Artificial Intelligence Driven Personalisation and Online Purchase Intention: The Mediating Role of Consumer Awareness and the Influence of Consumer Attitude toward AI in an Emerging Market

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ABSTRACT

Artificial intelligence (AI) has become an essential part of modern e-commerce, primarily through algorithm-driven personalisation that customises product suggestions and content for individual consumers. Although AI applications are spreading rapidly, there is limited empirical evidence on how AI-driven personalisation influences online purchase intentions in emerging markets, particularly regarding the psychological processes underlying this relationship. This study investigates the impact of AI-driven personalisation and consumer attitudes towards AI on online purchase intentions, with consumer awareness acting as a mediating variable.

Rooted in the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), the study uses a quantitative, cross-sectional research design. Data were gathered from online shoppers in major cities across South-East Nigeria through a structured questionnaire. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to examine both direct and indirect relationships among the study's constructs.

The results show that consumer attitude towards AI has a significant positive direct effect on online purchase intention. Conversely, AI-driven personalisation does not significantly influence purchase intention. Instead, its impact works indirectly via consumer awareness. Further analysis reveals that consumer awareness significantly mediates the relationship between consumer attitude towards AI and online purchase intention, emphasising awareness as a vital cognitive pathway through which positive perceptions of AI are converted into behavioural intention.

The study concludes that AI personalisation alone is not enough to encourage online purchasing in emerging markets unless consumers clearly understand how AI systems operate and the value they offer. By empirically positioning consumer awareness as a key mediating factor, the study expands TAM and TPB in AI-enabled consumption contexts. It offers practical insights for e-commerce platforms seeking to deploy AI responsibly and effectively in emerging digital economies.

Keywords: Artificial Intelligence; AI-Driven Personalisation; Consumer Attitude toward AI; Consumer Awareness; Purchase Intention; Emerging Markets

INTRODUCTION

Artificial intelligence (AI) has quickly transformed online shopping environments by enabling companies to offer personalised, data-driven consumer experiences (Aggarwal, Sharma, & Saxena, 2024). AI-driven personalisation, through customised recommendations, adaptive interfaces, and predictive suggestions, has become central to modern e-commerce strategies (Gujar, 2024). By analysing consumers' browsing histories, preferences, and behavioural patterns, AI systems aim to reduce information overload and make decisions easier (Ward, 2023). However, the behavioural effectiveness of these systems remains inconsistent, especially in emerging markets where consumer familiarity with AI is still developing.

While studies conducted in developed economies suggest that AI personalisation increases relevance and engagement, evidence from developing regions offers a more nuanced view. In emerging markets such as

Nigeria, online shoppers often show scepticism towards algorithmic decision-making, driven by limited digital literacy, uncertainty about AI processes, and a weak understanding of data-driven technologies. As a result, AI personalisation may not lead to purchase intention unless consumers are adequately aware of its purpose and benefits.

Consumer awareness refers to how well individuals understand the nature, function, and consequences of AI systems embedded within online platforms. Awareness allows consumers to process personalised content, assess its relevance, and develop informed attitudes towards AI-mediated interactions (Huang & Liu, 2025). Without awareness, personalisation may be seen as intrusive or manipulative rather than helpful (Kim & Han, 2025). Therefore, awareness likely acts as a psychological bridge between AI stimuli and behavioural outcomes.

Additionally, consumer attitude towards AI plays a vital role in shaping behavioural intentions. Attitude reflects an individual's overall evaluative judgement of AI technologies, including perceptions of usefulness, ease of use, and comfort (Geddam, Nethravathi, & Hussian, 2024). According to Mattson, Aurigemma, and Ren (2023), behavioural theories posit that positive attitudes increase the likelihood of intention formation, while negative attitudes reduce adoption tendencies. In AI-driven shopping environments, attitudes towards AI may independently influence purchase intention and indirectly affect how personalisation is perceived (Arachchi & Samarasinghe, 2025).

Despite growing academic interest in AI and consumer behaviour, research that integrates AI-driven personalisation, consumer attitudes towards AI, and consumer awareness within a single explanatory framework remains scarce, especially in Sub-Saharan Africa. Most current studies either focus on technological efficiency or direct behavioural outcomes, with limited exploration of the mediating cognitive mechanisms.

