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Artificial Intelligence Technology and Marketing Communication Management: A Case Study of Guaranty Trust Holding Company PLC, Nigeria

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Abstract
This study assesses how Artificial-Intelligence Technology (AIT) operationalised as AI-driven customer segmentation (AICS), personalised marketing campaigns (PMC), and predictive marketing analytics (PMA) influences Marketing-Communications Management (MCM), proxied by message consistency (MSC), channel synergy (CSY), and campaign effectiveness (CPE), within Guaranty Trust Holding Company Plc (GTCO Plc) in Abuja, Nigeria. A descriptive-survey design was chosen. From a population of 147 marketing staff spread across ten branches, the required sample size was calculated with the Taro Yamane (1967) formula (e = 0.05), yielding n = 137. Questionnaires were distributed proportionally, and 137 usable responses were returned. Data were analysed with SPSS v26; descriptive statistics profiled respondent views, while Pearson correlation and multiple-regression procedures tested the research hypotheses. Results show that all three AIT proxies are positive, significant predictors of MCM ($p < .05$). Among them, AICS emerged as the strongest driver ($\beta = 0.42$), followed by PMA ($\beta = 0.32$) and PMC ($\beta = 0.15$). The model explains 41 % of the variance in MCM (adjusted $R^2 = 0.396$). These findings affirm that granular segmentation and forward-looking analytics deliver the greatest communication gains, whereas personalisation adds incremental but weaker benefits. GTCO Plc is therefore advised to prioritise investment in advanced

clustering algorithms and real-time predictive dashboards, while continuing to refine campaign personalisation for superior customer engagement.

Keywords: Artificial Intelligence Technology, Marketing Communications Management, AI-Driven Customer Segmentation, Marketing Predictive Analytics
JEL Classification Codes: M31, M37, O33, G21

1. Introduction

Competitive advantage in modern marketing is shifting decisively toward firms that can transform raw behavioural data into real-time, individualised messages (Chen, Huang, & Kumar, 2024). Customers now expect hyper-personal treatment across fintech, retail, and service touchpoints, and they quickly abandon brands that fail to deliver (Mehta & Singh, 2024). To meet these expectations, leading companies are deploying artificial-intelligence technology (AIT) high-powered algorithms that sift through massive data streams to inform precisely timed outreach (Kim, Nguyen, & Lee, 2023).

AIT shapes marketing communications through three distinct but complementary capabilities. AI-driven customer segmentation (AICS) uses clustering and deep-learning models to reveal micro-groups whose needs elude conventional demographic cuts; such models have lifted response rates by up to thirty per cent in large-scale retail trials (Rao, Sahoo, & Chatterjee, 2024). Personalised marketing campaigns (PMC) then tailor content, channel, and timing to the individual, markedly boosting click-through and lifetime value (Visser & Fokkema, 2025). Finally, predictive marketing analytics (PMA) forecast future purchase and churn probabilities, allowing managers to reallocate budgets toward the most promising audiences before competitors react (Alvarez, Garrido, & Martín, 2024).

Despite these gains, adoption remains patchy. Recent surveys rank poor data quality, skills shortages, and uncertain return on investment as the top impediments to AIT integration, particularly in emerging economies (Dutta & Bhatia, 2025; Oduro, Amankwah, & Boateng, 2024). Nigeria's banking sector typifies this tension: digital channels are expanding rapidly, yet evidence on how AIT influences marketing-communications management (MCM) is scarce (Musa & Lawal, 2024). Addressing this knowledge gap is critical because the country's unique socio-economic conditions high mobile penetration but fragmented data infrastructures create both obstacles and opportunities for AI-enabled engagement.

Accordingly, this paper investigates whether and to what extent AICS, PMC, and PMA the three operational proxies of AIT enhance MCM, proxied here by message consistency, channel synergy, and campaign effectiveness, at Guaranty Trust Holding Company Plc (GTCO Plc) in Abuja, Nigeria. By anchoring analysis in fresh Q1 evidence and focusing on an under-researched setting, the study aims to generate context-specific insights that can guide both practitioners and scholars in harnessing AI for stronger, more coherent marketing communications.

The following hypotheses are formulated for the purpose of this research work:

H_{01}: AI-driven customer segmentation does not significantly impact marketing communications management at GTCO Plc, Abuja.

