



Artificial Intelligence-Driven Environmental Management and Sustainable Performance: The Mediating Role of Green Business Model Innovation

Nguyen Thi Phuong Anh¹, Nguyen Quang Thu², Bui Huy Khoi¹, Nguyen Tan Trung^{2*}

¹Faculty of Business Administration, Industrial University of Ho Chi Minh City, Ho Chi Minh City, Vietnam.

²School of Management, University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam.

ABSTRACT

The integration of artificial intelligence (AI) into environmental management practices has emerged as a transformative strategy for firms operating in emerging economies. This study develops and empirically examines a conceptual model linking AI capability, environmental process optimization (EPO), green business model innovation (GBMI), environmental performance (EP), and sustainable firm performance (SFP) in the Vietnamese manufacturing context. Drawing on dynamic capability theory, the natural resource-based view, and corporate sustainability theory, we hypothesize a sequential mediation pathway wherein AI capability shapes sustainable outcomes through EPO and GBMI. Using partial least squares structural equation modeling (PLS-SEM) and survey data collected from 312 senior managers and environmental officers across Vietnamese manufacturing enterprises, the results confirm all six hypotheses. AI capability significantly and positively influences EPO ($\beta = 0.483, p < 0.001$), which in turn drives GBMI ($\beta = 0.512, p < 0.001$). GBMI subsequently enhances EP ($\beta = 0.467, p < 0.001$), which meaningfully advances SFP ($\beta = 0.531, p < 0.001$). Mediation analyses confirm that EPO fully mediates the AI-GBMI relationship ($\beta = 0.247, p < 0.001$), and GBMI fully mediates the EPO-EP relationship ($\beta = 0.239, p < 0.001$). These findings contribute novel theoretical insights to the AI-sustainability nexus in developing economy settings and offer practical guidance for policymakers and enterprise managers seeking to leverage AI for green transformation.

Keywords: Artificial intelligence capability, Environmental process optimization, Green business model innovation, Environmental performance, Sustainable firm performance

Corresponding author: Nguyen Tan Trung

e-mail ✉ tantrungtkd@ueh.edu.vn

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INTRODUCTION

The intersection of digital technology and environmental sustainability represents one of the most consequential frontiers in contemporary management research. As global climate imperatives intensify and regulatory frameworks tighten, organizations across all sectors are under unprecedented pressure to align operational strategies with environmental stewardship. Among the emerging digital technologies reshaping firm-level environmental management, artificial intelligence (AI) stands out for its unparalleled capacity to process large volumes of environmental data, optimize resource consumption patterns, and generate predictive insights that facilitate proactive green decision-making (Chui *et al.*, 2018).

Vietnam presents a particularly instructive empirical context for examining these dynamics. As one of Southeast Asia's most rapidly industrializing economies, Vietnam has witnessed remarkable manufacturing-led growth over the past two decades, simultaneously accompanied by mounting environmental degradation, carbon-intensive production systems, and increasing regulatory pressure aligned with its

commitments under the Paris Agreement and the 2021 COP26 pledges (World Bank, 2022). Vietnamese firms are thus caught in a transitional nexus: compelled to pursue growth while transforming environmental practices under resource constraints and institutional ambiguity typical of emerging markets (Luu, 2019).

Although academic inquiry into the intersection of artificial intelligence and environmental management is expanding, the current body of literature exhibits three notable gaps. First, while research highlights AI's operational advantages, such as supply chain efficiency, the precise mechanisms linking AI capabilities to sustainable corporate results remain theoretically underdeveloped and under-tested (Wang *et al.*, 2015; Vinuesa *et al.*, 2020). Second, the function of green business model innovation as a mediator between operational improvements and wider sustainability goals lacks investigation, specifically within emerging economies (Boons & Lüdeke-Freund, 2013; Bocken *et al.*, 2014). Finally, there is no empirical validation of the comprehensive causal chain connecting AI capability, process optimization, business model innovation, and overall environmental firm performance. Consequently, a unified framework integrating these critical sequential pathways is essential to advance this academic field significantly.

