Navigating the Dual Transition: AI Energy Consumption, Energy-efficient AI Practices, and Green Business Performance in Emerging Economies

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Abstract: The proliferation of artificial intelligence (AI) across global industries has intensified debates surrounding digital transformation and environmental sustainability. This study develops and tests a moderated mediation framework that examines how AI energy consumption influences green business performance, with energy-efficient AI practices as a mediating mechanism and organizational sustainability commitment as a dual moderator. Drawing on survey data from 385 managers and IT professionals across diverse industries in an emerging economy undergoing rapid digital and green transitions, and employing Partial Least Squares Structural Equation Modeling, we find that AI energy consumption exerts a significant negative direct effect on green business performance. This negative effect is substantially attenuated through energy-efficient AI practices, which partially mediate this relationship. Critically, sustainability commitment operates as a dual moderator: it amplifies the transformation of AI energy consumption challenges into energy-efficient AI practices and simultaneously enhances the effectiveness of energy-efficient AI practices in generating environmental performance gains. These findings extend the established sustainable technology management theory to emerging economy contexts and offer novel insights into the complementary rather than competitive relationship between digital advancement and environmental stewardship. The practical implications for managers and policymakers seeking to align AI deployment with national sustainability objectives are discussed.

Keywords: artificial intelligence; energy consumption; energy efficiency; green business performance; sustainability commitment.

1. Introduction

The global economy is simultaneously experiencing two transformative transitions: a digital revolution driven by artificial intelligence (AI) and a sustainability imperative demanding unprecedented reductions in environmental impact[1]. For enterprises worldwide, particularly those in rapidly industrializing economies, the intersection of these transitions presents both extraordinary opportunities and formidable challenges. AI technologies promise to accelerate sustainability by optimizing energy grids, reducing industrial waste, and enabling evidence-based environmental management[2,3]. However, these technologies have substantial environmental costs. Global data centers could potentially double their electricity consumption by 2026, reaching over 1,000 terawatt-hours annually[4], with AI-specific workloads representing an increasingly significant portion of this demand.

This paradox, wherein technologies promoted as sustainability enablers consume enormous resources, creates urgent questions for businesses and policymakers. Training a single large-scale transformer model can generate carbon emissions equivalent to five automobiles over their entire operational lifetimes[5]. As AI adoption accelerates across manufacturing, financial services, logistics, and other sectors in emerging economies, understanding the net environmental implications of these deployments is critically important. Enterprises in developing nations face compounded pressures: ambitious national sustainability targets, evolving regulatory frameworks, integration into environmentally demanding global supply chains, and the aspirational drive toward digital-first competitive strategies[6].

Despite the growing scholarly attention to AI's environmental dimensions of AI, existing research exhibits significant limitations. First, empirical evidence predominantly originates from developed Western

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economies[7,8], leaving the distinct institutional, resource, and capability contexts of emerging economies under-explored. Second, prior research typically examines AI-environment relationships as direct effects, overlooking the organizational processes and capabilities through which firms translate AI deployment into environmental outcomes. Third, studies examining sustainability commitment as a contextual factor generally consider its influence on a single pathway, missing its potential dual moderating role across sequential organizational processes. Fourth, the mediating mechanism of energy-efficient AI practices, distinct from simple operational efficiency routines, has not been adequately examined in connecting AI energy challenges to environmental performance.

This study addresses these gaps through four specific contributions. First, we provide empirical evidence regarding the effects of AI energy consumption on sustainable business performance in an emerging economy context, Vietnam, which is undergoing simultaneous digital transformation and green development transitions of global significance. Second, we conceptualize and test energy-efficient AI practices as a mediating mechanism that encompasses not only energy-efficient operational practices but also the organizational capacity to develop novel environmental solutions in response to AI-related energy challenges, which is a theoretically richer construct than operational efficiency routines alone. Third, we advance dual moderation theory by demonstrating that sustainability commitment influences both the development of green innovation capabilities in response to AI energy challenges and the subsequent effectiveness of these capabilities in generating environmental performance. Fourth, we contribute methodologically by employing a moderated mediation framework with rigorous PLS-SEM analysis, addressing the reliance of prior research on single-stage models.

The study context is both theoretically and practically significant. Many countries have committed to achieving net-zero carbon emissions by 2050 while simultaneously ranking among Asia's fastest-growing AI adoption markets. This creates an ideal natural laboratory for examining the digital-green transition tensions. These findings contribute to global debates on sustainable AI governance and offer actionable guidance for enterprises worldwide confronting analogous challenges in aligning digital transformation with environmental responsibilities.

The remainder of this paper is organized as follows. We first review the relevant literature on AI energy consumption, green business performance, and sustainability commitment, and develop our theoretical framework and hypotheses. We then describe our methodology, including the sampling procedures, measurement development, and analytical approach. Subsequently, we present our empirical findings, followed by a discussion of the theoretical and practical implications. We conclude by acknowledging the limitations of our study and suggesting directions for future research.

2. Literature review

2.1. AI Energy Consumption: Global Dimensions and Emerging Economy Contexts

The environmental footprint of AI has emerged as a critical concern in academic, policy, and industry discourse. Training large-scale AI models requires substantial computational resources, with energy consumption measured in megawatt-hours and carbon emissions quantified in tons of CO_2 equivalents[5]. Beyond the training phases, the operational deployment of AI technologies continuously consumes energy through data center operations, model inference, and supporting infrastructure[9]. The International Energy Agency[4] projects that AI-driven data centers will account for increasingly significant portions of national electricity demand in rapidly digitalizing economies such as Korea. Enterprises adopting AI technologies inherit environmental liabilities that extend throughout the technology lifecycle, from hardware manufacturing through operational deployment to eventual disposal[10].

The environmental calculus of AI is further complicated by the rebound effect. Luccioni et al. [11] demonstrate that efficiency gains from AI adoption can be offset by behavioral responses that increase overall resource consumption, a manifestation of Jevons' paradox in the digital domain. This finding challenges optimistic assessments of AI's net sustainability contribution and underscores the importance of examining the organizational and institutional contexts that shape AI deployment outcomes. In emerging economies, where digital infrastructure development and energy system transitions coincide, rebound effects may be particularly pronounced. The carbon intensity of electricity supply, sectoral distribution of AI adoption, and availability of complementary sustainability capabilities all mediate the net environmental impact of AI deployment[12].

It is important to distinguish between two distinct energy cost categories associated with AI systems. Training-stage energy costs are one-time but exceptionally large expenditures associated with building foundation models from scratch, primarily borne by AI platform developers (e.g., OpenAI, Google DeepMind) rather than enterprise end-users. In contrast, deployment and inference-stage energy costs are recurring costs accumulated across every prediction, query, or automated decision generated by deployed AI models; these costs are directly observable and manageable by enterprises in their day-to-day operations. The AIEC construct operationalized in this study (see Appendix A) captures the deployment and operational energy perspective: the AI energy consumption that enterprise managers can monitor, report, and respond to within their organizations. Training-stage costs, while environmentally significant at a societal level, are largely outside the direct observation and control of most enterprise respondents and therefore represent the scope boundary of this study.

