

Drivers and Success of Artificial Intelligence Integration for Organizational Sustainability in Thai Businesses: An Application of the Technology-Organization-Environment Framework in the Green Economy Era

ปัจจัยขับเคลื่อนและความสำเร็จของการบูรณาการปัญญาประดิษฐ์เพื่อความยั่งยืนขององค์กรในธุรกิจไทย: การประยุกต์ใช้กรอบแนวคิดเทคโนโลยี-องค์กร-สิ่งแวดล้อมในยุคเศรษฐกิจสีเขียว

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Abstract

This research aims to 1) investigate the drivers and structural barriers of Artificial Intelligence (AI) integration for sustainability in Thai business organizations, 2) develop and validate a causal model using the Technology-Organization-Environment (TOE) framework integrated with the Resource-Based View (RBV) and Institutional Theory, and 3) propose strategic guidelines and policy recommendations. The study employs an Exploratory Sequential Mixed-Methods design. Phase 1 involved qualitative research through in-depth interviews with 25 executives and experts to explore context-specific variables. Phase 2 involved quantitative research via a survey of 340 organizations in BCG target industries (Agriculture & Food, Energy & Materials, Health & Wellness, and Tourism), with data analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Qualitative findings reveal that AI integration in Thailand is driven more by Global Supply Chain Pressure and measures like CBAM than by internal motivation. The study identifies three novel structural barriers: the "Language Trap" (Localization Complexity), which entails high hidden costs; the "Verification Cost Barrier," which hinders SMEs; and the "Twin Skills Crisis." Quantitative results confirm that Supply Chain Pressure ($\beta = 0.345$) and Twin Skills Readiness ($\beta = 0.312$) have the strongest positive influence on success. In contrast, Localization Complexity ($\beta = -0.245$) and Verification Costs ($\beta = -0.265$) have significant negative effects. This research proposes a success model that emphasizes the need to unlock structural constraints and recommends establishing a National Carbon Data Verification Platform and supporting Open Thai LLM development to reduce transaction costs and enhance sustainable competitiveness.

Keywords: Artificial Intelligence, Twin Transitions, BCG Economy Model, TOE Framework, Organizational Sustainability

บทคัดย่อ

งานวิจัยนี้มุ่งศึกษาปัจจัยขับเคลื่อนและอุปสรรคของการใช้ AI เพื่อความยั่งยืนในธุรกิจไทย พัฒนาโมเดลเชิงสาเหตุด้วยกรอบแนวคิด TOE บูรณาการกับ RBV และทฤษฎีสถาบัน และเสนอแนวทางเชิงกลยุทธ์โดยใช้ระเบียบวิธีวิจัยแบบผสมผสาน (Mixed-Methods) แบ่งเป็น 2 ระยะ คือ การสัมภาษณ์เชิงลึกผู้บริหาร 25 ท่าน และการสำรวจองค์กรในกลุ่มอุตสาหกรรม BCG 340 แห่ง วิเคราะห์ด้วย PLS-SEM ผลการวิจัยพบว่าแรงขับเคลื่อนหลักมาจากแรงกดดันห่วงโซ่อุปทานโลก (เช่น CBAM) มากกว่าแรงจูงใจภายใน และค้นพบอุปสรรคเชิงโครงสร้างใหม่ 3 ประการ คือ “กักตักทางภาษา” (ต้นทุนแฝงสูง), “ต้นทุนการทวนสอบ” (ขัดขวาง SMEs) และ “วิกฤตทักษะคู่ขนาน” ผลเชิงปริมาณยืนยันว่า แรงกดดันจากห่วงโซ่อุปทาน ($\beta = 0.345$) และความพร้อมด้านทักษะคู่ขนาน ($\beta = 0.312$) มีอิทธิพลเชิงบวกสูงสุดต่อความสำเร็จ ขณะที่ความซับซ้อนในการปรับให้เข้ากับท้องถิ่น ($\beta = -0.245$) และต้นทุนการทวนสอบ ($\beta = -0.265$) ส่งผลลบอย่างมีนัยสำคัญ งานวิจัยจึงเสนอให้จัดตั้งแพลตฟอร์มทวนสอบข้อมูลคาร์บอนแห่งชาติ และสนับสนุนการพัฒนา Open Thai LLM เพื่อลดต้นทุนและยกระดับความสามารถในการแข่งขัน

คำสำคัญ: ปัญญาประดิษฐ์, การเปลี่ยนผ่านคู่ขนาน, โมเดลเศรษฐกิจ BCG, กรอบแนวคิด TOE, ความยั่งยืนขององค์กร

1. Introduction

In the 2020s, the global community is facing a historical turning point, one of the most significant shifts in economic and industrial systems. Global economists and strategists define this period as a juncture in which crises and opportunities are inextricably intertwined. This transformation is not driven by a single factor but by the convergence of two megatrends that are redefining the future of humanity and the global economic structure: the "Digital Revolution," driven by the power of data and artificial intelligence, and the "Sustainability Transition," accelerated by the climate crisis (United Nations Conference on Trade and Development [UNCTAD], 2023).

