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MARKETING | RESEARCH ARTICLE

From Browsing to Buying More: The Journey of Cross-Selling and Upselling in E-Commerce

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Abstract:
Background: The rapid growth of e-commerce has positioned algorithm-driven recommendation systems, such as cross-selling and upselling, as key tools for enhancing customer engagement and transaction value. However, how consumers in developing countries like Nigeria view and react to these systems has received little empirical attention.
Purpose: The study examines how cross-selling and upselling recommendation systems affect consumers' purchasing decisions in Nigeria's rapidly expanding e-commerce sector.
Method: The study used a quantitative cross-sectional research design based on survey data obtained from 778 Nigerian customers sampled using the snowball sampling technique, who have previous experience shopping using e-commerce sites. PLS-SEM was used for data analysis.
Findings: Perceived usefulness is influenced by perceived ease of use. Purchase intention is positively impacted by perceived usefulness. It has been demonstrated that trust plays a significant role in positively influencing both purchase intention and acceptance of recommendations.
Conclusions: This research offers three noteworthy insights. The first contribution relates to TAM's usefulness in algorithm-based recommendation systems, where the theory continues to be useful.
Second, the concept of trust is added to the theory and serves as another dimension influencing consumer behavior. Third, the channel from acceptance to higher transaction value is validated empirically.
Research Implications: In practical terms, the results imply that e-commerce websites should concentrate on creating user-friendly interfaces, ensuring better recommendations through data personalization, and focus on building trust in customers by ensuring transparency and dependable service delivery.

Keywords: cross-selling, upselling, technology acceptance model, trust, purchase intention, recommendation systems

JEL Classification: M31, D12, L81

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PUBLIC INTEREST STATEMENT

Personalized product recommendations have become a common feature of online shopping, yet many consumers remain cautious about trusting these suggestions. This study examines the factors that influence consumers' acceptance of cross-selling and upselling recommendations on e-commerce platforms. The findings show that while recommendations that are easy to use and perceived as useful can encourage purchasing, consumer trust is the strongest factor influencing purchase decisions and increased spending. The study provides valuable insights for e-commerce businesses, policymakers, and digital marketers seeking to develop secure, transparent, and trustworthy online shopping environments that enhance consumer confidence and support the sustainable growth of digital commerce.

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1. Introduction

The emergence of e-commerce has fundamentally changed the dynamic between consumers and retailers, transforming the purchasing process from a one-sided transaction into an interactive, algorithm-driven interaction (Borah et al., 2024; May et al., 2025; Rohit, 2024; Vogel et al., 2021). In this new environment, the role of cross-selling and upselling recommendation engines in generating sales for online stores has become increasingly important, allowing websites to manipulate shopper behavior in real-time through the presentation of additional or higher-quality products at the point of sale (Givan & Pancasilawan, 2025; Sharabati et al., 2024; Emadi et al.,2021; Ghoshal et al., 2021). The success of platforms like Amazon and Alibaba in generating enormous profits through their recommendation engines is a testament to the immense sales-generating power of these tools, with personalized recommendations contributing significantly to overall platform sales worldwide (Ariawan & Ariadi, 2025; Hunia & Krynytsia, 2025).

Nevertheless, even though recommendation systems are extensively used in the context of e-commerce, emphasis was mainly on technical and organizational consequences rather than cognitive behaviour. He et al. (2024) carried out an experimental study on 1,200 users of e-commerce and found that the accuracy of recommendations increased the level of satisfaction by 31%, and the diversity of recommendations increased engagement by 19%. However, their research is limited to system-related factors (precision, recall, coverage) and does not consider consumer cognitive processing factors. Xu et al. (2022) meta-analysis of 47 cross-selling studies in the retail context reveals that cross-selling boosts sales by 18 to 25%; however, the study is limited to only firm-level sales effects and does not address customer choice behavior or the mental barriers to recommendation acceptance.

Despite the widespread adoption of recommendation systems in e-commerce, existing studies have predominantly emphasized technical performance and organizational outcomes rather than the psychological processes underlying consumer responses. For example, He et al. (2024) found that recommendation accuracy increased customer satisfaction by 31%, while recommendation diversity improved engagement by 19%. However, their study focused primarily on system-performance indicators and did not examine how consumers cognitively evaluate or interpret recommendation outputs. Similarly, Xu et al. (2022), in a meta-analysis of 47 cross-selling studies, reported that cross-selling strategies significantly enhanced sales performance. Nevertheless, their investigation concentrated on firm-level outcomes and provided limited insight into the psychological mechanisms that drive consumers' acceptance of recommendations.

Likewise, Van der Borgh et al. (2023) highlighted the strategic value of cross-selling for revenue growth and business development, but their analysis was conducted from an organizational perspective, offering little understanding of how consumers perceive and respond to recommendation systems. Furthermore, Kashef and Pun (2022) developed a clustering-based recommendation model that substantially improved recommendation accuracy; however, their study was restricted to algorithmic performance measures such as precision and recall and did not consider the roles of trust, perceived usefulness, or consumer decision-making processes.

Collectively, these studies demonstrate the technical and commercial effectiveness of recommendation systems but provide limited evidence regarding the technology and psychological factors that influence consumers' willingness to trust, accept, and act upon

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algorithm-generated recommendations. Consequently, there remains a significant gap in understanding how technology acceptance factors and trust jointly shape recommendation acceptance and purchase behaviour, particularly in emerging e-commerce markets such as Nigeria.

In Particular, there seems to be a notable dearth of studies investigating the impact of technology acceptance variables, including Perceived Ease of Use and Perceived Usefulness, on customer behaviours related to recommendation systems. The Technology Acceptance Model (TAM), developed by Davis (1989), provides the theoretical foundation for understanding technology adoption. Davis' (1989) Theory of Technology Acceptance Model (TAM) provides a theoretical framework for explaining technology acceptance. According to TAM, PEOU refers to how easy a person believes the system will be to use, whereas PU refers to how much an individual believes that utilizing the system will boost his/her work efficiency. According to the notion, the more user-friendly the system is, the more likely it is regarded to be useful, resulting in behavioral intention to utilize the technology.