Simultaneously, AI offers genuine potential for environmental optimization. Machine learning algorithms optimize energy distribution networks, reduce waste in manufacturing processes, and enhance building energy management systems[13]. Google's application of AI in data center cooling achieved a 40% energy reduction[7], demonstrating tangible efficiency gains. In emerging economies, AI applications in agriculture, urban mobility, and industrial process optimization offer substantial environmental co-benefits alongside productivity improvements. Wang et al.[14] documented AI's positive contributions to high-quality energy development across 186 countries, while Liu et al.[8] found evidence of AI reducing carbon intensity in China's industrial sector. These diverse findings reflect the conditionality of AI's environmental impact of AI on deployment contexts and organizational capabilities.

2.2. Green Business Performance: Multidimensional Conceptualization

Green business performance encompasses multidimensional organizational capabilities to achieve environmental objectives while maintaining economic viability[15]. This construct extends beyond simple pollution reduction, incorporating resource efficiency, waste minimization, renewable energy adoption, and circular economy principles[16]. For enterprises globally, green business performance has become increasingly salient due to converging pressures, including government environmental regulations, international supply chain requirements, consumer environmental consciousness, and competitive positioning imperatives. In emerging economies, integration into global value chains exposes enterprises to international environmental standards, with multinational partners increasingly imposing sustainability requirements on suppliers and collaborators.

Beyond compliance, proactive environmental strategies can generate competitive advantages. Environmental innovations reduce operational costs through resource efficiency, enhance brand reputation among environmentally conscious consumers, and facilitate access to green finance[17]. Enterprises adopting proactive environmental strategies demonstrate stronger innovation performance and long-term competitiveness[18]. The relationship between digital technologies and sustainable business performance is theoretically ambiguous. While digital transformation can facilitate environmental improvements through enhanced monitoring, optimization, and innovation capabilities[19], the energy intensity of computing infrastructure can simultaneously increase environmental burdens[7]. For enterprises navigating simultaneous digital and green transitions, understanding how specific technologies, such as AI, influence environmental outcomes is critically important.

2.3. Energy-efficient AI practices as Mediating Mechanism

We conceptualize energy-efficient AI practices as an organizational capacity encompassing routines for minimizing AI energy consumption and the dynamic ability to develop novel environmental solutions in response to AI-related energy challenges. This construct extends beyond simple energy-efficient AI practices[20,21] to incorporate the learning, reconfiguration, and innovation dimensions of organizational capability theory[22]. Energy-efficient AI practices include monitoring AI energy consumption, optimizing algorithms for energy efficiency, selecting appropriate hardware platforms, avoiding unnecessary computational expenditure, implementing energy-aware deployment strategies, andcriticallydeveloping novel solutions that leverage AI energy challenges as catalysts for broader environmental innovation.

The theoretical rationale for examining energy-efficient AI practices as a mediating mechanism is based on resource-based and dynamic capability perspectives. Simply adopting AI technologies does not predetermine environmental outcomes; rather, how organizations implement and manage these technologies and the capabilities they develop in response to associated challenges shape actual environmental impacts. Zhou and Bu[1] demonstrate that green innovation channels AI adoption into corporate sustainability outcomes, while Shaik, et al.[23] show AI-driven strategic innovations can enable carbon-neutral business models. Benabdellah et al.[24] established that design-for-environment competencies mediate the relationship between technological adoption and green product development outcomes. These converging streams suggest that energy-efficient AI practices represent a critical organizational bridge between AI energy challenges and environmental performance.

Importantly, energy-efficient AI practices likely mediate the AI energy consumption-performance relationship through multiple reinforcing pathways[1]. Organizations developing such capabilities may simultaneously enhance their broader environmental management competencies, creating positive spillovers to other green initiatives. Visible commitment to green innovation may also strengthen the organizational environmental culture, reinforcing employee behaviors and management priorities aligned with sustainability objectives[23]. Recent European research demonstrates that organizations committed to clean energy goals show higher adoption rates of energy-efficient AI practices[25], suggesting that sustainability objectives catalyze operational efficiency innovation.

2.4. Sustainability Commitment as Dual Moderating Condition

Organizational sustainability commitment represents the degree to which firms prioritize environmental and social objectives in strategic decision-making and resource allocation processes[26]. This construct encompasses the substantive integration of sustainability principles into organizational identity, governance structures, and operational practices. Enterprises exhibit substantial heterogeneity in sustainability commitment, ranging from firms treating environmental issues as peripheral compliance matters to organizations embedding sustainability as a core strategic imperative.

We propose that sustainability commitment functions as a dual moderator at two critical junctures in the AI-environment relationship. First, in shaping organizational responses to AI energy consumption challenges (moderating the path from AI energy consumption to energy-efficient AI practices), sustainability-committed organizations possess heightened sensitivity to environmental issues, triggering proactive organizational responses when confronting AI energy challenges[17]. These firms maintain environmental management systems that provide the infrastructure for integrating new practices, cultivate networks with sustainability-focused technology providers that facilitate knowledge access, and implement organizational learning processes that enable rapid adaptation[18]. Glavas[25] found that organizations committed to Sustainable Development Goal 7 demonstrated 2.4 times higher odds of adopting energy-efficient AI practices, suggesting that sustainability goals catalyze rather than constrain operational efficiency innovation.

Second, sustainability commitment moderates the effectiveness of green innovation capabilities in generating environmental performance outcomes (moderating the path from energy-efficient AI practices to sustainable business performance). Organizations deeply committed to sustainability create favorable conditions for translating innovation capabilities into actual performance through clearer accountability structures[27], greater resource investments in complementary systems[28], and stronger normative cultural pressures supporting consistent execution[29]. Furthermore, sustainability commitment facilitates organizational learning processes, enabling continuous capability improvement[19]. Conversely, organizations with weak sustainability commitments may superficially implement green innovation practices to satisfy external pressures without a genuine commitment to environmental outcomes[1]. This dual moderation perspective advances the theoretical understanding beyond prior research examining sustainability commitment through single pathways.

2.5. Hypothesis Development

The energy-intensive nature of AI technologies, encompassing training, deployment, and supporting infrastructure, creates environmental burdens that directly conflict with green business objectives[30]. Firms adopting AI without corresponding efficiency measures will experience increased energy consumption, elevated carbon emissions, and greater resource utilization, thereby undermining their environmental performance[5]. This negative relationship reflects the direct environmental costs associated with the deployment of AI technology.

H1: AI energy consumption negatively influences green business performance among enterprises.

