Algorithmic Advertising and Student Behaviour in Nigeria: Implications for Youth Enterprise and Digital Markets

Gbenga-Julius, O; Oyekunle, O.B; Fagbemide T.M; Dauda, S.O; Akanji, J.O; Adeeko, J.D; Dairo, I.K

University of Ibadan

DOI: https://doi.org/10.47772/IJRISS.2026.1014MG0012

Received: 05 January 2026; Accepted: 10 January 2026; Published: 24 January 2026

ABSTRACT

Purpose: AI is reshaping the world of digital marketing and changing the way consumers are engaging with personalized content. This research examines the influence of AI marketing knowledge, algorithmic recommendations, trust in AI-mediated advertising, type of institution and entrepreneurial involvement on student consumers' behaviours.

Design/Methodology: Using a convergent mixed methods design, survey data on 327 students from six tertiary institutions in Southwest Nigeria was complemented with qualitative interviews.

Findings: Results of quantitative analyses (ANOVA, regression, PROCESS Macro) and qualitative analysis grounded in TAM, TPB, Effectuation, and Opportunity Recognition indicate that AI awareness ($\beta = 0.19$, $p < .001$), recommendations ($\beta = 0.22$, $p < .001$), and trust ($\beta = 0.24$, $p < .001$) are significant predictors of purchase frequency, impulse buying, and platform engagement. Entrepreneurial students from both groups responded more strongly, with student entrepreneurs use algorithmic cues to prompt micro-venture possibilities.

Practical Implications: The findings indicate that marketers and platform developers can leverage AI-powered persuasion with transparency to enhance consumer learning and youth-focused digital entrepreneurship in developing countries.

Originality/Value: This paper conceptualizes the consumer–entrepreneur dual identity as a boundary modifier, rethinking AI-enabled marketing as a persuasion tool and informal market-learning system.

Keywords: Artificial intelligence; digital marketing; consumer behaviour; algorithmic recommendations; student entrepreneurship; Nigeria

INTRODUCTION

The use of Artificial Intelligence (AI) is proving to be a game-changer in today's online marketing, allowing marketers to provide hyper-personalized recommendations, bring about automated ad targeting, and generate predictive customer analytics. These skills are also shaping how consumers are searching for the information, evaluating options, and deciding on their purchases, increasingly substituting "slow thinking" deliberative decision making towards more intuitive and faster decisions under the guidance of algorithmic and multisensory stimulation (Nagy & Hajdu, 2022; Huang & Rust, 2021). This change is most significant in Nigeria where the majority of the population is young and mobile first and they live and breathe in social media ecosystems. For many students attending tertiary institutions, popular social media platforms such as Instagram, TikTok and WhatsApp are not just sites or places where they consume, but where informally they engage in entrepreneurship learning and take a gamble to see if they could make it as one.

Although prior studies have examined social media usage and online buying behaviour among Nigerian youth (Gbandi & Ugbechie, 2023; Ladokun et al., 2023), empirical research on AI-enabled marketing within African and emerging-market contexts remains limited. In particular, little is known about how algorithmic awareness, recommendations, and trust in AI-generated advertising shape student consumer behaviour, or how these effects may vary across institutional contexts such as universities, polytechnics, and colleges of education. Existing research often assumes homogeneity across tertiary institutions, overlooking how differences in curricular orientation, practical exposure, and entrepreneurial emphasis may produce distinct patterns of digital engagement and behavioural response (Suleiman et al., 2024).

This study addresses these gaps by examining the influence of AI marketing awareness, algorithmic recommendations, and trust in AI-based advertisements on student consumer behavior, measured in terms of impulse buying, purchase frequency, and platform engagement-across tertiary institutions in Nigeria. Based on the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), the research describes the cognitive processing that students go through when assessing the trustiness of, and forming behavioural intentions towards, AI-mediated marketing stimuli. These consumer-level explanations are complemented by the Effectuation Theory (Sarasvathy, 2001) and Opportunity Recognition Theory (Ardichvili et al., 2003), which explain how some students convert repetitive algorithmic engagement into adaptive entrepreneurial actions.

Importantly, these theories are not treated as competing explanations. TAM and TPB account for consumer cognition and intention formation, while Effectuation and Opportunity Recognition explain behavioural adaptation beyond consumption. TAM and TPB do not explain venture creation or opportunity enactment, just as Effectuation does not explain initial trust in AI advertisements or purchase intention. By assigning each theory a distinct analytical role, the study avoids theoretical overlap and positions students not merely as passive recipients of algorithmic persuasion but as active economic actors who sometimes repurpose AI-mediated cues for informal entrepreneurial practice.

Consequently, the research aims at three goals :

1. To analyze the impact of AI awareness, algorithm acumen and trust in AI-based generated advertisement on students purchase behaviour
2. To evaluate if consumer reactions to marketing powered by AI vary among University, Polytechnic and College of Education students.
3. To determine whether institutional type and student entrepreneurial engagement moderate the relationship between AI marketing variables and consumer behaviour.

By doing so, the study contributes to marketing literature by extending AI-enabled marketing research to an under-examined emerging-market context and by introducing the consumer–entrepreneur dual identity as a boundary condition under which algorithmic marketing shifts from a purely persuasive mechanism to an informal learning infrastructure.

LITERATURE REVIEW

Driving marketing by AI has redefined the digital consumer space with customization, predictive marketing and content curation via algorithms. Marketing algorithms rank and suggest products, advertisements and information streams, influencing what users pay attention to and the decisions they make – blurring traditional lines between consuming and producing. But much of the existing AI marketing research continues to focus on Western contexts, overlooking youth-driven, resource-constrained environments in the Global South, where digital adaptation is often linked to informal entrepreneurship rather than lifestyle consumption.

In Nigeria, tertiary students comparatively hold a unique place within these algorithmic frameworks. They participate with AI-driven services as consumers of persuasive hints and as informal digital traders who watch, mimic and modify marketing signals. Understanding this dual engagement requires theoretical perspectives that explain both consumer cognition and behavioural adaptation.

Theoretical Foundations

The Technology Acceptance Model (TAM) asserts that the individuals adoption of technology depends on two factors; perceived ease of use and perceived usefulness (Davis, 1989). In parallel, Theory of Planned Behaviour

(TPB) suggests that behavioural predictions and subsequent behaviours are influenced by attitudes, subjective norms and perceived behavioural control (Ajzen, 1991). In combination, TAM and TPB offer a strong theoretical lens through which to analyze how learners assess AI-powered marketing content, establish trust in algorithmic systems and decide whether to participate in AI- mediated ads.

Nevertheless, TAM and TPB do not clarify how people are transforming their role as consumers and become opportunity enactors. A further dimension of explanatory power is added by Effectuation Theory and Opportunity Recognition Theory in an environment where students actually monetise digital platforms. Effectuation Theory focuses on means-based thinking and iterative learning in an environment of uncertainty (Sarasvathy, 2001), whereas Opportunities Recognition Theory focuses in how persons recognize market opportunities in the environment and through pattern recognition (Ardichvili et al., 2003). They explain how such repeated visits to algorithmic cues could become market intelligence rather than simple persuasion.