This issue is even more complicated when it comes to emerging markets, because consumer behaviour in such countries differs significantly from behaviour in developed nations (Pandya & Dholakia, 2021; Hunia & Krynytsia, 2025; Van et al., 2023; Winarso et al., 2025; Yang & Ji., 2022). Many emerging markets could provide fruitful areas for empirical study, but one of the most promising examples is Nigeria. Being the biggest African digital market, Nigeria has recently seen fast growth of e-commerce thanks to applications like Jumia (Nursania2024; Sharma et al., 2023). However, various structural problems, ranging from mobile browsing to high-risk perception and security issues related to payments, create a specific consumer context that does not coincide with what has been seen by far in the West-based empirical literature on technology acceptance (Obieze et al., 2024; Olarinde et al., 2024; Nnindini et al.,2024; Aroszewicz,2023; Lee et al.,2024). Thus, there is a need to study Nigerian consumers' reactions to recommendation systems in the light of theoretical knowledge of consumer psychology. Indeed, trust deserves special consideration in this regard. In environments where consumer protection institutions have not fully evolved, trust in the platform's competence, integrity, and intentions is necessary to facilitate consumers' involvement with the algorithms used to recommend products (Pan et al., 2025; Rauhaus et al., 2024).

Technology Acceptance Model (TAM) has been extensively used in technology adoption literature; most of the applications do not consider the role of trust and risk perception within the algorithmic environment. The constructs such as perceived usefulness and perceived ease of use have been extensively validated in prior studies; however, their impact on trust within the algorithmic environment, specifically their relationship with trust and how they affect the acceptance and purchase behavior, has not yet been explored. Most of the literature has focused on developed countries with established digital infrastructure, creating an obvious contextual gap. Although the Technology Acceptance Model (TAM) has consistently demonstrated that perceived ease of use and perceived usefulness are important determinants of technology adoption, recommendation systems operate within algorithmic environments where consumers often have a limited understanding of how recommendations are generated. Consequently, users must rely not only on cognitive evaluations of system usefulness but also on their trust in the platform delivering the recommendations. Trust reduces perceived uncertainty and risk associated with algorithm-driven suggestions, particularly in emerging markets where concerns regarding payment security, privacy protection, and service reliability remain prevalent. Therefore, integrating trust with TAM provides a more comprehensive framework for explaining consumer acceptance of cross-selling and upselling recommendations in e-commerce environments. The current study contributes to the literature by considering TAM and trust in conjunction and exploring the impact of both on the acceptance of a recommendation system, purchase intention, and average order value.

However, there is limited understanding of how trust influences the relationship between TAM Constructs and purchase intention within the context of Nigerian e-commerce platforms (Ezekiel, 2021; Kalkan& Şahin, 2022; Rosário & Raimundo, 2021; Timoumi et al., 2022). This paper seeks to address this gap in the literature by formulating and validating a conceptual model that includes PEU, PU, and Trust as predictors of PI and AR, and PI as the predictor of AOI among Nigerian consumers. The study surveyed 778 active users of e-commerce platforms in Nigeria and utilized PLS-SEM for data analysis. The findings will contribute to extending the theoretical framework of TAM into the realm of algorithms (Cai & Chen, 2022). The findings will add to the body of literature in three ways: (1) they will advance the theoretical understanding of cross-selling and upselling in e-commerce; (2) they will provide empirical evidence on the role of these strategies in e-commerce; and (3) they will provide useful insights for online marketing actors and policymakers (Winarso et al., 2025; Yu et al., 2024). Existing studies have primarily examined recommendation systems from technical and organizational perspectives, emphasizing algorithm performance, recommendation accuracy, and sales outcomes. Consequently, little is known about the psychological mechanisms through which consumers evaluate, trust, and accept recommendation systems, particularly in emerging markets characterized by higher perceived risk and weaker institutional safeguards. This study addresses this gap by integrating Technology Acceptance Model constructs (Perceived Ease of Use and Perceived Usefulness) with Trust to explain recommendation acceptance, purchase intention, and average order value intention among Nigerian e-commerce consumers.

2. Literature Review

2.1 The Technology Acceptance Perspective

One of the most reliable and extensively used theoretical frameworks for understanding how customers react to information systems and digital technologies is the Technology Acceptance Model (TAM), which was first put forth by Davis in 1989. Fundamentally, TAM asserts that two mental concepts, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), are the primary determinants of an individual's behavioural intention to use a technology, with PEOU exerting both a direct influence on behavioural intention and an indirect influence mediated through (Huang & Yang, 2025; Venkatesh & Davis, 2000). Subsequent research efforts have extensively tested the validity of the model in different technological settings such as internet banking, m-commerce, and online services (Lee et al., 2025; Shaw et al., 2020; Cai & Chen, 2022).

When examining the use of recommendation systems in electronic commerce, the constructs of PEOU measure how consumers view cross-selling and upselling interfaces as mentally simple and effortless to use, whereas the construct of PU assesses the extent to which consumers view these systems as efficient in terms of shopping and decision making (Xu et al., 2022; Van et al., 2023).

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While the application of TAM in technology adoption is quite extensive, its application in personalization technologies such as recommendation systems is relatively underdeveloped (Nnindini et al., 2024), especially in developing markets where technological perceptions are influenced by infrastructural and institutional factors (Obieze et al., 2024).

2.2 Relationship between variables

2.2.1 Perceived Ease of Use and Perceived Usefulness

Due to the expansion of e-commerce, the number of competitors for online retailers has increased, leading to the adoption of personalization technologies to enhance engagement and transactional value. In this context, recommendation systems have emerged as the most effective technology for online retailers. They use customers' behavior to gather information to generate recommendations that help reduce decision-making complexity for customers (Anggraini et al., 2022; Tanjung et al., 2024). This has been demonstrated by Amazon to generate revenue. Technology Acceptance Model implies that Perceived Ease of Use (PEOU) influences Perceived Usefulness (PU). Perceived Ease of Use means “the degree to which a person believes that using the system or technology will be effort-free,” whereas Perceived Usefulness means “the degree to which a person believes that using the system would improve his or her job performance.” The recommendation system should be easy for users and embedded into the Cross-Selling and Upselling interface and online browsing process (Meliawati et al., 2023).