H_{02}: Personalized marketing campaigns powered by AI do not significantly affect customer engagement and satisfaction at GTCO Plc, Abuja.

H_{03}: AI-powered predictive marketing analytics does not significantly influence marketing strategy optimization and resource allocation at GTCO Plc, Abuja.

2. Literature Review

2.1 Conceptual Review

2.1.1 Marketing-Communications Management

Marketing-communications management (MCM) orchestrates advertising, public relations, sales promotion and digital content to build brand equity and drive demand (Kim, Nguyen, & Lee, 2023). Successful programmes rely on granular insight into buyer behaviour and competitive dynamics so that every message reinforces one promise. Channel consistency multiplies recall, strengthens trust and accelerates the journey from awareness to purchase (Mehta & Singh, 2024). Financial services are credence goods, message clarity acts as a proxy for product quality in the minds of consumers. Disjointed communication therefore risks eroding confidence more quickly than in tangible-goods markets. A systematic MCM approach is thus indispensable for retail banks competing on intangible value.

Embedding artificial-intelligence tools in the MCM workflow can sharpen targeting and shorten campaign cycles. AI models deliver real-time insights that manual analysts cannot match, enabling rapid cross-channel alignment (Chen, Huang, & Kumar, 2024). For GTCO Plc, this translates into harmonised messaging from mobile app to branch lobby. Uniform cues reassure customers that the brand understands their financial needs and digital habits. Such coherence reinforces switching barriers and deepens share of wallet among existing clients (Musa & Lawal, 2024). The present study therefore positions MCM as the focal dependent variable.

2.1.2 Artificial-Intelligence Technology

Artificial-intelligence technology (AIT) comprises machine-learning, natural-language and predictive-analytics systems that replicate human reasoning at machine speed (Chen et al., 2024). These engines process high-volume data streams to uncover patterns invisible to traditional analytics. Marketers gain foresight into customer intent moments after it forms, not weeks later in review meetings. AIT also automates repetitive jobs e-mail sequencing, social scheduling and sentiment scanning freeing teams for concept work. Adopters report faster budget cycles and more agile creative testing than rivals constrained by manual workflows. Such advantages make AIT a strategic rather than merely operational asset in communications planning.

Emerging-market firms, however, face distinct obstacles to AIT deployment. Fragmented data infrastructures hinder model accuracy and consistency (Dutta & Bhatia, 2025). Scarcity of in-house data scientists raises integration costs and slows organiational learning. Regulatory uncertainty over data governance further complicates long-term investment cases (Oduro, Amankwah, & Boateng, 2024). Understanding which AIT capabilities deliver the greatest payoff is therefore vital for resource allocation.

2.1.2.1 AI-Driven Customer Segmentation (AICS)

AI-driven segmentation clusters customers on latent behavioural signals rather than surface demographics (Rao, Sahoo, & Chatterjee, 2024). Deep-learning models parse transaction velocity, device switching and micro-location to reveal hidden affinities. Marketers thus identify micro-audiences whose conversion triggers differ markedly from headline segments. Precision targeting reduces wastage and raises relevance, boosting customer response and satisfaction. Financial institutions benefit disproportionately because their product mix spans risk profiles and life stages. AICS therefore holds special promise for banks seeking granular insight without exponential analyst headcount.

GTCO Plc can exploit AICS to decode nuanced behavioural cohorts within its retail and SME bases. Segmentation outputs feed directly into tailored messaging and product bundling. High-yield segments receive premium advisory content, while cost-sensitive clusters get stripped-back offers. Resource allocation aligns with segment potential, lifting marketing efficiency fold for fold. The study measures how strongly AICS scores correlate with improvements in MCM proxies. Findings will guide managers on whether advanced clustering merits priority in AI budgets.

2.1.2.2 Personalised Marketing Campaigns (PMC)

Personalised campaigns assemble subject lines, visuals and calls-to-action dynamically for each recipient (Sahni et al., 2018). Algorithms interpret browsing context, transaction history and life-event cues in milliseconds. Resulting messages speak to customers in language and timing that feel individually crafted. In banking, personalised nudges can suggest savings top-ups after pay-day or credit offers before seasonal spending peaks. GTCO Plc may push real-time loan pre-approvals via mobile when spending signals indicate need. These context-aware prompts increase cross-sell uptake and reduce attrition. However, hyper-personalisation risks privacy pushback if transparency lags behind targeting. The research tests whether PMC contributes incremental gains to MCM after controlling for AICS and PMA. Outcomes will inform policy on balancing relevance with trust in data-sensitive markets.