This study addresses these gaps by developing and testing an integrated theoretical model grounded in dynamic capability

theory (Teece *et al.*, 1997), the natural resource-based view (Hart, 1995), and corporate sustainability theory (Hahn *et al.*, 2015). We employ PLS-SEM—a rigorous variance-based method well-suited to predictive modeling in complex causal chain structures—on original survey data from 312 Vietnamese manufacturing firms. The study makes the following specific contributions: (1) it develops a novel sequential mediation model linking AI capability to sustainable firm performance through EPO and GBMI; (2) it provides among the first empirical tests of these relationships in a major emerging economy in Southeast Asia; (3) it advances theoretical dialogue on how digital-environmental capabilities are institutionalized through business model innovation; and (4) it offers actionable implications for managers and policymakers navigating the digital-green transition. The remainder of the paper is structured as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 develops the theoretical framework and hypotheses. Section 4 describes the research methodology. Section 5 presents empirical findings. Section 6 discusses results in a theoretical and managerial context. Section 7 concludes with limitations and directions for future research.

Literature review

AI capability and environmental management

Artificial intelligence capability (AIC) refers to an organization's ability to exploit AI-based tools—including machine learning, natural language processing, computer vision, and intelligent automation—to generate value from data and augment human decision-making (Davenport & Ronanki, 2018; Rai *et al.*, 2019). From a dynamic capability perspective (Teece *et al.*, 1997), AIC constitutes a higher-order organizational capability that enables firms to sense environmental opportunities and threats, seize competitive advantages, and reconfigure internal resources in line with strategic goals.

In the environmental domain, AI applications span a wide range of functions: predictive maintenance to reduce industrial waste, smart energy management systems, AI-enhanced environmental monitoring platforms, and data-driven lifecycle assessment tools (Vinueza *et al.*, 2020). Studies from developed economy contexts have demonstrated that AI adoption correlates positively with resource efficiency, emissions reductions, and regulatory compliance. However, the context of emerging economies—characterized by weaker institutional environments, limited AI infrastructure, and heterogeneous firm-level digital maturity—has received considerably less attention.

Environmental process optimization

Environmental process optimization (EPO) involves the methodical enhancement of operational workflows to mitigate adverse ecological impacts, such as carbon emissions, excessive waste, water depletion, and toxic material usage (Diabat & Govindan, 2011; Zhu *et al.*, 2012). Grounded in the natural resource-based view (Hart, 1995), EPO functions as a critical pollution-prevention capability, enabling businesses to secure competitive advantages via cost reductions and environmental distinctiveness. The integration of artificial intelligence (AI) with EPO offers a robust theoretical synergy, as AI-driven

systems leverage real-time sensor analytics to detect operational inefficiencies and suggest interventions with unprecedented speed (Wang *et al.*, 2015). Although existing empirical research within Chinese and European manufacturing sectors confirms a strong positive correlation between AI and EPO, these outcomes lack sufficient generalizability, necessitating further investigation into the specific institutional dynamics prevalent within the Vietnamese industrial context.

Green business model innovation

Green business model innovation (GBMI) involves the deliberate redesign of a firm's value creation, delivery, and capture mechanisms to incorporate ecological sustainability principles (Boons & Lüdeke-Freund, 2013; Bocken *et al.*, 2014). GBMI goes beyond incremental product greening to encompass systemic changes in supply chain relationships, customer value propositions, and resource flows aligned with circular economy principles. Scholars have positioned GBMI as a critical mediating mechanism through which operational capabilities translate into market-facing sustainability outcomes (Chesbrough, 2010; Teece, 2018). EPO-generated improvements in environmental process efficiency can serve as a foundation and catalyst for GBMI, providing the operational credibility and cost savings necessary to invest in and sustain novel green value propositions (Lüdeke-Freund *et al.*, 2018). This EPO-GBMI pathway remains theoretically articulated but empirically underdeveloped.

Environmental performance and sustainable firm performance

Environmental performance (EP) refers to measurable outcomes related to a firm's ecological impact, encompassing emission levels, resource efficiency, biodiversity effects, and environmental compliance (Klassen & McLaughlin, 1996; Trumpp & Guenther, 2017). EP is increasingly recognized as both a moral imperative and a strategic asset, with superior EP linked to enhanced reputation, customer loyalty, regulatory goodwill, and investor confidence (Flammer, 2015). Sustainable firm performance (SFP) extends financial performance metrics to include environmental and social dimensions (Elkington, 1997), reflecting a triple-bottom-line orientation.

