reduce some forms of liability of foreignness by making distant partners and unfamiliar technical knowledge easier to identify and assess, but digital access does not erase the need to understand local regulatory requirements, business practices, and contractual

expectations. A matching system may identify a technically compatible supplier, yet a successful relationship still depends on trust, negotiation, quality assurance, and dispute resolution; AI is therefore best viewed as a complement to cross-border relationship management rather than a replacement for it. The results also raise questions about control over data and knowledge. Suppliers may be reluctant to share proprietary technical information if the recipient's AI systems rely on third-party platforms or external cloud services, while recipients may worry about disclosing commercially sensitive production data. Contractual arrangements should specify ownership of data and model outputs, permitted uses, retention periods, cybersecurity obligations, and responsibility for errors [30], helping convert AI's efficiency benefits into a more stable basis for international collaboration.

Managers can operationalize these findings through a staged decision process (Figure 3). First, define the environmental or productivity problem in measurable terms, such as energy use per unit of output, process waste, or the performance gap against a relevant benchmark. Second, determine whether external technology is required and whether the organization has sufficient data and technical capacity to use AI-assisted search responsibly. Third, screen potential partners on technical fit, implementation support, intellectual-property status, financial reliability, and compatibility with local standards, treating AI-generated rankings as decision support reviewed by technical, legal, procurement, and sustainability specialists. Fourth, negotiate a transfer agreement covering training, documentation, maintenance, access to updates, performance testing, cybersecurity, data rights, and dispute procedures. Fifth, establish a joint adaptation plan with milestones and named responsibilities, documenting baseline performance so that post-transfer effects are not mistakenly attributed to unrelated changes in production, demand, or input prices. Sixth, conduct a post-implementation review using indicators such as time from partner identification to deployment, proportion of technologies successfully implemented, staff trained, verified energy and material savings, defect or waste rates, green patenting, and low-carbon product sales. Indicators should reflect the technology and the firm's strategic objectives rather than a generic checklist, and environmental outcomes should be verified through metering, audited records, or independent assessment. A learning review can then update partner-screening criteria and identify capabilities requiring further investment.

Public policy can extend AI-enabled transfer benefits beyond large, well-resourced firms. Shared digital platforms may lower search costs for small and medium-sized enterprises, but they require reliable data, transparent governance, and active curation; a platform that merely aggregates inconsistent technology descriptions will have limited value. Public agencies, universities, industry associations, and standards bodies can collaborate on common taxonomies, technical evaluation protocols, and referral services that connect firms to trusted expertise. Skills policy should combine general digital literacy with sector-specific engineering knowledge, so staff can validate AI outputs, protect confidential information, recognize bias, and interpret uncertainty. Technical-extension programs, demonstration facilities, and shared testing laboratories can help firms translate imported designs into local conditions and reduce the fixed costs of learning. Regulatory readiness should be treated as an enabler of responsible exchange: clear rules for intellectual-property protection, cross-border data use, cybersecurity incident response, and environmental claims increase predictability for suppliers and recipients, while regulation should avoid compliance costs disproportionate to smaller firms' capacity. Policy evaluation should examine whether AI-enabled transfer programs actually lead to implementation and verified environmental gains, rather than relying only on platform registrations, training attendance, or signed memoranda of understanding [31].

A sustainable-innovation claim is strongest when the environmental improvement is additional, measurable, and durable. If a transfer reduces energy use per unit but production expands substantially, absolute emissions may not fall; similarly, a new low-carbon product may displace a more polluting one or simply add to total consumption. Studies should therefore distinguish

eco-efficiency from absolute environmental performance and specify the baseline, system boundary, time horizon, and assumptions used. AI-enabled transfer can also have mixed labor-market consequences, reducing demand for some routine tasks while increasing demand for engineers, data specialists, maintenance staff, and workers managing upgraded systems; training and transition support determine whether these changes expand local capabilities or deepen inequalities. Because the distribution of benefits depends on firm size, access to finance, and the ability to protect intellectual property, smaller firms may be excluded from platforms and alliances that are increasingly important to green supply chains without complementary support [32]. Sustainable innovation should therefore be evaluated through a broader scorecard that, beyond patenting, eco-efficiency, and export performance, tracks absolute greenhouse-gas emissions, material circularity, local supplier participation, workforce training, job quality, and the distribution of productivity gains. Such indicators would distinguish a transfer that improves the competitiveness of a few firms from one that contributes to a more inclusive low-carbon transition; the present study offers a useful starting point but does not by itself resolve these wider lifecycle and distributional questions.