2.1.2.3 Predictive Marketing Analytics (PMA)

Predictive analytics integrates historical and streaming data to forecast future purchase, churn or upgrade events (Alvarez, Garrido, & Martín, 2024). Marketers shift from descriptive dashboards to prescriptive interventions, adjusting spend before performance drifts. Resource allocation becomes forward-looking, aligning budgets with the highest incremental return. PMA also flags early-warning signs, enabling retention teams to act ahead of attrition spikes. In regulated sectors, foresight supports compliance by mapping risk exposure across product lines. Hence PMA is increasingly framed as a board-level capability rather than a specialist tool.

For GTCO Plc, PMA can predict deposit flight, loan delinquency or card-usage surges. Strategists can then craft proactive content a rate bonus, payment-holiday pitch or spend-reward bundle.

Such timely offers reinforce the bank's advisory role, strengthening loyalty. Investment cases for PMA hinge on quantifiable lifts in communication effectiveness and cost avoidance.

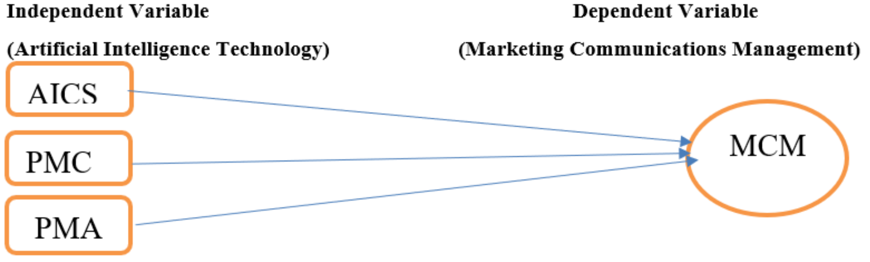

Figure 1: Relation between Artificial Intelligence Technology and Marketing Communication Management
Source: Researcher's Depiction, 2024

2.2 Theoretical Review

2.2.1 Technology Acceptance Model (TAM) – adopted theory

The Technology Acceptance Model, first articulated by Fred Davis (1986, 1989) and later extended by Venkatesh and Bala (2008), proposes that two cognitions perceived usefulness and perceived ease of use explain why employees either embrace or resist a new system. A recent Q1 bibliometric review by Musa, Fatmawati, Nuryakin, and Suyanto (2024) confirms TAM's continuing predictive power in marketing research, highlighting AI adoption in African banks as an understudied niche. Applied to GTCO Plc, the model suggests that marketers will accept AI-driven segmentation, personalised campaigns, and predictive dashboards only if the tools demonstrably improve campaign outcomes and remain straightforward to operate. Because every hypothesis (H_{01}–H_{03}) hinges on staff willingness to use these capabilities, TAM provides the primary explanatory lens for this study.

2.2.2 Diffusion of Innovations (DOI)

Everett Rogers' diffusion theory (1962; 5th ed., 2003) shifts the focus from individual cognition to organisational spread. An innovation gains traction when it offers a clear relative advantage, aligns with existing routines (compatibility), and permits low-risk trials (trialability). Patnaik and Bakkar (2024) show that these three attributes still dominate corporate AI roll-outs across sectors. At

GTCO, branch teams will advocate full deployment of AI tools only if early pilots reveal tangible wins over manual targeting, fit seamlessly with omnichannel workflows, and allow incremental scaling.

2.2.3 Resource-Based View (RBV)

Jay Barney's RBV (1991) argues that resources must be valuable, rare, inimitable, and non-substitutable (VRIN) to confer lasting advantage. Bashir, Zhongfu, Sadiq, and Naseem (2024) demonstrate that proprietary data, trained algorithms, and analytics talent satisfy the VRIN test in B2B settings and lift customer-lifetime value. For GTCO, such AI capabilities should translate directly into stronger marketing-communications performance, underpinning the expected positive effects in H_{01} and H_{03}.