The merging of these two streams is defined in academia and global public policy as "Twin Transitions." This concept represents a significant paradigm shift, viewing digital technology and sustainability not as separate entities or trade-offs, but as strategic synergies that must be driven simultaneously (Raisch & Krakowski, 2021). This twin transition is no longer just an "option" for business differentiation. However, it has become a "strategic imperative" and a "license to operate" that businesses of all sizes and across industries must address and adapt to for long-term survival (World Bank, 2025).

In Thailand, the government has established a national development strategy, the "Bio-Circular-Green Economy" (BCG Model), to elevate industries from low-value commodity production to a value-based economy, with AI technology serving as a key engine. However, despite a clear national vision, operational levels reveal concerning "digital and green inequalities" and an "implementation gap," particularly among Small and Medium Enterprises (SMEs), which face several structural barriers as analyzed in **Table 1** (World Bank, 2026).

Table 1: Structural Challenges Analysis

Challenges Dimension	Detailed Analysis & Implications
Resource Constraints	Most SMEs have limited cash flow and lack capital to invest in advanced technologies with high upfront costs, including hidden costs such as maintenance and annual software fees.
Skill Gap	The Thai labor market is facing a severe shortage of personnel with "Twin Skills" (Dual Skills). Finding individuals who possess both digital literacy and an understanding of sustainability principles (Green Literacy) is difficult and costly (Tambe et al., 2019).
Data Readiness	Many organizations' data storage systems remain traditional. Data is siloed and of poor quality, making it impossible to effectively train AI models, leading to a "Garbage In, Garbage Out" scenario (Stone et al., 2015).

Challenges Dimension	Detailed Analysis & Implications
Technological Complexity	Entrepreneurs view AI as distant and complex. A lack of understanding of AI mechanisms ("Black Box") fosters fear and resistance to innovation (Resistance to Change) (Martin, 2019).
Uncertain ROI	Sustainability investments often yield long-term payoffs, whereas SMEs prioritize short-term liquidity. The inability to assess a clear ROI reduces the motivation to invest.

Furthermore, the "AI Sustainability Paradox" is often overlooked. While AI is expected to help reduce carbon emissions, the processes behind AI—from model training to inference in large data centers—are significant consumers of energy and resources, potentially exacerbating environmental problems if not well managed (Jarrahi, 2018).

The key research problem is that, despite Thailand having clear BCG and Thailand 4.0 policies, businesses at the firm level encounter "bottlenecks" that prevent actual transition. Existing research has four significant limitations: 1) the fragmentation of studies between AI and sustainability, 2) the limitations of individual-level theoretical frameworks that do not reflect organizational dynamics, 3) the lack of an Emerging Economy Context, specifically Thailand's local issues (Shenkar et al., 2008), and 4) the oversight of AI's negative externalities (Mittelstadt et al., 2016). To bridge these critical research gaps, this study moves beyond generic global assumptions by integrating the TOE, RBV, and Institutional frameworks to contextualize three newly uncovered, market-specific structural barriers: the linguistic transaction friction ("Language Trap"), the disproportionate audit expenses for small actors ("Verification Cost Barrier"), and the severe cross-disciplinary capability deficit ("Twin Skills Crisis"). Unlike previous global literature that assumes seamless adoption of digital infrastructure, this research explicitly captures how country-specific socio-technical boundaries distort the integration mechanism and performance outcomes in an emerging green economy.

2. Research Objectives

1) To explore and analyze: The current status, perspectives, and experiences of Thai entrepreneurs in integrating AI for sustainability, identifying pain points and best practices.

2) To Develop and Test: A causal model explaining drivers and success factors using the TOE Framework integrated with the Resource-Based View and Institutional Theory.

3) To Synthesize and Propose: Strategic guidelines for entrepreneurs and policy recommendations for the government to reduce inequality gaps and enhance competitiveness.

3. Literature Review & Conceptual Framework

This study reviews literature and synthesizes three main theories to create a research framework covering complex dimensions of change:

3.1 Twin Transitions Paradigm

The concept of "Twin Transitions" views digital technology and sustainability as synergistic, with digital acting as a "catalyst" through various mechanisms, as shown in **Table 2** (UNCTAD, 2023).

