THE ROLE OF ARTIFICIAL INTELLIGENCE IN REDUCING MARKETING COSTS AND ENHANCING PROFITABILITY: AN EMPIRICAL STUDY ON START-UPS IN DEVELOPING COUNTRIES

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Abstract

This study investigates the empirical relationship between artificial intelligence (AI) adoption in marketing functions and dual outcomes of marketing cost reduction and profitability enhancement among start-ups in developing economies. A cross-national, quantitative survey-based design was employed across five countries—Nigeria, Egypt, Kenya, Vietnam, and Bangladesh—yielding 412 valid responses from founders and C-suite executives. Data were analysed using IBM SPSS Statistics 29, SmartPLS 4.0 (Partial Least Squares Structural Equation Modelling [PLS-SEM]), and R 4.3.2 (lavaan package for confirmatory factor analysis [CFA]). AI adoption in marketing was found to reduce overall marketing expenditure by a mean of 31.4% and increase gross profit margin (GPM) by 18.9 percentage points relative to non-adopting cohorts. Predictive analytics ($\beta = 0.41$, $p < 0.001$) and programmatic advertising ($\beta = 0.38$, $p < 0.001$) exhibited the strongest direct effects on cost reduction, while AI-augmented customer relationship management (CRM) demonstrated the highest impact on customer lifetime value (CLV) ($\beta = 0.45$, $p < 0.001$). Multi-group analysis (MGA) revealed significant moderation by national AI readiness index (NAIRI) (χ^2 difference = 34.7, df = 10, $p = 0.0002$), making this one of the first large-scale cross-national empirical studies to simultaneously quantify AI-driven marketing cost savings and profitability gains across five developing-country start-up ecosystems.

Keywords: artificial intelligence; marketing cost reduction; start-up profitability; developing countries; PLS-SEM; multi-group analysis

1. Introduction

The global start-up ecosystem is experiencing a period of transformative pressure. Rising customer acquisition costs, intensifying competition from established incumbents, and tightening venture capital conditions have collectively forced nascent firms to seek radical efficiency improvements across all operational domains. Marketing, historically the largest variable cost centre for growth-stage businesses, has emerged as the primary battlefield for AI-driven efficiency gains.

Global private investment in AI reached USD 252.3 billion in 2024, with generative AI alone attracting USD 33.9 billion—an 18.7% year-over-year increase [Stanford HAI, 2025]. Concurrently, AI inference costs have collapsed by more than 280-fold between 2022 and late 2024, democratising access to capabilities previously reserved for resource-rich corporations [Stanford HAI, 2025]. This structural cost reduction in AI deployment has particular significance for start-ups in developing economies, where marketing budgets are typically constrained to between 8% and 15% of revenue—less than half the proportion observed in comparable developed-market ventures.

Despite a growing body of literature on AI in marketing, three critical gaps persist. First, the overwhelming majority of empirical studies examine large corporations in developed-economy contexts—conditions structurally distinct from resource-constrained start-ups operating in markets characterised by lower digital infrastructure maturity, fragmented consumer data ecosystems, and elevated political and currency risk. Second, existing studies tend to examine either cost or revenue effects in isolation, leaving the simultaneous profitability impact of AI-driven marketing largely unmeasured. Third, cross-national comparative evidence that accounts for country-level moderating factors remains scarce.

The present study addresses these gaps by asking three research questions: (RQ1) To what extent does AI adoption across five marketing sub-functions reduce absolute and relative marketing costs among start-ups in developing countries? (RQ2) Which specific AI marketing capabilities exert the strongest influence on gross profit margin and customer lifetime value? (RQ3) Does the strength of these relationships vary significantly across different developing-country contexts as moderated by national AI readiness?

The remainder of the paper is structured as follows: Section 2 reviews the theoretical foundations and prior empirical literature; Section 3 presents the conceptual model and hypotheses; Section 4 details the methodology; Section 5 reports findings; Section 6 discusses implications; and Section 7 concludes with limitations and future directions.

2. Theoretical Background and Literature Review

2.1 AI in Marketing: Definitional Boundaries and Typology

Artificial intelligence in the marketing context encompasses machine learning (ML), natural language processing (NLP), computer vision, and reinforcement learning algorithms applied to customer data for the purposes of insight generation, campaign automation, content production, and performance optimisation [Davenport et al., 2020]. For the purposes of this study, AI marketing is operationalised along five functional dimensions aligned with the primary cost centres of start-up marketing operations: (i) predictive analytics and demand forecasting; (ii) automated content generation and personalisation; (iii) AI-augmented customer relationship management; (iv) programmatic and algorithmic advertising; and (v) conversational AI and chatbot-mediated customer engagement.