When consumers perceive recommendation prompts as easy to navigate and requiring little cognitive effort, they are more likely to perceive them as functionally beneficial. Ease of navigation allows consumers to process information with little mental effort, leading to better decision-making. In addition, when consumers experience difficulties with recommendation prompts, this friction can lead to a negative perception of the recommendation's value, even when the information is relevant to their needs (Mollel & Chen, 2025). In the context of the emerging markets with mobile-centric usage patterns, ease of navigation will be crucial. If cross-selling and upselling functions are well designed and easy to navigate, consumers are more likely to perceive them as beneficial. In line with the causal logic of TAM.

H1: Perceived ease of use has a positive influence on Perceived Usefulness.

2.2.2 Perceived Usefulness and Purchase Intention

As TAM theory suggests, the primary driver of behavioral intention to use technology is perceived usefulness. When applied to the specific example of an e-commerce platform's recommendation system, the factor of PU represents the level to which the consumer perceives the usefulness of the cross-selling or upselling recommendations in terms of improving the shopping experience in general (Vinodh et al., 2024).

As long as the consumer perceives that the additional products recommended are truly beneficial to the original purchase decision, the consumer is more likely to have a positive attitude toward these additional products or services. This can be realized in terms of improved convenience or better value propositions. This would naturally enhance the factor of purchase intention, which represents the level to which the consumer intends to complete a purchase based on the given recommendation system.

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According to Cai and Chen (2022), cross-selling and upselling practices have shown support for the idea that perceived functional value has a strong predictive role in making the decision to purchase something in electronic commerce settings. In emerging markets, it may be the case that the cognitive evaluation of how useful the system is could have an even more important impact.

H2: Perceived usefulness has a positive influence on purchase intention.

2.2.3 Trust and Acceptance of Recommendations

In addition to cognitive evaluations of utility and simplicity, trust is an important factor in consumer decision-making in the online environment. It is an evaluation of the integrity, dependability, and technology savvy of the platform. Consumers in algorithm-based environments have to rely on the algorithm to provide suggestions that are relevant to their interests. However, if the algorithm is viewed as biased, manipulative, or even overly commercial, the level of acceptance of the recommendation may decrease. In the new e-commerce environments, factors such as data privacy, payment security, and delivery may make the consumer more responsive to trust-related factors. Therefore, even if the recommendation algorithm is highly efficient, the consumer may still not accept the recommendation if they do not have trust in the platform (Djamaludin & Fahra, 2023). Trust is an important component in reducing risk perceptions and increasing the likelihood of accepting personalized product suggestions. Therefore, the more the consumer trusts the recommendation algorithm and the platform through which the recommendation is made, the more they are likely to perceive the cross-selling and upselling suggestions as helpful rather than exploitative, making trust a direct influencer of recommendation acceptance.

H3: Trust has a positive influence on the acceptance of recommendations.

2.2.4 Purchase Intention and Average Order Value

Whereas purchase intention is a measure of a consumer's psychological commitment to a transaction, Average Order Value (AOV) is a measure of a specific outcome. Cross-selling and upselling are specific strategies geared towards maximizing transactional value beyond a consumer's initial selection choices. As a result, there is a need to link intention to outcome to measure commercial success (Nora & Sriminarti, 2023). Whereas a consumer's intention to purchase certain products is stronger, this consumer is more likely to add more to their shopping cart, hence increasing AOV (Rahmah & Satyaninggrat, 2023; Thirumuruganathane et al., 2023). This, therefore, is a measure of how purchase intention acts as a mediator between constructs of technology acceptance (PEOU, PU, and Trust) and outcome-based financial results. This study extends TAM to link intention to outcome, hence providing a link between psychological acceptance constructs and retail outcome-based constructs.

H4: Purchase intention has a positive influence on average order value.

2.2.5 Trust and Purchase Intention

Trust is widely recognized as a foundational antecedent of consumer behavioural intentions in online commercial environments. In e-commerce environments, customers are commonly faced with algorithm-based recommendation engines that operate through a hidden logic system. Therefore, their level of acceptance in response to such recommendations depends

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on how much they consider the platform as competent, benevolent, and truthful (Petcharat & Leelasantitham, 2021). If a customer views a platform positively, he or she becomes more likely to see its cross-selling and upselling suggestions as adding value to the customer's experience rather than being coercive, hence turning favorable attitudes towards the platform into actual purchase actions. In the context of Nigeria's nascent e-commerce sector, institutional risks such as payment insecurity, data confidentiality, and shipping dependability make it more likely for consumers to give greater weight to trust before making any purchase commitment (Nguyen et al., 2024; Singh et al., 2024; Kofi & Graeme,2018).

H5: Trust has a positive influence on Purchase Intention.

3. Conceptual framework

The study formulates a theoretical framework, as shown in Figure 1, based on the Technology Acceptance Model (TAM) to investigate the impact of recommendation systems for cross-selling and upselling on purchase behavior among consumers in Nigeria's e-commerce environment. In the proposed framework, Perceived Ease of Use (PEOU) is taken as the first antecedent, presumed to positively contribute to Perceived Usefulness (PU), which will determine Purchase Intention (PI). Trust (TR) is proposed to have both a direct impact on Purchase Intention (PI) and to positively reinforce Acceptance of Recommendation Systems (AR), considering the high-risk consciousness prevalent among consumers in emerging markets. Finally, Purchase Intentions are expected to act as the main proximal factor behind Average Order Value (AOV).