By integrating these theoretical viewpoints, the study conceptualizes student interaction with AI marketing as a multi-level process: cognitive evaluation and intention generation at the consumer level, and adaptive entrepreneurial behaviour at the behavioural level.

AI Marketing Awareness

AI marketing awareness refers to the extent to which users recognize that digital content and media advertising is filtered through algorithms rather than equal incidental exposure. Previous studies have indicated that awareness could increase the elaboration of persuasion messages, however, this will not necessarily influence level of acceptance when convenience or personalization of the service outweigh perceived risks (Lu et al., 2023). Within TAM, awareness aligns with perceived usefulness and ease of use, supporting technology acceptance and engagement.

In addition, within the context of Nigerian students, awareness serves as a resource for learning. Entrepreneurially involved students tend to interact with algorithmic logics —like trend intensification, automated captioning and audience targeting— not only as consumers but as casual marketers. Consistent with effectual reasoning, such awareness channels student experimentation with digital tools for micro enterprises.

Algorithmic Recommendations

Algorithmic recommendations direct users to particular products, content, or trends based on predictive analytics and feedback mechanisms. Such recommendations are “digital nudges,” which direct attention and help to make decisions faster and more intuitively (Ricci et al., 2015; Kahneman, 2011). Although such nudges are traditionally linked with impulse buying, Nigerian students often read into recommendation signals as signals of the mass market and demand (coming) in.

In terms of Opportunity Recognition, algorithmic recommendations enable users to recognize patterns, as they draw users’ attention to popular items, such as products, hashtags, or types of content. As a result, recommendations don’t just shape what students buy, but also how they spot potential opportunities to resell, build a brand, or generate content within platform ecosystems.

Trust in AI-Based Advertising

The trust of users in AI-generated advertising is an indicator of their perception of the reliability, fairness and security of the content generated by algorithms (Choung et al., 2022). Trust is also positively associated with engagement and purchase intention (Ghose & Todri-Adamopoulos, 2016); however, it seems to be fragile in an environment of poor data governance and privacy-related concerns (Siau & Wang, 2018).

In line with TPB, trust also seems to be conceptualized as a subjective norm influenced by social and platform norms, and as perceived behavioural control, which impacts users’ confidence in processing and acting on AI-mediated information. In both cases, among students pursuing entrepreneurial careers, trust could likewise inform the algorithmic practices adoption or rejection, with some casting their ventures as “authentic” alternatives to automated persuasion.

AI Marketing and Student Buying Behaviour

The effect of AI-powered marketing on impulse purchasing, shopping frequency, and platform engagement has been closely associated with, especially on visual-based platforms like Instagram and TikTok (Mohan et al., 2013; Liu et al., 2022). In Nigerian tertiary institutions, these behaviours acquire additional significance as consumer feedback—likes, shares, and comments—often serves as informal market research for student entrepreneurs.

From an effectual perspective, consumer behaviors in response to AI marketing become iterative learning and business experimentation inputs. This dynamism challenges the consumer-producer binary and makes the relevance of the consumer–entrepreneur hybrid identity even more pertinent in AI-mediated markets.

Conceptual Framework

Consequently, the research develops a conceptual model relating the AI-enabled marketing and student consumer behavior in the context of higher education institutions in Nigeria. TAM provides the cognitive foundation by explaining how AI awareness and perceived usefulness shape engagement, while TPB incorporates social and motivational influences on behavioural intention. Effectuation and Opportunity Recognition theories complement these models by explaining adaptive responses that emerge when students reinterpret algorithmic cues as entrepreneurial resources.

Accordingly, AI marketing awareness, algorithmic recommendations, and trust in AI-based advertisements are proposed to influence student buying behaviour, operationalized as impulse buying, purchase frequency, and platform utilization. The institutional type (university, polytechnic, or college of education) and student entrepreneurship involvement are proposed as moderators, as each exhibits distinct curricular focus, exposure to digital, and adaptive approaches.

As the consumer–entrepreneur dual identity is assumed to be a boundary condition, the framework implies that AI-enabled marketing in the context of emerging markets is not only a tool for promotion but also an informal education instrument. This theoretical integration extends AI marketing research by demonstrating how algorithmic persuasion may simultaneously shape consumption and entrepreneurial sensemaking among digitally embedded youth.

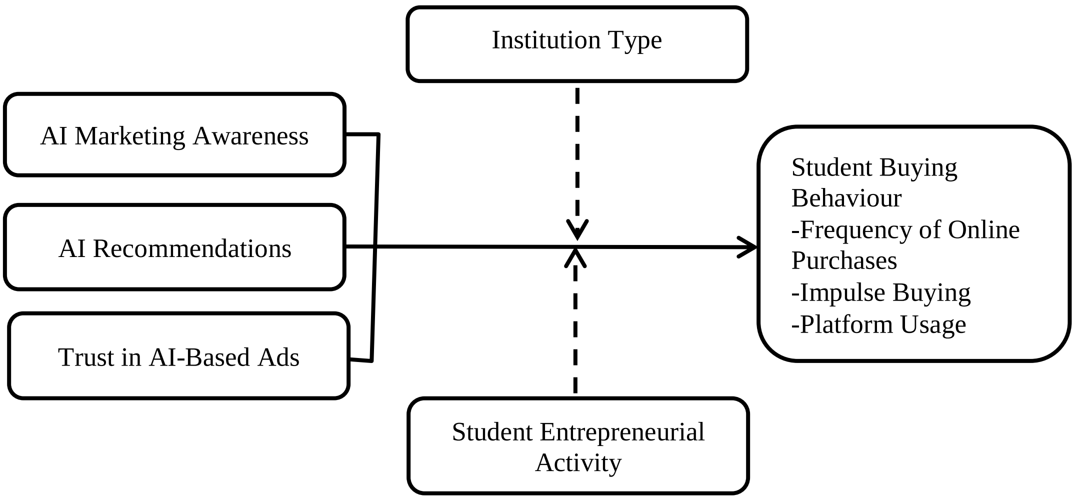

Figure 1. Conceptual Framework of AI-Driven Marketing and Student Consumer Behaviour

MATERIALS AND METHODS

Study Design and Context

This research adopted the convergent mixed methods design to study the impact of AI-based marketing on student consumers in higher education in Nigeria. The quantitative part of study investigated hypothesized links based on the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB), considering the moderating effect institutional type and student entrepreneurial involvement. The qualitative component provided interpretive insights into how students make sense of, adapt to, and occasionally repurpose algorithmic marketing exposure in everyday economic practices.