Although AI energy consumption creates environmental challenges, organizational practices for managing this consumption can substantially mitigate these negative impacts[20]. Enterprises implementing energy monitoring systems, optimizing algorithms, and avoiding unnecessary computational expenditure can reduce AI's environmental footprint[21]. These practices transform the AI energy consumption-green performance relationship, attenuating negative direct effects while potentially generating positive indirect effects through enhanced environmental management capabilities[25]. The mediating role of energy-efficient practices suggests that organizational agency shapes AI's environmental implications of AI.

H2: Energy-efficient AI practices mediate the relationship between AI energy consumption and green business performance.

Organizations that are deeply committed to sustainability create favorable conditions for translating energy-efficient AI practices into improved environmental outcomes[26]. A strong sustainability commitment signals the organizational prioritization of environmental objectives, manifesting in resource allocation decisions, performance evaluation systems, and organizational culture[18]. Enterprises with robust sustainability orientations leverage energy-efficient AI practices more effectively for enhanced green performance through clearer accountability structures, greater resource investments, and stronger normative pressures supporting environmental behaviors[1].

H3: Sustainability commitment moderates the relationship between energy-efficient AI practices and green business performance, such that the positive relationship is stronger among firms with higher sustainability commitment.

Organizations with strong sustainability commitments demonstrate heightened sensitivity to environmental challenges, triggering proactive organizational responses when confronted with AI energy consumption problems[17]. Sustainability-oriented cultures mobilize resources toward addressing energy efficiency challenges, establish accountability mechanisms ensuring follow-through, and

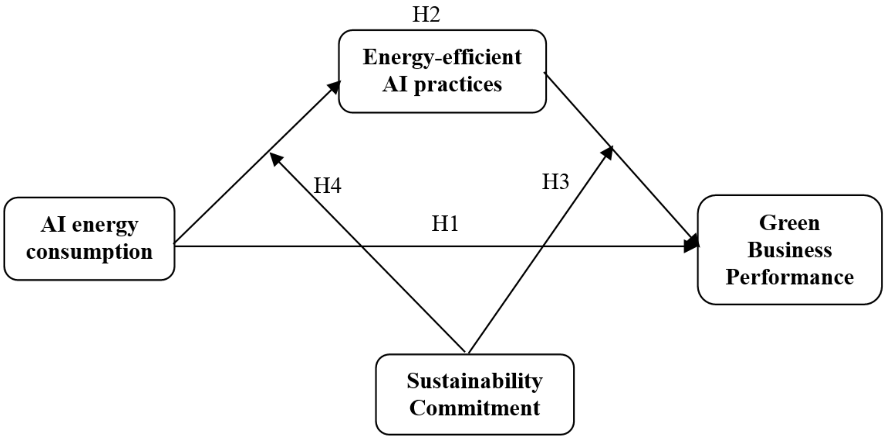

Fig. 1: Theoretical model

maintain superior absorptive capacity for environmental innovations[25]. Enterprises deeply committed to sustainability more readily translate AI energy consumption challenges into energy-efficient practice adoption compared to firms with weak sustainability orientations[23]. This moderating effect suggests that sustainability commitment catalyzes rather than constrains operational efficiency innovation.

H4: Sustainability commitment moderates the relationship between AI energy consumption and energy-efficient AI practices, such that the positive relationship is stronger among firms with higher sustainability commitment.

Figure 1 illustrates our complete theoretical model, which incorporates these hypothesized relationships.

3. Methodology

3.1. Research Design and Sampling

This study employs a cross-sectional survey design to examine the relationships among AI energy consumption, energy-efficient AI practices, sustainability commitment, and green business performance within enterprises. The target population comprised organizations across diverse industries that adopted AI technologies in their operations, including manufacturing, services, finance, telecommunications, and energy sectors.

We employed purposive sampling techniques to identify appropriate respondents, targeting managers and IT professionals with direct knowledge of their organizations' AI implementations and environmental practices. Initial contact was established through professional networks, industry associations and academic partnerships. To ensure data quality, we implemented several screening criteria: respondents must work in organizations employing at least 50 employees, hold positions enabling familiarity with both AI deployment and environmental initiatives, and possess a minimum of three years of organizational tenure providing sufficient institutional knowledge.

Data collection will occur between September 2024 and January 2025 using online and paper-based questionnaires. We distributed surveys to 600 potential respondents across enterprises, receiving 412 responses, representing a 68.7% response rate. After excluding incomplete responses and those failing attention check questions, our final sample comprised 385 usable questionnaires. This sample size exceeds the recommended thresholds for structural equation modeling analysis, providing adequate statistical power for hypothesis testing[31].

3.2. Sample Characteristics

Our final sample represents diverse organizational and respondent characteristics, reflecting Vietnamese enterprise heterogeneity. Regarding organizational size, 18% of the participating firms employ 50-200 employees, 31% employ 201-500 employees, 27% employ 501-1,000 employees, 16% employ 1,001-5,000 employees, and 8% employ over 5,000 employees. The industry distribution includes manufacturing (32%), financial services (19%), telecommunications and IT services (15%), professional services (13%), energy and utilities (11%), and retail and consumer goods (10%).

The respondents’ characteristics demonstrated appropriate expertise in addressing the survey questions. Mean organizational tenure is 6.8 years ($SD = 3.2$), indicating substantial institutional knowledge. The respondents’ position levels included middle managers (42%), senior managers (35%), IT specialists (15%), and directors/executives (8%). The educational attainment is high, with 67%, 28 %, and 5% of the respondents holding bachelor’s, master's, and 5% doctoral degrees, respectively. The age distribution spans 25-34 years (31%), 35-44 years (43%), 45-54 years (21%), and 55-64 years (5%). The gender distribution is 58% male and 42% female, roughly reflecting the Vietnamese workforce composition in technology-oriented sectors.

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3.3. Measurement Development

All constructs were measured using multi-item scales adapted from established instruments in prior literature, with modifications ensuring contextual appropriateness for the enterprises. We employed seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree) for all measurement items. Following the recommended translation procedures, the original English-language scales were translated into Vietnamese by bilingual scholars, back-translated to English by independent translators, and reconciled through iterative comparison to ensure semantic equivalence[32]).

AI Energy Consumption was measured using four items adapted from the International Energy Agency[4) and] Zhong et al.[9)] guidelines, capturing the perceived energy intensity of organizational AI deployments. Energy-efficient AI practices were assessed using six items adapted from Mischos et al.[20) and] Tabbakh et al.[21)], measuring organizational routines for minimizing AI energy consumption. Sustainability Commitment was measured using five items adapted from Arco-Castro et al.[17) and] Luqman et al.[26)], assessing the organizational prioritization of environmental objectives. Green Business Performance was assessed using seven items adapted from Song et al.[15),] Balsalobre-Lorente and Shah[16)], capturing multiple dimensions of environmental outcomes.