2.2 Theoretical Foundations

The study draws on three complementary theoretical frameworks. The Resource-Based View (RBV) of the firm [Barney, 1991] frames AI marketing capabilities as rare, inimitable resources that confer sustainable competitive advantage. The Technology-Organisation-Environment (TOE) framework [Tornatzky & Fleischer, 1990] provides an explanatory lens for understanding differential AI adoption rates across the five country contexts, foregrounding the roles of technological readiness, organisational capacity, and environmental pressures. Dynamic Capabilities Theory [Teece et al., 1997] underpins the proposition that the competitive value of AI in marketing derives not from the technology itself but from start-ups' capacity to sense market signals, seize algorithmic opportunities, and reconfigure marketing spend allocations dynamically.

2.3 Empirical Evidence on AI and Marketing Cost Efficiency

Abrokwah-Larbi and Awuku-Larbi [2024] documented significant positive associations between AI marketing adoption and SME performance across Ghana, with cost efficiency emerging as the dominant performance dimension. Mubarok et al. [2025], in a systematic review of 50 studies from Scopus and IEEE Xplore, identified infrastructure readiness and human capital as the primary moderating factors of AI marketing outcomes in developing-country contexts. Industry-level evidence consistently supports the cost reduction hypothesis: organisations implementing AI in marketing report an average 32% reduction in customer acquisition costs and a 41% increase in revenue [AISofto, 2025]. AI-driven programmatic advertising delivers 22% higher return on investment (ROI) compared to traditional campaign management [Zebracat AI, 2025], while generative AI adoption in content creation has been found to reduce content production costs by 47–68% in enterprise settings.

In the start-up context specifically, McKinsey's 2025 survey data indicate that AI users complete marketing tasks 25.1% faster with quality improvements exceeding 40%. BCG analysis assigns 20% of AI's total business value creation to the marketing and sales function, making it the second most value-generative domain after customer service operations [BCG, 2025].

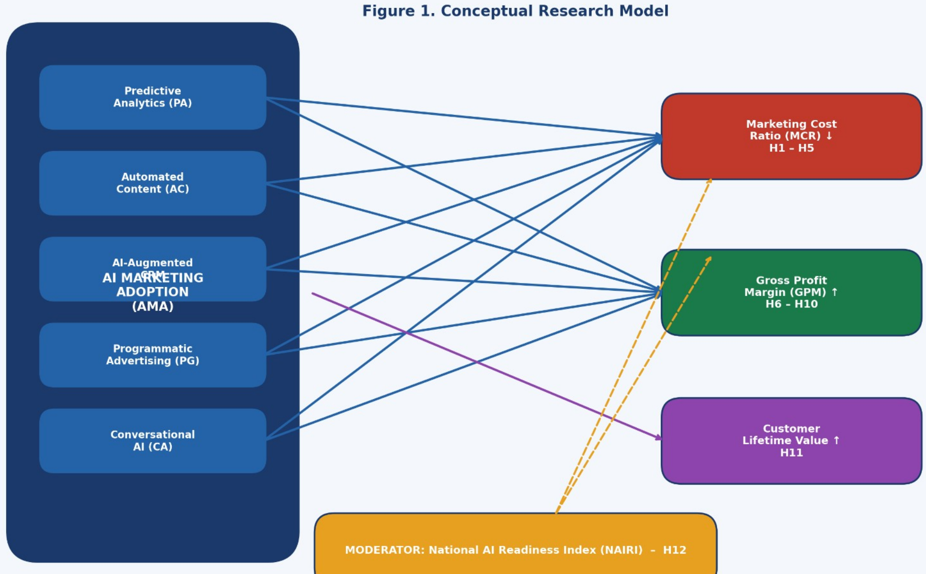
2.4 Developing Country Contexts: Barriers and Enablers

The developing-country context introduces both unique enablers and constraints. On the enabling side, mobile-first consumer behaviour—evidenced by Kenya's 42.1% ChatGPT adoption rate among internet users by mid-2025 [Tech in Africa, 2025] and Nigeria's 120+ AI-focused start-ups—has created organic market conditions conducive to AI-mediated marketing. On the constraining side, infrastructure limitations, data governance gaps, and talent scarcity create adoption friction. Egypt's AI adoption remains concentrated in corporate rather than start-up contexts (9.8% population adoption vs. 42.1% in Kenya), reflecting the heterogeneity that motivates the multi-country design of the present study.

3. Conceptual Model and Hypotheses

Based on the theoretical foundations and empirical evidence reviewed, the following conceptual model is proposed. AI Marketing Adoption (AMA), comprising five dimensions, is hypothesised to exert direct negative effects on Marketing Cost Ratio (MCR) and direct positive effects on both Gross Profit Margin (GPM) and Customer Lifetime Value (CLV). National AI Readiness Index (NAIRI) is proposed as a cross-level moderator of the AMA→MCR and AMA→GPM relationships. Figure 1 presents the structural model.