The EP-SFP linkage is theoretically grounded in stakeholder theory (Freeman, 1984) and instrumental stakeholder theory (Jones, 1995): firms demonstrating credible environmental commitments attract broader stakeholder support, reduce regulatory risks, and access green market premiums that collectively enhance long-run sustainability performance.

Theoretical gaps and research positioning

Synthesizing the foregoing review, we identify three principal theoretical gaps. First, no prior study has empirically tested the sequential pathway from AIC through EPO and GBMI to EP and SFP as an integrated model. Second, the mediating roles of EPO and GBMI in this chain have not been tested using rigorous variance-based structural modeling. Third, the Vietnamese manufacturing context—an archetypical emerging economy undergoing rapid digital-green co-transformation—has been largely overlooked in this stream of literature. The present study directly addresses all three gaps.

Theoretical framework and hypotheses development

Figure 1 presents the proposed research model, which is grounded in three complementary theoretical perspectives: dynamic capability theory (Teece et al., 1997), which frames AI capability as a higher-order dynamic capability enabling environmental sensing and reconfiguration; the natural resource-based view (Hart, 1995), which positions EPO as a pollution-prevention capability underpinning competitive advantage; and corporate sustainability theory (Hahn et al., 2015), which conceptualizes GBMI as the mechanism translating operational environmental gains into sustainable value creation.

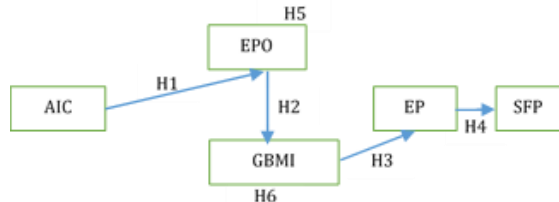


Figure 1. Proposed Research Model

According to dynamic capability theory, organizations possessing advanced higher-order capabilities are better equipped to reconfigure internal operations in response to external shifts (Teece et al., 1997). As a specific dynamic capability, AI proficiency allows firms to utilize machine learning for real-time emission tracking, energy optimization, and predictive waste management, thereby fostering environmental process optimization. By constantly evaluating sensor data from machinery, AI identifies irregular energy patterns and initiates corrective adjustments, surpassing the effectiveness of traditional monitoring techniques. Consequently, these systems facilitate a level of operational excellence previously unreachable by conventional methods (Vinuesa et al., 2020).

H1: AI capability positively influences environmental process optimization.

Environmental process optimization and green business model innovation

The natural resource-based view (Hart, 1995) identifies pollution prevention as a first-order environmental capability that can serve as a foundation for higher-order sustainable development capabilities. When firms systematically optimize environmental processes, they develop organizational routines, technical knowledge, and cost structures that create enabling conditions for GBMI. EPO-generated efficiencies provide financial slack and credibility signals to internal and external stakeholders that encourage investment in green value proposition innovation and circular supply chain redesign (Boons & Lüdeke-Freund, 2013).

H2: Environmental process optimization positively influences green business model innovation.

GBMI represents a systemic transformation of how firms create, deliver, and capture value in ways that reduce ecological footprints across the value chain (Bocken et al., 2014). By redesigning value propositions around sustainable products and services, restructuring supply chains toward circular economy principles, and developing revenue models premised

on resource efficiency, firms achieve measurable improvements in emission intensity, waste generation rates, and biodiversity impacts. Corporate sustainability theory frames GBMI as the organizational pathway through which sustainability-oriented strategy is institutionalized into measurable EP outcomes (Hahn et al., 2015).

H3: Green business model innovation positively influences environmental performance.

Drawing on stakeholder theory (Freeman, 1984) and the instrumental view of corporate social responsibility (Jones, 1995), superior EP generates multiple channels of sustainable firm performance enhancement. Firms with strong environmental track records attract environmentally conscious consumers, access preferential financing from ESG-oriented investors, benefit from lighter-touch regulatory enforcement, and build reputational capital that sustains competitive differentiation. Meta-analytic evidence confirms a positive EP-financial performance relationship across contexts (Orlitzky et al., 2003), and the broader SFP construct captures these multi-dimensional value creation pathways.

