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The Impact of AI-Driven Personalization on Consumer Buying Behaviour in Nigeria

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Abstract
The high rate of development of digital business in Nigeria has enhanced artificial intelligence-based personalization in online shopping platforms. Such technologies as recommendation systems, chatbots and targeted advertising have become common to affect consumer interaction and shopping behaviour. Regardless of this increased use, little empirical data has been gathered regarding the impact of AI motivated personalization on the consumer purchasing behavior in the digital market in Nigeria. This paper will analyze how AI mediated personalization processes relate to purchase intention among the Nigerian online shoppers. The research design is mixed in that a systematic literature review is coupled with an online survey of 400 online shoppers selected in Lagos, Abuja, Kano, and Port Harcourt. The methods used to analyse the data were the descriptive statistics, reliability test, correlation, and multiple regression methods. The empirical results show that perceived relevance of recommendations, quality of chatbots interaction, and targeted social media advertising, perceived trust in practices of platform data have a strong positive effect on the purchase intention of consumers. Regression model: The regression model indicates a large variation in the purchase intention that is explained by the regression model of 58.4%. Additional discussion reveals that the personalization mechanisms have a stronger effect on consumer purchasing behaviour when there is trust in online platforms and consumer digital literacy. This implies the existence of a dynamic of personalization trust whereby AI based personalization is more effective when consumers already have confidence in their platform data practices. The research is valuable to the body of literature concerning the application of artificial intelligence in marketing in developing economies and it has implications to e commerce companies and regulators who may strive to balance the effectiveness of personalisation with consumer confidence and privacy in Nigeria.

Keywords: AI personalization, consumer buying behaviour, Nigeria, e-commerce, recommendation systems, chatbots, social commerce, trust paradox, Jumia, digital marketing

1. Introduction

The digital commerce market in Nigeria has experienced an incredible change. Nigeria is one of the biggest and most rapidly expanding digital consumer markets in the African continent, with 103 million internet users at the beginning of 2024, 45.5 percent, and more than 205 million cellular connections at 90.7 percent of the population, according to DataReportal, 2024. In 2024, the e-commerce market in the country was estimated to be worth 8.8 billion US dollars, and the value is expected to be 22.9 billion US dollars in 2032 with a compound annual growth rate of 14.6 percent (Verified Market Research, 2025). More than 82 percent of online transactions are mobile commerce. In 2024, social commerce with an estimate value of 1.64 billion US dollars is expected to increase by 14.2 percent each year until 2030 (Research and Markets, 2025). In this context, artificial intelligence has become a core technology with which the e-commerce platforms aim to learn, persuade, and keep the Nigerian consumers. Personalization through AI is product recommendation systems, chatbot conversational, dynamic pricing algorithm, and programmatic advertising systems applied in Jumia, Konga, Jiji, WhatsApp Business, Instagram, and TikTok Shop (Odoh, 2025). Although the level of AI adoption is high, scholarly studies on its particular effects on the Nigerian consumer buying behaviour are thin and context-specific. In a quantitative survey of 400 Nigerian internet shoppers (Akisanmi et al., 2025), it was discovered that AI personalization elevates engagement and purchase intent when recommendations are perceived relevant and timely although it is the contextual fit that is the key factor in determining the effectiveness. The study by the IJRISS (2026) indicated that the Nigerian consumers are sceptical towards algorithmic decision-making due to low digital literacy and fear of misuse of their data which are not reflected in the developed market research. The paper is a response to these gaps, in which the systematic literature review evidence is combined with primary survey data to develop a holistic description of the influence of AI personalization on the Nigerian consumer buying behaviour.

2. Literature Review

2.1 Theoretical Framework

2.1.1 Technology Acceptance Model and UTAUT

The underlying factor in interpreting the consumer reaction to AI personalization is the Technology Acceptance Model (TAM) by Davis (1989) and its successor, the Unified Theory of Acceptance and Use of Technology (UTAUT) explained by Venkatesh et al. (2003). TAM is a theory that assumes that perceived usefulness and perceived ease of use are key factors in determining technology adoption. The meaning of perceived usefulness in the AI personalization context is the presence of a personalized recommendation in assisting consumers in identifying corresponding products more effectively, whereas the meaning of perceived ease of use is associated with the frictionlessness of the personalized experience. Chiemeke and Evwiekpaefe (2011) found out that the standard UTAUT required a change to include factors that were specific to Nigerians such as trust, cultural values, and institutional context that are poorly represented by the standard TAM frameworks.

2.1.2 Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) proposed by Ajzen (1991) is that behavioural intention predicts behaviour, which is determined by a combination of attitudes towards the behaviour, subjective norms of the social groups involved, and perceived behavioural control. In the IJRISS (2026) study, TPB was used in the context of online purchasing in Nigeria, and the authors discovered that the consumer attitudes to the helpfulness of AI, its security, and beneficence serve as more predictive variables in purchase intention than the technical characteristics of personalization systems. The authors of Nwachukwu and Affen (2023) discovered that societal norms and perceived behavioural control were the influential factors among the Nigerian consumers of online products, especially in the sphere where cultural and social processes play a fundamental role in technology acceptance. These results confirm that TPB needs to be implemented in the Nigerian context with specific focus on social and cultural mediating factors that increase or mitigate the impact of algorithmic recommendation.