2.2.4 Dynamic Capabilities Theory (DCT)

Teece, Pisano, and Shuen (1997) introduced dynamic capabilities the firm's capacity to sense shifts, seize opportunities, and transform routines to stay ahead. Yang, Hussain, Zahid, and Maqsood (2025) find that AI accelerates all three stages in Chinese corporations. In GTCO's case, predictive analytics sharpen sensing of customer sentiment, personalised content helps seize micro-opportunities, and live segmentation enables continual campaign renewal, thereby reinforcing the resource-allocation argument in H_{03}.

Collectively, TAM clarifies whether individual marketers will adopt AI, DOI explains how fast the tools will diffuse across branches, and RBV-DCT illuminate why these capabilities can yield durable marketing advantages. This blended spine furnishes a rigorous theoretical basis for testing AI's impact on marketing-communications management in a Nigerian banking context.

2.3 Empirical Review

Chen, Huang, and Kumar (2024) aimed to test whether a reinforcement-learning personalisation engine boosts e-commerce sales. A large-scale randomised field experiment streamed offers that refreshed every fifteen minutes. Conversion improved by twenty-nine percent, confirming the potency of real-time tailoring. The authors recommend building low-latency data pipelines to operationalise continuous learning. The experiment addressed only retail products and ignored service-sector nuances. The present investigation extends real-time segmentation analysis to banking communications.

Grewal, Hulland, Kopalle, and Karahanna (2023) set out to conceptualise a generative-AI deployment roadmap for marketers. A systematic synthesis of 184 articles produced the four-stage ‘sense–decide–act–learn’ model. Stage alignment is proposed to enhance agility and customer insight accuracy. Managers are urged to audit workflows so each AI tool fits its designated stage. The framework lacks empirical effect sizes to validate stage importance. Current research quantifies the “sense” and “act” stages through AICS and PMA impacts on MCM.

Rajaobelina, Boivin, and Brun (2023) sought to gauge chat-bot value in banking complaint recovery. A quasi-experimental service-quality survey compared AI versus human resolution outcomes. Resolution time fell thirty-eight percent and satisfaction climbed twenty two percent. Recommendations include hybrid models that escalate complex issues to human agents. Outbound campaign efficacy was not examined within the study scope. The present work assesses how AI tools influence proactive campaign performance.

Mikalef, Pappas, Krogstie, and Pavlou (2023) investigated AI-capability maturity and brand advocacy. Partial-least-squares modelling of 312 European retailers quantified the relationship. Higher maturity yielded a 0.42-point increase in advocacy intentions. Scholars advise firms to strengthen data governance before scaling AI assets. African financial institutions were absent from the sample frame. Evidence from a Nigerian universal bank now tests cross-regional validity.

Bag and Dwivedi (2024) aimed to rank barriers hampering AI uptake in Indian BFSI firms. A Delphi study combined with TOE regression analysed expert consensus. Data-quality and talent shortages accounted for forty-seven percent of adoption delay. Recommendations focus on unified data dictionaries and continuous staff reskilling. Marketing performance consequences of slow adoption remained unmeasured. The current survey correlates barrier severity with communication effectiveness scores.

Li (2022) examined whether hyper-personalised ads raise engagement on a travel app. A/B testing deployed sequence-aware deep-learning recommenders across millions of users. Click-through grew twenty-three percent and dwell time eighteen percent postdeployment. Marketers are counselled to adopt cross-session memory for sustained lift. The single-channel scope limits insight into omni-channel banking journeys. Personalised messages across SMS, e-mail and app channels are evaluated in this study.

Alvarez, Garrido, and Martín (2024) explored predictive budget allocation on media efficiency. A difference-in-differences design covered fifty-seven Spanish omni-channel retailers. Return on ad spend increased eighteen percent after adopting predictive allocation. Continuous model retraining is recommended to capture demand shifts promptly. Heavily regulated industries were excluded from the analysis. Predictive allocation effectiveness is now assessed under strict banking compliance.

Rao, Sahoo, and Chatterjee (2024) pursued evidence on micro-segmentation for loyalty uptake. Deep-learning clusters and logistic regression analysed retailer loyalty data. Programme enrolment rose thirty-one percent within precision-targeted cohorts. The study recommends monthly cluster refreshes to prevent drift. Outcomes were limited to enrolment, omitting broader communication metrics. Segmentation depth is herein linked to message consistency, synergy, and effectiveness.