H4: Environmental performance positively influences sustainable firm performance.

We propose that EPO mediates the relationship between AIC and GBMI rather than AI directly driving GBMI. This reasoning follows from the sequential capability-building logic in dynamic capability theory: AI capability first generates operational-level environmental improvements through EPO, and these improvements then serve as the organizational foundation and strategic springboard for broader GBMI initiatives. Without first achieving process-level environmental gains, firms lack the operational credibility, cost savings, and technical knowledge necessary to sustain innovative green business models. This EPO-mediated pathway represents a theoretically coherent and practically grounded mechanism.

H5: Environmental process optimization mediates the relationship between AI capability and green business model innovation.

Similarly, we argue that GBMI mediates the EPO-EP relationship because operational process improvements alone are insufficient to generate the full range of environmental performance gains captured in our EP construct. EPO creates the preconditions for GBMI, and it is through GBMI—specifically through the wholesale redesign of value chains, supply relationships, and customer interfaces around ecological sustainability—that EPO gains are amplified, institutionalized, and extended across the value network, producing significantly larger improvements in firm-level environmental outcomes than process optimization alone could achieve.

H6: Green business model innovation mediates the relationship between environmental process optimization and environmental performance.

MATERIALS AND METHODS

Research design and context

This study adopts a quantitative cross-sectional survey design, consistent with the positivist research tradition and the hypothetico-deductive logic underpinning PLS-SEM applications in management research (Hair et al., 2017, 2019). Vietnam was selected as the research context for theoretical and

practical reasons. Theoretically, Vietnam represents an archetypical emerging economy: it combines rapid industrialization, institutional transition, and growing digitalization with environmental vulnerability and regulatory reform pressures—conditions that render the AI-sustainability nexus particularly salient and generalizable to comparable developing economies. Practically, Vietnam's manufacturing sector has witnessed substantial AI adoption in recent years, driven by foreign direct investment and government digital transformation initiatives (Ministry of Information and Communications, 2022).

Sample and data collection

The target population comprised senior managers, environmental managers, and operations directors of Vietnamese manufacturing enterprises registered with the Vietnam Chamber of Commerce and Industry (VCCI) and the Vietnam Business Forum (VBF). A stratified random sampling approach was employed to ensure representativeness across firm size (small, medium, and large); industry sector (electronics, textiles, food processing, chemicals, and automotive components); and geographic region (North, Central, and South Vietnam). A structured questionnaire was administered via both online survey platform (Google Forms) and direct site visits between January and May 2024. A total of 412 questionnaires were distributed, yielding 338 returned responses. After removing incomplete questionnaires and outliers identified through Mahalanobis distance analysis, 312 valid responses were retained for analysis, representing a 75.7% usable response rate. This sample size exceeds the minimum threshold recommended for PLS-SEM analysis of models with five constructs and bootstrapping with 5,000 subsamples (Hair et al., 2019). Non-response bias was assessed using Armstrong and Overton's (1977) procedure, comparing early and late respondents on key demographic variables. No significant differences were detected ($p > 0.05$), supporting the absence of serious non-response bias. Common method bias was addressed through procedural remedies (temporal separation between predictor and criterion variables in the questionnaire) and Harman's single-factor test; the variance explained by the first unrotated factor was 24.7%, well below the 50% threshold.

Measurement instruments

All constructs were operationalized using multi-item reflective scales adapted from established measures in the literature. AI capability (4 items) was adapted from Rai et al. (2019). Environmental process optimization (5 items) drew on Zhu et al. (2012) and Diabat and Govindan (2011). Green business model innovation (5 items) was adapted from Bocken et al. (2014) and Boons and Lüdeke-Freund (2013). Environmental performance (5 items) was based on Klassen and McLaughlin (1996) and Trumpp and Guenther (2017). Sustainable firm performance (5 items) was adapted from Elkington (1997) and Orlitzky et al. (2003). All items were measured on a seven-point

Likert scale (1 = strongly disagree; 7 = strongly agree). The questionnaire was originally developed in English and subsequently translated into Vietnamese by two bilingual researchers, with back-translation conducted to ensure linguistic equivalence.