3.4. Common Method Bias Assessment

Given the cross-sectional survey data collection from single respondents per organization, common method bias represents a potential validity threat[33)]. We implemented several procedural remedies during the survey design and data collection. First, we ensured respondent anonymity to reduce the social desirability bias. Second, we randomized the item order to prevent systematic response patterns. Third, we separated the predictor and criterion variable sections using buffer items. Fourth, we employed clear and non-leading question wording. Statistically, we conducted Harman's single-factor test through exploratory factor analysis.

To assess potential non-response bias, we conducted a wave analysis following the procedure of Armstrong and Overton[34)], comparing early respondents (first 20%, n = 77) with late respondents (last 20%, n = 77) on four key demographic variables: organization size, industry sector, position level, and age group. Independent-samples t-tests revealed no statistically significant differences across any variable (all p > .05), providing evidence that non-response bias did not substantially affect our findings.

3.5. Analytical Approach

We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS software to test our hypothesized relationships. SEM enables the simultaneous examination of measurement properties and structural relationships while accounting for measurement errors. Our analytical approach was conducted in two stages. First, we assessed the measurement model quality through confirmatory factor analysis, examining construct validity and reliability. Second, we estimated the structural model to test the hypothesized relationships among the constructs. For mediation hypothesis testing (H2), we followed an approach supplemented with bootstrapping procedures for indirect effect significance testing[35,36)]. Specifically, we estimated (a) the total effect of AI energy consumption on green business performance, (b) the direct effect of AI energy consumption on energy-efficient AI practices, (c) the direct effect of energy-efficient AI practices on green business performance, and (d) the indirect effect of AI energy consumption on green business performance through energy-efficient AI practices. Bootstrap estimates with 5,000 resamples and 95% bias-corrected confidence intervals provided robust inferences regarding indirect effects.

For moderation hypothesis testing (H3 and H4), we employed latent interaction modeling using product indicator approaches[37)]. We created interaction terms between (a) energy-efficient AI practices and sustainability commitment (H3) and (b) AI energy consumption and sustainability commitment (H4) to examine whether sustainability commitment moderates these relationships. Simple slope analysis at high (+1 SD) and low (-1 SD) sustainability commitment levels illustrates interaction patterns.

4. Research result

4.1. Measurement Model Assessment

Internal consistency reliability was assessed using Cronbach's alpha (CA) and Composite Reliability (CR). As shown in Table 1, all constructs exceeded the recommended thresholds, with Cronbach's alpha values ranging from 0.880 to 0.933 (all > 0.70) and Composite Reliability values ranging from 0.896 to 0.937 (all > 0.70), indicating excellent internal consistency.

Convergent validity was evaluated using two criteria: (1) individual item loadings and (2) Average Variance Extracted (AVE). Table 1 presents the outer loadings of all measurement items. All indicator loadings ranged from 0.742 to 0.891, exceeding the recommended threshold of 0.70 (Hair et al., 2019). Additionally, all AVE values surpassed 0.50 (ranging from 0.643 to 0.714), confirming adequate convergent validity.

Table 2 presents the discriminant validity assessment using the Fornell-Larcker criterion. The diagonal elements (in bold) represent the square root of the AVE for each construct[38)]. For discriminant validity to be established, these values must exceed all correlations in the corresponding rows and columns. Our results confirm that this requirement is met for all constructs. All HTMT values

Table 1: Convergent Validity

Variable	Outer Loading	CR	AVE	CA
AI Energy Consumption (AIEC)	0.763 - 0.874	0.896	0.673	0.880
Energy-efficient AI practices (EEAP)	0.742 - 0.884	0.921	0.682	0.912
Sustainability Commitment (SC)	0.777 - 0.848	0.900	0.643	0.895
Green Business Performance (GBP)	0.764 - 0.891	0.937	0.714	0.933

Notes: CR = Composite Reliability; AVE = Average Variance Extracted; CA = Cronbach's Alpha

Table 2: Discriminant Validity

Variable	1	2	3	4	VIF
Fornell-Larcker criterion					
1. AIEC	0.82				1.114
2. EEAP	0.31	0.83			1.537
3. SC	0.18	0.54	0.80		1.672
4. GBP	-0.29	0.49	0.58	0.84	1.892
HTMT criterion					
1. AIEC		0.341	0.201	0.319	
2. EEAP			0.581	0.531	
3. SC				0.621	
SRMR = 0.061, NFI = 0.872					

Notes: Bold values on the diagonal are square roots of AVE

are below the conservative threshold of 0.85, confirming discriminant validity[39,40]. SRMR = 0.061 (below the 0.08 threshold) and NFI = 0.872 to the model fit paragraph in, citing Hair, et al.[41] as recommended.

Since data were collected from single respondents, we assessed the potential common method bias using the full collinearity approach[42]. All Variance Inflation Factor (VIF) values in Table 2 were below the threshold of 3.3, suggesting that common method bias was not a significant concern in this study.

4.2. Structural Model Results

Before interpreting the path coefficients, we examined the collinearity among the predictor constructs using the VIF values. Table 3 shows that all VIF values are well below the threshold of 5.0, indicating that collinearity is not a concern in the structural model.

Table 3 presents the results of the direct path coefficients, including the standardized beta coefficients, standard errors, t-values, p-values, and 95% confidence intervals based on 5,000 bootstrap samples. Hypothesis 1 (H1) proposes that AI energy consumption negatively influences green business performance. The results in Table 4 strongly support this hypothesis (β = -0.287, t = 4.159, $p < 0.001$, 95% CI = [-0.422, -0.152]). This finding indicates that enterprises with higher AI energy consumption demonstrate significantly lower green business performance, confirming the environmental burden associated with energy-intensive AI technologies. The control paths show that AI energy consumption positively influenced energy-efficient AI practices (β = 0.278, t = 4.212, $p < 0.001$), and energy-efficient AI practices positively influenced green business performance (β = 0.341, t = 5.590, $p < 0.001$). Additionally, sustainability commitment significantly and positively affects both energy-efficient AI practices (β = 0.489, t = 8.016, $p < 0.001$) and green business performance (β = 0.427, t = 6.672, $p < 0.001$).

The R^2 values indicate the amount of variance explained by the endogenous constructs. Table 3 presents the R^2 values and their assessment based on the established guidelines[31]. The structural model explains 35.2% of the variance in energy-efficient AI practices and 48.7% of the variance in green business performance, both of which represent moderate explanatory power. These results suggest that the model captures important predictors of both constructs while leaving room for additional factors in future research.

The predictive relevance was assessed using a blindfolding procedure with an omission distance of 7. Table 3 presents the Q^2 values obtained using the cross-validated redundancy approach. All Q^2 values were substantially above zero (EEAP: Q^2 = 0.254; GBP: Q^2 = 0.311), confirming that the model had adequate predictive relevance for the endogenous constructs. Following recent PLS-SEM guidelines, Q^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large predictive relevance, respectively. Our results indicate a medium predictive relevance for both constructs.