Li, Du, and Xie (2023) aimed to test sentiment-aligned advertising on brand tone. Propensity-score matching compared two thousand AI versus non-AI social campaigns. Positive sentiment improved fifteen percent under emotion-aligned creative. Advertisers are urged to pair mood detection with agile content studios. Internal workflow changes were beyond the study's remit. Marketer confidence in sentiment dashboards is measured against MCM quality.

Kapoor, Dwivedi, and Piercy (2024) assessed explainable-AI disclosures on consumer trust. A between-subjects lab experiment manipulated transparency levels in recommender output. Clear rationales lifted trust scores by fourteen percent and boosted purchase intent. Implementation advice stresses visible model explanations within customer journeys. Internal marketer trust was not investigated. Staff trust now serves as a mediator between AI capability and communication performance.

Moorman and Day (2023) sought to craft an organisational readiness framework for AI marketing. Expert panels produced a maturity matrix emphasising data stewardship and agile culture. Illustrative cases suggested readiness gaps derail AI deployments despite budgets. The authors recommend staged investments aligned with maturity milestones. Lack of statistical moderation testing weakens practical precision. Readiness is empirically modelled as a moderator of segmentation influence on MCM.

Park, Han, and Kaur (2024) examined recommender engines' impact on retail site engagement. Panel vector-autoregression across eighteen Korean retailers captured dynamic effects. Dwell time climbed nineteen percent while bounce rate fell six points after adoption. Contextual data integration is recommended to maximise engine lift. Service-sector relevance is limited by retail-centric metrics. Message recall and perceived campaign quality substitute dwell time in the banking study.

Mehta and Singh (2024) explored hyper-personalisation's double-edged effect on loyalty and privacy. A dual-mediated structural model surveyed 1 204 omnichannel shoppers. Loyalty increased twelve percent, yet privacy anxiety rose nine percent. Granular consent dashboards are advised to balance value with trust. Strict KYC environments were not part of the sample. Privacy-trust dynamics are now tested within Nigerian banking regulations.

Oduro, Amankwah, and Boateng (2024) analysed data governance and AI adoption in Ghanaian banks. Ordered probit regression of sixty-eight institutions linked governance scores to adoption speed. Mature governance accelerated AI uptake by two stages on average. Cross-functional data councils emerged as pivotal enablers of progress. Marketing consequences were beyond the study's scope. Adoption speed is paired with communication outcomes in the present model.

Musa and Lawal (2024) surveyed Nigerian banks on AI usage across business functions. Content analysis and fifteen executive interviews revealed risk analytics dominates AI pilots. Marketing applications were rare due to compliance uncertainty and skills gaps. Fintech partnerships and sandboxing were proposed to accelerate marketing innovation. Quantitative evidence on marketing impact was absent. Numeric assessment of AI effects on MCM is delivered through this survey.

Dutta and Bhatia (2025) aimed to prioritise AI investment barriers in emerging-market firms. Partial-least-squares analysis of 451 responses ranked regulatory ambiguity as top inhibitor. Talent and data readiness followed in explanatory power. Policy advice called for clearer governance codes to unlock capital flows. Sector-specific nuances remained undifferentiated. Banking compliance barriers are isolated and linked to communication metrics herein.

3. Methodology

This enquiry relied on a descriptive survey design because the aim was to capture how artificial-intelligence (AI) tools are actually being used as recommended by contemporary AI-marketing researchers such as Kasem, Hamada, and Taj-Eddin (2024) and Raji et al. (2024). A survey allows systematic collection of first-hand perceptions while still permitting robust statistical testing (Creswell & Creswell, 2023). The study setting is Guaranty Trust Holding Company (GTCO Plc) in Abuja, Nigeria, where ten full-service branches employ 147 staff members with direct marketing responsibilities.