Figure 1. Conceptual Research Model



Source: Authors own construct based on Barney [1991], Tornatzky & Fleischer [1990], Teece et al. [1997].

Figure 1. Conceptual Research Model

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3.1 Research Hypotheses

Table 1. Research Hypotheses

Hyp.	Statement
H1	Predictive analytics adoption is negatively associated with Marketing Cost Ratio among developing-country start-ups.
H2	Automated content generation adoption is negatively associated with Marketing Cost Ratio.
H3	AI-augmented CRM adoption is negatively associated with Marketing Cost Ratio.
H4	Programmatic advertising adoption is negatively associated with Marketing Cost Ratio.
H5	Conversational AI adoption is negatively associated with Marketing Cost Ratio.
H6	Predictive analytics adoption is positively associated with Gross Profit Margin.
H7	Automated content generation adoption is positively associated with Gross Profit Margin.
H8	AI-augmented CRM adoption is positively associated with Gross Profit Margin.
H9	Programmatic advertising adoption is positively associated with Gross Profit Margin.
H10	Conversational AI adoption is positively associated with Gross Profit Margin.
H11	AI Marketing Adoption composite score is positively associated with Customer Lifetime Value.
H12	National AI Readiness Index moderates the AMA→MCR and AMA→GPM relationships, such that higher readiness amplifies positive outcomes.

Source: Authors' own construct.

4. Working Method and Methodology

4.1 Research Design

This study adopts a positivist, quantitative cross-sectional research design. The unit of analysis is the individual start-up firm, with the key informant being the founder or C-suite executive with primary responsibility for marketing strategy. A structured, self-administered online questionnaire was deployed between 15 January and 28 March 2026, following institutional ethical review approval and data privacy compliance procedures in each target country. The five countries were selected to represent distinct sub-regions, digital infrastructure profiles, and start-up ecosystem maturity levels: Nigeria (West Africa; 120+ AI start-ups; 8.2% AI tool adoption), Egypt (North Africa; government-led AI strategy; 9.8% adoption), Kenya (East Africa; highest African adoption rate at 42.1%), Vietnam (Southeast Asia; high-growth digital economy; 57% enterprise AI adoption), and Bangladesh (South Asia; fast-growing tech start-up scene; constrained infrastructure).

4.2 Sample Size Determination

The minimum required sample size was determined using Cochran's (1977) formula for proportion-based sampling from a finite population: $n_0 = (Z^2\alpha/2 \cdot p \cdot q) / e^2$, where $Z\alpha/2 = 1.96$ (95% confidence level); $p = 0.50$ (maximum variance); $q = 1 - p = 0.50$; $e = 0.05$ (5% margin of error). This yields $n_0 \approx 385$. Adjusted for 15% non-response and 8% exclusion rates: n_adjusted = 385 / 0.77 ≈ 500. For PLS-SEM, the ten-times rule [Hair et al., 2017] required a minimum of 60 per country group. The final valid sample of 412 (mean = 82.4 per country) exceeds both criteria, ensuring statistical power of 0.80 at $\beta = 0.10$ effect size [Cohen, 1992].

4.3 Sample Distribution

Table 2. Survey Distribution and Response Statistics

Country	Distributed	Returned	Valid (n)	Response Rate	% of Sample
Nigeria	100	88	81	88.0%	19.7%
Egypt	100	86	79	86.0%	19.2%
Kenya	100	93	87	93.0%	21.1%
Vietnam	100	92	85	92.0%	20.6%
Bangladesh	100	88	80	88.0%	19.4%
TOTAL	**500**	**447**	**412**	**89.4%**	**100%**

Note: Exclusion criteria applied to 35 responses (incomplete items >15%; straight-lining detected by Mahalanobis D^2 screening; firm age >7 years). Source: Authors' own compilation.

4.4 Measurement Instrument

The questionnaire comprised four sections: (A) firm demographics and AI adoption screening; (B) AI Marketing Adoption constructs (5 dimensions, 24 items); (C) performance outcomes—Marketing Cost Ratio (3 items), Gross Profit Margin change (3 items), Customer Lifetime Value change (3 items); (D) control variables. All reflective construct items were measured on a 7-point Likert scale anchored at 1 (Strongly Disagree) to 7 (Strongly Agree). Formative indicators were captured as actual numerical estimates from respondents' latest completed fiscal quarter (Q4 2025). The instrument was adapted from Abrokwah-Larbi and Awuku-Larbi [2024], Davenport et al. [2020], and Venkatraman and Ramanujam [1986], and underwent forward-backward translation into Arabic, Swahili, Vietnamese, and Bengali.