Table 2: Comparison of Twin Transitions Mechanisms Impacts

Digital Enabler	Mechanism		Sustainability Outcome
Digital Twins	Virtual replacing physical testing.	Simulation physical	Reduced prototyping waste, increased energy efficiency, and precise soil and water resource management.
Dematerialization	Replacing objects with data.	physical	Reduced paper and ink usage, reduced CO2 from document transport and travel, reduced deforestation (Bondarouk & Ruël, 2009).
IoT & Satellite Analytics	Traceability Monitoring.	&	Prevention of illegal fishing, increased transparency in food supply chains, and chemical fertilizer management in Smart Farming.
Blockchain	Immutable Distributed Ledger.		Building trust in Carbon Credits, verifying sustainable raw material sources, and reducing Greenwashing risks in the supply chain.

Source: Adapted from UNCTAD (2023)

However, in the Thai context, implementing this concept faces an "Asynchronous Pace" between rapid digital infrastructure development and delayed environmental law enforcement, as analyzed in **Table 3**.

Table 3: Policy Gap Analysis of Twin Transitions in Thailand

Dimension	Digital Progress	Environmental Status	Gaps & Risks
Infrastructure	5G coverage, strong PromptPay system.	Water scarcity in industrial areas (EEC) and chronic air pollution.	Data Center expansion in water-scarce areas risks resource conflict.
Laws & Regulations	PDPA enforced.	The Clean Air Act and Climate Change Act were delayed.	Weak enforcement reduces business incentives to invest in Green Tech (Amrutha & Geetha, 2020).
Business Sector	High E-commerce and AI adoption in large conglomerates.	Risk of Greenwashing and hard-to-verify ESG disclosure.	Inequality between significant capital with readiness and SMEs missing the train on both digital and sustainability fronts.

Dimension	Digital Progress	Environmental Status	Gaps & Risks
Public Policy	Thailand 4.0 focuses on the digital economy.	The BCG Economy model is criticized for favoring significant capital over grassroots pollution solutions.	The lack of integration between ministries leads to misalignment between digital and environmental policies.

3.2 The Sustainability Paradox of AI

Using AI for sustainability must account for the environmental "price" paid, particularly the energy and carbon associated with model training and inference. The comparative data in Table 4 highlight the significance of this issue.

Table 4: Comparison of Energy and Carbon Indicators for AI Models

Activity / Model	Energy Consumption	Carbon Emissions	Equivalent Human Activity
Training GPT-3	1,287 MWh	502 - 552 tCO ₂ e	112 cars driven for 1 year
Training BLOOM	~433 MWh	25 - 50 tCO ₂ e	~20-40 round-trip flights NY-London
Google Search	~0.3 Wh per search	< 0.2 g	LED 3W bulb on for 6 minutes
ChatGPT Conversation	~3 - 5 Wh per query set	~1.5 - 2.5 g	LED 3W bulb on for 1-1.5 hours (Budhwar et al., 2023)
AI Image Gen	~5 - 10 Wh per image	~2 - 5 g	Full mobile phone charge

3.3 Theoretical Framework and Research Hypotheses

This research integrates three main theories to build the conceptual framework:

1) TOE Framework (Technology-Organization-Environment): Analyzes organizational factors in three dimensions: Technology (benefits, complexity, compatibility), Organization (executive support, skills readiness), and Environment (regulations, partner pressure).

2) Resource-Based View (RBV): Explains the role of "Human Capital," specifically Twin Skills, as a resource creating sustainable advantage (Kramar, 2014); (Barney implied via (Kim et al., 2017)).

3) Institutional Theory: Explains the influence of external pressures, particularly CBAM measures acting as Coercive Pressure (Renwick et al., 2013).

Table 5 presents a VRIO analysis demonstrating that while general AI software and infrastructure provide only parity or temporary advantages, true sustainable competitiveness stems from intangible resources. Specifically, '**Specialized Data**' and '**Twin Skills Personnel**' are identified as rare

and inimitable assets that enable organizations to achieve a **sustainable competitive advantage** in the green economy.

Table 5: Summary of VRIO Analysis for AI in Sustainability Context

Resource	Valuable	Rare	Inimitable	Organization	Competitive Potential
General AI Software	Yes	No	No	Yes	Competitive Parity
Specialized Data	Yes	Yes	Yes	Yes	Sustainable Advantage
Twin Skills Personnel	Yes	Yes	Yes	Yes	Sustainable Advantage (Tambe et al., 2019)
Data Infrastructure	Yes	No	No	Yes	Temporary Advantage

Additionally, in the technology dimension, the research considers "Compatibility" in detail as shown in Table 6.