The two strands were integrated at the interpretation stage, allowing statistical patterns in consumer behaviour to be contextualised with students' lived experiences of algorithmic platforms. Such design facilitates analytical triangulation-explanatory quantitative and interpretive qualitative methods to objectives were analysed (Section 4). Following a maximum variation purposive sampling strategy six higher education institutions (two universities, two polytechnics and two colleges of education) from Southwest Nigeria were selected this was to ensure inclusion of diverse perspectives: University of Ibadan (UI); Federal University of Agriculture, Abeokuta, (FUNAAB), The Polytechnic Ibadan (TPI); Moshood Abiola Polytechnic (MAPOLY) and Federal College of Education, Osiele (FCE-Osiele); Sikiru Adetona College of Education, Science and Technology (SACEST)). These are similar to one another in some respects and quite different in others, notably in focus and level of pedagogy, and amount of applied entrepreneurship education.

Population and Sampling

The study population consisted of full-time undergraduate students who were 18 years and above with recent online shopping experience and use of social media platforms. Inclusion criteria were possession of an internet-enabled device and willing consent to participate.

In light of above, 370 was the minimum sample size using Yamane's (1967) sample size formula from total population of 5,000 students at the level of precision of 5%. A sum of 360 questionnaires was distributed (60 per university), and the rate of return was 90.8%, implying that 327 questionnaires were valid and usable. A stratified convenience sampling technique was used to ensure diversity in academic levels and faculties across each university. Although this approach improved the institutional coverage and response rates, it reduces the ability to statistically generalise. Findings should be read as contextually bound not nationally representative.

For the qualitative strand, 30 students who self-identified as being engaged in entrepreneurial activities (e.g. online selling, digital content monetisation) were purposively selected. This criterion ensured relevance to the study's focus on adaptive responses to algorithmic marketing.

Instrumentation and Measures

Quantitative data were collected using a structured, self-administered questionnaire comprising five sections: (1) demographic characteristics; (2) AI marketing awareness; (3) trust in AI-generated advertising; (4) exposure to algorithmic recommendations; and (5) student buying behaviour and entrepreneurial engagement.

Measurement scales were adapted from established studies in AI-enabled marketing and digital consumer behaviour (e.g., Chatterjee & Rana, 2020; Huang & Rust, 2021; Ricci et al., 2015). Items were contextualised to reflect platform-based interactions common among Nigerian students. All answers were given in five-point Likert scales.

A pilot study with 20 students was conducted to evaluate the clarity and understanding. Internal consistency reliability was acceptable and Cronbach's alpha coefficients for the constructs were between 0.76 – 0.88. Full measurement items are provided in Appendix A**.**

Data Collection and Analytical Strategy

Quantitative data were collected via self-completion questionnaires administered in person and electronically. Qualitative data were obtained through open-ended questionnaire responses and short semi-structured interviews focusing on students' experiences with algorithmic recommendations, trust formation, and entrepreneurial adaptation.

Quantitative analyses were conducted using SPSS version 26. Descriptive statistics were computed to summarise sample characteristics. Three multiple regression models were estimated, corresponding to the three dependent variables: impulse buying, purchase frequency, and platform usage. Each model included AI marketing awareness, algorithmic recommendations, and trust in AI-based advertising as predictors.

Moderation analyses were conducted using PROCESS Macro (Model 1) to test the moderating effects of (a) institutional type and (b) student entrepreneurial engagement on the relationship between AI marketing variables and consumer behaviour. Interaction terms were mean-centred prior to analysis. Where significant interactions were identified, conditional effects were examined to support interpretation. Non-significant interactions were explicitly reported as unsupported.

Qualitative data were analysed thematically, guided by constructs from TAM, TPB, Effectuation Theory, and Opportunity Recognition Theory. These frameworks guided coding without dictating any deterministic codes. Integration was at the level of interpretation rather than at testing, with qualitative findings elaborating and contextualizing rather than serving as stand-alone tests of theory.

Ethical Considerations

The research was conducted in accordance with the ethical standards of the Nigerian national codes for social sciences research. Informed consent was obtained (participation was voluntary and anonymity was guaranteed).I.Ds were not collected and data were handled with confidentiality.

RESULTS AND ANALYSIS

This section presents the descriptive statistics of respondents' socio-demographic and institutional background, it is then followed by the mean comparisons among institutions. For the purpose of development of hypotheses, inferential analyses are conducted to assess the impact of AI Marketing Awareness, AI Recommendations, and Trust in AI Ads on three behavioural outcomes, i.e., purchase frequency, impulse buying, and platform usage. Finally, moderation analyses investigate the extent to which the type of institution and the level of entrepreneurial activity influence these relationships, with additional insights offered with respect to platform-specific engagement.

Descriptive Statistics

Sociodemographic Profile of Respondents

Table 1. Sociodemographic characteristics of respondents (N = 327)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	178	54.4%
	Female	149	45.6%
Age Group	18–20 years	92	28.1%
	21–23 years	156	47.7%
	24 years and above	79	24.2%
Institution Type	University	112	34.3%
	Polytechnic	109	33.3%
	College of Education	106	32.4%
Academic Level	ND I / 100 Level	98	30.0%
	ND II / 200 Level	115	35.2%
	HND I / 300+ Level	114	34.8%
Entrepreneurial Status	Runs business	131	40.1%
	Intends to start soon	124	37.9%
	Not engaged	72	22.0%

Source: Field Survey (2025)

The sample was evenly divided by gender and type of institution. Almost half of the respondents (47.7%) were aged 21–23 years, which is the normal age range of undergraduates. Significantly, 40.1 percent of the respondents were already operating a business and 37.9 percent intended to start one in the near future, showing a high level of entrepreneurial involvement which is a crucial context in which to consider the effects of AI marketing.

Supplementary Comparison across Institution Types

Table 2: Mean Scores for AI Marketing Variables and Buying Behaviours by Institution Type (N = 327)

Variable	College of Education	Polytechnic	University
AI Marketing Awareness	2.95	2.87	3.02
Frequency of Online Purchases	2.99	3.09	3.00
Influence of AI Recommendations	2.98	3.05	2.94
Impulse Buying Tendency	2.83	3.13	3.14
Trust in AI-Based Ads	2.98	2.97	3.02
Monthly E-commerce Spend (₦)	9,860.77	10,840.42	10,750.86

Source: Field Survey (2025)

Note. Values represent mean responses on a 5-point Likert scale, except for monthly spending (₦).These descriptive averages are shown as additional information and are not at the core of hypothesis testing.

The descriptive means indicate that there is some institution-specific variation in the extent to which students engage with AI-based marketing. University students (M = 3,02) had the highest level of awareness of AI marketing, but the polytechnic students had the highest frequency of online purchase (M = 3,09) and the highest level of impulse buying (M = 3,13). In contrast, colleges of education tend to have relatively less impulse buying (M = 2.83). Confidence in AI-powered ads was consistent for all the organizations.