This study fills this gap by examining how AI-driven personalisation and consumer attitudes towards AI affect online purchase intention, with consumer awareness serving as a mediating variable. Focusing on South-East Nigeria, the research provides context-specific insights into AI-enabled commerce within an emerging digital economy. It improves both theory and practice by clarifying when and how AI personalisation becomes behaviourally effective.

REVIEW OF RELEVANT LITERATURE

AI-Driven Personalisation

AI-driven personalisation involves the algorithmic adjustment of content, recommendations, and interfaces to suit individual consumer profiles. Prior research shows that personalisation boosts perceived relevance and lowers search costs (Grewal et al., 2017). However, recent studies warn that personalisation may not constantly improve behavioural outcomes, especially when consumers lack understanding of how AI systems work (Huang & Rust, 2021). In emerging markets, opaque personalisation mechanisms may increase discomfort rather than foster trust.

Consumer Attitude toward AI

Consumer attitudes towards AI reflect a learned evaluative disposition towards AI technologies. Based on TAM and TPB, attitude is influenced by beliefs about usefulness, ease of use, and control (Davis, 1989; Ajzen, 1991). Recent empirical research confirms that positive attitudes towards AI are significant predictors of technology adoption and behavioural intention (Rane et al., 2024). In online shopping, favourable attitudes towards AI enhance acceptance of automated recommendations and decrease resistance to algorithmic mediation.

Consumer Awareness

Consumer awareness includes understanding AI functions, data use, and the benefits of personalisation. Awareness lessens uncertainty and helps people make better decisions. Recent research shows that awareness

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improves consumers' ability to understand AI outputs and reduces perceptions of intrusiveness (Laki & Miklosik, 2025). In developing economies, awareness is uneven and heavily influences AI effectiveness.

Purchase Intention

Purchase intention reflects a consumer's readiness to buy and is a reliable predictor of actual behaviour. In AI-mediated contexts, intention is shaped not only by system performance but also by cognitive understanding and attitudinal acceptance. Scholars increasingly argue that AI influences intention indirectly through psychological mechanisms rather than direct automation effects (Grewal et al., 2021).

Theoretical Framework and Hypotheses

The study is anchored in:

Technology Acceptance Model (TAM): Explains how perceived usefulness shapes attitudes toward AI.

Theory of Planned Behaviour (TPB): Positions attitude as a determinant of intention.

Consumer awareness extends these theories by explaining how AI inputs are cognitively processed before intentions are formed.

H_1: AI-driven personalisation has a significant effect on online purchase intention.

H_2: Consumer attitude toward AI has a significant effect on online purchase intention.

H_3: AI-driven personalisation has a significant effect on consumer awareness.

H_4: Consumer attitude toward AI has a significant effect on consumer awareness.

H_5: Consumer awareness mediates the relationship between AI-driven personalisation, consumer attitude toward AI, and online purchase intention.