Analytical approach: PLS-SEM

Partial least squares structural equation modeling (PLS-SEM) was employed using SmartPLS 4.0 (Ringle et al., 2022). PLS-SEM was preferred over covariance-based SEM (CB-SEM) for three reasons: (1) the research model is primarily predictive in orientation (Hair et al., 2019); (2) the model includes a complex sequential mediation structure; and (3) the relatively small-to-moderate sample size relative to model complexity recommends the statistical efficiency of PLS algorithms (Hair et al., 2017). The analysis proceeded in two stages following Anderson and Gerbing's (1988) two-step protocol. In Stage 1, the measurement model was evaluated for internal consistency reliability, convergent validity (Average Variance Extracted [AVE] ≥ 0.50 ; composite reliability [CR] ≥ 0.70 ; standardized loadings ≥ 0.70), and discriminant validity using both the Heterotrait-Monotrait (HTMT) ratio criterion (HTMT < 0.85 ; Henseler et al., 2015) and the Fornell-Larcker criterion. In Stage 2, the structural model was assessed via path coefficients, t-statistics from 5,000-iteration bootstrapping, and effect sizes (f^2). Mediation hypotheses (H5 and H6) were tested using the percentile bootstrap confidence interval approach recommended by Preacher and Hayes (2008).

RESULTS AND DISCUSSION

Respondent profile

Of the 312 valid respondents, 67.3% were male and 32.7% were female. In terms of managerial position, 41.3% were senior/top-level managers, 38.5% were middle managers, and 20.2% held operational management roles. Firm size distribution: 18.6% small firms (< 50 employees), 43.9% medium firms (50–299 employees), and 37.5% large firms (≥ 300 employees). Industry sector distribution: electronics and electrical equipment (24.0%), textiles and garments (19.6%), food and beverage processing (18.3%), chemicals and plastics (17.0%), and other manufacturing (21.1%). Respondents reported an average organizational tenure of 8.4 years (SD = 4.2), providing confidence in their knowledge of firm-level environmental and digital practices.

Descriptive statistics

Table 1 presents descriptive statistics for all latent constructs. Mean scores ranged from 4.48 (GBMI) to 4.73 (AIC), suggesting moderate-to-high levels of all constructs within the sample. Skewness values (–0.19 to –0.33) and kurtosis values (0.14 to 0.24) fell within acceptable bounds for PLS-SEM, which is robust to violations of multivariate normality (Hair et al., 2017).

Table 1. Descriptive Statistics of Latent Constructs

Variable	N	Min	Max	Mean	SD	Skew	Kurtosis
AI Capability	312	1.00	7.00	4.73	1.24	-0.31	0.18

Env. Process Opt.	312	1.00	7.00	4.61	1.31	-0.27	0.21
Green BM Innovation	312	1.00	7.00	4.48	1.38	-0.19	0.14
Env. Performance	312	1.00	7.00	4.56	1.29	-0.33	0.24
Sustainable Firm Perf.	312	1.00	7.00	4.64	1.22	-0.28	0.19

Note. SD = Standard Deviation; N = 312.

Measurement model evaluation

Table 2 reports the results of the measurement model assessment. All standardized factor loadings exceeded the 0.70 threshold (range: 0.764–0.821), indicating adequate item reliability. Composite reliability (CR) values ranged from 0.887 to 0.902, exceeding the 0.70 benchmark. Average Variance

Extracted (AVE) values ranged from 0.612 to 0.641, all surpassing the minimum threshold of 0.50, thereby confirming convergent validity. Cronbach's alpha values ranged from 0.849 to 0.871, exceeding 0.80 and confirming strong internal consistency. Variance Inflation Factor (VIF) values ranged from 1.987 to 2.534, all well below the conservative threshold of 5.0, ruling out problematic collinearity among indicators.