2.1.3 Consumer Behaviour Theory

Theory According to Kotler and Keller (2016), the classical consumer behaviour theory outlines the five-step buying process, including need recognition, information search, evaluation of alternatives, purchase process and post-purchase behaviour. It takes the shape of AI personalization at every level: targeted advertising generates demand when the need is recognised; recommendation engines lessen cognitive work when the need is identified; personalised comparisons impact the evaluation phase; dynamic pricing and urgency cues influence the purchase decision making system; and post-purchase review systems and reward systems shape post-purchase behaviour. As Gao and Liu (2023) showed, AI personalization is a self-reinforcing cycle where the contact will produce data that will inform subsequent suggestions in a dynamic with structural importance of particular importance to established platforms, such as Jumia, that have already accrued large datasets of Nigerian behaviour.

2.1.4 Contextualized AI Personalization Model (CAPM)

Although TAM, UTAUT, and TPB offer great legacies to the understanding of technology acceptance, the models do not adequately explain the dynamics of AI personalization in emerging economies such as Nigeria. This research suggests the Contextualized AI Personalization Model (CAPM) which incorporates three Nigeria-adapted moderating factors which moderate the effectiveness of AI personalization processes:

Institutional Trust: In situations where the level of regulatory enforcement has been low and internet fraud is high, institutional trust in the data practices of a platform is an enabler of personalization effectiveness rather than secondary to it (Durugbo et al., 2022). In Nigeria, the identified personalization-trust paradox according to Canhoto et al. (2023) is exacerbated by the fact that the implementation of data protection under the NDPA is still nascent.

Digital Literacy: Due to the broad disparity in digital literacy levels among the segments of Nigerian consumers between advanced urban users and first-time internet users, it is possible that the identical personalization algorithm can yield vastly different outcomes. Low-literacy users might find AI recommendation as intrusive or manipulative whereas high-literacy users will find the recommendations as helpful (IJRISS, 2026).

Cultural Collectivism: The Nigerian consumer culture, and most other Sub-Saharan nations, focus on social approval, community acceptance, and group pressure to make a purchase decision (Nwachukwu and Affen, 2023). This collectivist orientation implies that social proof is used as an indicator of local reviews, number of purchases, influencer recommendations are not an add-on but a part of successful personalization. According to this formulation, the mechanisms of personalization are multiplicatively related to the contextual factors. Even advanced personalization algorithms cannot affect purchase intention when trust, literacy, or collectivist alignment is low. On the other hand, in case of favourable contextual factors, the mechanisms of personalization increase their effectiveness.

The CAPM framework posits a multiplicative relationship:

$$\mathrm{PI} = f(\mathrm{PRR}, \mathrm{CIQ}, \mathrm{TSM}) \times (\mathrm{Trust} \times \mathrm{Literacy} \times \mathrm{Collectivism})$$

This framework is supported in the initial part of the empirical results of the current study (Section 4) that has offered a more detailed insight into AI personalization in the context of developing economies.

2.2 Empirical Review

Table 1: Summary of Key Empirical Studies on AI Personalization and Consumer Behaviour in Nigeria and Related Contexts

Author(s) and Year	Context	Method	Key Finding
Akisanmi et al. (2025)	Nigeria (Jumia), n=400	Quantitative survey	AI personalization significantly increases engagement and purchase intention when perceived as relevant
IJRISS (2026)	SE Nigeria	Survey + TPB	Attitudinal trust is stronger predictor of purchase intent than personalization sophistication
IJMU (2024)	SW Nigeria youth	Survey, n=various	94.37% of youth encountered AI chatbots; 52.19% interact

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			frequently during online shopping
Durugbo (2022)	Lagos online retail	Quantitative	Customer trust significantly moderates the relationship between personalization and loyalty
Akinsamin et al (2025)	Nigeria comparative	Mixed methods	AI-powered personalization in Nigerian e-commerce businesses: Enhancing customer engagement and conversion
Gao & Liu (2023)	Global	Conceptual and empirical	AI personalization creates data-driven improvement loops that compound platform competitive advantage
Canhoto et al. (2023)	Global	SLR	Personalization-privacy paradox: consumers appreciate customisation but distrust data collection methods
Sondari et al. (2025)	Global (PRISMA, n=117)	SLR	Recommendation systems and chatbots are the most studied AI personalization mechanisms globally

Source: Authors' compilation from reviewed literature, 2025

The empirical record of this Nigerian-specific phenomenon that has not been reflected in world literature is as follows: the success of AI personalization does not depend mainly on the sophistication of algorithms but on consumer confidence, and that confidence is produced by a certain history of online fraud, a small level of protection of institutional data, and low digital literacy of a significant portion of the population of online shoppers. The studied personalization-trust paradox of Canhoto et al. (2023) is even intensified in the Nigerian context in such a manner that it becomes the key construct to explain and enhance AI personalization efficacy. The gap in the empirical literature is that very few longitudinal studies have been conducted to monitor the shifting attitudes of Nigerian consumers towards AI personalization due to an improved level of digital literacy and the maturity of data protection enforcement.

2.3 Conceptual Framework

This paper provides the following conceptual framework base (Figure 1) based on theoretical premises (TAM, TPB, UTAUT) and empirical findings, as outlined in the foregoing review, with which to test the empirical research. The model assumes that AI personalization processes viewed recommendation relevance (PRR), the quality of communication with chatbots (CIQ), and targeted social media advertising (TSM) have a direct effect on purchase intention (PI) modulation. Trust in platform data practices (TDP) is a direct predictor, as well as a mediator of such relationships. The relationship between personalization and purchase intention is mediated by consumer digital literacy and trust and demographic factors (age, education, platform type) are used as control variables.