Effect sizes (f^2) indicate the relative impact of a predictor construct on the endogenous construct. Table 3 presents the f^2 values and their interpretations. Sustainability commitment demonstrates medium effect sizes for both energy-efficient AI practices (f^2 = 0.207) and green business performance (f^2 = 0.198), highlighting its substantial importance in the model. Energy-efficient AI practices have a small to medium effect on green business performance (f^2 = 0.126), whereas AI energy consumption has small effects on both constructs.

Table 3: PLS-SEM result

Path	β	SE	t-value	p-value	95% CI	f²	VIF	R²	Q²
H1: AIEC → GBP	−0.287	0.069	4.159	< .001	[−0.422, −0.152]	0.098	1.106	0.352	0.254
EEAP → GBP	0.341	0.061	5.590	< .001	[0.221, 0.461]	0.126	1.488		
SC → GBP	0.427	0.064	6.672	< .001	[0.302, 0.552]	0.198	1.565		
AIEC → EEAP	0.278	0.066	4.212	< .001	[0.149, 0.407]	0.067	1.033	0.487	0.311
SC → EEAP	0.489	0.061	8.016	< .001	[0.370, 0.608]	0.207	1.033		

Note. Bootstrap samples = 5,000; CI = Confidence Interval; f² = Cohen's effect size.

Table 4: Mediation Analysis

Effect	Path	β	SE	t-value	p	95% CI
Total Effect	AIEC → GBP	−0.192	0.063	3.048	.002	[−0.315, −0.069]
Direct Effect	AIEC → GBP	−0.287	0.069	4.159	< .001	[−0.422, −0.152]
Indirect Effect	AIEC → EEAP → GBP	0.095	0.027	3.519	< .001	[0.047, 0.156]
VAF	49.5%	—	—	—	—	Partial mediation

Note. VAF = Variance Accounted For; Bootstrap samples = 5,000.

Table 5: Moderation Effects Analysis

Hypothesis	Path	β	SE	t-value	p	f²	Decision
H3	EEAP × SC → GBP	0.198	0.079	2.506	.012	0.039	Supported
	High SC slope (EEAP→GBP)	0.439	0.075	5.853	< .001	—	—
	Low SC slope (EEAP→GBP)	0.243	0.086	2.826	.005	—	—
H4	AIEC × SC → EEAP	0.223	0.084	2.655	.008	0.043	Supported
	High SC slope (AIEC→EEAP)	0.401	0.082	4.890	< .001	—	—
	Low SC slope (AIEC→EEAP)	0.155	0.091	1.703	.089	—	—

Hypothesis 2 (H2) proposes that energy-efficient AI practices mediate the relationship between AI energy consumption and green business performance. We tested this mediation hypothesis using the bootstrap approach recommended by Qin and Wang[43]. Table 4 presents the decomposition of the total, direct, and indirect effects.

First, both the direct (β = -0.287, p < 0.001) and indirect effects (β = 0.095, p < 0.001) were statistically significant, confirming partial mediation. The negative direct effect indicates that AI energy consumption directly undermines the green business performance. However, the positive indirect effect of energy-efficient AI practices demonstrates that organizations can substantially mitigate this negative impact. Second, the significant positive relationship between AI energy consumption and energy-efficient AI practices (β = 0.278, p < 0.001) suggests that organizations confronting higher AI energy consumption challenges respond proactively by developing efficiency-enhancing practice. This finding contradicts the notion that high energy consumption inevitably leads to poor environmental outcomes in developing countries. Third, energy-efficient AI practices significantly enhance green business performance (β = 0.341, p < 0.001), demonstrating their effectiveness in improving environmental performance. Organizations that implement monitoring systems, optimize algorithms, and avoid unnecessary computational expenditures achieve superior green performance. Fourth, the partial mediation pattern (VAF = 49.5%) indicates that although energy-efficient AI practices are important, they do not completely eliminate AI's environmental burden of AI. The remaining direct negative effect suggests that other mechanisms or contextual factors influence the AI-environment relationship. Hence, hypothesis 2 is strongly supported. Energy-efficient AI practices serve as a critical mediating mechanism through which enterprises can reconcile AI adoption with environmental sustainability objectives.

We tested two moderation hypotheses to examine how sustainability commitment influences relationships in the model. The moderating effects are presented in Table 5. Hypothesis 3 predicted that sustainability commitment would moderate the energy-efficient AI practices-green performance relationship. The interaction term between energy-efficient AI practices and sustainability commitment is positive and statistically significant ($\beta = 0.198$, $SE = 0.079$, $p < 0.05$), supporting this hypothesis. Simple slope analysis reveals the practices-performance relationship is stronger among firms with high sustainability commitment ($\beta = 0.439$, $SE = 0.075$, $p < 0.001$) compared to those with low sustainability commitment ($\beta = 0.243$, $SE = 0.086$, $p < 0.01$). The difference between slopes is statistically significant ($\Delta\beta = 0.196$, $p < 0.05$).

Hypothesis 4 proposed that sustainability commitment moderates the relationship between AI energy consumption and energy-efficient practices. The interaction term between AI energy consumption and sustainability commitment is positive and statistically significant ($\beta = 0.223$, $SE = 0.084$, $p < 0.01$), providing strong support for this hypothesis. Simple slope analysis demonstrates the consumption-practices relationship is stronger among firms with high sustainability commitment ($\beta = 0.401$, $SE = 0.082$, $p < 0.001$) compared to those with low sustainability commitment ($\beta = 0.155$, $SE = 0.091$, $p = 0.089$). The difference between slopes is statistically significant ($\Delta\beta = 0.246$, $p < 0.01$).

5. Discussion and Contributions

5.1. Theoretical Implications

Our findings make several important contributions to the emerging literature on AI's environmental implications of AI and sustainable technology management in developing economies. First, we provide empirical evidence that AI energy consumption directly undermines green business performance among enterprises. This finding extends predominantly Western research[5,30] to the context of developing countries, confirming that the environmental costs associated with AI deployment transcend geographic and institutional boundaries. However, the magnitude of the negative effects suggests that firms face meaningful environmental trade-offs when adopting energy-intensive AI technologies without corresponding mitigation strategies.

Second, and more importantly, our mediation findings challenge simplistic trade-off narratives by illuminating the organizational agency in shaping AI-environment relationships. The positive indirect effect of energy-efficient AI practices demonstrates that enterprises can substantially mitigate AI's environmental burden through deliberate management practices[20]. This finding aligns with recent European evidence suggesting that sustainability commitments and operational efficiency can be complementary rather than conflicting[25], extending this insight to the context of a developing economy. The partial mediation pattern indicates that energy-efficient practices do not completely eliminate AI's environmental costs of AI but meaningfully attenuate negative impacts[21]. An alternative interpretation of the positive AIEC→EEAP relationship warrants acknowledgment. From an institutional theory perspective, organizations with more AI-intensive operations are simultaneously more exposed to both the energy consumption problem and its potential solutions; they have more AI infrastructure to optimize, more personnel familiar with AI operational parameters, and more economic incentives to pursue efficiency improvements. Under this interpretation, the AIEC→EAP relationship may reflect AI adoption intensity rather than a genuine problem-response mechanism: more AI-intensive firms develop more energy-efficient practices not because they reactively respond to energy challenges but simply because they have more AI to manage efficiently. This interpretation does not negate the practical implications of our findings but suggests that the causal pathway requires longitudinal investigation. Future research should track whether energy-efficient practice development follows observed increases in AI energy consumption within the same organization over time or whether both variables co-develop as functions of overall AI adoption maturity.