While informative, these results are supplementary rather than central: they provide contextual texture but do not substitute for the regression and moderation analyses that formally test the study's hypotheses. Their main purpose is to highlight background patterns; such as universities scoring higher on awareness and polytechnics spending slightly more, that justify deeper inferential analysis.

Hypotheses Testing: Main Regression Models

Testing the hypotheses, institution type was included as dummy variables in all the models to account for educational context effects, and the control variables were also included. The College of Education was treated as the reference (baseline) category, while Polytechnic and University were coded as comparison dummies.

Predictors of Purchase Frequency

Table 3: Multiple regression predicting online purchase frequency (N = 327)

Predictor Variable	β (Unstd.)	Std. Error	t-value	p-value
AI Marketing Awareness	0.19	0.05	3.80	< .001
AI Recommendations	0.22	0.06	4.20	< .001
Trust in AI Ads	0.24	0.06	4.00	< .001
Institution (Polytechnic = 1)	0.18	0.07	2.57	< .05
Institution (University = 1)	0.12	0.06	2.00	< .05

Model Summary: $R^2 = .41$, Adjusted $R^2 = .40$, $F(5, 321) = 22.35$, $p < .001$

Source: Field Survey (2025)

Note. *C*ollege of Education serves as the reference category for institution type.

Trust in AI Ads (β = .24, p < .001) was the strongest predictor of online purchase frequency, followed by AI Recommendations (β = .22) and AI Awareness (β = .19). The inclusion of institution type revealed that Polytechnic (β = .18, p < .05) and University (β = .12, p < .05) students had significantly higher purchase frequency than their College of Education counterparts, implying stronger technology-induced buying tendencies in more digitally active learning environments.

Predictors of Impulse Buying

Table 4: Multiple regression predicting impulse buying (N = 327)

Predictor Variable	*B* (Unstd.)	*SE*	*t*	*p*
AI Marketing Awareness	0.16	0.05	3.20	< .01
AI Recommendations	0.27	0.07	3.86	< .001
Trust in AI Ads	0.18	0.06	3.00	< .01
Institution (Polytechnic = 1)	0.15	0.07	2.14	< .05
Institution (University = 1)	0.10	0.06	1.96	< .05

Model Summary: R^2 = .39, Adjusted R^2 = .38, F(5, 321) = 20.47, p < .001

Source: Field Survey (2025)

Note. College of Education serves as the reference category for institution type.

AI Recommendations (β = .27, p < .001) emerged as the strongest predictor of impulse buying, reflecting their persuasive and "nudging" effect in online shopping behaviour. Polytechnic (β = .15, p < .05) and University (β = .10, p < .05) students were more prone to impulsive purchasing than College of Education students, possibly due to higher levels of exposure to AI-enabled digital platforms and social media marketing.

Predictors of Platform Usage

Table 5: **Multiple regression predicting platform usage (N = 327)**

Predictor Variable	*B* (Unstd.)	*SE*	*t*	*p*
AI Marketing Awareness	0.21	0.05	4.20	< .001
AI Recommendations	0.17	0.06	2.83	< .01
Trust in AI Ads	0.19	0.06	3.17	< .01
Institution (Polytechnic = 1)	0.16	0.07	2.25	< .05
Institution (University = 1)	0.11	0.06	1.98	< .05

Model Summary: R^2 = .36, Adjusted R^2 = .35, F(5, 321) = 19.10, p < .001

Source: Field Survey (2025)

Note. College of Education serves as the reference category for institution type.

AI Marketing Awareness (β = .21, p < .001) was the most consistent predictor of platform usage, followed by Trust in AI Ads (β = .19) and AI Recommendations (β = .17). The positive significant coefficients for Polytechnic (β = .16, p < .05) and University (β = .11, p < .05) suggests more platform activity than College of Education students, highlighting the role of institutional access to technology in promoting permanent digital contact.

Cross-Model Insight

Across all three models, AI Marketing Awareness**,** AI Recommendations, and Trust in AI Ads consistently influenced online consumer behaviour, specifically, *purchase frequency*, *impulse buying*, and *platform usage*. The results partially support the proposed hypotheses, with consistent main effects across behavioural outcomes and selective moderation effects.

Including institution type dummies (Polytechnic, University and College of Education) enhances the internal validity of this study. The findings support the hypothesis that Polytechnic and University students are more digitally responsive to AI marketing than students in the College of Education.This differentiation might be attributed to varying levels of technology adoption and digital literacy in different institutional environments - which is a useful lesson for crafting AI-based marketing strategies in the context of higher education in Nigeria.

Supplementary Analysis of Digital Platform Usage and Behavioural Dynamics

Table 6. Most used digital marketing platforms among students (N = 327)

Platform	Frequency	Percentage (%)	Behavioural Intensity
WhatsApp	88	26.9%	Moderate frequency, low switching
Instagram	85	26.0%	High impulse buying & switching
Facebook	79	24.2%	Moderate engagement
TikTok	75	22.9%	High impulsivity & trend-driven switching

Source: Field Survey (2025)

AI-embedded platforms like Instagram and TikTok generated stronger behavioural volatility compared to WhatsApp and Facebook, which are less algorithmically intensive.

Table 7. Behavioural impact of AI marketing by platform preference

Platform	AI Feature Engagement	High Purchase Frequency	Impulse Buying	Product Switching
Instagram	Yes	↑ High	↑ High	↑ Frequent
TikTok	Yes	↑ High	↑ High	↑ Frequent
WhatsApp	Limited	Moderate	Moderate	Low
Facebook	Limited	Moderate	Low	Low

Note. ↑ = relative behavioural intensity based on mean score distribution. These descriptive results are reported as *supplementary context*, not as central hypothesis tests.

Source: Field Survey (2025)

Platform choice offers additional insight into how AI-enabled marketing environments shape student consumer behaviour. While WhatsApp (26.9%) and Instagram (26.0%) were the most frequently used platforms, with TikTok (22.9%) closely following, behavioural intensity was markedly higher on Instagram and TikTok. Students who were active only on these platforms purchased more often, and had stronger tendencies to buy on impulse and to switch products. This pattern reflects differences in platform architecture and not volume of use alone. Algorithmically intensive platforms such as Instagram and TikTok are characterized by opaque recommendation systems, rapid content turnover, and continuous feedback loops. Consistent with attention economics and AI-enabled choice architecture models, these features heighten cognitive salience and compress deliberation time, thereby strengthening impulse-oriented behavioural pathways. In contrast, messaging-dominant platforms like WhatsApp, which rely less on algorithmic curation, primarily facilitate utilitarian and goal-directed interactions.

These platform-specific findings are reported as supplementary evidence rather than central hypothesis tests. Their contribution is to situate the main regression and moderation results, by showing that differences in algorithmic intensity among digital platforms can strengthen and weaken the impact of AI-powered marketing on behaviour.