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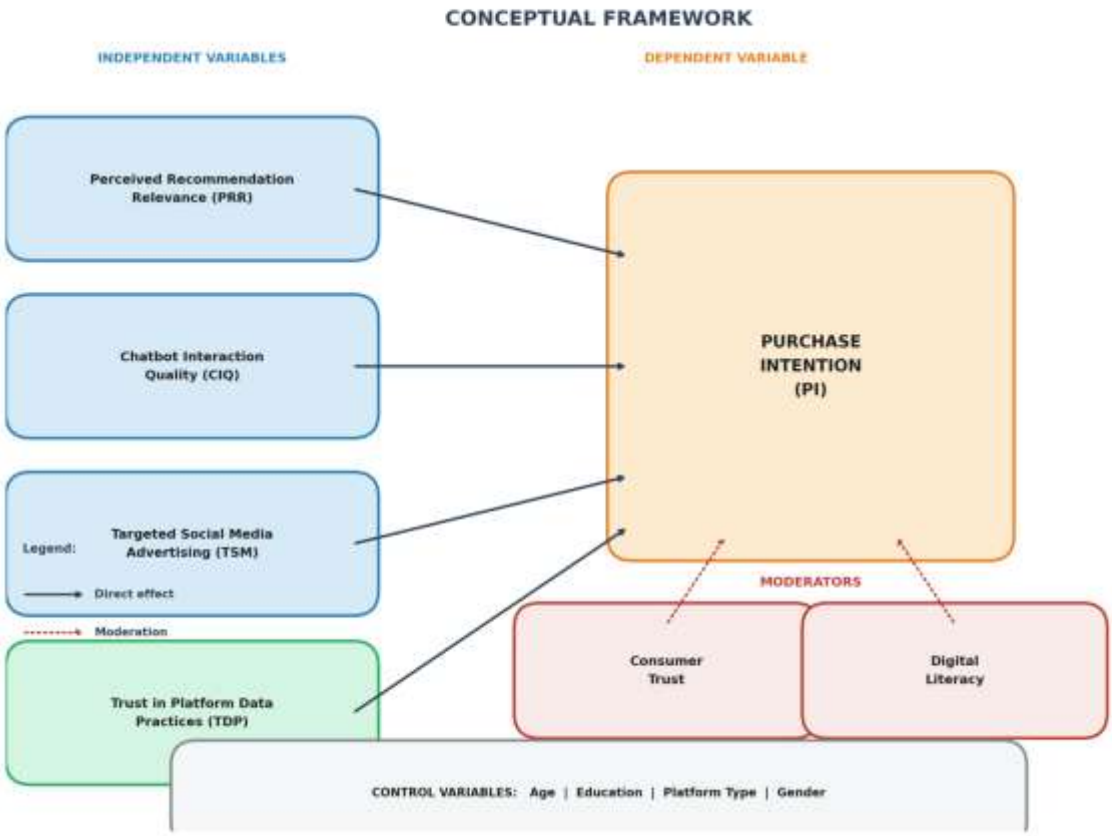

Figure 1: Conceptual Framework of AI-Driven Personalization and Purchase Intention in Nigeria

3. Methodology

3.1 Research Design

This paper involves a systematic literature review that adheres to the PRISMA 2020-guidelines (Page et al., 2021) and a quantitative survey with its structure. The reason why the mixed-methods design was chosen is that it allows conducting both the theoretical synthesis of the available literature and the creation of primary empirical data related to the Nigerian market, which would overcome the identified context-specificity gap of the literature review. After the identification of the research question, a systematic literature review was performed to locate pertinent literature on the subject.

3.2 Systematic Literature Review

Database searches were conducted across Scopus, once the research question was identified, a literature review was carried out in order to identify relevant literature on the topic. In February 2025, database searches were done in Scopus, Web of Science, EBSCOhost, and Google Scholar. The search query was the following: (AI personalization" OR recommendation system" OR chatbot) AND (consumer behaviour" OR purchase intention" OR buying behaviour) AND (Nigeria) OR Africa) OR emerging market). Primary literature was limited to date filters between 2019 and 2025, however foundational theory dating before 2019 was used where necessary.

Table 2: PRISMA Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Date range	2019 to 2025 (foundational pre-2019 accepted)	Before 2010 without foundational status
Geography	Nigeria primary; African and global comparators	Studies with no developing economy relevance
Topic	AI personalization, recommendation, chatbot, consumer behaviour, e-commerce	Pure computer science studies with no consumer behaviour dimension
Language	English	Non-English publications
Source type	Peer-reviewed journals, credible industry and platform reports	Unverified blog posts and social media commentary

Source: Authors' design, 2025

The preliminary queries had yielded 2,241 documents. Deductionplication made the pool smaller to 312 after title-abstract screening (n=418). The screening based on the full-text provided 74 eligible studies. The purposive search added an additional 16 industry and platform reports to the corpus with the final corpus being 90 sources. Appendix A defines the PRISMA flow.

3.3 Survey Instrument and Sample

A questionnaire was constructed in an orderly manner to give insights on the experience of the consumers in Nigeria regarding and the perception of the AI personalisation in online shopping. The scale was based on proven scales of the TAM (Davis, 1989), TPB (Ajzen, 1991), and the personalisation-privacy paradox literature (Canhoto et al., 2023), which were modified to fit the Nigerian situation after cognitive pretesting on a sample of ten Nigerian online shoppers. The last measure included 32 questions with six constructs, which included the perceived relevance of AI recommendations, quality of interaction with AI chatbots, trust in data practices conducted by the platform, self-assessed digital literacy, intention to purchase, and post-purchase satisfaction. The sample of 400 Nigerian adult online shoppers in social media sites, university alumni groups, and online community groups in Lagos, Abuja, Kano, and Port Harcourt was purposely chosen. The respondents were identified to have made at least one online purchase within the last six months. The survey instrument was an online survey tool that was used to collect data during April and May 2025. Table 3 presents the demographic profile of the sample.