Third, our dual moderation findings represent a significant theoretical advancement by revealing how sustainability commitment influences AI-environment relationships at multiple critical points. The first moderation effect demonstrates that sustainability commitment catalyzes organizational responses to AI energy consumption challenges, transforming environmental problems into opportunities for capability development[26]. This finding challenges resource-constraint perspectives, suggesting that sustainability commitments divert resources away from operational efficiency initiatives. Instead, our results indicate that committed organizations mobilize resources to address energy efficiency precisely because sustainability priorities heighten their sensitivity to environmental challenges[18].

The second moderation effect reveals that sustainability commitment also enhances the translation of energy-efficient practices into environmental performance outcomes[17]. This suggests that organizational priorities influence not only whether firms adopt practices but also how effectively they implement them[25]. Together, these dual moderation effects create a multiplicative enhancement, wherein sustainability commitment strengthens both practice adoption and practice effectiveness, generating substantially amplified indirect effects, as demonstrated in our moderated mediation analysis[23].

Fourth, our evidence contributes to the broader debate regarding digital-green transitions in developing economies. While prior research primarily examines these transitions in developed Western contexts[7, 44], our findings suggest that enterprises navigate similar tensions between technological advancement and environmental responsibility. However, the specific manifestations differ. Firms face resource constraints, developing institutional frameworks, and evolving stakeholder pressures that create distinctive challenges and opportunities compared to their Western counterparts.

Fifth, our findings advance the understanding of how organizational commitment shapes technology-environment relationships more broadly[45]. The dual moderation pattern suggests that commitment operates through multiple mechanisms: enhancing environmental alertness that triggers practice adoption, mobilizing resources enabling implementation, establishing accountability structures ensuring thoroughness, and creating cultural contexts supporting consistent execution. This multi-mechanism perspective enriches organizational capability theories applied to environmental management[22].

5.2. Practical Implications

Our findings generate several actionable recommendations for managers navigating AI deployment. First, organizations should recognize that AI energy consumption creates genuine environmental costs, but these costs can be substantially mitigated through proactive management. The negative direct effect combined with a positive indirect effect demonstrates that strategic responses are important. Managers cannot ignore the energy implications of AI, but they should not abandon AI adoption because of environmental concerns.

Second, organizations should implement comprehensive energy monitoring systems for AI technologies as foundational capabilities to ensure their sustainability. Simply measuring AI energy consumption creates awareness, enabling targeted interventions. Enterprises that currently lack such monitoring capabilities should prioritize the development of these systems before expanding AI deployments. Practical steps include installing energy measurement devices on AI computing infrastructure, implementing software-based monitoring tools to track model training and inference energy consumption, and establishing regular reporting mechanisms to connect IT departments with environmental management functions.

Third, managers should adopt energy-conscious AI development practices throughout the technology lifecycle. During the algorithm selection and design phases, organizations should evaluate multiple modeling approaches, considering both accuracy and computational efficiency. Simpler models frequently deliver adequate performance for enterprise applications while consuming a fraction of the energy of over-parameterized alternatives. Four AI-specific energy efficiency mechanisms deserve particular attention: (1) model compression and pruning, which reduce parameter counts by 40–90% with minimal accuracy loss by eliminating redundant network weights; (2) federated learning, which trains models locally on distributed devices and eliminates the energy cost of centralizing large datasets to a single server; (3) carbon-aware scheduling, which defers non-urgent AI workloads to time windows when the electricity grid is powered predominantly by renewable sources; and (4) hardware-aware neural architecture search, which jointly optimizes model accuracy and energy efficiency during the design phase rather than treating energy as an afterthought. These mechanisms represent concrete operationalizations of the EEAP construct and offer enterprises practical entry points for reducing their AI energy burdens. During the training phase, techniques such as transfer learning, model compression, and pruning can substantially reduce energy requirements without sacrificing model quality. During deployment, organizations should implement dynamic resource allocation by adjusting computational resources to actual demand rather than maintaining a constant maximum capacity.

5.3. Findings-Driven Policy Recommendations

Our findings also have implications for policymakers seeking to promote digital transformation and environmental sustainability. First, government agencies should consider implementing AI energy efficiency standards or certification schemes similar to appliance energy ratings. Such standards would create transparency regarding the environmental footprints of AI systems, enabling organizations to make informed technology choices. Certification programs could incentivize technology vendors to develop energy-efficient solutions while helping enterprises identify green AI options.

Second, policymakers should design policy interventions that recognize the critical role of organizational sustainability commitment, as demonstrated in our findings. Rather than solely focusing on technical standards or economic incentives, policies should aim to cultivate sustainability-oriented organizational cultures. Potential approaches include (a) public recognition programs highlighting enterprises that successfully combine AI adoption with environmental performance, (b) sustainability reporting requirements creating transparency and peer pressure, (c) stakeholder engagement forums facilitating knowledge sharing among sustainability-committed organizations, and (d) integration of sustainability principles into business education curricula to prepare future managers.

Third, government agencies should provide institutional support for energy-efficient AI capability development, particularly among small and medium enterprises lacking internal expertise. Government-sponsored training programs, technology demonstration projects, and knowledge-sharing platforms could accelerate the diffusion of best practices across enterprises. Subsidies or tax incentives for energy-efficient AI infrastructure might also encourage adoption; however, careful design is necessary to prevent unintended consequences.

5.4. Limitations and Future Research Directions

Despite these contributions, this study has several limitations that suggest directions for future research. First, our cross-sectional design prevents causal inference regarding the relationships among the constructs. Although we employed rigorous analytical techniques, including moderated mediation analysis, alternative model testing, and supplementary analyses addressing reverse causality concerns, longitudinal research tracking enterprises' AI deployments and environmental performance over time would provide stronger causal evidence. Such studies could examine whether (a) sustainability commitment causally enhances energy-efficient practice adoption or whether environmentally proactive organizations selectively develop sustainability commitments; (b) energy-efficient practices causally improve green performance or whether high-performing organizations selectively adopt these practices; and (c) feedback loops exist wherein improved green performance reinforces sustainability commitment.

Second, our reliance on perceptual measures for key constructs introduces potential measurement errors. Future research should incorporate objective metrics of AI energy consumption, such as actual kilowatt-hour measurements from data centers or model training processes. Similarly, objective environmental performance indicators, such as measured emissions reductions, energy consumption per output unit, or waste generation rates, would complement self-reported assessments. Combining perceptual and objective measures would strengthen the construct validity and provide more robust findings. However, perceptual measures can be valid indicators when assessing organizational phenomena that require managerial judgment.