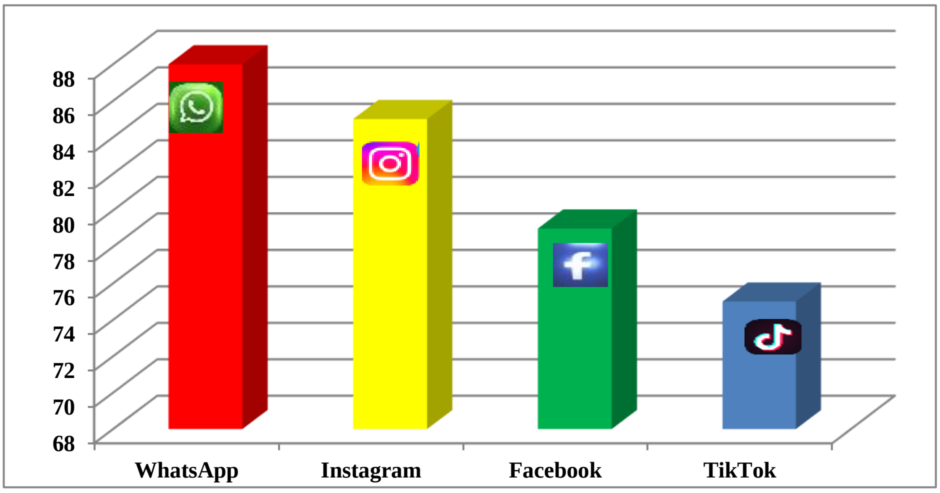

Figure 2. Distribution of digital platform use among Nigerian tertiary students

Moderation Analysis

PROCESS Macro Model 1 was used to test moderation to investigate if the type of institution and entrepreneurial Activity moderate the relationships between AI marketing variables and students' behavioural intentions. Interaction effects were interpreted only when statistically significant, with non-significant interactions explicitly reported and not over-interpreted. Where moderation was supported, effects were interpreted as conditional rather than universal behavioural mechanisms.

Institutional Type as Moderator

Table 8 presents the moderation results for institutional type. Overall, the moderating role of institutional type yielded mixed results across behavioural outcomes.

Purchase Frequency: The effect of AI marketing awareness and institutional type was significant for university students ($b = 0.11$, $p < .05$), suggesting that awareness had a stronger influence on purchase frequency among university students than their counterparts in the College of Education. In the same way, the interaction between AI recommendations and polytechnic status was significant ($b = 0.14$, $p < .05$), indicating that the practice-oriented institutional environment is more receptive to algorithmic suggestions.

In contrast, the interaction between trust in AI advertisements and institutional type was not significant ($b = 0.08$, $p = .11$), indicating that trust operates uniformly across institutional settings for purchase frequency.

Impulse Buying: Only the interaction between trust in AI advertisements and institutional type reached significance ($b = 0.09$, $p < .05$). Simple slope analysis indicated that trust cues positively related to impulse buying for university and polytechnic students, and the positive effect was less pronounced and non-significant among students of Colleges of Education. Interactions involving awareness and recommendations were not supported.

Platform Usage: Polytechnic status significantly moderated the relationship between AI recommendations and platform usage ($b = 0.13$, $p < .05$), while all other interaction terms were non-significant.

Overall, these results suggest that the institutional context acts as a selective moderator of AI marketing effects. The type of institution also influenced the effect of some, but not all AI cues on behaviour. Obvious from the results is that although university students' awareness of marketing in AI translated far more strongly into frequency of purchase potentially reflecting a higher level of digital literacy and longer exposure to algorithmic systems. Polytechnic students, on the other hand, reported higher levels of sensitivity to AI-based suggestions, in line with an approach-driven rather than a avoidance-driven interaction with implicit marketing signals. Institutional technological exposure as contextual boundary condition in AI-driven consumer behaviour College of Education students demonstrated relatively weaker behavioural responsiveness The current results revealed a contextual boundary condition for AI-driven consumer behavior, specifically the extent to which consumers and products alike are exposed to technology in the institution matters.

It is noteworthy that for a number of trust-related interactions no significant moderation effects were found, which implies that some persuasive mechanisms are perhaps invariant to institutional differences. This pattern is broadly consistent with the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), which emphasize stable cognitive and attitudinal pathways in technology acceptance while allowing contextual variation in behavioural enactment.

Table 8: Moderation Analysis of Institution Type (N = 327)

Dependent Variable	Predictor × Moderator	*B* (Unstd.)	*SE*	*t*	*p*	Interpretation
Purchase Frequency	Awareness × Institution	0.11	0.05	2.20	< .05	Stronger effect in universities
Purchase Frequency	Recommendations × Institution	0.14	0.06	2.33	< .05	Stronger effect in polytechnics
Purchase Frequency	Trust × Institution	0.08	0.05	1.60	0.11	NS
Impulse Buying	Awareness × Institution	0.05	0.04	1.25	0.21	NS
Impulse Buying	Recommendations × Institution	0.07	0.05	1.40	0.16	NS
Impulse Buying	Trust × Institution	0.09	0.04	2.25	< .05	Colleges less responsive
Platform Usage	Awareness × Institution	0.06	0.05	1.20	0.23	NS
Platform Usage	Recommendations × Institution	0.13	0.06	2.17	< .05	Higher usage in polytechnics
Platform Usage	Trust × Institution	0.07	0.05	1.40	0.16	NS

Source: Field Survey (2025)

Note. All tested interaction terms are included. NS = non-significant at $p > .05$. Institution type was dummy-coded into Polytechnic and University, with College of Education as the reference category (see Appendix B).

Entrepreneurial Activity as Moderator

Table 9 presents moderation results for entrepreneurial activity. The analysis shows that entrepreneurial activity exhibited selective moderation effects.

Purchase Frequency: The interaction between AI recommendations and entrepreneurial activity was significant ($b = 0.15$, $p < .01$), indicating that entrepreneurial students converted algorithmic prompts into purchasing actions more readily than non-entrepreneurial peers. Interactions involving awareness and trust were not supported.

Impulse Buying: AI marketing awareness interacted significantly with entrepreneurial activity ($b = 0.12$, $p < .05$), suggesting that awareness intensified spontaneous purchasing only among students already engaged in entrepreneurial behaviour.

Platform Usage: Trust in AI advertisements significantly predicted platform usage among entrepreneurial students ($b = 0.18$, $p < .01$), whereas no moderation effects were observed for awareness or recommendations.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue XIV January 2026| Special Issue on Management

The results of the moderation analysis suggest that entrepreneurial activity is a selective, rather than general, conditioner of AI marketing effects. Entrepreneurial students were more sensitive in terms of behavioural reaction only via certain paths and especially when market information had been actionable, such as in the case of AI-generated recommendations and trust cues.

In line with Effectuation Theory, entrepreneurial students seem more willing to act in uncertainty leveraging on the information provided by algorithmic cues (i.e., recommendations, trust indicators) as heuristics in their decision making process. Similar to Opportunity Recognition Theory, algorithmic cues may also be decoded as informational cues that surface emerging consumer preference and new market opportunities, rather than as motivational cues. These results help to explain why moderation was detected for the recommendations-driven purchase frequency and trust-driven platform engagement axes, but not across all AI marketing dimensions.