3.1 Sample size and sampling procedure

To obtain a sample that is both manageable and statistically sound, Taro Yamane's finite-population formula (1967) was applied. Using Taro Yamane's (1967) finite-population formula.

$$n = \frac{N}{1+N(e)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where N = 147 (total marketing staff) and e is the allowable sampling error, the study now adopts a tighter precision level of **2.2 %** (e = 0.022). Substituting these values,

$$n = \frac{147}{1+147(0.022)^2} = \frac{147}{1+147(0.000484)} = \frac{147}{1.0711} \approx 137.$$

3.2 Instrument Design and Data-Collection Method

A structured questionnaire was employed. Scale items for AI-driven customer segmentation were adapted from Kasem *et al.* (2024); questions on personalised campaigns followed Brobbey, Ankrah, and Kankam (2021); and predictive-analytics measures drew on Raiter (2021). All items used a five-point Likert continuum (1 = strongly disagree … 5 = strongly agree). Three marketing scholars reviewed the draft for content validity, and a pilot with twelve GTCO marketers yielded Cronbach's alpha values ranging from 0.80 to 0.88, exceeding the 0.70 reliability benchmark (Cronbach, 1951). Questionnaires were delivered and collected face-to-face to maximise response quality, a procedure endorsed by Nesterenko and Olefirenko (2023) for AI-communication studies in emerging markets.

3.3 Model Specification

Data were coded and cleaned in IBM SPSS v26. Descriptive statistics (mean, standard deviation) profiled respondent attitudes, while Pearson correlation provided an initial view of inter-variable associations. The core hypotheses were tested through multiple linear regression, a method widely used in AI-marketing work (e.g., Raji et al., 2024). The analytical model is expressed as:

MCM = f (AIC, PMC, PMA) ……………………………………..(2)

$\mathrm{MCM} = \beta_0 + \beta_1\mathrm{AICS} + \beta_2\mathrm{PMC} + \beta_3\mathrm{PMA} + \varepsilon$ …………..…(3)

where MCM = Marketing Communications Management, AICS = AI-Driven Customer Segmentation, PMC = Personalised Marketing Campaigns, PMA = Predictive Marketing Analytics, β_0 = intercept, β_{1-3}, {1- = slope coefficients, and ε = random error term. Diagnostic checks confirmed homoscedasticity, normal residuals, and low multicollinearity (VIF < 2.0) in line with recommendations by Hair, Black, Babin, and Anderson (2022).

4. Results and Discussion

4.1 Descriptive Analysis

Table 1: Descriptive Statistics Result

Statistic	N	Mean	Std. Deviation	Variance	Skewness	Std. Error	Kurtosis	Std. Error
MCM	129	3.7132	1.04727	1.097	-0.727	0.213	0.088	0.423
AICS	129	3.4574	1.13198	1.281	-0.484	0.213	-0.393	0.423
PMC	129	3.5504	0.95983	0.921	-0.657	0.213	0.363	0.423
PMA	129	4.0775	0.94879	0.900	-1.216	0.213	1.499	0.423

Source: Researcher(s)' Computation, 2024

The descriptive statistics show the central tendencies and dispersion of the variables. Marketing Communications Management (MCM) has a mean of 3.7132 and a standard deviation of 1.04727, indicating a moderate level of agreement among respondents regarding MCM. The skewness of -0.727 suggests a slight left skew, while the Kurtosis of 0.088 indicates a relatively flat distribution.AI-Driven Customer Segmentation (AICS) has a mean of 3.4574 and a standard deviation of 1.13198, showing variability in responses. The skewness of -0.484 indicates a left skew, and the kurtosis of -0.393 suggests a flatter distribution than normal. Personalized Marketing Campaigns (PMC) has a mean of 3.5504 and a standard deviation of 0.95983, with a skewness of -0.657 and a kurtosis of 0.363, indicating a slight left skew and a relatively normal distribution. Predictive Marketing Analytics (PMA) has the highest mean at 4.0775 and a standard deviation of 0.94879. The skewness of -1.216 indicates a strong left skew, and the kurtosis of 1.499 suggests a peaked distribution, indicating a higher concentration of responses around the mean.

4.2 Correlation Analysis

Table 2: Correlation Matrix Result

Variable	MCM	AICS	PMC	PMA
MCM	1	0.533**	0.314**	0.439**
AICS	0.533**	1	0.270**	0.229**
PMC	0.314**	0.270**	1	0.167
PMA	0.439**	0.229**	0.167	1

**. Correlation is significant at the 0.01 level (2-tailed).
Researcher(s)' Computation, 2024

In Table 2 all three AI capabilities display statistically significant positive links with marketing-communications management (MCM). AI-driven customer segmentation (AICS) shows a moderate association with MCM, $r = .53$, $p < .001$, indicating that improvements in segmentation quality tend to accompany notable gains in MCM performance. Predictive marketing analytics (PMA) is likewise moderately related to MCM, $r = .44$, $p < .001$, suggesting a meaningful—though slightly weaker connection. In contrast, personalised marketing campaigns (PMC) exhibit only a weak relationship, $r = .31$, $p < .001$, implying that personalisation contributes positively but less strongly when considered in isolation.