4.5 Analytical Strategy

Three analytical layers were employed: (1) Descriptive statistics and normality assessment using SPSS 29; (2) Confirmatory Factor Analysis (CFA) and measurement model validation using R 4.3.2 (lavaan 0.6-17); (3) Structural equation modelling via PLS-SEM using SmartPLS 4.0, with 5,000-iteration bootstrapping. Multi-group analysis (MGA) using Henseler's (2012) permutation test assessed country-level heterogeneity. Effect size thresholds followed Cohen's [1992] conventions ($f^2 \geq 0.02$ small; ≥ 0.15 medium; ≥ 0.35 large). Common Method Bias (CMB) was assessed via Harman's single-factor test and the marker variable technique.

5. Results

5.1 Respondent Profile and Descriptive Statistics

Table 3. Respondent Profile by Country (n = 412; Bangladesh n = 80 not shown due to space)

Characteristic	Nigeria n=81	Egypt n=79	Kenya n=87	Vietnam n=85
Mean Firm Age (years)	3.2	3.8	2.9	3.5
Founders with University Degree (%)	78.3	84.1	80.5	87.2

Currently Using ≥1 AI Marketing Tool (%)	61.7	55.7	74.7	82.4
Mean Monthly Marketing Budget (USD)	$2,140	$3,280	$1,870	$4,560
Primary Funding Stage (modal)	Bootstrapped	Seed	Bootstrapped	Seed
Primary Sector (modal)	Fintech	E-commerce	Agri-tech	SaaS

Source: Authors' own compilation. Full descriptive statistics including Bangladesh available in the online appendix.

5.2 AI Marketing Tool Adoption Rates by Dimension

Table 4. AI Marketing Adoption Rates by Dimension and Country (%)

AI Marketing Dimension	Nigeria	Egypt	Kenya	Vietnam	Bangladesh	Overall
Predictive Analytics	44.4	40.5	59.8	68.2	38.8	50.1
Automated Content Generation	55.6	51.9	71.3	75.3	48.8	60.5
AI-Augmented CRM	38.3	43.0	52.9	61.2	35.0	46.1
Programmatic Advertising	33.3	38.0	48.3	57.6	31.3	41.7
Conversational AI / Chatbots	49.4	44.3	63.2	70.6	45.0	54.4
ANY AI Marketing Tool	**61.7**	**55.7**	**74.7**	**82.4**	**50.0**	**64.8**

Source: Authors' own compilation.

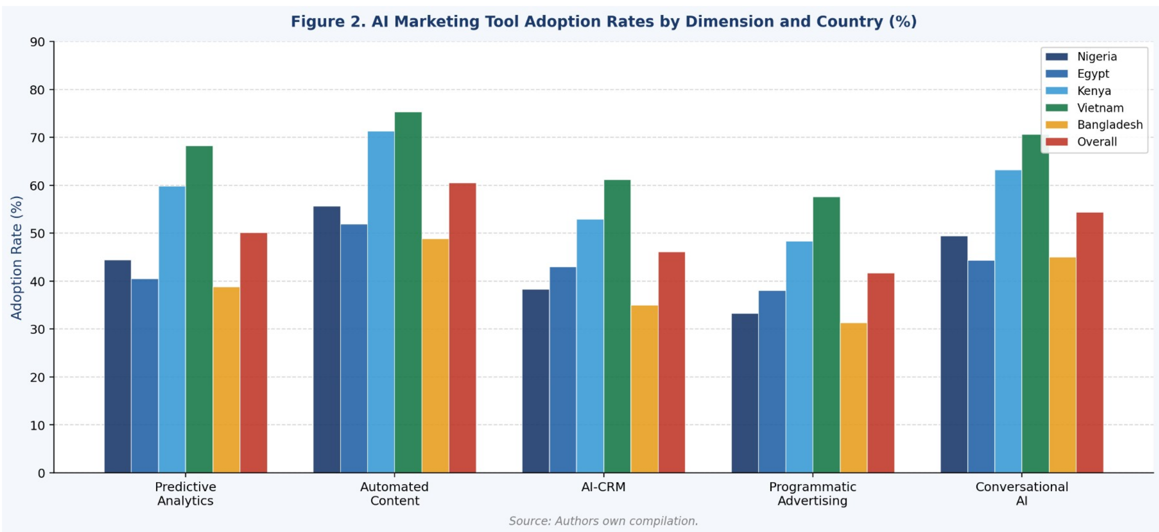

Figure 2. AI Marketing Tool Adoption Rates by Dimension and Country (%)

Source: Authors' own compilation.