Importantly, several interaction effects involving entrepreneurial activity were not statistically significant. This suggests that entrepreneurial orientation does not uniformly heighten sensitivity to all forms of AI-driven persuasion. Non-entrepreneurial students, by contrast, exhibited comparatively weaker and more consumption-oriented responses, indicating a more passive engagement with AI-enabled platforms. Collectively, these results bolster the argument that the influence of AI marketing is conditionally moderated by entrepreneurship, guiding the way in which certain algorithmic cues are interpreted and acted upon rather than having an amplifying effect on all consumers responses to marketing or AI marketing stimuli.

Table 9: Moderation Analysis of Entrepreneurial Activity (N = 327)

Dependent Variable	Predictor × Moderator	*B* (Unstd.)	*SE*	*t*	*p*	Interpretation
Purchase Frequency	Awareness × Entrepreneurship	0.08	0.05	1.60	0.11	NS
Purchase Frequency	Recommendations × Entrepreneurship	0.15	0.05	3.00	< .01	Entrepreneurs respond more
Purchase Frequency	Trust × Entrepreneurship	0.10	0.05	1.95	0.052	NS
Impulse Buying	Awareness × Entrepreneurship	0.12	0.05	2.40	< .05	Entrepreneurs more impulsive
Impulse Buying	Recommendations × Entrepreneurship	0.07	0.04	1.75	0.08	NS
Impulse Buying	Trust × Entrepreneurship	0.06	0.04	1.50	0.13	NS
Platform Usage	Awareness × Entrepreneurship	0.05	0.04	1.25	0.21	NS
Platform Usage	Recommendations × Entrepreneurship	0.09	0.05	1.80	0.07	NS
Platform Usage	Trust × Entrepreneurship	0.18	0.06	3.10	< .01	Entrepreneurs rely on AI trust

Source: Field Survey (2025)

Note. All tested interaction terms are included. NS = non-significant at $p > .05$. Entrepreneurial activity was dummy-coded as 1 = entrepreneur**,** 0 = non-entrepreneur.

Unsupported Moderation Hypotheses

Several proposed moderation effects were not supported. Specifically, institutional type did not moderate the effects of trust on purchase frequency, nor did it condition most relationships involving awareness and recommendations across behavioural outcomes. Likewise, entrepreneurial activity failed to moderate multiple awareness– and trust–behaviour links.

The lack of these moderation effects implies that AI-enhanced persuasion techniques are similarly effective across student subgroups. This challenges ideas that influence with algorithms is always situational and suggests that some AI marketing effects may actually function as baseline drivers of behaviour, rather than as situational mechanisms.

Summary of Hypotheses Testing

These results, therefore, provide robust evidence that supports the main effect of AI marketing awareness, AI recommendations and the trust in AI advertisements on student consumer behavior. Moderation effects were selective rather than universal, having institutional type and enterprise activity influence only two pathways of behaviour. These results strengthen the dominance of AI-driven persuasion mechanisms whilst warning against too much assumptions of contextual differentiation.

Qualitative Findings

To contextualize and explain the quantitative results, qualitative insights were drawn from open-ended responses and short interviews with 30 purposively selected students. Thematic analysis, guided by TAM, TPB, Effectuation, and Opportunity Recognition frameworks, revealed three themes that clarify why students across institutions respond differently to AI-powered marketing and how entrepreneurial activity moderates their behaviours.

Theme 1: "Selling Through the Same System" – Mimicking AI Marketing Tools

Students reported that they do not only consume AI-curated content but also repurpose the same platforms (Instagram, WhatsApp, TikTok) to market their own products. This explains the stronger behavioural responsiveness among entrepreneurial students observed in the regressions. Mimicking algorithmic strategies reflects *effectual logic* in resource-constrained contexts (Sarasvathy, 2001) and shows how entrepreneurial students convert consumer experiences into marketing practice.

> *"I study which content gets the most reactions, just like the way ads reach me too." - Male, 24, University of Ibadan*

> *"WhatsApp Status helps me sell shoes. I test my captions the same way marketers test theirs." - Female, 22, MAPOLY*

Theme 2: "The Algorithm Is My Market" – Informal Analytics and Opportunity Recognition

Participants described recommendations as cues about what is popular, treating them as informal market signals. This supports the quantitative result that recommendations had the strongest influence on buying on impulse. Students treat trending content as a form of proxy data for demand, indicating potential for recognition of opportunities (Ardichvili et al., 2003) within digitally mediated environments.

> *"I watch what Instagram pushes and follow that format for my own posts." - Female, 23, FCE Osiele*

> *"TikTok trends decide what I sell; if it goes viral there, I know people will buy." - Male, 21, The Polytechnic Ibadan*

Theme 3: "Being a Student Is Not Enough" – Entrepreneurial Identity Formation

Throughout the comments, students stressed that studying in itself was no longer enough for them to be able to survive or have a future. Rather, many portrayed themselves as "student-preneurs," splitting their time between studying and pursuing informal enterprises that address immediate needs. This is illustrative of entrepreneurial identity formation, in that the business of doing business is increasingly integral to one's self-definition and source of livelihood.

> *"School is just the background now. Business is real life." - Female, 20, SACEST*

> *"My certificate is for the future, but right now I need something that pays my daily expenses. That's why I run my Instagram store more seriously than I follow lectures." - Male, 22, FUNAAB*

These narratives are consistent with Effectuation Theory (Sarasvathy, 2001) as students use the means (social platforms) at their disposal to manage uncertainty and its TPB component of perceived behavioural control, where belief in their own capacity to act as entrepreneurs makes them more likely to act. Such findings are also resonant with research such as Fauchart and Gruber (2011) on entrepreneurial identity and Buli and Yesuf (2015) on the youth entrepreneurship under necessity in challenged environments.

DISCUSSION AND CONTRIBUTIONS

The aim of the study is to examine how marketing-based on artificial intelligence (such as through awareness, algorithmic recommendations, and trust in AI ads) influences Nigerians students in tertiary institution on their buying, impulsive and platform use behaviour. By combining quantitative with thick qualitative narratives, the results show that students are not just digital consumers but nascent economic actors who make sense of algorithmic cues as informal "market signals." This consumer–entrepreneur identity epitomizes a wider transformation among African youth, where engagement with the digital is increasingly intertwined with strategies of livelihood, opportunity recognition, and informal entrepreneurship.

Synthesis of Key Findings

The quantitative analyses revealed that AI awareness, algorithmic recommendations, and trust were significant predictors of purchase frequency, impulse buying, and platform engagement. Moderation analyses also revealed that these relations vary across types of institutions and engagement in entrepreneurship. University students turned awareness into more frequent purchasing; polytechnic students were most reactive to algorithmic recommendations; and colleges of education were the least responsive, highlighting structural inequalities in digital exposure.