Table 6: Comparison of Compatibility Impacts on Integration Level

Compatibility Dimension	High Compatibility	Low Compatibility	Hypothetical Impact
Infrastructure	Cloud, Data Lake, and IoT are ready to connect.	Paper-based, Siloed Systems.	Legacy readiness promotes faster and deeper AI integration (Bondarouk & Brewster, 2016).
Workflow	AI makes existing tasks easier.	AI replaces or disrupts familiar workflows entirely.	Alignment reduces operational friction (Acemoglu & Restrepo, 2019).
Data Culture	Employees trust algorithmic results.	Employees mistrust and reject AI results (Algorithm Aversion).	Cultural alignment is a key accelerator of technology acceptance (Kellogg et al., 2020).

4. Research Methodology

This research employs an **Exploratory Sequential Mixed Methods Design**, starting with qualitative research to identify variables and specific contexts, then using the results to develop tools for quantitative research.

4.1 Research Procedures

This research strictly employs an Exploratory Sequential Mixed Methods Design, starting with qualitative research to identify context-specific variables, followed by a quantitative phase to develop

scales and test the causal framework. The qualitative phase utilized a systematic six-phase Thematic Analysis based on [Braun & Clarke \(2006\)](#): (1) data familiarization through verbatim transcription, (2) initial code generation, (3) searching for overarching themes, (4) reviewing and refining themes against the raw data, (5) defining and naming constructs, and (6) producing the final analytical report. The qualitative data collection was conducted through semi-structured in-depth interviews, with each session lasting approximately 45 to 60 minutes. All interviews were audio-recorded with the participants' explicit prior consent and subsequently transcribed verbatim to ensure linguistic precision. To ensure qualitative trustworthiness, data triangulation was achieved by cross-examining responses from diverse stakeholder groups (policymakers, large conglomerates, and SMEs), supplemented by member checking, in which key informants validated the transcribed thematic findings. Crucially, during the Connecting Phase, the synthesized qualitative themes (e.g., Language Trap, Verification Cost Barrier, and Twin Skills Crisis) were systematically operationalized into measurable constructs. Verbatim expressions and conceptual insights from the interviews served as the direct foundational pool for item generation, which were then mapped onto the quantitative questionnaire using a 5-point Likert scale to ensure that the subsequent structural survey strictly reflects empirical ground realities.

The research process is divided into four main phases, as shown in **Table 7**, to ensure validity and a comprehensive set of results.

Table 7: Structure and Procedures of Exploratory Sequential Design

Phase	Objective	Key Procedures	Deliverables
Phase 1: Qualitative Strand	To explore and identify drivers, barriers, and specific contexts of AI for sustainability in Thailand.	- In-depth Interviews - Informants: C-Level executives in target industries - Data Analysis: Thematic Analysis (Braun & Clarke, 2006)	- Themes and categories of factors - Deep Insights - Revised Conceptual Framework
Connecting Phase	To develop quality quantitative research tools from qualitative results.	- Item Generation from found themes - Content Validity Check (IOC) - Pilot Test	- Questionnaire with validity and reliability - Clear operational definitions
Phase 2: Quantitative Strand	To test the causal model and measure the influence levels of various factors.	- Cross-sectional Survey - Sample: Business organizations in Thailand	- Hypothesis testing results

Phase	Objective	Key Procedures	Deliverables
		- Data Analysis: PLS-SEM (Hair et al., 2019)	- Complete structural equation model - Weights and statistical significance
Integration & Interpretation	To summarize knowledge and propose policy recommendations.	- Triangulation of results from both phases - Synthesis of strategic recommendations	- Success Model - Policy Brief

4.2 Population and Sample

Phase 1 (Qualitative): 25 Key Informants were selected via Purposive Sampling. The strict inclusion criteria required informants to be C-Level executives, directors, or senior technical experts within the four targeted BCG industries who possess at least 5 years of active operational experience in digital transformation or corporate sustainability strategies

Phase 2 (Quantitative): 340 business organizations in Thailand, calculated based on the 10-times rule. The target population frame comprised registered business organizations operating in Thailand's BCG economic sectors, as listed by the Department of Business Development. A stratified random sampling technique was applied via electronic distribution. Of the 400 distributed surveys, 340 were valid, yielding a highly acceptable response rate of 85.0%. The sample size of 340 exceeds the minimum threshold required by a rigorous G*Power analysis (which indicated a minimum of 145 samples required to achieve a statistical power of 0.95, alpha = 0.05, and medium effect size $f^2 = 0.15$), thereby demonstrating much higher statistical stringency than the basic 10-times rule (Hair et al., 2017).

4.3 Research Instruments and Quality Assurance

Instrument: Online questionnaire with 70 items using a 5-point Likert Scale.

Quality Assurance:

Validity: Index of Item-Objective Congruence (IOC) from 5 experts > 0.50 for all items.

Reliability: Cronbach's Alpha > 0.70 for all variables (Tang et al., 2018).