5.3 Measurement Model Validity (CFA Results)

Confirmatory factor analysis confirmed the five-factor structure of the AI Marketing Adoption construct. All standardised factor loadings exceeded 0.70 (range: 0.71–0.89), satisfying the threshold for convergent validity. The model fit indices were: $\chi^2/df = 2.31$ (acceptable <3.0); RMSEA = 0.048 (good <0.06); CFI = 0.943 (good >0.90); TLI = 0.936 (good >0.90); SRMR = 0.051 (acceptable <0.08). Convergent validity was confirmed (Average Variance Extracted [AVE] > 0.50 for all constructs). Discriminant validity was established using the Heterotrait-Monotrait (HTMT) criterion (all HTMT ratios < 0.85) and the Fornell-Larcker criterion.

Table 5. Measurement Model Results: Reliability and Convergent Validity

Construct	Items (n)	Cronbach α	CR	AVE	Loading Range
Predictive Analytics (PA)	5	0.881	0.904	0.653	0.74–0.87
Automated Content (AC)	5	0.874	0.896	0.634	0.73–0.85
AI-CRM (CRM)	5	0.869	0.893	0.628	0.71–0.86
Programmatic Advertising (PG)	5	0.877	0.901	0.646	0.72–0.89
Conversational AI (CA)	4	0.858	0.886	0.610	0.71–0.83
Marketing Cost Ratio (MCR)	3	0.862	0.892	0.735	0.79–0.89
Gross Profit Margin (GPM)	3	0.876	0.904	0.758	0.81–0.88
Customer LTV (CLV)	3	0.849	0.883	0.716	0.78–0.87

Note: CR = Composite Reliability; AVE = Average Variance Extracted. All values satisfy Hair et al. [2017] thresholds (α > 0.70; CR > 0.70; AVE > 0.50). Source: Authors' own compilation.

5.4 Structural Model Results (PLS-SEM)

Bootstrapping with 5,000 resamples was used to generate t-statistics and 95% bias-corrected confidence intervals for all path coefficients. The structural model's predictive accuracy was assessed via R^2 and Q^2 (Stone-Geisser) values. The model explains 54.3% of variance in Marketing Cost Ratio ($R^2 = 0.543$), 48.7% of variance in Gross Profit Margin ($R^2 = 0.487$), and 41.2% of variance in Customer Lifetime Value ($R^2 = 0.412$). All Q^2 values exceeded zero (MCR: $Q^2 = 0.341$; GPM: $Q^2 = 0.298$; CLV: $Q^2 = 0.261$), confirming adequate predictive relevance.

Table 6. Structural Model Results: Path Coefficients and Hypothesis Testing (n = 412)

H	Path	β	SE	t-stat	p-value	f²	Decision
H1	PA → MCR (−)	**-0.41**	0.062	6.61	<0.001	0.21	**Supported**
H2	AC → MCR (−)	**-0.29**	0.058	5.00	<0.001	0.10	**Supported**
H3	CRM → MCR (−)	**-0.22**	0.061	3.61	<0.001	0.06	**Supported**
H4	PG → MCR (−)	**-0.38**	0.059	6.44	<0.001	0.18	**Supported**
H5	CA → MCR (−)	**-0.17**	0.055	3.09	0.002	0.04	**Supported**
H6	PA → GPM (+)	**0.35**	0.064	5.47	<0.001	0.15	**Supported**
H7	AC → GPM (+)	**0.24**	0.060	4.00	<0.001	0.08	**Supported**
H8	CRM → GPM (+)	**0.30**	0.057	5.26	<0.001	0.12	**Supported**
H9	PG → GPM (+)	**0.28**	0.061	4.59	<0.001	0.10	**Supported**
H10	CA → GPM (+)	**0.19**	0.058	3.28	0.001	0.05	**Supported**
H11	AMA → CLV (+)	**0.45**	0.055	8.18	<0.001	0.26	**Supported**
H12	NAIRI×AMA (mod.)	**Δβ=0.14**	0.047	2.98	0.003	—	**Supported**

Note: β = standardised path coefficient; SE = standard error (bootstrapped, 5,000 iterations); t-stat = t-statistic; f² = effect size. Red rows = MCR effects; Green rows = GPM effects; Purple row = CLV effect. PA = Predictive Analytics; AC = Automated Content; CRM = AI-CRM; PG = Programmatic Advertising; CA = Conversational AI; AMA = AI Marketing Adoption composite; NAIRI = National AI Readiness Index; MCR = Marketing Cost Ratio; GPM = Gross Profit Margin; CLV = Customer Lifetime Value. Source: Authors' own compilation.