Table 2. Measurement Model Results: Reliability and Validity Indicators

Construct / Indicator	Loading	AVE	CR	Cronbach's α	VIF
AI Capability (AIC)		0.623	0.891	0.853	
AIC1 - AI-driven data analytics capability	0.791				2.341
AIC2 - AI-powered decision-support systems	0.812				2.518
AIC3 - AI-enabled process automation	0.774				2.207
AIC4 - AI-based predictive modeling	0.803				2.412
Environmental Process Optimization (EPO)		0.641	0.902	0.871	
EPO1 - Emission reduction through AI-enabled monitoring	0.783				2.187
EPO2 - Energy optimization using intelligent systems	0.821				2.534
EPO3 - Waste minimization via predictive analytics	0.794				2.298
EPO4 - Resource efficiency through process digitization	0.808				2.411
EPO5 - Carbon footprint tracking and optimization	0.786				2.203
Green Business Model Innovation (GBMI)		0.612	0.887	0.849	
GBMI1 - Green value proposition development	0.776				2.024
GBMI2 - Eco-innovative product/service design	0.803				2.213
GBMI3 - Sustainable supply chain integration	0.787				2.107
GBMI4 - Circular economy business model adoption	0.764				1.987
GBMI5 - Green revenue model diversification	0.798				2.156
Environmental Performance (EP)		0.629	0.895	0.859	
EP1 - Reduction in hazardous waste generation	0.788				2.241
EP2 - Decrease in greenhouse gas emissions	0.814				2.467
EP3 - Improvement in air and water quality	0.779				2.178
EP4 - Biodiversity conservation outcomes	0.803				2.389
EP5 - Environmental compliance performance	0.791				2.204
Sustainable Firm Performance (SFP)		0.618	0.893	0.856	
SFP1 - Long-term financial sustainability	0.793				2.119
SFP2 - Reputational capital and green branding	0.807				2.233
SFP3 - Stakeholder satisfaction with ESG outcomes	0.782				2.087
SFP4 - Market share in green product segments	0.771				2.013
SFP5 - Regulatory compliance cost reduction	0.816				2.312

Note. AVE = Average Variance Extracted; CR = Composite Reliability; VIF = Variance Inflation Factor. All factor loadings significant at $p < 0.001$.

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio. Table 3 shows that all HTMT values were below 0.85 (range: 0.554–0.741), satisfying the criterion

proposed by Henseler et al. (2015). The Fornell-Larcker criterion was also met: the square root of each construct's AVE exceeded its correlations with all other constructs.

Table 3. Discriminant Validity: HTMT Ratios

Construct	AIC	EPO	GBMI	EP	SFP
AI Capability (AIC)	—				
Env. Process Opt. (EPO)	0.712	—			
Green BM Innovation (GBMI)	0.643	0.731	—		
Env. Performance (EP)	0.598	0.684	0.719	—	
Sustainable Firm Perf. (SFP)	0.554	0.631	0.672	0.741	—

Note. HTMT values below 0.85 indicate adequate discriminant validity (Henseler et al., 2015). AIC = AI Capability; EPO = Environmental Process Optimization; GBMI = Green Business Model Innovation; EP = Environmental Performance; SFP = Sustainable Firm Performance

Structural model and hypotheses testing

Table 4 presents the structural model results. The R² values for endogenous constructs ranged from 0.233 (EPO) to 0.411 (SFP), indicating that the model explains between 23.3% and 41.1% of variance in endogenous constructs—ranging from moderate to substantial predictive accuracy (Hair et al., 2019). Q² values

from blindfolding (omission distance = 7) ranged from 0.141 to 0.252, all exceeding zero, confirming the model's predictive relevance. Effect sizes (f²) for significant paths ranged from 0.127 to 0.219, indicating small-to-medium effects per Cohen's (1988) benchmarks.

Table 4. Hypotheses Testing

H	Path Relationship	β	S.E.	t-value	p-value	Decision
H1	AIC → EPO	0.483	0.061	7.918	< 0.001	Supported
H2	EPO → GBMI	0.512	0.058	8.827	< 0.001	Supported
H3	GBMI → EP	0.467	0.063	7.413	< 0.001	Supported
H4	EP → SFP	0.531	0.055	9.655	< 0.001	Supported
H5	AIC → EPO → GBMI (mediation)	0.247	0.038	6.513	< 0.001	Supported
H6	EPO → GBMI → EP (mediation)	0.239	0.041	5.829	< 0.001	Supported

Note. β = standardized path coefficient; S.E. = standard error (bootstrapped, 5,000 subsamples); t-values and p-values from two-tailed bootstrapping. All paths significant at p < 0.001.