Conceptual Framework

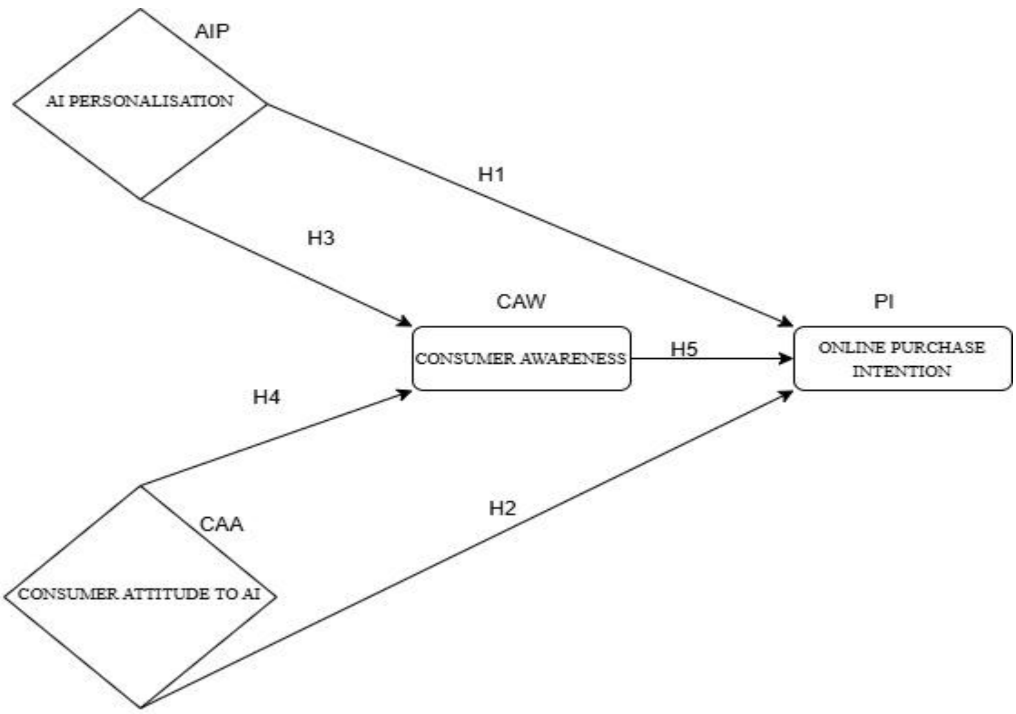

Figure 1: The research Conceptual Framework
Source: The researcher's Conceptualisation

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MATERIALS AND METHODS

This study employed a quantitative, explanatory research design to test the proposed hypotheses and examine the relationships among AI-driven personalisation, consumer attitude toward AI, consumer awareness, and online purchase intention. Data were collected through a structured questionnaire administered electronically to online shoppers in five major cities in South-East Nigeria: Awka, Owerri, Enugu, Umuahia, and Abakaliki, chosen for their high levels of digital and commercial activity. Given the nearly infinite population of online shoppers, Cochran's formula was used to determine a minimum sample size of 384 respondents. At the same time, a convenience sampling technique ensured participation by individuals with relevant online shopping experience. Primary data were supplemented by secondary data from peer-reviewed journals and reports to provide theoretical support. Purchase intention was the dependent variable, consumer awareness served as the mediating variable, and AI-driven personalisation and consumer attitude toward AI were the independent variables. Each construct was measured using three to four items adapted from validated scales and assessed on a four-point Likert scale to improve response clarity and reliability. Data analysis employed Structural Equation Modelling (SEM) in SPSS and JASP, enabling the simultaneous estimation of multiple relationships and mediation effects via bootstrapping. Before hypothesis testing, reliability, validity, and model adequacy were evaluated using descriptive statistics, confirmatory factor analysis, and reliability tests to confirm the robustness of the measurement and structural models.

ANALYSIS AND RESULT

Table 1 Socio-demographic variables

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	172	56.77
	Female	131	43.23
Age Group	18–25 years	46	15.18
	26–35 years	87	28.71
	36–45 years	41	13.53
	46–55 years	88	29.04
	56 years and above	41	13.53
Marital Status	Single	86	28.38
	Married	154	50.83
	Divorced/Widowed	63	20.79
Educational Qualification	Secondary education	54	17.82
	Diploma / NCE	89	29.37
	Bachelor's degree	114	37.62
	Postgraduate degree	46	15.18
Monthly Income Level	Very low income	42	13.86
	Low income	58	19.14
	Middle income	104	34.32
	High income	78	25.74
	Very high income	21	6.93

Table 1 summarises the demographic characteristics of the 303 respondents. The gender distribution shows a slight male dominance (56.77%), with females constituting 43.23%, indicating balanced participation in online shopping. Most respondents fall within the economically active age groups, particularly 26–35 years (28.71%) and 46–55 years (29.04%), suggesting a mix of technologically inclined and financially stable consumers. Over half of the respondents are married (50.83%), highlighting the presence of household decision-makers. The educational profile reveals that a majority possess tertiary education, with 52.80% holding bachelor's or postgraduate qualifications, indicating adequate digital and cognitive capacity to engage with AI-enabled platforms. In terms of income, most respondents fall into the middle- and high-income categories, demonstrating sufficient purchasing power to support online shopping and AI-driven consumption decisions.