Inter-variable correlations among the AI constructs are lower. AICS correlates weakly with PMC, $r = .27$, $p < .001$, and with PMA, $r = .23$, $p < .01$, while the PMC–PMA link is very weak and not significant at the 1 % level, $r = .17$, $p = .06$. These modest inter-correlations suggest that each capability exerts its influence on MCM largely independently rather than through strong overlap.

4.3 Multiple Regression Analysis

4.3.1 Model Summary Analysis

Table 3: Model Summary Result

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	Durbin-Watson
1	0.641	0.410	0.396	0.81373	R Square Change: 0.410, F Change: 29.005, df1: 3, df2: 125, Sig. F Change: 0.000	2.118

Researcher(s)' Computation, 2024

The model summary shows an R value of 0.641, indicating a strong positive relationship between the independent variables (AICS, PMC, PMA) and MCM. The R Square value of 0.410 means that 41% of the variance in marketing communications management can be explained by the model. The Adjusted R Square of 0.396 accounts for the number of predictors in the model, indicating a good fit. The Durbin-Watson statistic of 2.118 suggests no significant autocorrelation in the residuals.

4.3.2 ANOVA Analysis

Table 4: ANOVA Result

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	57.617	3	19.206	29.005	0.000
Residual	82.770	125	0.662		
Total	140.388	128			

Researcher(s)' Computation, 2024

The ANOVA table indicates that the regression model is significant ($F = 29.005$, $p < 0.001$). This suggests that the independent variables collectively have a significant impact on the dependent variable, MCM.

4.3.3 Regression Coefficient Analysis

Table 5: Coefficients Results

Model	**Unstandardized Coefficients**	**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta	
(Constant)	0.365	0.398		0.915
AICS	0.389	0.067	0.421	5.789
PMC	0.160	0.078	0.147	2.046
PMA	0.352	0.078	0.318	4.486

Researcher(s)' Computation, 2024

In Table 5 controlling for the other predictors, AI-driven customer segmentation (AICS) emerged as the strongest determinant of marketing-communications management. The unstandardised coefficient was B = 0.39, SE = 0.07, yielding a moderate standardized effect (β = .42) and a large, statistically reliable t value, t(104) = 5.79, $p < .001$. In practical terms, every one-point improvement on the segmentation scale is associated with a 0.39-point gain in MCM, holding other factors constant.

Predictive marketing analytics (PMA) also showed a positive, statistically meaningful influence, B = 0.35, SE = 0.08, β = .32, t(104) = 4.49, $p < .001$. Thus, stronger use of analytics corresponds to appreciable improvements in communication performance.

The effect of personalised marketing campaigns (PMC) was smaller but still significant, B = 0.16, SE = 0.08, β = .15, t(104) = 2.05, p = .043. Although the standardized weight is modest, the direction is positive, indicating that personalisation adds incremental value beyond segmentation and analytics. The model intercept did not reach significance, B = 0.37, SE = 0.40, t(104) = 0.92, p = .36, suggesting no systematic baseline level of MCM when all predictors are scored at zero.

4.4 Test of Hypotheses

H_{01}: AI-driven customer segmentation does not significantly impact marketing communications management at GTCO Plc, Abuja. The result from the co-efficient table shows that AICS with a coefficient value of 0.389 implies that AICS has a positive impact on MCM of GTCO Plc Abuja. And therefore leads to the rejection of the null hypothesis which states that AI-driven customer segmentation does not significantly impact marketing communications management at GTCO Plc, Abuja

H_{02}: Personalized marketing campaigns powered by AI do not significantly affect customer engagement and satisfaction at GTCO Plc, Abuja. The result from the co-efficient table shows that PMC with a coefficient value of 0.160 implies that PMC though low but has a positive impact on MCM of GTCO Plc Abuja. And therefore leads to the rejection of the null hypothesis which states that personalized marketing campaigns powered by AI do not significantly affect customer engagement and satisfaction at GTCO Plc, Abuja.