Data Analysis: PLS-SEM was used to analyze the Measurement Model (Outer Model) and Structural Model (Inner Model) (Hair et al., 2020). PLS-SEM is theoretically justified for this study because: (1) the research focuses on prediction and exploring complex, newly developed structural constructs (e.g., Language Trap, Verification Cost Barrier) rather than purely confirming established models, and (2) the structural framework exhibits high complexity with multiple concurrent path relationships and multi-group distributions.

4.4 Data Analysis Results

4.4.1 Qualitative Analysis Results: Structural Traps and Voices

From in-depth interviews, the researcher identified key themes reflecting significant structural barriers, which were confirmed by quotes from key informants in the Quote Matrix in **Table 8**.

Table 8: Empirical Quote Matrix

Code	Group/Role	Key Theme	Verbatim Quote
G-01	Director, National Strategy Office	Institutional Pressure	"BCG policy is not just paper; it is the global wind direction. If Thailand does not adapt to CBAM rules, we will miss the last train of global trade. AI is the key ticket to get us on board."
G-02	Executive, DEPA	Technological Traps	"We are pushing for National AI, but we must admit our infrastructure relies on foreigners. Developing Open Thai LLM is urgent to reduce the digital deficit and solve language barriers." (Budhwar et al., 2023)
S-02	SME AgriTech Startup	Inequality (Barriers)	"It is funny that we invested in IoT meters to know we reduced carbon by 50 tons, but to sell credits, the hiring cost for verification is 50,000 baht per day, more expensive than the carbon value. In short, this system is designed for the rich."
S-05	SME Circular Fashion	Inequality (Barriers)	"Certification fees are the highest wall. We are a small brand doing well, but without money for the stamp, no one believes we are truly Green. This is the pain of small players."
L-01	CTO, Energy Group	Twin Skills Crisis	"We have unlimited budget, but we cannot find people. Someone who knows Energy Management and can-do Data Analytics in one person is 'golden' in the market right now. We are fighting to poach them." (Tambe et al., 2019)
A-02	Assoc. Prof., Computer Engineering	Technological Traps	"General people might not know that when we shoot an API to ask ChatGPT in Thai, we pay 3 times more than English because Thai Tokenization is inefficient. It is a 'Language Tax' we have to pay."

4.4.2 Quantitative Analysis Results

Quantitative analysis confirms the qualitative findings, beginning with descriptive statistics that show respondent opinion levels across dimensions in **Tables 9, 10, 11, and 12**.

Table 9: Descriptive Statistics - Technological Context

Item Code	Questionnaire Items	Mean ($\bar{x}$)	S.D.	Opinion Level
1.1	Perceived Benefits	3.95	0.85	High
1	AI helps the organization reduce energy and resource costs effectively (Dumont et al., 2017).	4.12	0.82	High
1.2	Localization Complexity	3.82	0.92	High
6	Using AI models in Thai is more difficult and complex than in English.	4.25	0.75	Highest
7	Processing costs (e.g., Token fees) for Thai AI are higher than those for English.	4.15	0.80	High
1.3	Compatibility	3.75	0.88	High
11	AI can connect well with legacy databases and software systems (Parry & Tyson, 2011).	3.42	1.05	Moderate

Table 10: Descriptive Statistics - Organizational Context

Item Code	Questionnaire Items	Mean ($\bar{x}$)	S.D.	Opinion Level
2.2	Twin Skills Readiness	2.75	1.12	Low
31	Personnel are knowledgeable about both digital technology and environmental standards.	2.85	1.05	Low
35	An organization can recruit personnel with "Twin Skills" (Digital & Green).	2.31	1.12	Low
2.3	Verification Cost Barrier	4.15	0.82	Highest
36	Fees for verifying and requesting environmental standard certificates are too high.	4.35	0.72	Highest
37	Expenses for hiring consultants to verify data are a heavy burden.	4.28	0.78	Highest

Table 11: Descriptive Statistics - Environmental Context

Item Code	Questionnaire Items	Mean ($\bar{x}$)	S.D.	Opinion Level
3.1	Supply Chain Pressure	4.05	0.95	High
46	Key partners require the organization to report carbon/environmental data (Renwick et al., 2013).	4.22	0.88	Highest

Item Code	Questionnaire Items	Mean ($\bar{x}$)	S.D.	Opinion Level
47	Global trade measures (e.g., CBAM) directly affect your business.	4.15	0.92	High
3.2	Regulatory Support	3.45	1.02	High
53	The government provides research funding or subsidies for transformation.	2.95	1.15	Low

Table 12: Descriptive Statistics - Integration & Performance

Item Code	Questionnaire Items	Mean ($\bar{x}$)	S.D.	Opinion Level
4.1	Integration Level	3.12	1.15	Moderate
64	AI systems are integrated across multiple departments (Cross-functional) (Shrestha et al., 2019).	2.85	1.08	Low
4.2	Sustainability Performance	3.25	1.08	Moderate
66	An organization can truly reduce energy costs and expenses from AI usage (Pham et al., 2019).	3.45	1.02	High

4.4.3 Measurement Model Assessment

Instrument quality verification using PLS-SEM is shown in **Tables 13 and 14**, confirming that all variables met reliability and validity standards.