Descriptive Statistics and Normality Assessment

Table 2 below presents the descriptive statistics of the study constructs. Responses were measured on a four-point Likert scale, and no missing values were observed. Mean values above the scale midpoint indicate a general tendency toward agreement among respondents.

Table 2 Descriptive Statistics of Study Constructs

Construct	Mean	Std. Deviation	Skewness	Kurtosis
AI-Driven Personalisation (AIP)	2.7	0.88	Negative	Negative
Consumer Attitude toward AI (CAA)	2.9	0.81	Negative	Negative
Consumer Awareness (CAW)	2.8	0.85	Negative	Negative
Purchase Intention (PI)	3.0	0.79	Negative	Negative

The negative skewness across constructs suggests that respondents generally agreed with the statements, while the negative kurtosis values indicate relatively flat distributions. Normality tests (Kolmogorov–Smirnov and Shapiro–Wilk) were significant for all items ($p < 0.05$), confirming non-normal data distribution. This justified the use of PLS-SEM with bootstrapping, which does not assume multivariate normality.

Confirmatory Measurement Model Assessment (PLS-CCA)

Given the study's predictive orientation, Confirmatory Composite Analysis (CCA) within PLS-SEM was employed. Indicator reliability was assessed using outer loadings, with weak items removed to improve construct quality.

Table 3 Indicator Loadings after Item Purification

Construct	Indicator	Loading	Decision
AIP	AIP2	0.731	Retained
	AIP3	0.758	Retained
	AIP4	0.701	Retained
	AIP5	0.722	Retained
CAA	CAA1–CAA4	0.708–0.781	Retained
CAW	CAW1–CAW5	0.702–0.769	Retained
PI	PI1–PI5	0.715–0.783	Retained

Indicators with loadings below the recommended threshold (0.40) were removed at earlier stages. All retained items exhibit acceptable to strong loadings (≥ 0.70), confirming indicator reliability and supporting the adequacy of the confirmatory measurement model.

Reliability and Convergent Validity

Internal consistency, reliability, and convergent validity were evaluated using Cronbach's Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE).

Table 4 Reliability and Convergent Validity Results

Construct	Cronbach's α	Composite Reliability	AVE
AIP	0.730	0.763	0.539
CAA	0.721	0.764	0.564
CAW	0.750	0.780	0.522
PI	0.756	0.720	0.549

All constructs exceed the minimum thresholds of $\alpha \geq 0.70$, $CR \geq 0.70$, and $AVE \geq 0.50$, indicating adequate internal consistency and strong convergent validity. This confirms that the indicators reliably measure their respective latent constructs.

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Discriminant Validity Assessment

Discriminant validity was examined using the Fornell–Larcker criterion and the Heterotrait-Monotrait ratio (HTMT).

Table 5 Fornell–Larcker Criterion

Construct	AIP	CAA	CAW	PI
AIP	**0.582**			
CAA	0.431	**0.681**		
CAW	0.398	0.512	**0.650**	
PI	0.367	0.546	0.568	**0.591**

Table 6 HTMT Ratios

Constructs Compared	HTMT
AIP – CAA	< 0.85
AIP – CAW	< 0.85
CAA – CAW	< 0.90
CAW – PI	< 0.90

For the Fornell–Larcker test, the square root of AVE for each construct exceeds its correlations with other constructs. Additionally, HTMT values fall below recommended thresholds, and bootstrapped confidence intervals do not include 1.00. These results confirm adequate discriminant validity, indicating that all constructs are empirically distinct.

Table 7 Bootstrapped Measurement Model Summary

Assessment Area	Result
Indicator loadings	All significant ($p < 0.05$)
Reliability estimates	Stable across resamples
HTMT confidence intervals	Did not include 1.00
Model suitability	Supported

Bootstrapping results show that all retained indicators are statistically significant and stable across resamples. This confirms the robustness of the measurement model and provides strong empirical justification for proceeding to structural model evaluation and hypothesis testing.