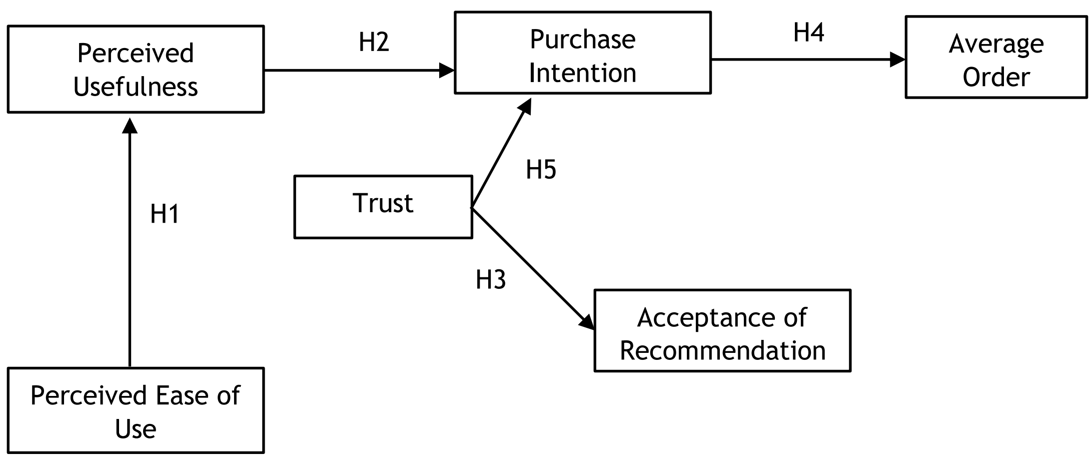

Figure 1. Conceptual framework of the study showing the relationships among the variables

H1: Perceived ease of use has a positive influence on perceived usefulness
H2: Perceived usefulness has a positive influence on purchase intention
H3: Trust has a positive influence on the acceptance of recommendations
H4: Purchase intention has a positive influence on average order value
H5: Trust has a positive influence on purchase intention

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4. Methods

4.1 Research Design

This study adopts a quantitative, cross-sectional survey research design, which is deemed appropriate for testing hypothesized relationships among theoretically derived constructs within a large consumer population (Hair et al., 2021).

4.2 Sampling

The sample population was made up of active internet shoppers in Nigeria who had used e-commerce sites like Jumia and Konga before, since their knowledge about cross-selling and upselling recommendation systems is essential for their participation in the study. A snowball sampling method was used, where the first respondents were asked to recommend others within their social media circles. This was ideal for Nigeria because there is no comprehensive list of internet shoppers available, and social media networks provide the best medium to reach out to them. The survey instrument was sent through electronic means to the participants on social networking sites and apps.

The total number of responses collected was 1,055, of which 778 were deemed suitable for analysis after eliminating responses with missing values or inconsistent answers, yielding a usable Response rate of approximately 73.7%. The sufficiency of the sample size was evaluated beforehand using G*Power software, and it was concluded that 778 participants provided more than enough observations to test medium-sized effects with 0.95 statistical power and a 0.05 alpha level for the given number of predictor variables in the structural model.

4.3 Measurement

Table 1 show that all measurement scale items were adapted from well-established instruments in the literature. Items related to perceived ease of use and usefulness were adapted from Meliawati et al. (2023). Trust-related items were adopted from Wang et al. (2022), whereas Purchase Intention items were adopted from Petcharat and Leelasantitham (2021). Acceptance of Recommendation items was adopted from Singh et al. (2024). According to Xiao et al. (2019), Average Order Value Intention elements were developed and adapted from conceptual literature on cross-selling and upselling, as well as consumer purchasing behavior. All measurement scale items were validated by marketing and consumer behavior researchers and have since been contextualized for Nigeria's e-commerce environment. This ensured that all measurement items were content- and contextually valid. All constructs were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Before the poll, a pilot test was conducted with 25 experienced internet customers. Minor changes were made to some elements in response to participant comments.

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Table 1. Operational definitions and measurement variables

Construct	Operational Definition	Indicators	Source
Perceived Ease of Use (PEOU)	The degree to which a consumer believes that using an e-commerce recommendation system requires minimal effort.	Easy to understand, easy to navigate, interaction is clear, recommendation system is user-friendly, easy to use.	Adapted from Meliawati et al. (2023)
Perceived Usefulness (PU)	The extent to which a consumer believes that the recommendation system enhances shopping effectiveness and improves purchase decisions.	Improves shopping efficiency, helps identify suitable products, enhances decision-making, and increases shopping effectiveness.	Adapted from Meliawati et al. (2023)
Trust (TR)	The consumer's confidence that the recommendation system and the e-commerce platform are reliable, secure, and act in the consumer's best interest.	The platform is trustworthy, recommendations are reliable, personal information is secure, and confidence in the platform's integrity.	Adopted from Wang et al. (2022)
Acceptance of Recommendation (AR)	The willingness of consumers to accept and act upon product recommendations generated by the recommendation system.	Willingness to consider recommendations, likelihood of accepting suggested products, intention to follow recommendations, perceived relevance of recommendations.	Adapted from Singh et al. (2024)
Purchase Intention (PI)	The likelihood that a consumer intends to purchase products recommended by the recommendation system.	Intention to purchase recommended products, willingness to buy, likelihood of future purchase, purchase consideration.	Adapted from Petcharat and Leelasantitham (2021)
Average Order Value (AOV)	The consumer's intention to increase the value of purchases by accepting cross-selling and upselling recommendations during online shopping.	Intention to add complementary products, willingness to purchase higher-value alternatives, intention to increase cart value, likelihood of purchasing additional recommended products.	Developed from the conceptual literature on cross-selling, upselling, and purchase behavior (Xiao et al., 2019)

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4.4 Data Collection

The study collected data from Nigerians who are regular online shoppers. The study targeted online shoppers due to the relevance of the study, using the snowball sampling technique to reach out to the respondents. Snowball sampling was used due to the reason that the respondents were located in different locations. Data duration spans between the period from November 2025 and January 2026.