Table 5. Model Fit Indicators: R², R² Adjusted, and Q²

Endogenous Construct	R ²	R ² Adjusted	Q ²	Interpretation
Env. Process Optimization (EPO)	0.233	0.229	0.141	Moderate
Green BM Innovation (GBMI)	0.319	0.314	0.198	Moderate
Environmental Performance (EP)	0.378	0.371	0.231	Substantial
Sustainable Firm Performance (SFP)	0.411	0.406	0.252	Substantial

Note. R² values: <0.25 = weak; 0.25-0.50 = moderate; >0.50 = substantial (Hair et al., 2019). Q² > 0 indicates predictive relevance.

H1 predicted that AI capability positively influences EPO. The path coefficient was positive and significant (β = 0.483, t = 7.918, p < 0.001), providing strong support for H1. H2 predicted that EPO positively influences GBMI and was supported (β = 0.512, t = 8.827, p < 0.001), representing the strongest direct effect in the model. H3 predicted that GBMI positively influences EP (β = 0.467, t = 7.413, p < 0.001), confirming H3. H4 predicted that EP positively influences SFP (β = 0.531, t = 9.655, p < 0.001), the largest total structural effect, supporting H4. For mediation hypotheses, the indirect effect of AIC on GBMI via EPO (H5) was β = 0.247 (SE = 0.038, t = 6.513, p < 0.001), with a 95% bootstrapped confidence interval of [0.174, 0.323] excluding zero, confirming full mediation and supporting H5. The indirect effect of EPO on EP via GBMI (H6) was β = 0.239 (SE = 0.041, t = 5.829, p < 0.001), 95% CI [0.161, 0.319], also excluding zero and supporting H6. Variance Accounted For (VAF) analyses indicated that EPO accounts for 33.8% of the AIC-GBMI total effect (partial-to-full mediation), and GBMI accounts for 31.5%

of the EPO-EP total effect, suggesting complementary rather than suppressive mediation in both cases.

The results presented in **Table 5** demonstrate that all endogenous constructs achieve acceptable levels of explanatory and predictive power. Specifically, Environmental Process Optimization (EPO) and Green Business Model Innovation (GBMI) exhibit moderate explanatory capacity, with R² values of 0.233 and 0.319, respectively, indicating that a meaningful proportion of variance is explained by the model. In contrast, Environmental Performance (EP) and Sustainable Firm Performance (SFP) show higher explanatory strength, with R² values of 0.378 and 0.411, suggesting substantial model effectiveness in capturing sustainability-related outcomes. Furthermore, all Q² values are greater than zero, confirming the model's predictive relevance. Overall, these findings indicate that the model performs particularly well in explaining environmental and sustainable performance, while maintaining adequate predictive capability across all constructs.

The findings of this study advance theoretical literature on AI, environmental management, and sustainable performance in several meaningful ways. First, by confirming H1 (AIC → EPO), we extend dynamic capability theory to the environmental-digital nexus, demonstrating that AI capability functions as a sensing-and-reconfiguring capability that enables systematic environmental process improvements in manufacturing firms. This finding adds empirical granularity to Teece *et al.*'s (1997) foundational framework by specifying how digital higher-order capabilities generate first-order environmental operational outcomes. Second, the confirmation of H2 (EPO → GBMI) provides an important theoretical contribution by establishing that operational-level environmental improvements serve as a precondition and catalyst for strategic-level business model innovation. This finding bridges the natural resource-based view (Hart, 1995)—which has traditionally focused on pollution prevention as an operational capability—with the emergent literature on green business model innovation (Bocken *et al.*, 2014), demonstrating that the two are sequentially rather than independently related. Third, by confirming H5 and H6—the two mediation hypotheses—we demonstrate that the AI-sustainability value chain is characterized by sequential mediation rather than direct causation. This theoretical insight has important implications: it suggests that AI's contributions to environmental performance are institutionalized through organizational capability development (EPO) and strategic transformation (GBMI) rather than through direct technological determinism. This finding resonates with sociotechnical systems theory (Trist, 1981) and social-technical-environmental interaction frameworks (Geels, 2004). Fourth, our findings in the Vietnamese context contribute to the limited but growing body of literature on digital-environmental co-transformation in emerging economies. The confirmation that the theorized model holds in a manufacturing-intensive developing economy with significant institutional and digital-maturity heterogeneity strengthens the cross-contextual generalizability of the proposed relationships.