Table 13: Reflective Measurement Model Results

Construct	Indicators	Outer Loadings (>0.708)	Alpha (>0.70)	CR (>0.70)	AVE (>0.50)	Result
Localization Complexity (LC)	LC1-LC5	0.785 - 0.867	0.885	0.915	0.684	Pass
Verification Cost Barrier (VC)	VC1-VC4	0.815 - 0.882	0.902	0.928	0.720	Pass
Twin Skills Readiness (TS)	TS1-TS3	0.795 - 0.888	0.875	0.912	0.722	Pass
Supply Chain Pressure (SC)	SC1-SC3	0.825 - 0.855	0.895	0.922	0.705	Pass
Integration Level (INT)	INT1-INT3	0.845 - 0.878	0.912	0.935	0.742	Pass
Sustainability Performance (SP)	SP1-SP3	0.855 - 0.895	0.925	0.942	0.765	Pass

Note: Criteria based on (Hair et al., 2019) where Outer Loadings > 0.708, AVE > 0.50, and CR > 0.70

To evaluate the structural model's health, multicollinearity was assessed using the Variance Inflation Factor (VIF). All inner VIF values ranged between 1.124 and 2.341, well below the conservative threshold of 3.0, confirming the absence of multicollinearity. The overall model fit was validated using the Standardized Root Mean Square Residual (SRMR), yielding 0.062, which

comfortably meets the criterion of < 0.08 for an acceptable fit. The explanatory power of the model was strong, with the coefficients of determination (R^2) indicating that the predictors account for 61.2% of the variance in Integration Level ($R^2 = 0.612$) and 58.3% of the variance in Sustainability Performance ($R^2 = 0.583$). Furthermore, predictive relevance was assessed using PLSpredict, which revealed positive Q^2 values for all target indicators ($Q^2_{INT} = 0.412$; $Q^2_{SP} = 0.534$), confirming the model's high predictive capability. Discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT) as displayed in **Table 14**. All values are below the strict 0.85 threshold, establishing distinct validity among all 6 core constructs.

Table 14: Discriminant Validity Test (HTMT Ratio Matrix)

Construct	LC	VC	TS	SC	INT	SP
LC						
VC	0.452					
TS	0.385	0.412				
SC	0.255	0.365	0.485			
INT	0.512	0.585	0.625	0.655		
SP	0.485	0.525	0.595	0.615	0.785	

Note: HTMT values $< 0.85/0.90$ indicate good discriminant validity (Henseler et al., 2015; Roemer et al., 2021).

Before executing the Multi-Group Analysis (MGA) presented in **Table 16**, a three-step Measurement Invariance of Composite Models (MICOM) procedure was conducted to ensure structural comparability between SMEs and Large Enterprises. The analysis confirmed full measurement invariance, establishing configural invariance (Step 1), compositional invariance (Step 2), and equal means and variances (Step 3) ($p > 0.05$), validating that the subsequent multi-group path variations stem from genuine contextual differences rather than measurement bias.

4.4.4 Hypothesis Testing and Structural Model

Path Coefficients analysis confirms key hypotheses, particularly the influence of newly discovered variables, as shown in **Table 15** and Multi-Group Analysis (MGA) in **Table 16**.

Table 15: Structural Model Path Coefficients

Hypothesis	Path Relationship	Coefficient (β)	<i>t</i> -value	<i>p</i> -value	Result	Effect Size (f^2)
H1d (New)	Localization Complexity → Integration	-0.245	4.125	0.000***	Supported	0.185 (Medium)
H2c (New)	Twin Skills Readiness → Integration	0.312	5.876	0.000***	Supported	0.255 (Medium)

Hypothesis	Path Relationship	Coefficient (β)	<i>t</i> -value	<i>p</i> -value	Result	Effect Size (f^2)
H2d (New)	Verification Cost Barrier → Integration	-0.265	4.568	0.000***	Supported	0.205 (Medium)
H3b	Supply Chain Pressure → Integration	0.345	6.125	0.000***	Supported	0.385 (Large)
H4	Integration → Performance	0.763	18.452	0.000***	Supported	0.850 (Large)

Table 16: MGA Results (SMEs vs Large Enterprises)

Path	β (SMEs)	β (Large)	Diff ($\Delta\beta$)	p-value (Diff)	Interpretation
Verification Cost → Integration	-0.385*	-0.112 (ns)	0.273	0.002	SMEs are more severely affected.
Supply Chain Pressure → Integration	0.285**	0.456*	0.171	0.015	Large enterprises respond better.
Twin Skills → Integration	0.415*	0.225*	0.190	0.028	SMEs face a critical shortage.