4.5 Data Analysis

The hypothesized model was analyzed using partial least squares structural equation modeling (PLS-SEM) through SmartPLS 4.0. PLS-SEM was chosen because it is preferable to covariance-based SEM, considering the predictive nature of the objectives of the study, the non-normality of the data, and the composite-based measurement model used. The analysis followed two steps, where first, the measurement model was tested for reliability and validity (convergent and discriminant), before moving forward to evaluate the significance and effect sizes in the structural model. Bootstrapping with 5,000 replications was conducted to obtain t-values and p-values for the hypotheses proposed in the model (Hair et al., 2021). Since the study depended on single-source self-reported survey data, common method bias (CMB) was checked using the full collinearity variance inflation factor (VIF). All VIFs were less than 3.3, implying CMB is not likely to be a threat to validity.

5. Findings

5.1 Respondent Characteristics

The results of the demographic characteristics (Table 2) show that the sample consists mainly of males (54%), with the majority of the respondents being in the age group of 25-34 years old (39.2%), indicative of the digitally-savvy youth generation of Nigeria. Furthermore, the majority of the respondents had a bachelor's degree or HND (49.5%), an income level of ₦100,000 - ₦199,999 per month (28.3%), and mostly came from the South-West geopolitical zone (33.4%). Moreover, smartphones were used to carry out transactions online by 83.5% of the respondents.

Table 2. Demographic details of the respondents (n = 778)

Demographic Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	420	54
	Female	358	46
Age Group (years)	18–24	225	28.9
	25–34	305	39.2
	35–44	155	19.9
	45–54	73	9.4
	55 and above	20	2.6

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Table 2. Demographic details of the respondents (n = 778) (Continue)

Demographic Characteristic	Category	Frequency (n)	Percentage (%)
Highest Education Level	Secondary School or below	45	5.8
	Diploma/OND/NCE	115	14.8
	Bachelor's Degree/HND	385	49.5
	Master's Degree	190	24.4
	PhD or Professional Qualification	43	5.5
Monthly Income (₦)	< 50,000	140	18
	50,000–99,999	185	23.8
	100,000–199,999	220	28.3
	200,000–499,999	160	20.6
	≥ 500,000	73	9.4
Geographic Region	North-West	95	12.2
	North-East	65	8.4
	North-Central	85	10.9
	South-West	260	33.4
	South-East	125	16.1
	South-South	148	19
Employment Status	Student	160	20.6
	Private Sector Employee	230	29.6
	Public Sector Employee	130	16.7
	Self-employed/Entrepreneur	170	21.9
	Unemployed	48	6.2
	Retired/Other	40	5.1
Primary Device for Online Shopping	Smartphone	650	83.5
	Laptop	110	14.1
	Tablet/Other	18	2.3
Frequency of Online Shopping (past 12 months)	More than once a week	210	27
	Once a week	180	23.1
	2–3 times a month	190	24.4
	Once a month	120	15.4
	Less than once a month	78	10

5.2 Measurement Model

The model's measurement construct was tested for reliability, convergent validity (Table 2), and discriminant validity (Table 3). The Cronbach's alpha values were between 0.825 and 0.933, while the values for composite reliability ranged between 0.882 and 0.942. All of these are above the minimum threshold value of 0.70. AVE values also exceed the minimum benchmark value of 0.50, implying adequate convergent validity.

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Table 3. Validity and reliability of the measurement items

Construct	Items	Outer loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Perceived Ease of Use	PEOU1	0.826	0.864	0.902	0.65
	PEOU2	0.786			
	PEOU3	0.871			
	PEOU4	0.856			
	PEOU5	0.751			
Perceived Usefulness	PU1	0.787	0.825	0.882	0.606
	PU2	0.769			
	PU3	0.766			
	PU4	0.728			
	PU5	0.741			
	PU6	0.786			
Purchase Intention	PI1	0.785	0.888	0.915	0.642
	PI2	0.694			
	PI3	0.803			
	PI4	0.752			
	PI5	0.698			
	PI6	0.761			
	PI7	0.672			
Average Order Value	AOV1	0.805	0.91	0.926	0.582
	AOV2	0.797			
	AOV3	0.821			
	AOV4	0.743			
	AOV5	0.722			
Trust	TR1	0.754	0.933	0.942	0.576
	TR2	0.798			
	TR3	0.766			
	TR4	0.805			
	TR5	0.794			
Acceptance of Recommendation	AR1	0.822	0.889	0.916	0.644
	AR2	0.814			
	AR3	0.782			
	AR4	0.798			
	AR5	0.774			
	AR6	0.807			
	AR7	0.857			

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Discriminant validity was established using the heterotrait-monotrait (HTMT) ratio as shown in Table 4, with all construct-pair values falling below the recommended threshold of 0.85, as suggested by Henseler et al. (2015). This indicates that the constructs are empirically distinct and measure conceptually different phenomena within the model.

Table 4. Discriminant validity (HTMT Criterion)

	AOV	AR	PEOU	PI	PU	TR
AOV						
AR	0.442					
PEOU	0.639	0.282				
PI	0.231	0.585	0.354			
PU	0.419	0.357	0.591	0.652		
TR	0.398	0.534	0.284	0.405	0.571	

Note: AOV=Average Order Value; AR=Acceptance of Recommendation; PU= Perceived Usefulness; PI= Purchase Intention; TR= Trust; PEOU = Perceived Ease of Use

5.3 Structural Model

The structural model was tested using Smart-PLS 4 with 5,000 bootstrapping resamples. The hypothesis's significance was assessed using the usual beta coefficient (β), t-value, p-value, and effect size (f^2). All hypotheses were determined to be significant, as illustrated in Table 5 and Figure 2 below. The study found that Perceived Ease of Use (PEOU) substantially influenced Perceived Usefulness (PU) ($\beta = 0.663$, $t = 21.232$, $p < 0.001$, $f^2 = 0.784$), supporting H1. Perceived usefulness significantly increased purchase intention (PI) ($\beta = 0.311$, $t = 4.888$, $p < 0.001$, $f^2 = 0.227$), confirming hypothesis 2. TR had a substantial impact on both AR ($\beta = 0.852$, $t = 42.308$, $p < 0.001$, $f^2 = 0.883$) and PI ($\beta = 0.615$, $t = 9.300$, $p < 0.001$, $f^2 = 0.642$), supporting H3 and H5. Purchase Intention strongly predicts Average Order Value Intention (AOVI) ($\beta = 0.796$, $t = 35.992$, $p < 0.001$, $f^2 = 0.825$), supporting hypothesis 4.