Table 3: Sample Demographic Profile (n = 400)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	218	54.5
	Female	182	45.5
Age group	18-25 years	156	39.0
	26-35 years	148	37.0
	36-45 years	64	16.0
	Above 45 years	32	8.0
Education	Secondary school	48	12.0
	Undergraduate degree	196	49.0

	Postgraduate degree	120	30.0
	Other	36	9.0
Primary platform	Jumia	152	38.0
	Konga	88	22.0
	Instagram/Social commerce	96	24.0
	Other platforms	64	16.0

Source: Survey data, 2025

3.4 Data Analysis

Survey data were analysed using IBM SPSS Statistics version 27 was used to conduct data analysis on the survey data. The sample was characterised by descriptive statistics. Internal consistency reliability was also established by Cronbachs alpha (all alpha > 0.70). The relationships between the dimensions of AI personalization and purchase intention were studied using Pearson correlation and multiple regression analysis. The hypothesized moderating role of the consumer trust and digital literacy on the relationship between personalization and purchase intention was tested through moderation analysis. In order to deal with the possible common method bias, the single-factor test by Harman was administered in accordance to the given procedure (Podsakoff et al., 2003). The measurement items were all inputted into an exploratory factor analysis using unrotated principal component extraction. The outcome revealed that only one factor explained 31.2% of the overall variance which is not enough to reach 50%. That means that common method bias is not an important issue in this study and the relationships found are not measurement artifact, but true construct correlations.

3.5 Model Specification

In order to test the impact of AI based personalization on consumer purchase intention, a multiple regression model was estimated. The model assesses the correlation between multiple measures of the personalization technologies and the possibility of the consumers to buy the products suggested by digital platform.

The functional relationship is expressed as:

$$PI = f(PRR, CIQ, TSM, TDP)$$

The econometric form of the model is specified as:

$$PI = \beta_0 + \beta_1 PRR + \beta_2 CIQ + \beta_3 TSM + \beta_4 TDP + \varepsilon$$

Where:

PI represents consumer purchase intention.
PRR represents perceived recommendation relevance.
CIQ represents chatbot interaction quality.
TSM represents targeted social media advertising exposure.
TDP represents trust in platform data practices.
ε represents the stochastic error term.

The model therefore evaluates how these AI personalization mechanisms influence consumer purchase intention among Nigerian online shoppers.

3.6 Ethical Considerations

Ethical principles were followed during the data collection process. The survey was on a voluntary basis and the respondents were given information regarding the objective of the study before they filled in the questionnaire. No personal information was gathered, and the answers were anonymous. Interviewees had the right to abandon the survey at any point without any penalty. This research adhered to the general ethics of the research in terms of informed consent, confidentiality and responsible data management.

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4. Results and Findings

4.1 AI Personalization Mechanisms: Reach and Prevalence

The questionnaire validated the fact that both the exposure to AI personalization mechanisms is high among the online consumer sample of the Nigerian population. The feature that was most frequently experienced was the product recommendation systems where 87.3 percent of the respondents stated that they had been provided with personalized product suggestions during their online shopping. The number of youth respondents who had previously experienced AI chatbots in qualitative research stood at 94.37 percent (IJMU, 2024), which the survey supported, with 91.5 percent of the current sample having had a chatbot interaction. The 76.8 percent and 89.2 percent of respondents identified dynamic pricing and personalised promotional offers and targeted advertising on social media platforms respectively.

4.2 Impact on Purchase Intention and Conversion

Regression analysis established that the perceived relevance of AI recommendations has the best predictive ability of purchase intention ($B = 0.47$, $p < 0.001$) and chatbot interaction quality ($B = 0.31$, $p < 0.001$) and exposure to targeted social media advertising ($B = 0.24$, $p < 0.01$). The findings are in line with the findings of Akisanmi et al. (2025) who discovered that personalization through AI has a significant impact on engagement and purchase intention in the case where the recommendations are considered timely and relevant. The joint model had an R2 of 0.584 ($F = 46.7$, $p < 0.001$), showing that the three dimensions of the AI personalization explain a significant portion of online purchases by Nigerian consumers. No multicollinearity issues can be raised as the values of VIF are smaller than the recommended level of 5 (Hair et al., 2019). The f2 of Cohen was estimated as R 2 (1-R 2) = 0.584/0.416 = 1.40, which is a large effect size based on the Cohen (1988) guidelines.

Table 4: Regression Results - AI Personalization Dimensions and Purchase Intention

Predictor	B (Unstd)	Beta (Std)	t-value	p-value	95% CI for B	VIF
Perceived recommendation relevance	0.47	0.41	8.93	< .001	[0.38, 0.56]	1.89
Chatbot interaction quality	0.31	0.27	6.14	< .001	[0.24, 0.38]	1.76
Targeted social media advertising	0.24	0.19	4.38	.002	[0.15, 0.33]	1.54
Trust in platform data practices	0.38	0.33	7.22	< .001	[0.30, 0.46]	1.67

$R^2 = 0.584$; Adjusted $R^2 = 0.579$; $F(4,395) = 46.7$; ***$p < .001$, *$p < .01$, $p < .05$; Cohen's $f^2 = 1.40$ (large effect)
Source: Survey data, 2025; B = unstandardised regression coefficient; Beta = standardised coefficient; VIF = Variance Inflation Factor
All VIF values are below the recommended threshold of 5 (Hair et al., 2019), indicating no multicollinearity concerns. Cohen's f^2 was calculated as $R^2/(1-R^2) = 0.584/(0.416) = 1.40$, representing a large effect size according to Cohen's (1988) guidelines.