For enterprise managers, the study findings provide actionable guidance on three levels. First, the AI → EPO pathway (H1) implies that investments in AI-based environmental monitoring, predictive maintenance, and intelligent process control systems should be prioritized as entry points for environmental capability building—especially given that EPO subsequently drives GBMI and EP. Managers in Vietnamese manufacturing enterprises should evaluate AI tools (e.g., IoT-enabled emissions-monitoring platforms, AI-powered energy management systems) as strategic assets rather than merely operational tools. Second, the EPO → GBMI pathway (H2) suggests that managers should treat environmental process gains as platforms for business model innovation rather than ends in themselves. Firms that have achieved EPO maturity should be encouraged to invest in green product line extensions, circular supply chain redesigns, and sustainable customer value propositions that leverage their operational environmental credentials. Third, the EP → SFP pathway (H4)—with the largest path coefficient in the model ($\beta = 0.531$)—reinforces the business case for proactive environmental management in Vietnamese manufacturing. Firms should communicate environmental performance credibly to stakeholders, align ESG reporting with international standards, and integrate environmental KPIs into executive performance evaluation

frameworks. For policymakers, the findings support targeted AI adoption incentives within Vietnam's National Digital Transformation Program (Resolution 52-NQ/TW) and the National Green Growth Strategy (Decision 1658/QD-TTg, 2021). Policies that subsidize AI-based environmental monitoring technology for SMEs, establish digital-environmental competency standards, and create institutional frameworks supporting green business model experimentation would accelerate the sequential capability-building pathway identified in this study.

Limitations and future research directions

This study is subject to several limitations that simultaneously identify productive directions for future research. First, the cross-sectional design precludes causal inference; longitudinal studies tracking the sequential capability development pathway over time would substantially strengthen the causal claims. Second, the single-country, single-sector sample, while appropriate for establishing initial empirical evidence, limits generalizability. Comparative multi-country studies across ASEAN emerging economies would provide valuable cross-national validation and boundary condition analysis. Third, all data were collected from single-respondent self-reports, which may introduce mono-source bias despite methodological precautions. Future studies should consider multi-respondent designs, matched firm-level environmental performance data from regulatory databases, or longitudinal panel designs. Fourth, our treatment of AI capability as a unidimensional higher-order construct simplifies the heterogeneity of AI applications; future research might disaggregate AI capability into distinct sub-dimensions (e.g., machine learning, computer vision, natural language processing) and examine their differential effects on environmental processes. Fifth, boundary conditions of the proposed relationships—such as institutional environment quality, firm absorptive capacity, and industry regulatory intensity—merit investigation through moderated mediation models.

CONCLUSION

This study presents a theoretically grounded and empirically validated model of how AI capability drives sustainable firm performance in Vietnamese manufacturing enterprises through a sequential mediation pathway involving environmental process optimization and green business model innovation. Analyzing survey data from 312 manufacturing firms using PLS-SEM, we confirm all six hypotheses: AI capability positively shapes EPO (H1); EPO drives GBMI (H2); GBMI enhances EP (H3); EP advances SFP (H4); and both EPO and GBMI serve as mediators in the AI-sustainability value chain (H5, H6). These findings make substantive contributions to dynamic capability theory, the natural resource-based view, and corporate sustainability theory while providing practitioners and policymakers with actionable insights for accelerating Vietnam's digital-green co-transformation. As AI technologies become increasingly embedded in manufacturing operations globally, understanding the organizational pathways through which AI capability translates into sustainable outcomes becomes both theoretically essential and practically urgent. This study provides a foundational empirical reference point for

this emerging research agenda, particularly in the underexplored but economically vital context of emerging economies in Southeast Asia.

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