Table 5. Hypothesis between variables

Hypothesis	Structural Path	B	Std. Error	T-value	P-value	Decision
H1	PEOU → PU	0.663	0.031	21.232	0.001	Supported
H2	PU → PI	0.311	0.064	4.888	0.001	Supported
H3	TR → AR	0.852	0.020	42.308	0.001	Supported
H4	PI → AOV	0.796	0.022	35.992	0.001	Supported
H5	TR → PI	0.615	0.066	9.300	0.001	Supported
H6	PEOU → PU → PI → AOV	0.164	0.036	4.556	0.001	Supported
H7	TR → PI → AOV	0.490	0.056	8.750	0.001	Supported
H8	PEOU → PU → PI	0.206	0.045	4.578	0.001	Supported

Note: PU = Perceived Usefulness, PEOU = Perceived Ease of Use, PI = Purchase Intention, AOV = Average Order Value, AR = Acceptance of Recommendation, TR = Trust

The mediation study found considerable indirect effects. PEOU substantially impacted AOVI through the sequential mediation of PU and PI ($\beta = 0.164$, $t = 4.556$, $p < 0.001$), supporting H6. Similarly, Trust had a substantial indirect influence on AOVI through Purchase Intention ($\beta = 0.490$, $t = 8.750$, $p < 0.001$), supporting hypothesis 7. PEOU substantially impacted Purchase Intention via Perceived Usefulness ($\beta = 0.206$, $t = 4.578$, $p < 0.001$), supporting H8. Overall, the data corroborate the robustness of the proposed model and reveal that

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Perceived Usefulness and Purchase Intention serve as crucial mediators linking technology acceptability and trust to customers' average order value intention.

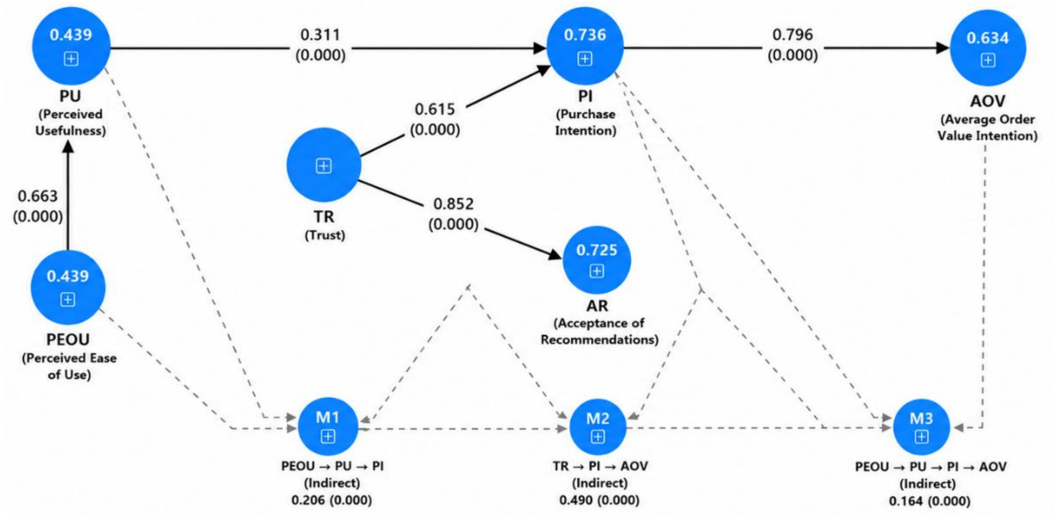

Figure 2. Structural model result showing the relationships among the variables

6. Discussion

The findings of this study provide strong empirical support for the hypothesized relationships and reinforce the relevance of the Technology Acceptance Model (TAM) within the context of an algorithm-driven recommendation system in Nigerian e-commerce.

6.1 Perceived Usefulness and Perceived Ease of Use

The results indicate that H1 is accepted, as Perceived Ease of Use (PEOU) exerts a strong and significant positive effect on Perceived Usefulness (PU). This finding not only confirms the core causal logic of the Technology Acceptance Model (TAM) but also suggests that cognitive effort reduction plays a particularly critical role in shaping value perceptions in algorithm-driven environments. Beyond confirming prior studies such as Anggraini et al. (2022, the magnitude of the effect size indicates that ease of use is not merely an antecedent but a dominant driver of perceived value in this context. This contrasts with some studies in developed markets, where usefulness often outweighs usability. The stronger effect observed here can be interpreted through the lens of cognitive load theory and infrastructural constraints: in mobile-dominant environments such as Nigeria, users are more sensitive to interface complexity due to bandwidth limitations, smaller screen sizes, and intermittent connectivity. Thus, the study extends TAM by demonstrating that in emerging digital ecosystems, usability is not simply a hygiene factor but a primary determinant of value construction, reinforcing calls for contextualizing TAM across institutional environments.

6.2 Perceived Usefulness and Acceptance of Recommendation

The result shows that H2 is accepted, as Perceived Usefulness significantly predicts Purchase Intention. While this finding is consistent with TAM and prior e-commerce studies such as Cai& Chen (2022), the moderate effect size suggests a more balanced interpretation. Specifically, although usefulness remains important, its influence is comparatively weaker than that of trust in this model. This indicates that functional value alone is insufficient to drive behavioural intention in high-risk environments. In contrast to findings from more mature e-commerce markets, where efficiency and convenience dominate decision-making, the Nigerian context reflects a hybrid decision logic in which risk mitigation competes with utility maximization. This finding contributes to the literature by suggesting that PU operates as a necessary but not sufficient condition for purchase intention in emerging markets. It supports extensions of TAM that integrate risk and uncertainty frameworks, highlighting that consumers may recognize usefulness but still refrain from acting unless relational assurances are present.