Qualitative data elaborated on this result. Students said they "study which content gets the most reactions," they reapply algorithmic recommendations and do real-time marketing lessons using AI-curated feeds. One participant noted:

"I monitor which content is most engaged with content, just like the way ads I get alerted as well." (Male, 24, University of Ibadan)

Another spoke of how trends inform the business:

"TikTok trends dictate what I sell; if it goes viral there, I know people will buy." (Male, 21, The Polytechnic Ibadan)

These findings suggest that algorithmic recommendations serve as informal market analytics, building upon Opportunity Recognition Theory (Ardichvili et al., 2003). The refrain "Being a student is not enough" resonated throughout the interviews, suggesting that young Nigerians are more than ever combining formal education with micro-enterprise — echoing Effectuation Theory's tenet of "making do" in under- resourced surroundings.

In addition to the positive aspects identified, the results also indicate emerging threats to the AI marketing milieu. Some students worried about what could be called the "creepy factor," in which hyper-personalized and overly targeted ads make them feel like they're being digitally watched. Such sentiments can contribute to attrition from platforms or an increase in use of ad-blocking tools, which in turn can erode engagement in the digital economy. Also, the risk of algorithmic bias is raised, as AI might favor established brands over new student enterprises, or inadvertently discriminate against certain demographic groups, among other possibilities. These concerns underscore the importance of ethical, transparent, and inclusive AI development within youth-centric digital marketplaces.

Theoretical Discussion

These findings support the core tenets of TAM and TPB in the context of AI-mediated African digital markets: awareness is a precursor to perceived usefulness; trust is consistent with normative and attitudinal beliefs; and recommendations increase perceived behavioural control. The following underlying mechanisms had the strongest influence on the core behaviours studied: purchase frequency, impulse buying, and platform participation, which are consistent with global research (Huang & Rust, 2021; Chatterjee & Rana, 2020).

Nonetheless, the research contributes to these frameworks by revealing that AI-based consumption is inextricably linked with the adaptions of the entrepreneur. Entrepreneur students apply some these same algorithmic cues meant to manipulate them as learning tools—they observe viral content, study patterns of engagement, and reverse-engineer what's working in the market. This logic offers a pathway through which consumption entails learning which embeds learning within the behavioural repertoires of entrepreneurs.

Theoretically, also, institutional differentiation represents further refinement. While universities deliver awareness-driven exposure; polytechnics serve as hands-on digital training ground; and colleges of education seem the least digitally oriented. These distinctions demonstrate institutional structure as a key moderator of AI responsiveness within developing countries and mirror more profound disparities in access to digital instruments, digital know-how and environments conducive to innovation.

Validation of Previous Studies and Contributions of This Study

The present results support previous research suggesting that personalization, trust and algorithmic signals influence consumer decisions. Increased knowledge and trust led to more purchase and impulsive decisions, and suggestions always nudged behaviour - this is consistent with international findings on digital persuasion (Huang & Rust, 2021; Chatterjee & Rana, 2020). In other words, the behavioural foundations of TAM and TPB are still applicable within the context of the African digital environment.

However, the added value of the paper is that it introduces and empirically substantiates the consumer–entrepreneur dual identity among African youth. Students are at once the targets of AI-curated marketing and the semiotic participants who recode those signals as strategic business intelligence. Their qualitative statements - e.g. "TikTok trends tell me what I should sell" - suggest that algorithmic recommendations are not just persuasive triggers, but informal analytics tools for identifying opportunities and entering markets.

Lastly, the fact that type of institution was found to significantly moderate these processes further contributes to cross-context theory by indicating that the learning context determines digital literacy, entrepreneurial intention, and attitudes toward AI systems. Nigerian universities, polytechnics and colleges are not all the same in the country's digital revolution and these differences directly affect what kinds or how the AI is employed, understood and taken. In sum, the finding for the study is the demonstration that AI marketing is not simply an issue of technology uptake or penetration in Africa, it is issue tightly related to social structural, and developmental, and the manner in which youth agency and informal economy is tangled up with institutional.

Practical Implications

This study contributes to theory and practice offering implications for marketing strategy, platform governance, and consumer learning in emerging market AI-enabled digital context. The results show that students do business with AI marketing as consumers and as informal market learners, who makes sense of and consume algorithmic cues.

Implications for Marketing Strategy

AI-based personalization is a conversion tool as well as a learning tool. Trust to AI-based advertisements and recommendations is a significant determinant of purchase frequency and buying on impulse, which means that transparent and reliable AI systems can increase engagement rather than pushing with too much persuasion. Marketers need to consider this dual nature of young users as consumers-entrepreneurs.

Implications for the design and regulation of platforms

Both opaque recommendation systems and quick content expiration have been linked to stronger impulsive behaviour, identifying platform design as a behavioural mediator. Increased transparency of the recommendation logic and the performance could enable a more informed engagement.

Implications for consumer learning and market access

Platforms enabled by AI serve as informal education environments, with variations by institution suggesting that digital infrastructure mediates the translation of awareness into action.

The study points to the importance of a more ethical and governance-based approach to AI powered digital

advertising in developing countries. Although AI greatly improves engagement, customization and interaction with the consumer, it also raises even more concerns over data privacy, transparency, online fraud and consumer protection. Hence, policymakers, platforms and advertisers should work together to clearly define the regulatory framework, enhance data protection mechanisms, authentication systems and responsible advertising practices. With the right balance of innovation and trust, the use of AI in digital marketing could evolve from simply boosting engagement to facilitating safer, more trustworthy, and sustainable engagement in the Nigerian digital market.

Limitations of the Study

There are a number of limitations to the present study that provide avenues for future research. First, because the study was cross-sectional, this limits causal inference; students' reactions to AI-driven marketing may change as they gain experience with platform algorithms and as they use platforms. Longitudinal or multi-wave designs may be more adequate to portray such dynamics.

While stratified convenience sampling ensured participation from all institutions, it is possible that selection bias was introduced, limiting the generalizability of findings to the study context. Future studies employing probabilistic, multi-regional sampling would improve external validity. The use of self-reported measures also raises concerns of social desirability and recall bias, more so in case of impulse buying and entrepreneurial behaviour; these issues could be addressed by combining behavioural trace data or experiments. Lastly, the study was limited in its examination of short-term effects and did not consider long-term consequences such as customer loyalty, brand building and venture sustainability.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study examined how AI-enabled marketing—through awareness, algorithmic recommendations, and trust in AI-based advertisements—influences the consumer behaviour of students in Nigerian tertiary institutions. Drawing on the Technology Acceptance Model and the Theory of Planned Behaviour, alongside Effectuation and Opportunity Recognition perspectives, the findings show that AI-driven marketing shapes not only purchasing behaviour but also informal entrepreneurial learning.