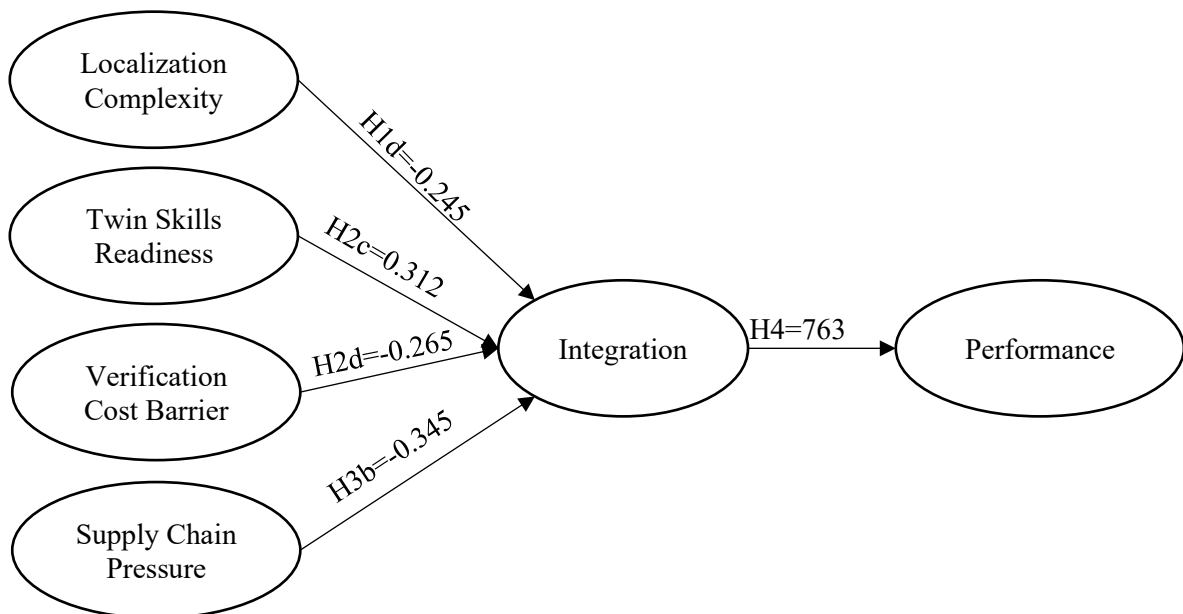


Figure 1: Structural Model Path Coefficients

5. Conclusion, Discussion, and Recommendations

5.1 Conclusion

This research proves that the success of AI integration for sustainability in Thailand relies not solely on technology, but on unlocking three "Structural Constraints": 1) Language Barrier: Hidden costs from Thai language processing, 2) Fee Trap: Transaction costs for standard certification are too high for SMEs, and 3) Twin Skills Crisis: A shortage of personnel with combined Digital & Green knowledge.

5.2 Discussion

This study makes a significant theoretical contribution by expanding the boundaries of the traditional TOE and RBV. Specifically, "Localization Complexity" (Language Trap) extends the Technological context of TOE by redefining technological compatibility not just as software integration, but as a "linguistic tax" that generates structural digital inequality in non-English contexts. From an RBV perspective, the "Twin Skills Crisis" deepens the concept of Human Capital by showing that digital proficiency alone no longer yields a sustainable competitive advantage unless it is structurally intertwined with environmental literacy (Green Literacy). Finally, the "Verification Cost Barrier" enriches Institutional Theory by demonstrating how Coercive Pressures (e.g., CBAM) paradoxically penalize smaller actors because of high compliance transaction costs, thereby transforming regulatory compliance into an unintended barrier to market entry for SMEs.

1) Technological Dimension: "Localization Complexity" (Language Trap) is a significant barrier creating a "Language Tax" for Thai businesses, consistent with the concept of Digital Inequality and confirming the need for National AI infrastructure ([Hofstede, 2011](#); [Budhwar et al., 2023](#)).

2. Organizational Dimension: "Twin Skills Crisis" is the internal factor with the highest influence, confirming RBV theory that human capital is a more critical resource than capital, and this shortage impacts SMEs more severely than large enterprises ([Kim et al., 2017](#); [Bankins & Formosa, 2023](#)).