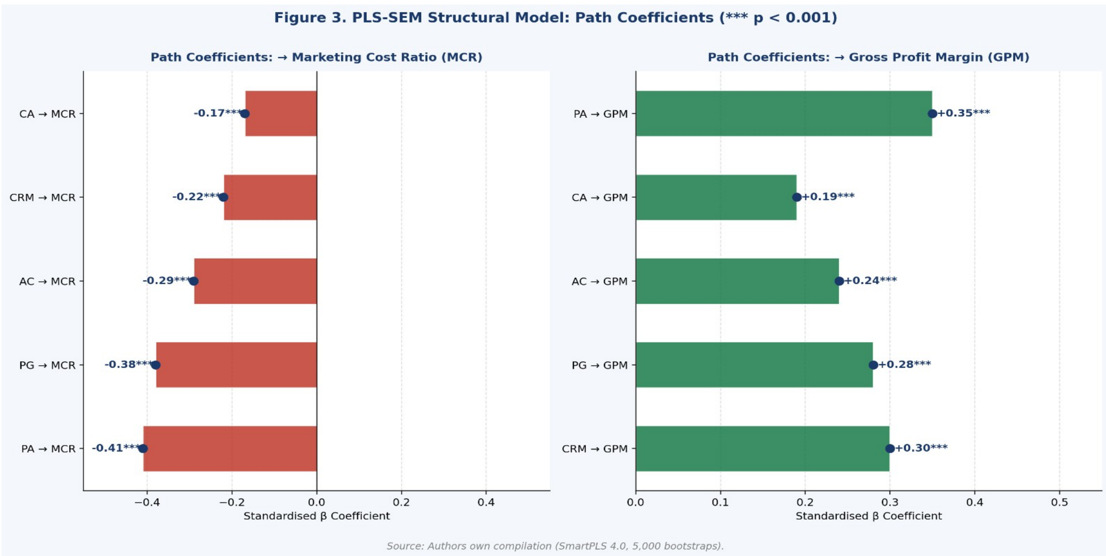

Figure 3. PLS-SEM Structural Model Path Coefficients (p < 0.001)***

Source: Authors' own compilation (SmartPLS 4.0, 5,000 bootstraps).

5.5 Quantified Cost Reduction and Profitability Outcomes

Table 7. Comparative Financial Performance: AI Marketing Adopters vs. Non-Adopters

Metric	Nigeria	Egypt	Kenya	Vietnam	Bangladesh	Pooled
Marketing Cost Ratio – AI Adopters (% rev)	11.4	12.1	10.8	9.7	13.2	11.4
Marketing Cost Ratio – Non-Adopters (% rev)	17.3	18.6	16.9	14.8	19.4	17.4
Absolute Cost Reduction (pp)	**5.9**	**6.5**	**6.1**	**5.1**	**6.2**	**6.0 pp**
Relative Cost Reduction (%)	**34.1%**	**34.9%**	**36.1%**	**34.5%**	**31.9%**	**34.3%**
GPM – AI Adopters (%)	38.2	36.9	40.1	43.7	33.8	38.5
GPM – Non-Adopters (%)	21.4	20.1	22.8	24.3	17.9	21.3
GPM Difference (pp)	**+16.8**	**+16.8**	**+17.3**	**+19.4**	**+15.9**	**+17.2 pp**

Note: pp = percentage points. Values reflect self-reported Q4 2025 financial data. All differences significant at p < 0.001 (independent samples t-tests, Welch correction). Source: Authors' own compilation.