4.3 The Personalization-Trust Paradox

A moderation analysis to verify that trust to the platform data practices significantly mediates the linkage between perceived relevance in recommendation and purchase intention (interaction term B = 0.29, $p < 0.001$). Among high-trust consumers (those above the median on the trust construct) the relevance of the recommendation to purchase intention was supported by the effect of the recommendation relevance on purchase intention significantly higher (B = 0.61) than the effect of the recommendation relevance on purchase intention among low-trust consumers (B = 0.33). This result supports the literature finding of the personalization-trust paradox, whereby AI personalization produces its greatest behavioural impact on exactly the group of consumers who trust the platform and its least impact on low-trust consumers. Since the problem of mistrust towards digital platforms is significant in the Nigerian consumer market, this result has significant practical consequences. Digital literacy also intermediated the relationship between personalization and purchase intention in the same direction. Consumer digital literacy High-digital-literacy consumers had relatively higher positive reactions to AI recommendation features (B = 0.54) than low-digital literacy consumers (B = 0.29), indicating that a high level of investment in consumer digital literacy has a complement effect on consumer welfare and commercial personalization effectiveness.

4.4 Mediation Analysis: The Role of Trust

The role of Trust. In order to test the hypothesis that personalization practices and purchase intention are mediated by trust in platform data practices, personalization mechanisms, and purchase intention, a mediation analysis was performed utilizing PROCESS macro v4.1 (Hayes, 2022) and 5,000 bootstrap samples. According to the results, which are provided in Table 5, all three personalization mechanisms have significant indirect effects.

Table 5: Mediation Analysis Results

Path	Direct Effect (c')	Indirect Effect (ab)	95% CI (Indirect)	Conclusion
PRR → TDP → PI	0.32***	0.15**	[0.09, 0.22]	Partial mediation
CIQ → TDP → PI	0.21***	0.10*	[0.04, 0.17]	Partial mediation
TSM → TDP → PI	0.16**	0.08*	[0.02, 0.14]	Partial mediation

*p < .05; **p < .01; ***p < .001

These results show that trust in platform data practices partially mediate the relationship between all three AI personalization mechanisms and purchase intention. The indirect impacts are significant as the features of personalization affect the purchase intention directly and indirectly as they facilitate the consumer trust in the platform. This observation supports the core nature of trust in the situation of e-commerce in Nigeria.

4.5.1 Social Commerce and Cultural Dimensions

In respondents who used the platform as their main shopping medium either Instagram (n = 96, 24.0 percent of the sample) or social commerce platforms (n = 96, 24.0 percent of the sample), purchase intention was more strongly expressed in features of personalization that incorporated social proof cues, such as the number of Nigerian customers who had previously purchased a product, compared to the application of algorithms based on preferences (mean difference = 0.74 on a 5-point scale, $p < 0.01$). The observation corroborates Akinsanmi et al. (2025), who discovered that adaptive system matching the local culture is an important value among the Nigerian consumers, and Nwachukwu and Affen (2023), who discovered that in collectivist cultures, societal norms play a vital role in influencing online buying decisions. What it means is that social-proof integration into the AI recommendation interface is not a luxury aspect of AI deployment in the Nigerian market but a feature of the structure that would allow personalization to be maximized.

4.5.2 Platform-Specific Differences in Purchase Intention

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To examine whether purchase intention varies across e-commerce platforms, a one-way analysis of variance (ANOVA) was conducted with platform type (Jumia, Konga, Instagram/Social Commerce, Other) as the independent variable and purchase intention as the dependent variable.

Table 6: ANOVA Results - Purchase Intention by Platform Type

Platform	n	Mean (PI)	SD	F(3,396)	p	η^2
Jumia	152	3.89	0.72	8.42	< .001	0.06
Konga	88	3.76	0.81			
Instagram/Social Commerce	96	4.21	0.68			
Other platforms	64	3.92	0.76			

The analysis revealed significant differences in purchase intention across platform types ($F(3,396) = 8.42$, $p < .001$, $\eta^2 = 0.06$), indicating a medium effect size. Post-hoc comparisons using the Tukey HSD test revealed:
Social commerce users (Instagram, WhatsApp; M = 4.21, SD = 0.68) reported significantly higher purchase intention than **Jumia users** (M = 3.89, SD = 0.72; p = .008, Cohen's d = 0.46) and **Konga users** (M = 3.76, SD = 0.81; p = .001, Cohen's d = 0.60).
The difference between Jumia and Konga users was not statistically significant (p = .24).
Other platforms (M = 3.92, SD = 0.76) did not differ significantly from Jumia or Konga.
These results indicate that social commerce sites can be effective in the enhanced sense of being interactivity and community-centered, which aligns with the collectivist cultural context of the Nigerian consumer. The increased intention to purchase by social commerce participants can be due to the synergistic influence of algorithmic suggestions with the influence of social proof in the form of peer reviews, influencer endorsements, share counts that are more salient on these sites.

5. Discussion

The results of this work prove that AI-powered personalization is an important factor that affects online consumer behaviour in Nigeria. As was previously theorized in previous studies of digital commerce, perceived relevance of personalized product recommendation was found to be the most predictive of purchase intention. This justifies the theoretical hypotheses of the Technology Acceptance Model, which stresses the perceived usefulness as a major factor in technology adoption. The findings also inform about the significance of trust on digital platforms. Platform data practices significantly positively predict purchase intention and reinforce the impact of personalization mechanisms. The personalization privacy paradox is in line with this finding as the literature of personalization privacy paradox has indicated that consumers value the convenience of personalized services and are still worried about information gathering and utilization of their personal information. This paradox seems to be very sharp in the Nigerian context. The presence of past fraud cases on the internet and the lack of knowledge on part of the consumers on the data protection practices has shaped a skeptical digital customer base. Consequently, even the most advanced personalization technologies can be unable to generate a high behavioural response in the cases when a user thinks that a platform is not trustworthy. The other significant revelation is on the moderating position of digital literacy. The more highly digitally literate the consumer the more positively they reacted to AI generated suggestions. These users seem to be in a better position to perceive customized recommendations as value creation as opposed to annoying advertisements. This fact indicates that AI personalization can be effective in the development of the economies in question not only due to the sophistication of the algorithm but also due to the level of digital competencies of the consumers. The research also demonstrates cultural factors on online purchases.
Nigerian consumers were more responsive to the recommendations, which contained the indicators of the social proof (local reviews, number of people who purchased a product, or endorsement of an influencer). The trend represents the oriental nature towards collectivism that is quite common in consumer decision making largely in most developing economies where social validation is significant in determining consumer buying behavior. On the whole, the results are an addition to the