Third, this study relies exclusively on a quantitative survey methodology, which, while well-suited for testing the hypothesized structural relationships, inevitably constrains the richness and contextual depth of the insights generated. The moderated mediation framework identifies that sustainability commitment amplifies the AIEC–EEAP–GBP pathway; however, the survey design cannot fully illuminate how this process unfolds within organizations—the specific managerial decisions, organizational routines, cultural dynamics, and institutional pressures through which sustainability-committed Vietnamese enterprises translate AI energy challenges into efficiency practices and, ultimately, environmental performance gains. Future research should employ mixed-methods designs that combine large-sample quantitative surveys with qualitative components, such as in-depth executive interviews, ethnographic observations of AI deployment decision-making, or longitudinal case studies across multiple industry sectors. Such designs would allow researchers to triangulate the statistical patterns identified here with process-level evidence, strengthening both the internal validity and transferability of the findings to other emerging economy contexts. In particular, qualitative inquiry into *why* organizations with lower sustainability commitment fail to convert energy-efficient AI practices into environmental performance gains—despite possessing similar technical capabilities—could yield actionable insights that quantitative path coefficients alone cannot.

Fourth, a methodological boundary condition specific to AI energy research deserves further emphasis. The AIEC construct measures respondents' perceptions of AI-related energy consumption within their organizational context, specifically the energy observable to local managers. However, in contemporary enterprise environments, significant AI workloads are increasingly hosted on international cloud infrastructures (e.g., hyperscale providers such as AWS, Azure, and Google Cloud). In such cases, local energy monitoring systems and managerial perceptions may systematically underestimate actual AI-attributable energy consumption, as physical energy expenditure occurs in remote data centers outside the respondent's observational frame. This concern is particularly relevant in the Vietnamese context, where cloud adoption rates are rapidly increasing among digitally transforming enterprises. Future research should attempt to triangulate perceptual measures with objective cloud provider carbon reporting data, energy billing records, and hardware utilization logs, where available.

6. Conclusion

This study examined the relationships among AI energy consumption, energy-efficient AI practices, sustainability commitment, and green business performance among enterprises. Our findings demonstrate that AI energy consumption directly undermines environmental outcomes, but organizations can substantially mitigate these negative effects through energy-efficient practices. Furthermore, sustainability commitment strengthens the effectiveness of such practices, highlighting the importance of organizational priorities and culture in sustainable technology management.

These results challenge simplistic narratives that portray AI adoption and environmental sustainability as inherently conflicting objectives. Enterprises can pursue both digital transformation and green development simultaneously through strategic technology management that emphasizes energy efficiency. However, realizing this potential requires deliberate organizational choices, managerial attention, and capability development that extends beyond the simple adoption of AI technologies.

Our findings contribute to the emerging 'AI governance for sustainability' debate in several ways: First, the dual moderation results suggest that AI governance frameworks should address organizational culture and sustainability commitment as critical enabling conditions alongside, and arguably prior to, technical standards and regulatory compliance mechanisms. Governance architectures that focus exclusively on technical benchmarks (e.g., energy-per-query metrics) may underperform if the organizational foundations for translating efficiency into performance outcomes are absent. Second, the positive AIEC→EEAP path implies that early and deliberate exposure to AI's environmental costs may catalyze institutional learning and capability development—a finding with implications for how national AI strategies might sequence adoption incentives and sustainability requirements rather than treating them as competing objectives. Third, the Vietnamese context studied here offers lessons for other lower-middle-income economies navigating simultaneous digital industrialization and green transition pressures: the moderated mediation architecture observed in Vietnam may be broadly applicable to institutional environments in which sustainability commitment is heterogeneous and AI adoption is accelerating.

As enterprises continue to navigate the pressures of digital transformation amidst mounting environmental challenges, understanding how to deploy AI sustainably has become increasingly critical. Our study provides empirical evidence and practical guidance to support this transition, while also highlighting areas that require further research and policy attention. Ultimately, whether AI serves as an environmental burden or sustainability enabler depends fundamentally on organizational choices, institutional contexts, and management practices shaping technology deployment.

Nomenclature

AI	Artificial Intelligence
AIEC	AI Energy Consumption
AVE	Average Variance Extracted
CI	Confidence Interval
CO_2	Carbon Dioxide
CR	Composite Reliability
EEAP	Energy-efficient AI practices
GBP	Green Business Performance
SC	Sustainability Commitment
VIF	Variance Inflation Factor

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Appendix A: Research Questionnaire

Instructions to Respondents

This questionnaire is designed to investigate how artificial intelligence (AI) energy consumption influences sustainable business performance in enterprises. There are no right or wrong answers; we are interested in your professional assessment based on your organizational experience. All responses are completely anonymous and will be used solely for academic research purposes. Please rate your level of agreement with each statement using the following scale:

1 = Strongly Disagree 2 = Disagree 3 = Somewhat Disagree 4 = Neutral 5 = Somewhat Agree 6 = Agree 7 = Strongly Agree

Section 1: AI Energy Consumption (AIEC)

Item	Statement	Rating (1–7)
AIEC1	Our organization's AI systems consume substantial amounts of electricity.	1 2 3 4 5 6 7
AIEC2	Training and operating AI models requires significant energy resources in our organization.	1 2 3 4 5 6 7
AIEC3	Our data centers supporting AI applications have high energy demands.	1 2 3 4 5 6 7
AIEC4	Energy consumption associated with AI technologies represents a notable expense for our organization.	1 2 3 4 5 6 7

Section 2: Energy-efficient AI practices (EEAP)

Item	Statement	Rating (1–7)
EEAP1	Our organization monitors energy consumption of AI systems regularly.	1 2 3 4 5 6 7
EEAP2	We optimize AI algorithms to reduce computational requirements.	1 2 3 4 5 6 7
EEAP3	Our organization selects energy-efficient hardware for AI applications.	1 2 3 4 5 6 7
EEAP4	We avoid deploying unnecessary AI models that provide limited value.	1 2 3 4 5 6 7
EEAP5	Our organization implements energy-aware strategies when deploying AI technologies.	1 2 3 4 5 6 7
EEAP6	We regularly review and optimize AI infrastructure for energy efficiency.	1 2 3 4 5 6 7

Section 3: Sustainability Commitment (SC)

Item	Statement	Rating (1–7)
SC1	Environmental sustainability is a core priority in our organization's strategy.	1 2 3 4 5 6 7
SC2	Our organization commits substantial resources to environmental initiatives.	1 2 3 4 5 6 7
SC3	Senior management strongly supports sustainability objectives.	1 2 3 4 5 6 7
SC4	Environmental considerations influence major business decisions in our organization.	1 2 3 4 5 6 7
SC5	Our organization's culture emphasizes environmental responsibility.	1 2 3 4 5 6 7