Structural Model Evaluation and Hypothesis Testing

Table 8 Structural Path Coefficients and Hypothesis Testing

Hypothesis	Path	β (Path Coefficient)	t-value	p-value	Decision
H_1	AIP → PI	0.067	1.868	0.062	Not Supported
H_2	CAA → PI	0.172	4.365	0.000	Supported
H_3	AIP → CAW	0.119	1.896	0.058	Not Supported
H_4	CAA → CAW	0.303	5.029	0.000	Supported

Direct Effects of AI-Driven Personalisation and Consumer Attitude toward AI

The results indicate that AI-driven personalisation does not have a statistically significant direct effect on online purchase intention ($\beta = 0.067$, $p > 0.05$). Although the relationship is positive, the effect size is weak and fails to meet conventional significance thresholds. This finding suggests that personalised recommendations, tailored offers, and algorithmic content alone are insufficient to motivate Nigerian consumers to make online purchase decisions directly.

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This outcome aligns with the Technology Acceptance Model (TAM), which posits that system features influence behavioural intention primarily through users' perceptions and attitudes rather than through direct technological exposure (Davis, 1989). In the Nigerian context, many consumers are already accustomed to algorithmic suggestions on e-commerce platforms; hence, personalisation may be perceived as a routine background function rather than a persuasive driver of purchasing behaviour. Similar findings have been reported by Grewal et al. (2017) and Davenport et al. (2020), who argue that personalisation delivers value only when users clearly understand and trust the underlying technology.

In contrast, consumer attitude toward AI exhibits a significant positive effect on online purchase intention ($\beta = 0.172$, $p < 0.001$). This result underscores the centrality of attitude as a behavioural determinant, consistent with both TAM and the Theory of Planned Behaviour (TPB). According to TAM, favourable attitudes toward a technology, shaped by perceived usefulness and ease of use, lead to stronger behavioural intentions (Davis, 1989). TPB similarly emphasises attitude as a primary antecedent of intention (Ajzen, 1991).

Within Nigeria's digital marketplace, where concerns about data misuse, online fraud, and system reliability persist, consumers' psychological acceptance of AI plays a decisive role. When consumers view AI as helpful, secure, and beneficial, they are more willing to engage in online purchasing, irrespective of the sophistication of personalisation features. This finding is consistent with recent studies in emerging markets that highlight trust-based and attitudinal mechanisms as stronger predictors of e-commerce behaviour than technological features alone (Bhatt & Singh, 2025; Rane et al., 2024).

Effects on Consumer Awareness

The results further reveal that AI-driven personalisation does not significantly influence consumer awareness ($\beta = 0.119$, $p > 0.05$). This suggests that exposure to personalised content does not necessarily lead to consumers' conscious understanding of AI systems. Many users interact with AI passively, benefiting from recommendations without recognising or reflecting on the technology behind them.

From a theoretical perspective, this finding challenges the simplistic assumption in TAM that exposure automatically leads to cognitive engagement. Instead, it supports arguments that awareness requires intentional communication, transparency, and learning, rather than mere system interaction (Grewal et al., 2017). In Nigeria, where digital literacy levels vary widely, AI-driven processes often operate invisibly, limiting their potential to enhance consumer awareness.

Conversely, consumer attitudes towards AI significantly influence consumer awareness ($\beta = 0.303$, $p < 0.001$). Consumers with positive attitudes are more attentive to AI functions, more curious about how systems operate, and more open to information about AI use. This aligns with TPB, which indicates that positive attitudes shape cognitive engagement and behavioural readiness (Ajzen, 1991). It also supports the view that awareness is not just a result of exposure but is strongly affected by existing beliefs and perceptions about technology.

Table 9 Mediation (Indirect Effects) Results

Mediation Path	Indirect Effect (β)	t-value	p-value	Mediation Result
AIP → CAW → PI	0.067	1.868	0.062	Not Supported
CAA → CAW → PI	0.172	4.365	0.000	Supported

Mediating Role of Consumer Awareness

The mediation analysis provides deeper insight into the mechanisms underlying AI-enabled online shopping behaviour. Consumer awareness does not mediate the relationship between AI-driven personalisation and online purchase intention, indicating that personalisation neither directly nor indirectly influences online purchase intention through awareness. This reinforces the view that personalisation alone is insufficient to shape consumer cognition or behaviour in meaningful ways.