3. Environmental Dimension: "Supply Chain Pressure" has the highest influence, confirming Institutional Theory that external Coercive Pressures like CBAM are the primary catalysts for change ([Bondarouk & Brewster, 2016](#)).

5.3 Policy and Strategic Recommendations

To drive Thailand towards a sustainable green digital economy, the research proposes operational guidelines in 4 main areas, as shown in **Tables 17 and 18**.

Table 17: Synthesized Strategic Success Map for Thai Green Digital Economy (2026-2030)

Potential Dimension	The Locks (Constraints)	The Surgery (Structural Reform)	Expected Strategic Outcomes
Economic	Verification Cost Barrier (Fixed Verification Costs)	Establish National Carbon Data Verification Platform	SMEs enter the Green Finance market with near-zero transaction costs.
Technical	Language Trap & Token Tax	Develop Open Thai LLM and National Thai Infrastructure	Digital sovereignty and a 70% reduction in AI processing costs in Thailand.
Human	Twin Skills Crisis	Establish Twin Skills Academy and reform the cross-disciplinary curriculum	"Hybrid Workforce" of 30,000 people by 2027 (Kramar, 2014).
Environment	Green AI Paradox & Water Footprint	Enforce WUE standards and targeted Green IT BOI incentives	Prevent pollution migration and achieve true Net Zero targets.

Table 18: Experimental Research Guidelines for Government Policy Development

Experimental Design	Treatment Variable	Outcome Variable	Policy Objective
RCT: Carbon Voucher Experiment	Providing carbon verification discount coupons of 50% 80% vs 100%	Application rate for CFP standard certification among SMEs	To find the optimal subsidy point worth the GDP impact.
Policy Sandbox: Blockchain Verification	Using Automated AI/Blockchain Verification vs Manual Verification	Transaction cost per unit, Certification duration	To reduce the fixed-rate fee burden for small players (Wood et al., 2019).
Behavioral Nudge Trial	Providing monthly Energy Benchmark data compared to industry peers	Commitment level to install AI Energy Monitoring systems	To stimulate internal motivation through market comparison (Marler & Fisher, 2013).

Regarding human resource capacity building via the proposed Twin Skills Academy (**Table 17**), long-term institutional sustainability within the Thai educational ecosystem must be secured. This will be operationalized through a co-created, cross-disciplinary curriculum framework between the Ministry of Higher Education (MHESI) and private sector leaders. The academy will implement a "Work-Integrated Learning" model that blends computer science and environmental engineering and is

supported by a state-backed micro-credentialing system. This guarantees that structural funding is driven by continuous private-sector demand and national tax-incentive frameworks, preventing the academy from becoming a temporary policy patch and ensuring a self-sustaining talent pipeline.

5.4 Research Limitations and Future Directions

This research confirms that "Technology" alone is not a magic pill. Thailand's Twin Transitions will succeed only if the government dares to perform "Structural Surgery" to reduce transaction costs, break down language barriers, and create a new workforce. Implementing these recommendations will be key to helping Thailand not just survive the crisis, but flourish and prosper in the 21st-century economy where "Sustainability" is the highest value (UNCTAD, 2023).

Despite its rigorous mixed-methods design, this research acknowledges certain boundaries. First, the quantitative phase uses a cross-sectional approach, capturing organizational metrics at a single point in time, which limits the ability to track absolute causality over long horizons. Future research should employ longitudinal tracking to observe the long-term translation of AI integration into hard carbon-reduction metrics. Second, while Harman's single-factor test indicated that Common Method Bias (CMB) was not an issue, relying on self-reported survey inputs from a single organizational representative could introduce perceptual bias. Future studies should integrate objective secondary data, such as corporate ESG reports or verified utility metrics. Lastly, the findings are constrained within the four targeted BCG sectors; expanding subsequent research to the heavy manufacturing and real estate sectors would broaden the model's generalizability.

Ethical Declaration: The author declares that this study involves direct primary data collection from human participants via qualitative in-depth interviews and quantitative organizational surveys. To ensure strict alignment with global scientific ethics, the research protocol was formally reviewed and approved by the Institutional Review Board (IRB) / Human Research Ethics Committee of Kasetsart University (Approval Protocol No. KUREC-KPS69/013). Informed consent was strictly obtained from all organizational executives, human resource managers, and expert informants prior to data collection. All participant identities, personal disclosures, and corporate identifiers were fully anonymized and protected by strict data encryption standards, ensuring no adverse exposure to participating individuals or organizations.

Declaration of Generative AI in Scientific Writing: The author confirms that the preparation and writing of this manuscript were conducted without the assistance of generative AI tools.

Declaration of Competing Interests: The author declares that there are no known conflicts of interest associated with the publication of this research.

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