The findings show that AI awareness, recommendations, and trust are significant predictors of purchase frequency, impulse buying, and platform usage, while some differences are found across types of institutions. University students had higher high-level conceptual awareness of AI marketing, while polytechnic students had stronger behavioural responsiveness towards algorithmic signals. Qualitative findings also illustrate how students make sense of AI-driven signals as market intelligence and use them within microscale venturing.

In general, this work advances AI marketing research by focusing on the dual consumer-entrepreneur role of students in a new market context. Thus, AI-enabled platforms serve not simply as persuasive marketing instruments, but also as informal learning spaces where youth engagement in digital markets is configured.

In general, AI advertising is the game changing in Nigerian student markets but the advantages must be balanced with concerns about privacy, fairness and inclusivity. A balanced policy and platform design approach are thus needed to ensure that AI bolsters youth innovation, entrepreneurship and sustainable digital engagement, rather than perpetuating short-term algorithmic capture.

Recommendations

From the study results, the following several targeted recommendations for higher education institutions, platform actors, and policymakers can be drawn.

First, tertiary education institutions need to infuse AI literacy and digital marketing analytics into entrepreneurship education. Enhancing the students' understanding of algorithmic systems can facilitate technology acceptance and help them to utilize AI-driven marketing as active market players, rather than as passive consumers.

Second, institutional-level policies need to take account of the differences in digital use among institutions (type of university, polytechnic, college of education). The transferability of experiential, practice-based digital training especially common in polytechnic education (institutions)—could be a means to foster positive perceived behavioural control and entrepreneurial intention amongst institutional types.

Third, a national digital strategy that promotes AI literacy, data protection, paid journalism and ethical platform use. Improving in these areas can increase trust in AI-enabled systems and thus potentially facilitate more responsible participation in digital markets.

Fourth, digital platforms and e-commerce companies should promote the empowerment of users, while maintaining the persuasion efficiency, by increasing algorithmic transparency, providing user-friendly analytics tools, and enabling better visibility of small-scale sellers. Such design decisions maybe promote both consumer learning and informal entrepreneurship.

Finally, collaborative forms of support – such as student incubators, mentoring initiatives, and micro-grant programmes, may assist in channeling algorithmic engagement into lasting entrepreneurial activity thereby buttressing the consumer–entrepreneur dual identity brought to light in this study.

REFERENCES

1. Ardichvili, A., Cardozo, R., & Ray, S. (2003). A theory of entrepreneurial opportunity identification and development. Journal of Business Venturing, 18(1), 105–123. https://doi.org/10.1016/S0883-9026(01)00068-4
2. Buli, B. M., & Yesuf, W. M. (2015). Determinants of entrepreneurial intentions: Technical-vocational education and training students in Ethiopia. Education + Training, 57(8/9), 891–907. https://doi.org/10.1108/ET-08-2014-0085
3. Chatterjee, S., & Rana, N. P. (2020). Understanding the role of AI-based personalization in influencing consumer engagement and loyalty: Evidence from emerging economies. Journal of Retailing and Consumer Services, 54. https://doi.org/10.1016/j.jretconser.2019.102030
4. Choung, Y., David, M. E., & Ross, M. W. (2022). The trust paradox in AI-based advertising: Personalization, control, and consumer responses. Journal of Consumer Behaviour, 21(3), 485–497. https://doi.org/10.1002/cb.2015
5. Fauchart, E., & Gruber, M. (2011). Darwinians, communitarians, and missionaries: The role of founder identity in entrepreneurship. Academy of Management Journal, 54(5), 935–957. https://doi.org/10.5465/amj.2009.0211
6. Gbandi, E. C., & Ugbechie, C. I. (2023). Social media influence and buying behaviour of university students in South-West Nigeria. Journal of Research in Interactive Marketing, 17(3), 512–532. https://doi.org/10.1108/JRIM-09-2022-0191

7. Ghose, A., & Todri-Adamopoulos, V. (2016). Toward a digital attribution model: Measuring the impact of display advertising on online consumer behaviour. MIS Quarterly, 40(4), 889–910. https://doi.org/10.25300/MISQ/2016/40.4.05
8. Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50. https://doi.org/10.1007/s11747-020-00754-1
9. Jannach, D., & Adomavicius, G. (2016). Recommendation systems: Challenges, insights, and research opportunities. Information & Management, 53(5), 584–594. https://doi.org/10.1016/j.im.2015.11.003
10. Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.
11. Kuratko, D. F., Morris, M. H., & Schindehutte, M. (2020). Understanding the dynamics of entrepreneurship through framework approaches. Small Business Economics, 54(4), 927–941. https://doi.org/10.1007/s11187-018-0118-1
12. Ladokun, I. O., Opatola, A. A., & Eyinade, G. O. (2023). Instagram marketing and student purchase decisions in Nigerian private universities. Journal of Research in Interactive Marketing, 17(2), 330–349. https://doi.org/10.1108/JRIM-02-2023-0041
13. Liu, Y., Ma, Q., & Li, H. (2022). How platform design stimulates impulse buying: Evidence from AI-based social commerce. Electronic Commerce Research and Applications, 53, 101146. https://doi.org/10.1016/j.elerap.2022.101146
14. Mohan, G., Sivakumaran, B., & Sharma, P. (2013). Impact of store environment on impulse buying behaviour. European Journal of Marketing, 47(10), 1711–1732. https://doi.org/10.1108/EJM-03-2011-0110
15. Nagy, G., & Hajdu, L. (2022). Understanding AI-based decision-making in online customer journeys: A consumer perspective. Journal of Research in Interactive Marketing, 16(4), 689–707. https://doi.org/10.1108/JRIM-06-2021-0142
16. Okeke, M., Eze, S. C., & Chinedu, I. (2021). Digital entrepreneurship in Nigeria: Challenges and implications for education and policy. Journal of Entrepreneurship in Emerging Economies, 13(3), 378–399. https://doi.org/10.1108/JEEE-11-2020-0413
17. Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems: Introduction and challenges. In F. Ricci, L. Rokach, & B. Shapira (Eds.), Recommender systems handbook (pp. 1–34). Springer. https://doi.org/10.1007/978-1-4899-7637-6_1
18. Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. Academy of Management Review, 26(2), 243–263. https://doi.org/10.5465/amr.2001.4378020
19. Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. In Cutting-edge technologies in higher education (Vol. 7, pp. 1–10). Emerald Publishing. https://doi.org/10.1108/S2044-996820180000007001
20. Sitaridis, I., & Kitsios, F. (2024). Entrepreneurial intention and digital marketing competence among university students: A cross-country study. Journal of Entrepreneurship Education, 27(1), 1–12.
21. Suleiman, I. U., Abdulkadir, S., & Yakubu, A. I. (2024). Social commerce and buying behaviour of Gen Z students: Evidence from Northern Nigeria. Journal of African Business, 25(1), 82–104. https://doi.org/10.1080/15228916.2023.2249152
22. Yamane, T. (1967). Statistics: An introductory analysis (2nd ed.). Harper & Row.