However, consumer awareness significantly mediates the relationship between consumer attitude toward AI and online purchase intention. These finding highlights awareness as a critical psychological pathway through

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which favourable attitudes toward AI are converted into purchase intentions. In other words, consumers who already hold positive views about AI become more aware of AI applications, and this heightened awareness, in turn, strengthens their intention to purchase online.

This result is theoretically consistent with both TAM and TPB. TAM suggests that attitudes influence intention through cognitive evaluations, while TPB recognises that beliefs and awareness shape behavioural control and intention formation (Ajzen, 1991; Davis, 1989). Empirically, this finding supports recent literature that positions consumer awareness as a key mechanism linking AI perceptions to marketplace behaviour, particularly in developing economies where technological understanding remains uneven (Rane et al., 2024).

DISCUSSION OF FINDINGS

This study aimed to explain how AI-driven personalisation and consumer attitudes towards AI influence online purchase intentions in an emerging market, with consumer awareness acting as a mediating factor. The findings indicate that AI-driven personalisation does not directly impact online purchase intention among consumers in South-East Nigeria. Although personalisation enhances the shopping interface and content relevance, it does not necessarily lead to purchase decisions. This suggests that Nigerian consumers may see AI-based recommendations as standard platform features rather than convincing decision cues. This outcome is consistent with the Technology Acceptance Model, which states that technological features affect behaviour mainly through users' perceptions and attitudes rather than through direct exposure (Davis, 1989). Similar conclusions have been drawn by Grewal et al. (2017) and Davenport et al. (2020), who argue that personalisation only provides behavioural value when consumers understand and trust the underlying AI systems.

In contrast, consumer attitude towards AI significantly influences online purchase intentions. This finding reinforces the central role of attitude in shaping behavioural intention, as proposed by both TAM and the Theory of Planned Behaviour (Ajzen, 1991; Davis, 1989). In the Nigerian context, where concerns about data privacy, online fraud, and algorithmic transparency are common, consumers' willingness to trust and accept AI plays a crucial role in their purchasing decisions. When AI is perceived as helpful, reliable, and supportive rather than intrusive, consumers are more inclined to engage in online transactions. This result aligns with recent studies in emerging markets that identify attitude and trust as key drivers of AI-enabled consumer behaviour (Rane et al., 2024; Bhatt & Singh, 2025).

The findings further show that AI-driven personalisation does not notably improve consumer awareness. This suggests that frequent engagement with personalised content does not necessarily result in a conscious understanding of how AI systems work. Many consumers benefit from AI-enabled features without actively considering the technology behind them. This supports the idea that awareness does not develop passively from system use but requires intentional transparency and communication (Laki & Miklosik, 2025). Conversely, consumer attitudes towards AI significantly influence consumer awareness, indicating that individuals with positive views of AI are more alert to AI processes and more eager to understand how such systems function.

Finally, the mediation analysis reveals that consumer awareness plays a meaningful role in converting favourable attitudes toward AI into online purchase intention. While awareness does not mediate the relationship between AI-driven personalisation and purchase intention, it significantly mediates the relationship between consumer attitude toward AI and purchase intention. These findings highlight awareness as a key cognitive pathway through which positive attitudes are transformed into behavioural readiness. It extends TAM and TPB by demonstrating that, in emerging digital markets such as Nigeria, understanding and awareness of AI are essential for translating favourable perceptions into actual purchase intentions.

CONCLUSIONS

This study explored how AI-driven personalisation and consumer attitudes towards AI affect online purchase intentions in an emerging market, with consumer awareness acting as a mediating factor. The findings show that AI-driven personalisation, although common on online shopping platforms, does not directly encourage purchase intentions among Nigerian consumers. This indicates that the mere presence of advanced AI features is not enough to influence behaviour when understanding and trust in AI are limited.