6.3 Trust and Acceptance of Recommendations

The result indicates that H3 is accepted, with trust exerting a very strong positive effect on the acceptance of Recommendations. The exceptionally large effect size indicates that trust is the primary mechanism through which algorithmic recommendations are legitimized. While prior studies, such as Pan et al (2025), identify trust as important, the present finding suggests a stronger role than typically reported. (e.g., consumer protection, payment security systems) shift reliance toward informal mechanisms such as perceived platform integrity. Importantly, this finding challenges the implicit assumption in algorithmic marketing literature that recommendation quality alone drives acceptance. Instead, it shows that algorithmic legitimacy is socially constructed, and trust acts as a filter through which recommendations are evaluated. This advances the literature by positioning trust not merely as an antecedent but as a gatekeeping construct in digital persuasion processes.

6.4 Acceptance of Recommendation and Average Order Value

The result demonstrates that H4 is accepted, as Purchase Intention strongly predicts Average Order Value. The strength of this relationship provides empirical validation for linking psychological intention to economic outcomes, a connection that is often assumed but rarely quantified in TAM-based studies. Beyond confirming prior research such as Nora and Sriminarti (2023) and Rahmah and Satyaninggrat (2023), this finding contributes by demonstrating that "behavioural intention functions as an important pathway linking cognitive and affective evaluations to economic outcomes."Notably, the very large effect size suggests that once intention is formed, conversion into higher spending is highly likely. This implies that the critical challenge for firms lies not in increasing basket size directly, but in strengthening upstream psychological drivers, particularly trust and perceived usefulness.

6.5 Trust and Purchase Intention

The result shows that H5 is accepted, with trust significantly influencing Purchase Intention. The strength of this relationship exceeds that of perceived usefulness, indicating that affective and relational factors dominate cognitive evaluations in this context. This finding extends the prior works of Wang et al. (2022) by demonstrating that trust is not only a complementary factor but a central determinant of behavioural intention in emerging e-commerce markets. From a theoretical standpoint, this supports the integration of TAM with trust-based models, reinforcing the argument that technology adoption cannot be fully explained without incorporating relational constructs. More critically, the results suggest that in high-uncertainty environments, consumers may override efficiency considerations in favour of perceived safety. This challenges the universality of TAM's cognitive emphasis and indicates that contextual risk conditions reweight the relative importance of TAM constructs.

6.6 Managerial Implications

The implications of this research are significant for e-commerce platform managers, digital marketers, and technologists working in Nigeria and similarly developing economies. The fact that Perceived Ease of Use has been shown to predict Perceived Usefulness means there is business value in designing user-friendly recommendation systems to facilitate cross-selling and upselling on these platforms. Recommendations: interfaces that are clean, contextually embedded, and do not strain the user's cognitive abilities must be considered paramount in this regard, especially considering the prevalence of smartphones among Nigerian Internet users. Any recommendation mechanisms that interfere with the browsing process, require a lot of scrolling, or have information presented in a complex manner will inevitably result in a negative impact on the usefulness and thus the consumer's intent to purchase.

The high predictive nature of Perceived Usefulness of Purchase Intentions also means that the usefulness of such recommendation engines within commerce will depend on whether the recommendations provided are relevant and accurate enough. It would be important for companies to work on improving the algorithms that they use for making recommendations, as these should correlate with what consumers have been searching for and buying. If recommendations made are not relevant at all, it might come across as an attempt by companies to make a profit without any genuine interest in serving consumers.

One of the most practical insights that could be derived from this research is the importance of building trust. In light of the massive effect size witnessed on the path of Trust → Purchase Intention, e-commerce platforms should prioritize building trust when executing operations within Nigeria. This means providing information on how personal data is used and protected, showcasing certifications that ensure secure transactions, having well-defined processes for returns and refunds, and consistently delivering orders. The Jumia platform should also explore implementing features that will allow social proof, including feedback, ratings, and endorsements from other customers, since these will complement the algorithms in recommending products. By focusing on both aspects, trust can be effectively established, helping minimize the risks associated with cross-selling and up-selling strategies employed by companies.

6.7 Theoretical Contribution

This study contributes to the body of knowledge by extending the Technology Acceptance Model beyond the sphere of technology adoption and describing customer reactions to algorithm-based recommendation systems in terms of cross-selling and upselling. In contrast to classical TAM-trust models (Gefen et al., 2003), which are primarily used to analyze technology adoption and online purchase intentions, this study contends that, in the case of algorithm-driven recommendation systems a psychological decision-making process occurs before accepting the algorithm's recommendations. Thus, this study conceptualizes Acceptance of Recommendation as a separate behavior-based construct that captures consumers' willingness to follow algorithm recommendations, broadening TAM's application reach beyond technology adoption consumer responses to algorithm-generated recommendations Furthermore, the study broadens TAM by investigating the relationship between technological acceptance mechanisms and average order value (AOV).

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While traditional TAM theories typically conclude their analyses at the stage of technology intention or adoption, the current study demonstrates how perceptions of ease of use, usefulness, trust, and recommendation acceptance, when combined, explain consumer intent to increase transaction value through cross-selling and upselling. More importantly, the current study demonstrates that trust can be viewed as a dominating rather than supplemental driver in algorithm-driven recommendation systems as consumer behavior is influenced by both perceptions of usefulness and the trustworthiness of suggestions. Thus, the theoretical innovation of this study stems not from the application of TAM theory in the Nigerian context, but rather from the re-conceptualization of TAM theory as an approach to explaining algorithmic recommendation acceptance, and the development of a new concept of Acceptance of Recommendation as a specific mechanism of behavior.