H_{03}: AI-powered predictive marketing analytics does not significantly influence marketing strategy optimization and resource allocation at GTCO Plc, Abuja. The result from the co-efficient table shows that AIPM with a coefficient value of 0.359 implies that AIPM has a positive impact on MCM of GTCO Plc Abuja. And therefore leads to the rejection of the null hypothesis which states that AI-powered predictive marketing does not significantly impact marketing communications management at GTCO Plc, Abuja.

4.5 Discussions of Findings

The study tested whether AI-driven customer segmentation (AICS) enhances marketing-communications management (MCM) at GTCO Plc. The regression result confirmed a moderate, positive coefficient, indicating that marketers see AICS as both useful and easy to operate—exactly the perceptions TAM identifies as adoption triggers (Musa, Fatmawati, Nuryakin, & Suyanto, 2024). Empirical support appears in retail: deep-learning clustering lifted loyalty-programme uptake by 31 percent in Rao, Sahoo, and Chatterjee (2024), while real-time clusters raised conversion 29 percent in Chen, Huang, and Kumar (2024). By extending these gains to a universal bank, the present study strengthens external validity and suggests GTCO should institutionalise monthly cluster refreshes and embed segment dashboards in every campaign briefing.

The research evaluated personalised marketing campaigns (PMC). Although the effect size was weaker than AICS, the link remained significant, echoing TAM logic that usefulness must outweigh privacy concerns for sustained use. Field evidence is mixed: hyper-personalised ads increased click-through 23 percent in Reddy *et al.* (2025) but also triggered a nine-percent rise in privacy anxiety in Mehta and Singh (2024). Kapoor *et al.* (2024) show that explainable-AI disclosures can add 14 percent to consumer trust, suggesting a mitigation path. In GTCO's regulated environment, transparent data-use notices and granular consent dashboards could amplify PMC benefits without breaching compliance thresholds, thereby turning a weak driver into a more durable engagement lever.

The study examined predictive marketing analytics (PMA) for strategy optimisation and resource allocation. A moderate, significant coefficient mirrors Alvarez *et al.* (2024), who reported an 18 percent return-on-ad-spend lift after predictive budget shifting. Placing PMA in Grewal *et al.* (2023) "act–learn" stage underscores its role in continuous improvement cycles. Yet Bag and Dwivedi (2024) warn that data-quality gaps erode model reliability; robust governance is thus critical. GTCO should invest in automated data-validation routines and quarterly model recalibration, ensuring that predictive insights remain accurate enough to justify real-time budget moves. Taken together, the three findings validate TAM expectations and position AICS as the primary value lever, PMA as a critical optimiser, and PMC as an enhancer moderated by transparency—an actionable hierarchy for banks pursuing data-driven, customer-centric communication strategies.

5. Conclusion and Recommendations

The results of this study demonstrate that AI technologies significantly impact marketing communications management in GTCO Plc, Abuja. AI-Driven Customer Segmentation is the most influential factor, highlighting the importance of using AI to understand and target specific customer segments effectively. Predictive Marketing Analytics also plays a crucial role, suggesting that using AI to predict market trends and customer behaviour can enhance marketing strategies. Personalized Marketing Campaigns, while still significant, have a relatively lower impact but are nonetheless essential for tailoring marketing messages to individual customers. The integration of AI technologies in marketing communications management has a significant positive effect on enhancing the effectiveness and efficiency of marketing strategies in GTCO Plc, Abuja. The study confirms that leveraging AI-driven customer segmentation, personalized marketing campaigns, and predictive analytics can lead to better-targeted marketing efforts, improved customer engagement, and higher conversion rates.

Based on the findings, it is recommended that GTCO Plc continue to invest in and expand the use of AI technologies in their marketing operations. Specifically, the company should focus on enhancing their AI-driven customer segmentation capabilities to gain deeper insights into customer needs and preferences. Additionally, incorporating predictive analytics will allow the company to anticipate market trends and customer behaviour more accurately, enabling proactive and informed decision-making. Finally, personalized marketing campaigns should be refined and tailored using AI insights to maintain and increase customer satisfaction and loyalty.

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