current literature on AI based marketing because they prove that technological effectiveness in new markets is influenced by the level of institutional trust, consumer education, and cultural aspects.

6. Recommendations and Conclusion

6.1 Recommendations

The paper presents five recommendations that are developed based on the concepts of the contextualised AI personalization framework. The operators of the platform should work on building trust and then proceed to investing in sophistication of personalization. Regression outcomes indicate that trust in data practices has independent predictability on purchase intention (B = 0.38) at a similar level as the direct influence of the relevance of the recommendations. Examples of tangible trust-building investments are proactive plain-language privacy notices in Nigerian English and major local languages, intuitive data access and deletion controls directly available within the shopping applications, and proactive communication when AI systems affect the prices or product suggestions that are offered to specific users. The recommendation systems implemented in the Nigerian e-commerce sites need to be re-trained with the Nigerian sourced behavioural data to enhance the contextual relevance. The regression result that perceived relevance has the highest predictive values in purchase intention (B = 0.47) means that an investment in the quality of recommendation will yield better returns than an investment in the volume of recommendation. Relevance of training data is a precondition of local representation in the Nigerian setting. AI recommendation interfaces to all key Nigerian e-commerce sites must include social proof signals. This design investment is empirically justified by the substantial positive difference of the social-proof-enhanced recommendations between the users of social commerce (mean difference 0.74). The presentation of approved reviews of buyers in Nigeria, local buyer volumes data and influencer recommendations and algorithmically paired products are expected to have a significant commercial effect on the Nigerian market recommendation systems. The regulatory bodies, especially the NDPC and the CBN, must formulate consumer-facing AI transparency principles, which will require the platform to report transparently when and how AI systems are shaping the product listings, pricing, and advertising content they are serving to individual users. This regulatory intervention would solve the problem of trust deficit, which the moderation analysis found to be the main limitation to the effectiveness of personalization in the Nigerian market. The operators of the platform and the government agencies must collaborate in investing in consumer digital literacy programmes that focus specifically on the awareness of the mechanics of AI personalization and the rights to data and the ability to recognize online fraud. The moderation result that high-digital-literacy consumers are more responsive in AI personalization (B = 0.54 as opposed to 0.29 low-literacy consumers) suggests that investing in digital literacy would promote consumer welfare, higher platform commercial performance, and, at the same time, decrease the susceptibility of low-literacy consumers to manipulative applications of personalization technology. To platform operators who may wish to put these suggestions to practice, a gradual process is recommended:

Short-term (0-6 months): Introduce plain-language privacy disclosures in Nigerian English and key local languages (Hausa, Yoruba, Igbo); include social proof indicators (proven Nigerian reviews, local numbers of people making purchases) on recommendation interfaces; run consumer awareness tools.

Medium-term (6-18 months) Retrain recommendation algorithms based on Nigeria-specific behavioural data instead of models trained on Western markets; create data access and deletion tools that are easy to use and can be accessed directly in shopping applications; collaborate with NDPC on joint consumer education efforts.

Long-term (18-36 months): Introduce active AI transparency alerts when algorithms affect pricing or product presentation; join national digital literacy programmes to under-served groups; engage in industry-wide AI personalization ethical standards development in the Nigerian market.

Table 7: Phased Implementation Recommendations

Timeline	Actions
Short-term (0-6 months)	Privacy disclosures, social proof signals, consumer awareness
Medium-term (6-18 months)	Retrain algorithms, data tools, NDPC partnership
Long-term (18-36 months)	AI transparency, digital literacy programmes, industry standards

6.2 Limitations and Future Research Directions
6.2.1 Limitation
The current research presents insightful results on the issue of AI personalization and consumer behaviour in Nigeria, but one must admit that there are a few constraints that can be hindered when reading the findings. The purposive methodology that is used by using online networking and social media platform can include disproportionate representation of digitally savvy, urban consumers with higher education levels. This restricts the ability to generalize to the rural population, aged consumers and consumers of limited access to the internet. The educational background of the sample (79% undergraduate or postgraduate) is also significantly more than the national average which may be an overstated measurement of digital literacy. Probability sampling techniques and rural-urban comparisons should be used in the future researches to represent the entire diversity of consumers in Nigeria. The research is based on the perceptions of personalization experience and the purchase intentions reported by the respondents, but there is no observed data regarding behaviour. Self-report measures are vulnerable to social desirability bias (respondents responding positively), recall error and common method variance (however, the test suggested by Harman indicates that this is not a significant problem). The next generation of research ought to combine the survey data with platform transaction data, clickstream data and the A/B test data to confirm self-reported research. The cross-sectional design will capture the relationships at one moment in time, but it will not be possible to determine causality and how the consumer reaction to AI personalization will change with the advancement of digital literacy and the trust that people will have towards the platform. Since the changes in AI technologies are great and the Nigerian consumer behaviour is changing quite rapidly, longitudinal studies that follow the same consumers through 12-24 months would be more convincing in terms of causal relationships and time dynamics. Although the research was in Nigeria, the results might not be generalized to other African or developing economies with a different regulatory environment (e.g., Kenya has a stronger data protection enforcement), culture (e.g., South Africa has a more individualist urban based population), or digital infrastructure profiles. Comparative research in various countries across Africa would assist in determining which results are country specific to Nigeria and those that can be applied to similar situations. The research concentrated on four AI personalization systems (recommendations, chatbots, targeted advertising, platform trust). Other mechanisms that might have a significant impact dynamic pricing algorithms, voice assistants, augmented reality try-on, AI-driven loyalty programmes were not investigated. The next generation research must widen the areas of research on AI mechanisms. This test has had limitations even though the single-factor test done by Harman does not raise concerns relating to common method bias. Some of the procedural remedies that should be considered in future studies include temporal separation of measurement (measuring independent and dependent variables at distinct points in time), multi-source data collection and use of markers variables.