Conversely, consumer attitudes towards AI are a key factor influencing online purchase intentions. Consumers who perceive AI as helpful, trustworthy, and supportive are more likely to engage in online shopping. Notably, the study shows that consumer awareness plays a vital mediating role by turning positive attitudes towards AI into purchase intentions. This highlights awareness as a crucial psychological process through which perceptions of AI are converted into behaviour.

Overall, the study confirms the importance of the Technology Acceptance Model and the Theory of Planned Behaviour in explaining AI-enabled consumer behaviour, while expanding these theories by empirically demonstrating that consumer awareness is a vital cognitive link in emerging digital markets such as Nigeria. The findings emphasise that successful AI adoption in e-commerce depends less on technological sophistication and more on how consumers perceive, understand, and cognitively engage with AI systems.

RECOMMENDATIONS

Managerial Recommendations: E-commerce firms operating in Nigeria should focus on shaping consumer attitudes and raising awareness as they deploy AI. Instead of relying solely on algorithmic personalisation, platforms should incorporate transparent explanation features, such as “why this recommendation appears,” simplified AI guides, and interactive onboarding tools. Previous research indicates that transparency and explainability enhance trust and acceptance of AI systems, especially in consumer-facing contexts (Grewal et al., 2017; Huang & Rust, 2021). Additionally, encouraging positive user experiences with AI has been shown to foster favourable attitudes, which directly influence behavioural intention (Davis, 1989; Rane et al., 2024). In Nigeria, where digital scepticism remains high, these strategies can help translate AI capabilities into actual purchasing behaviour.

Policy and Industry Recommendations: Policymakers and regulatory bodies should enhance AI governance and consumer protection frameworks to build trust in digital platforms. Research indicates that transparent data-privacy policies and visible regulatory safeguards significantly increase consumers’ willingness to engage with AI-driven services (Bhatt & Singh, 2025). Public-sector investment in digital and AI literacy programmes is also crucial, as raising consumer awareness has been shown to reduce uncertainty and perceived risks associated with algorithmic decision-making (Laki & Miklosik, 2025). In the Nigerian context, coordinated efforts among regulators, educational institutions, and industry stakeholders can encourage informed participation in the digital economy.

Academic and Research Recommendations: Future research should broaden existing technology adoption models by explicitly incorporating consumer awareness as a mediating factor in AI-enabled environments. Recent studies suggest that awareness plays a vital role in translating positive attitudes toward technology into behavioural outcomes, especially in emerging markets (Grewal et al., 2021; Rane et al., 2024). Scholars should also examine contextual moderators, such as cultural values, institutional trust, and digital infrastructure quality, to better explain variations in AI adoption across developing economies.

Contribution to Knowledge

This study makes several important contributions to the literature on artificial intelligence and consumer behaviour, particularly within emerging markets.

First, the study provides empirical evidence that AI-driven personalisation does not directly affect online purchase intention in an emerging economy context. This finding challenges the dominant assumption in much of the AI and e-commerce literature, which is based mainly on developed economies, that personalisation automatically leads to purchasing behaviour. By demonstrating this divergence, the study highlights the contextual limitations of existing AI adoption models.

Second, the study enhances the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) by empirically identifying consumer awareness as a crucial psychological mechanism through which positive attitudes towards AI are converted into purchase intentions. This builds upon earlier models that mainly emphasise perceived usefulness, ease of use, and attitude, by illustrating that awareness plays a distinct and mediating role in AI-driven consumption.

Third, the research provides context-specific insights from Nigeria, a setting that remains underrepresented in studies of AI-consumer behaviour. By focusing on South-East Nigeria, the study enriches the global discussion on AI adoption by demonstrating how digital trust issues, uneven AI literacy, and institutional factors shape consumer responses to AI technologies in emerging markets.

Finally, the study presents a practical theoretical integration by connecting technological features (AI-driven personalisation), psychological assessments (consumer attitude), and cognitive understanding (consumer awareness) within a unified explanatory framework. This holistic approach offers a deeper insight into how AI systems influence consumer decision-making beyond technological determinism.

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