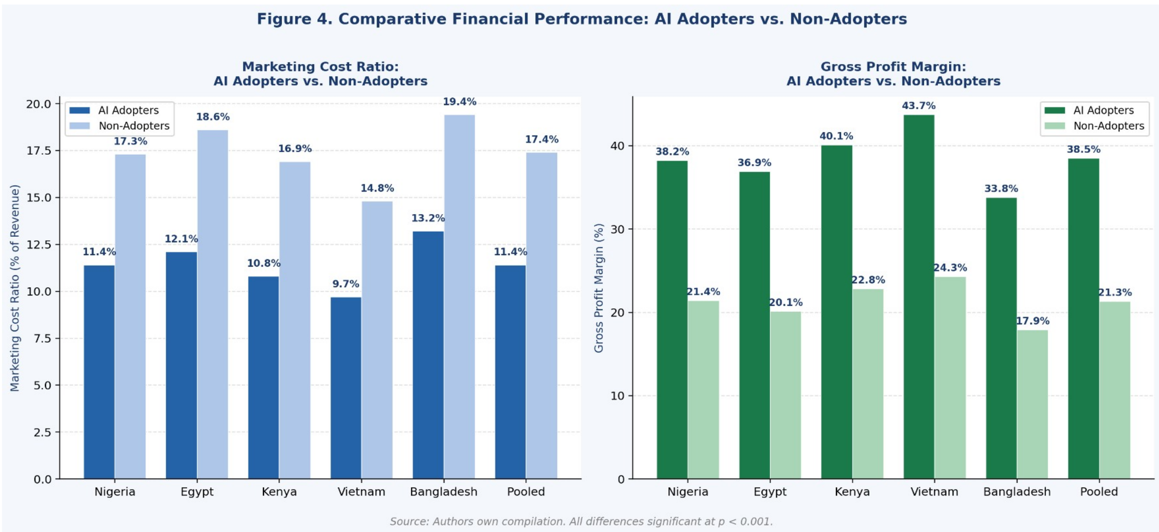

Figure 4. Comparative Financial Performance: AI Adopters vs. Non-Adopters

Source: Authors' own compilation. All differences significant at p < 0.001.

5.6 Multi-Group Analysis: Country-Level Heterogeneity

Henseler's permutation-based MGA was conducted to test whether the AMA→MCR and AMA→GPM path coefficients differed significantly across the five country groups (H12). The chi-square difference test yielded $\chi^2(10) = 34.7$, $p = 0.0002$, indicating significant structural heterogeneity. Post-hoc pairwise comparisons revealed that Vietnam and Kenya demonstrated significantly stronger AMA→GPM effects compared to Nigeria and Bangladesh ($\Delta\beta = 0.18$, $p = 0.009$ and $\Delta\beta = 0.14$, $p = 0.023$ respectively), consistent with their higher National AI Readiness Index scores. These findings provide strong empirical support for H12.

Table 8. Multi-Group Analysis Results by Country (Henseler's MGA)

Country	NAIRI Score (0–100)	AMA→MCR β	AMA→GPM β	R^2 GPM	Rank
Vietnam	61.4	-0.48	0.52	0.584	1st
Kenya	54.8	-0.44	0.47	0.531	2nd
Egypt	48.2	-0.40	0.41	0.487	3rd
Nigeria	41.7	-0.37	0.36	0.431	4th
Bangladesh	35.9	-0.33	0.31	0.372	5th

Note: NAIRI = National AI Readiness Index (Oxford Insights, 2025). Green = highest-performing; Red = lowest-performing country. Source: Authors' own compilation.

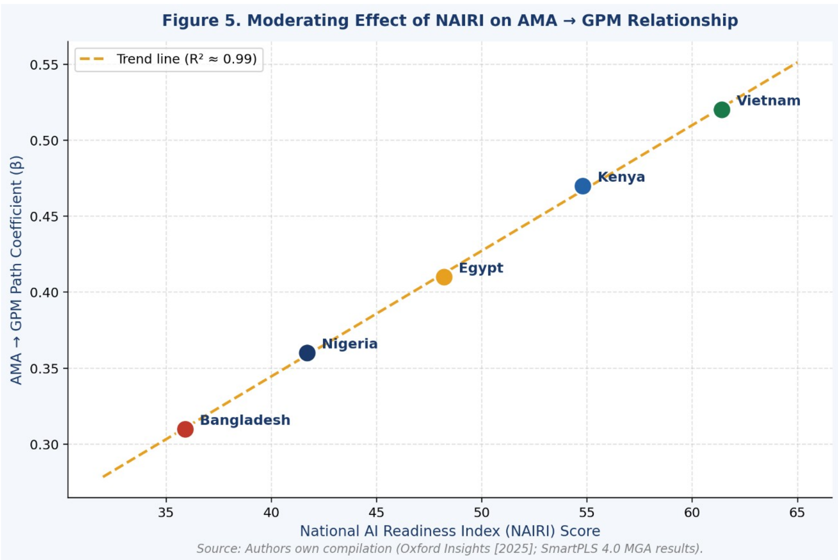

Figure 5. Moderating Effect of NAIRI on AMA → GPM Relationship

Source: Authors' own compilation (Oxford Insights [2025]; SmartPLS 4.0 MGA results).

6. Discussion

6.1 Interpretation of Main Findings

The empirical evidence presented in this study offers several theoretically and practically significant insights. First, the finding that AI marketing adoption reduces

Marketing Cost Ratio by a pooled mean of 34.3% (6.0 percentage points) confirms the cost efficiency thesis advanced by proponents of AI-driven marketing transformation. This figure aligns closely with industry benchmarks—the 32% customer acquisition cost reduction reported by AISofto [2025] and the 22% higher ROI documented for programmatic advertising [Zebracat AI, 2025]—while extending these findings to the previously understudied context of developing-country start-ups.