6.2.2 Future Research Agenda
Beyond addressing these limitations, future research should:

1. **Experimental Research:** Perform randomized A/B experiments of the Nigerian e-commerce sites to gain causal relationships of the particular design attributes of personalization (social proof integration, language localization, transparency labeling) and purchase conversion. Scale.

2. Development: Scale: Develop and psychometrically test a Nigeria specific Consumer AI Acceptance Scale (N-CAIAS) that uses trust, cultural collectivism, and infrastructure sensitivity as first-class constructs, as opposed to modifying Western-developed scales.
3. Weak Consumer Protection: Explore the ethical aspects of AI personalization on vulnerable consumer groups, specifically vulnerable consumer groups with low digital literacy, as well as come up with design principles of inclusive personalization.
4. Regulatory Impact Studies: Test the change in consumer trust and personalization effectiveness in the Nigeria Data Protection Act (NDPA) enforcement across time, performed on quasi-experimental designs of comparing the pre- and post-enforcement periods.
5. Cross-Cultural Comparisons: Compare various African markets (Ghana, Kenya, South Africa, Egypt) to determine the contextual variables which moderate the effectiveness of personalization.

6.3 Conclusion

The present paper has discussed how AI-based personalisation influences the consumer-buying behaviour in Nigeria by adopting a mixed-methods design comprising both systematic literature review and primary quantitative survey data. A number of theoretical and practical conclusions are provided. To begin with, the extent to which AI-driven personalization influences purchase intention, engagement, and conversion in online Nigerian shoppers are demonstrably positive, and the perceived relevance of recommendations, the quality of the chatbot interaction, and trust in data practices by the platform practices explain the purchase intention variance by 58.4 percent. These represent commercially relevant effect sizes, which warrant further and increasingly rapid investments into AI personalisation capabilities by the e-commerce platforms in Nigeria. Second, the moderating construct in the Nigerian market is the personalization-trust paradox: personalization of the AI has the greatest impact on consumers who already trust the product, and much less on consumers who do not trust it. As a significant portion of Nigerian online consumers have a low trust-level of platforms because of the history of online fraud and low institutional data protection in the country, the personalization-trust paradox is the main commercial issue and the main consumer protection problem in the field of AI-driven online commerce in Nigeria. Third, the social and collectivist aspects of the Nigerian consumer culture are not marginal moderators, but the structural characteristics of the personalization environment that need to be considered during the design of the recommendation systems initially. Integration of social proofs, algorithm influencer synergy, and community-referenced recommendation signs are not cultural adjustments but functional needs of personalization effectiveness in the Nigerian market. Future studies ought to engage in longitudinal studies on the changes in consumer trust in AI personalization amongst the Nigerians as the digital literacy level rises and enforcement of the NDPA becomes more advanced. By conducting experimental A/B tests on the Nigerian e-commerce platforms, causal evidence on the particular design features, be it social proof integration, language localisation, or transparency labelling, that achieve the maximum conversion of purchase would be obtained. A consumer AI acceptance scale tailored to Nigeria and using trust, cultural collectivism and infrastructure sensitivity as first-class constructs would contribute significantly to the theoretical body of study of AI-mediated consumer behaviour in the context of the developing economy.

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Appendix A: PRISMA Flow Diagram (Narrative)