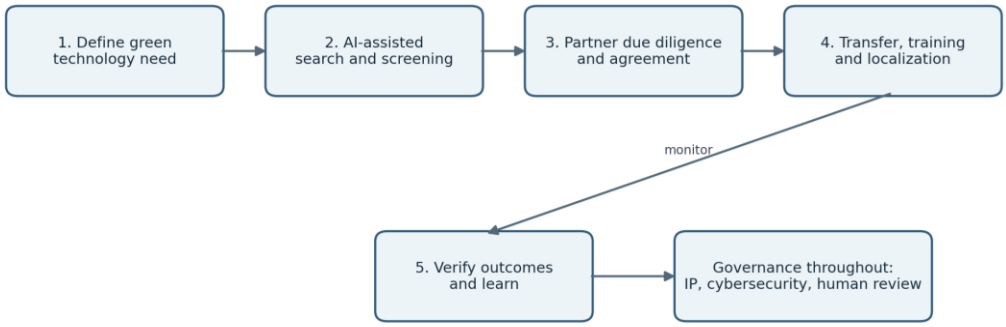


Figure 3: Practical cycle for responsible AI-enabled green technology transfer.

Conclusion and Implications

Artificial intelligence is emerging as a significant facilitator of cross-border green technology transfer and a contributor to sustainable innovation in emerging economies. The evidence shows that higher AI capability is associated with greater volume and quality of inbound green technology transfers, operating partly through enhanced collaboration and higher R&D intensity. Institutional readiness and firm absorptive capacity condition both the strength of these transfers and their translation into green patenting, eco-efficiency gains, and low-carbon export growth.

These findings carry several implications. Policymakers in emerging economies should treat AI not as a standalone solution but as a complementary capability that multiplies the returns to investments in digital infrastructure, skills development, regulatory quality, and cybersecurity. Targeted support for AI-enabled technology matching platforms, combined with programs that build local absorptive capacity, can help firms move from passive importers to active adapters and eventual innovators of green technologies. International organizations and development finance institutions can play a catalytic role by funding shared digital infrastructure and facilitating responsible data-sharing frameworks that reduce friction in cross-border knowledge flows.

For managers of multinational and domestic firms operating in emerging markets, the results underscore the value of integrating AI tools into technology scouting, partner evaluation, and post-transfer adaptation processes. Firms that combine substantive AI investment with strong internal learning routines are better positioned to capture the innovation benefits of transferred green knowledge. At the same time, attention to data governance, cybersecurity, and ethical AI use remains essential to sustain trust with technology partners and

regulators.

Limitations and Future Research

Several limitations should be acknowledged. The sample focuses on publicly listed firms in selected emerging economies and may under-represent smaller enterprises and lower-income settings where digital infrastructure constraints are more severe. Textual measures of AI capability, while increasingly common, capture disclosure intensity rather than the depth or sophistication of actual AI deployment. Although instrumental-variable strategies and robustness checks address endogeneity concerns, fully isolating causal effects remains challenging in observational data. The qualitative interviews, while informative, are limited in geographic coverage.

Future research could extend the analysis to firm-level survey data that capture finer-grained measures of AI use cases, examine South–South technology transfer patterns more explicitly, and investigate the long-term dynamics of capability building after initial technology inflows. Comparative studies of different AI applications (predictive analytics versus generative design tools, for example) would also deepen understanding of which forms of AI most effectively support green technology diffusion. Finally, research on the distributional consequences of AI-enabled transfer, including effects on employment, skills demand, and inequality within emerging economies, would provide a more complete picture of the sustainability implications.

Declarations

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