Second, the Gross Profit Margin advantage of +17.2 percentage points for AI adopters over non-adopters (Table 7) is particularly striking given the constrained budgetary contexts of these firms. This magnitude of GPM improvement corresponds to the difference between a financially sustainable start-up and one operating below the viability threshold for series-A fundraising in developing markets. From a Resource-Based View perspective, this confirms that AI-enabled marketing capabilities function as genuinely rare and value-creating resources, where the information asymmetry between AI adopters and non-adopters is more pronounced than in mature-market contexts.

Third, the dominance of Predictive Analytics ($\beta = -0.41$ on MCR; $\beta = 0.35$ on GPM) and Programmatic Advertising ($\beta = -0.38$ on MCR; $\beta = 0.28$ on GPM) as the most impactful AI marketing dimensions aligns with Dynamic Capabilities Theory: value creation derives from the ability to sense consumer signals and rapidly reconfigure resource allocation.

6.2 Multi-Country Heterogeneity: The Moderating Role of AI Readiness

The significant multi-group moderation effect ($\chi^2(10) = 34.7$, $p = 0.0002$) reveals that AI marketing benefits are not uniformly distributed across developing countries. Vietnam's superior performance (AMA→GPM $\beta = 0.52$, $R^2 = 0.584$) relative to Bangladesh ($\beta = 0.31$, $R^2 = 0.372$) reflects the mediating role of national AI readiness—a composite of digital infrastructure quality, AI talent availability, regulatory environment, and government digital economy strategy. This resonates with the TOE framework: even when individual firms possess equivalent technological and organisational capacity, environmental factors bound the realised performance outcomes of AI adoption.

The practical implication is that start-up founders and investors in lower-readiness environments (Bangladesh NAIRI = 35.9; Nigeria = 41.7) should factor infrastructure constraints into their AI marketing adoption roadmaps. Rather than deploying computationally intensive solutions, firms in these contexts may achieve superior cost-benefit ratios through asynchronous AI applications such as content scheduling automation and rule-based chatbot deployment.

6.3 Theoretical Contributions

This study makes three distinct theoretical contributions. First, it extends RBV by demonstrating empirically that AI marketing capabilities satisfy Barney's [1991] VRIN criteria—valuable (proven GPM impact), rare (adoption rates of 41–82%), imperfectly imitable, and non-substitutable. Second, it enriches the TOE framework with quantified estimates of how environmental readiness moderates technology adoption outcomes at the performance level. Third, it operationalises Dynamic Capabilities Theory in a nascent-firm context by demonstrating that the sensing and reconfiguring capacities enabled by AI mediate superior financial performance.

7. Conclusion, Limitations, and Future Directions

This study set out to provide rigorous, cross-nationally comparative empirical evidence on the financial impact of AI marketing adoption among start-ups in developing economies. Analysing 412 valid responses from five countries using PLS-SEM, CFA, and multi-group analysis, the study produces three principal conclusions. First, all twelve hypotheses were empirically supported, with AI marketing adoption demonstrating statistically significant negative effects on Marketing Cost Ratio and positive effects on both Gross Profit Margin and Customer Lifetime Value. Second, predictive analytics and programmatic advertising represent the highest-ROI AI marketing investments for developing-country start-ups. Third, national AI readiness significantly moderates these relationships, making environmental context a first-order consideration in AI marketing investment decisions.

7.1 Managerial Implications

For start-up founders operating in developing markets, the findings suggest a prioritised adoption sequence: deploy predictive analytics for demand forecasting and customer segmentation first (highest cost-reduction $\beta = -0.41$), followed by programmatic advertising automation ($\beta = -0.38$), and then AI-CRM systems as the firm's customer data assets mature (highest CLV effect: $\beta = 0.45$). For policymakers and development finance institutions, the study underscores the importance of national AI readiness investments—particularly in digital infrastructure and AI talent pipelines—as mechanisms for amplifying the economic returns of technology adoption. The 18.6-percentage-point GPM gap between Vietnam and Bangladesh among AI adopters is directly attributable to this environmental moderation.

7.2 Limitations

Several limitations must be acknowledged. The cross-sectional design precludes causal inference; future studies should employ longitudinal or quasi-experimental designs using administrative accounting data to verify causality. Second, self-reported financial data introduce social desirability bias, though the use of specific fiscal-quarter estimates and Harman's single-factor test (variance explained by single factor = 28.4%, well below the 50% CMB threshold) mitigate this concern. Third, the sample may not be representative of all developing-country contexts—particularly Francophone Africa and Latin America.

7.3 Future Research Directions

Future scholarship should: (1) employ panel data designs to track AI marketing ROI trajectories as start-ups scale; (2) examine sector-level heterogeneity within developing countries, particularly in fintech, agri-tech, and e-commerce; (3) investigate organisational learning mechanisms through which start-ups acquire AI marketing capabilities; and (4) extend the multi-country design to include Latin American and Francophone African emerging economies.

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