Section 4: Green Business Performance (GBP)

Item	Statement	Rating (1–7)
GBP1	Our organization has reduced energy consumption per unit of output.	1 2 3 4 5 6 7
GBP2	We have decreased waste generation in our operations.	1 2 3 4 5 6 7
GBP3	Our organization has increased use of renewable energy sources.	1 2 3 4 5 6 7
GBP4	We have reduced greenhouse gas emissions from our operations.	1 2 3 4 5 6 7

GBP5	Our organization has improved resource efficiency.	1	2	3	4	5	6	7
GBP6	We have enhanced our environmental management systems.	1	2	3	4	5	6	7
GBP7	Our organization's environmental performance has improved compared to industry peers.	1	2	3	4	5	6	7

Section 5: Organizational and Respondent Information

Item	Question / Category
D1. Organization Size	☐ 50–200 ☐ 201–500 ☐ 501–1,000 ☐ 1,001–5,000 ☐ Over 5,000
D2. Industry Sector	☐ Manufacturing ☐ Financial Services ☐ Telecom/IT ☐ Professional Services ☐ Energy/Utilities ☐ Retail/Consumer ☐ Other: _______
D3. Position Level	☐ IT Specialist ☐ Middle Manager ☐ Senior Manager ☐ Director/Executive
D4. Gender	☐ Male ☐ Female ☐ Prefer not to say
D5. Age Group	☐ 25–34 ☐ 35–44 ☐ 45–54 ☐ 55–64 ☐ 65+
D6. Education Level	☐ Bachelor's Degree ☐ Master's Degree ☐ Doctoral Degree ☐ Other
D7. Organizational Tenure	☐ < 1 year ☐ 1–3 years ☐ 3–5 years ☐ 5–10 years ☐ Over 10 years
D8. AI Adoption Duration	☐ < 6 months ☐ 6–12 months ☐ 1–2 years ☐ 2–5 years ☐ Over 5 years

Appendix B: Summary of Statistical Analysis

B.1. Descriptive Statistics

Construct	Mean	SD	Min	Max	Skewness	Kurtosis
AIEC	4.82	1.21	1.00	7.00	−0.34	0.12
EEAP	4.56	1.18	1.00	7.00	−0.28	−0.09
SC	4.71	1.24	1.00	7.00	−0.41	0.18
GBP	4.64	1.19	1.00	7.00	−0.31	0.07

Note. SD = Standard Deviation. N = 385.

B.2. Inter-Construct Correlations and Reliability Summary

	AIEC	EEAP	SC	GBP	CA	CR	AVE
AIEC	1.000				0.880	0.896	0.673
EEAP	0.310	1.000			0.912	0.921	0.682
SC	0.180	0.540	1.000		0.895	0.900	0.643
GBP	−0.290	0.490	0.580	1.000	0.933	0.937	0.714

Note. CA = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted. All correlations significant at p < .001 except where otherwise noted.

B.3. Discriminant Validity

Fornell-Larcker criterion

Variable	1	2	3	4
1. AIEC	0.82			
2. EEAP	0.31	0.83		
3. SC	0.18	0.54	0.80	
4. GBP	-0.29	0.49	0.58	0.84

Notes: Bold values on the diagonal are square roots of AVE

HTMT criterion

Variable	1	2	3	4
1. AIEC		0.341	0.201	0.319
2. EEAP			0.581	0.531
3. SC				0.621
SRMR = 0.061, NFI = 0.872				

B.4. Full Collinearity VIF Values

Construct	VIF	Assessment
AIEC	1.114	No collinearity issues

EEAP	1.537	No collinearity issues
SC	1.672	No collinearity issues
GBP	1.892	No collinearity issues

B.5. Structural Model Collinearity Assessment (VIF)

Dependent Variable	Predictor Variable	VIF	Assessment
EEAP	AIEC	1.033	No collinearity
EEAP	SC	1.033	No collinearity
EEAP	AIEC × SC	1.067	No collinearity
GBP	AIEC	1.106	No collinearity
GBP	EEAP	1.488	No collinearity
GBP	SC	1.565	No collinearity
GBP	EEAP × SC	1.354	No collinearity

B.6. Direct Hypotheses Testing

Path	β	SE	t-value	p
H1: AIEC → GBP	-0.287	0.069	4.159	< .001
AIEC → EEAP	0.278	0.066	4.212	< .001
EEAP → GBP	0.341	0.061	5.59	< .001

B.7. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Q^2	Assessment
Energy-efficient AI practices (EEAP)	0.352	0.254	Moderate
Green Business Performance (GBP)	0.487	0.311	Moderate

B.8. Effect Sizes (f^2)

Path	f^2	Assessment
AIEC → GBP	0.098	Small
AIEC → EEAP	0.067	Small
EEAP → GBP	0.126	Small to Medium
SC → EEAP	0.207	Medium
SC → GBP	0.198	Medium
AIEC × SC → EEAP	0.043	Small
EEAP × SC → GBP	0.039	Small

B.9. Mediation Analysis Results

Effect Type	Path	β	SE	t-value	p-value	95% CI	Result
Total Effect	AIEC → GBP	-0.192	0.063	3.048	0.002	[-0.315, -0.069]	Significant
Direct Effect	AIEC → GBP	-0.287	0.069	4.159	< 0.001	[-0.422, -0.152]	Significant
Indirect Effect	AIEC → EEAP → GBP	0.095	0.027	3.519	< 0.001	[0.047, 0.156]	Significant
Specific Indirect Effect Components							
Step 1	AIEC → EEAP	0.278	0.066	4.212	< 0.001	[0.149, 0.407]	Significant
Step 2	EEAP → GBP	0.341	0.061	5.590	< 0.001	[0.221, 0.461]	Significant

Notes: Bootstrap samples = 5,000; CI = Confidence Interval

B.10. Moderation Effects Analysis

Hypothesis	Path	β	SE	t-value	p-value	95% CI	f^2	Decision
H3: SC moderates EEAP → GBP								
Main effect	EEAP → GBP	0.341	0.061	5.590	< 0.001	[0.221, 0.461]	0.126	-
Main effect	SC → GBP	0.427	0.064	6.672	< 0.001	[0.302, 0.552]	0.198	-
Interaction	EEAP × SC → GBP	0.198	0.079	2.506	0.012	[0.043, 0.353]	0.039	**Supported**
H4: SC moderates AIEC → EEAP								
Main effect	AIEC → EEAP	0.278	0.066	4.212	< 0.001	[0.149, 0.407]	0.067	-
Main effect	SC → EEAP	0.489	0.061	8.016	< 0.001	[0.370, 0.608]	0.207	-
Interaction	AIEC × SC → EEAP	0.223	0.084	2.655	0.008	[0.058, 0.388]	0.043	**Supported**