6.8 Limitations

Despite the strengths of this study, there exist certain shortcomings. First, the limitation posed by the cross-sectional nature of this study is that it prevents the establishment of causality. In future studies, researchers can conduct a longitudinal study to find out changes in the perception of consumers over time. Second, the snowball sampling strategy might limit generalizability in this case, and future researchers can use probability sampling methods to overcome this problem. The research sample includes a rather well-educated group of internet buyers, with the majority having a third-level education. Such a demographic profile may not accurately represent the characteristics of all Nigerian online shoppers, particularly those with lower levels of education. As a result, broad generalizations regarding the entire customer group should be used with caution. Third, the study only considers Nigerian consumers, which may limit the generalizability of the findings to other emerging economies. Future studies should undertake comparative investigations across different developing countries to assess the stability of the proposed relationships across cultural institutional contexts. Moreover, this study only concentrated on direct relationship between the variables without considering any indirect relationships that might be there according to the theoretical framework. Future research must consider these indirect relationships using mediation analysis to gain complete insight into the mechanism operating between the variables. Moreover, future researchers may include other variables such as perception of risk, privacy concerns, transparency of algorithms, and innovativeness of consumers in order to have better insight into recommendation system acceptance and buying behaviors.

It should be highlighted that the high proportion of highly educated participants is due to the demographic characteristics of persons who regularly purchase on the Internet and are familiar with digital commerce technology. Education level may have influenced the study's high correlation between TAM elements, since educated users tend to evaluate the usefulness and usability of recommendation systems more accurately. Still, in the future, researchers should include participants with various levels of education.

7. Conclusion

The study set out to examine how cross-selling and upselling recommendation systems influence consumer purchasing behaviour within Nigeria's e-commerce environment by extending the Technology Acceptance Model (TAM) with trust as a central construct. The findings provide clear and consistent empirical support for all hypothesized relationships, offering several important insights. First, the results reaffirm the relevance of TAM in

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algorithm-driven contexts, demonstrating that perceived ease of use significantly enhances perceived usefulness, which in turn influences purchase intention. However, the study goes beyond mere validation by showing that the relative importance of these cognitive factors is context-dependent. In particular, perceived usefulness, while significant, exerts a weaker influence compared to trust, suggesting that functional efficiency alone is insufficient to drive consumer action in high-risk environments.

Second, trust emerges as the most influential determinant within the model, exerting strong effects on both acceptance of recommendations and purchase intention. This finding highlights the centrality of relational and affective considerations in shaping consumer responses to algorithmic systems, especially in emerging markets characterized by institutional uncertainty. It indicates that consumers evaluate recommendation systems not only on their utility but also on the credibility and integrity of the platform delivering them. Third, the study establishes a clear linkage between psychological intention and economic outcomes by demonstrating that purchase intention strongly predicts average order value. This provides empirical evidence that algorithmic recommendation systems can translate positive consumer perceptions into tangible financial performance, thereby bridging the gap between behavioural theory and firm-level outcomes.

Taken together, these findings contribute to the literature in three key ways. Theoretically, the study extends TAM by integrating trust as a dominant explanatory factor, supporting the need for hybrid models that combine cognitive and relational dimensions of technology acceptance. Contextually, it enriches the limited body of empirical research on e-commerce behaviour in emerging economies, demonstrating that consumer decision-making is shaped by risk perceptions and institutional conditions. Practically, it underscores the importance for e-commerce platforms to prioritize not only usability and personalization but also transparency, reliability, and trust-building mechanisms in order to enhance both user engagement and transaction value.Instead of being a contextual replication of TAM in Nigeria, this paper recasts technology acceptance theory for algorithmic recommendation systems by introducing Acceptance of Recommendation as a new behavioral construct and explains how technology acceptance leads to business value creation through cross-selling, upselling, and average order value.

8. Recommendation

Based on the empirical findings from this study, e-commerce platforms operating in emerging markets such as Nigeria should implement the following strategic initiatives to optimize the effectiveness of algorithm-driven recommendation systems.

Prioritize Trust-Building Mechanisms as a Core Business Strategy. Given that trust emerged as the most influential determinant of both recommendation acceptance and purchase intention, platforms must move beyond functional optimization to establish credibility and institutional legitimacy. This requires implementing transparent data governance policies that clearly communicate how consumer information is collected, stored, and utilized. Platforms should develop and prominently display privacy commitments, obtain explicit user consent for data usage, and provide accessible channels for consumers to understand and control their data. Additionally, establishing third-party certifications or partnerships with trusted institutions can serve as external validation of platform reliability in contexts characterized by institutional uncertainty.

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Enhance User Interface Design with a Focus on Simplicity and Clarity. While perceived ease of use demonstrates a significant relationship with perceived usefulness, platforms should invest in continuous interface refinement to reduce cognitive friction. This includes streamlining navigation pathways, minimizing the number of steps required to complete transactions, and ensuring that recommendation algorithms are presented understandably. User testing with target populations in emerging markets should inform design decisions, as usability preferences may differ from developed market contexts.

Improve Recommendation Relevance Through Contextually Sensitive Algorithms. The study's findings suggest that personalization quality directly influences consumer perception of system usefulness. Platforms should invest in machine learning models that account for local preferences, purchasing patterns, and cultural considerations specific to emerging markets. Rather than deploying standardized algorithms globally, platforms should develop market-specific recommendation engines that reflect the unique characteristics of Nigerian consumers and similar emerging market contexts.

Establish Reliable Service Delivery Infrastructure. Trust is reinforced through consistent, dependable performance. Platforms must ensure robust technical infrastructure that minimizes system downtime, provides fast loading times, and guarantees a seamless user experience. This includes implementing redundant systems, regular maintenance, and proactive monitoring to quickly identify and resolve issues. Additionally, investing in scalable solutions ensures the infrastructure can handle growth and increased demand without compromising performance. By prioritizing these aspects, platforms can build and maintain user trust through reliable and efficient service delivery.

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