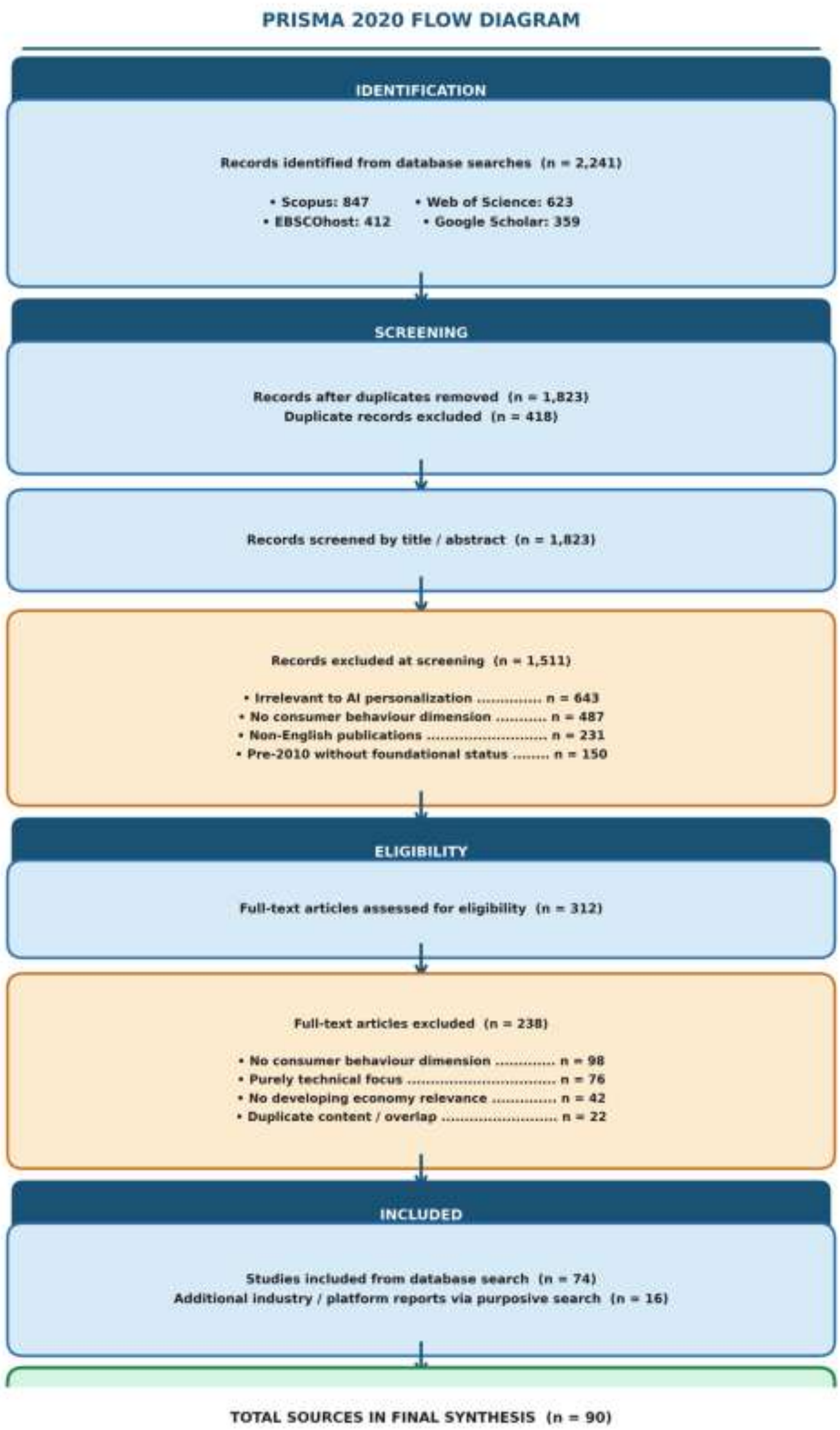

Figure A1: PRISMA 2020 Flow Diagram for Systematic Literature Review
Records identified through database searches: n = 2,241. Duplicates removed: n = 418. Records screened at title and abstract: n = 1,823. Records excluded at screening: n = 1,511. Full-text articles assessed for eligibility: n = 312. Full-text articles excluded: n = 238. Studies included from database search: n = 74. Additional industry and platform reports added through purposive search: n = 16. Total sources included in final synthesis: n = 90.

Appendix B: Survey Instrument (Abbreviated)
The following constructs and sample items were included in the survey instrument. All items used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) unless otherwise indicated.

Table B1: Survey Constructs and Sample Items

Construct	Sample Items	Source
Perceived Recommendation Relevance (PRR)	The product suggestions I receive online match my personal interests; I find recommended products useful when shopping	Adapted from Davis (1989); Akisanmi et al. (2025)
Chatbot Interaction Quality (CIQ)	The AI chatbot I have used understood my questions accurately; The chatbot provided helpful product guidance	Adapted from IJMU (2024)
Trust in Platform Data Practices (TDP)	I trust that online shopping platforms handle my personal data responsibly; I feel secure sharing my preferences with e-commerce platforms	Adapted from Canhoto et al. (2023)
Digital Literacy (DL)	I understand how websites use my browsing history to show me products; I can identify when content is being shown to me based on my past behaviour	Adapted from IJRISS (2026)
Purchase Intention (PI)	I intend to purchase products recommended to me by AI systems in the next month; AI recommendations positively influence my final purchase decisions	Adapted from Ajzen (1991)
Social Proof Sensitivity (SPS)	Knowing that many other Nigerians bought a product increases my confidence in purchasing it; I value seeing Nigerian user reviews before buying online	Adapted from Nwachukwu & Affen (2023)

Source: Authors' design, 2025; full instrument available from corresponding author on request

Appendix C: Reliability Statistics

Construct	Number of Items	Cronbach's Alpha	Interpretation
Perceived Recommendation Relevance	5	0.83	Good reliability
Chatbot Interaction Quality	5	0.79	Acceptable reliability
Trust in Platform Data Practices	6	0.87	Good reliability
Digital Literacy	4	0.76	Acceptable reliability
Purchase Intention	5	0.84	Good reliability
Social Proof Sensitivity	4	0.81	Good reliability

Source: Survey data, 2025; Cronbach's alpha > 0.70 considered acceptable (Nunnally, 1978)

Appendix D: List of Acronyms

Acronym	Full Form
AI	Artificial Intelligence
CAPM	Contextualized AI Personalization Model
CBN	Central Bank of Nigeria
CIQ	Chatbot Interaction Quality
DL	Digital Literacy
N-CAIAS	Nigeria-specific Consumer AI Acceptance Scale
NDPA	Nigeria Data Protection Act
NDPC	Nigeria Data Protection Commission
NITDA	National Information Technology Development Agency
PI	Purchase Intention
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRR	Perceived Recommendation Relevance
SLR	Systematic Literature Review
SPS	Social Proof Sensitivity
TAM	Technology Acceptance Model
TDP	Trust in Platform Data Practices
TPB	Theory of Planned Behaviour
UTAUT	Unified Theory of Acceptance and Use of Technology