Open Access Library Journal
2026, Volume 13, e15727
ISSN Online: 2333-9721
ISSN Print: 2333-9705

Artificial Intelligence and Consumer Decision-Making: AI-Powered Personalization, Trust Pathways, and Purchase Intentions in Nigeria

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How to cite this paper: Goodness Oluoma, N.U. and Yi, Y. (2026) Artificial Intelligence and Consumer Decision-Making: AI-Powered Personalization, Trust Pathways, and Purchase Intentions in Nigeria. *Open Access Library Journal*, **13**: e15727.
https://doi.org/10.4236/oalib.1115727

Received: July 1, 2026
Accepted: September 12, 2026
Published: September 15, 2026

Abstract

Artificial intelligence (AI)-powered personalization is reshaping how consumers in emerging digital economies encounter, evaluate, and commit to market offerings, yet prevailing scholarship continues to treat personalization as a uniformly trust-enhancing stimulus. This study challenges that assumption by advancing a capability-trust contingency model in which the effect of AI-powered personalization on purchase intention is neither direct nor uniform but routed through two analytically distinct trust pathways and conditioned by consumer beliefs about machine competence and data exposure. Drawing on initial trust theory and the personalization-privacy paradox, the model specifies cognitive and affective trust in the AI agent as parallel mediators, with perceived AI capability moderating the personalization-to-cognitive-trust path and privacy risk perception moderating the personalization-to-affective-trust path. The framework is examined in Nigeria, Africa's largest consumer market and a context where rapid mobile-commerce diffusion coexists with weak institutional data-protection enforcement, conditions under which Western trust assumptions cannot be presumed to transfer. Using survey data from 412 active online shoppers and a moderated-mediation estimation strategy, the analysis demonstrates that personalization elevates purchase intention primarily by building cognitive trust, that this indirect effect strengthens markedly as perceived AI capability rises, and that privacy risk perception attenuates the affective-trust pathway. The contribution is threefold: it decomposes a previously monolithic trust mechanism, it identifies the boundary conditions that govern when personalization helps or backfires, and it extends consumer AI theory to an understudied institutional setting. Implications for adaptive personalization strategy, transparency signalling, and trust calibration in low-institutional-trust markets are discussed.

Subject Areas

Marketing

Keywords

Artificial Intelligence, Personalization, Cognitive Trust, Affective Trust, Purchase Intention, Moderated Mediation, Privacy Risk, Nigeria, Emerging Markets

1. Introduction

The migration of consumer decision-making onto algorithmically curated digital surfaces represents one of the most consequential shifts in contemporary marketing practice. Artificial intelligence (AI)-powered personalization the real-time, machine-learning-driven tailoring of product recommendations, content, and offers to inferred individual preferences throughout, the focal "AI agent" refers to the algorithmic recommender system embedded within a consumer-facing online retail or marketplace platform that is, the machine-learning engine that generates personalized product recommendations and offers on e-commerce apps and websites rather than a conversational chatbot, a general-purpose platform ranking algorithm, or a single retailer's manual merchandising. has moved from a competitive embellishment to the organizing logic of digital commerce (Davenport *et al.* [1]; De Bruyn *et al.* [2]). Huang and Rust [3] frame AI as a strategic capability that reorganizes the marketing function itself, and Verhoef *et al.* [4] and Grewal *et al.* [5] situate that shift within the wider digital transformation of the firm, while the systematic reviews of Mariani *et al.* [6] and Vlačić *et al.* [7] document the speed at which consumer-facing AI research has accumulated and Dwivedi *et al.* [8] map the multidisciplinary challenges it raises. Yet the dominant theoretical posture in the marketing literature continues to frame personalization as a broadly relevance-enhancing, and therefore trust- and conversion-promoting, intervention (Kumar *et al.* [9]; Shankar [10]). This framing obscures a more unsettled reality: the same algorithmic apparatus that increases offer relevance simultaneously heightens consumers' awareness of surveillance and inference, generating a tension that personalization scholarship has long labelled the personalization-privacy paradox (Aguirre *et al.* [11]; Bleier and Eisenbeiss [12]; Aguirre *et al.* [13]). Puntoni *et al.* [14] further show that consumers do not experience AI as a neutral utility but as a series of felt encounters that can be enabling and unsettling at once. The strategic question is therefore not whether personalization works, but under what conditions, through which psychological mechanisms, and for whom.

Three limitations constrain the cumulative knowledge base. First, the mediating role of trust is routinely modelled as a single, undifferentiated construct, despite well-established evidence in the trust literature that consumer trust in an unfamiliar online actor is multidimensional, comprising a calculative, competence-based component and an emotional, benevolence-based component (McKnight *et al.* [15] [16]; Mayer *et al.* [17]; Johnson and Grayson [18]). Collapsing these into one latent variable conceals the possibility that personalization recruits them through different routes and that they respond to different boundary conditions. Second, the boundary conditions themselves are under-theorized. Personalization research has tended to treat algorithmic competence as a constant rather than a perception that consumers actively form and that conditions their willingness to defer to machine judgment, a perception that the algorithm-appreciation and algorithm-aversion literatures show to be both consequential and variable (Logg *et al.* [19]; Dietvorst *et al.* [20]; Castelo *et al.* [21]), and that Longoni *et al.* [22] show to vary sharply with the domain in which the machine is asked to judge. Third, the empirical canon is overwhelmingly situated in high-institutional-trust Western markets, where formal data-protection regimes underwrite a baseline of structural assurance. Whether the trust calculus transfers to settings with weak enforcement infrastructure remains largely an assumption rather than a finding.

Nigeria offers a theoretically generative site for confronting these limitations. As Africa's most populous nation and largest consumer economy, it combines accelerating mobile-commerce penetration with a comparatively nascent data-governance environment, producing a configuration in which consumers must extend trust to AI systems in the relative absence of the institutional guarantees that anchor trust in Western contexts (Sheth [23]; Hoffman and Novak [24]). This is not a context to which existing models can be presumed to generalize; it is one in which their scope conditions become visible. We therefore ask: through which trust pathways does AI-powered personalization shape purchase intention among Nigerian online consumers, and how do perceived AI capability and privacy risk perception condition those pathways?

We answer this question by developing and testing a capability-trust contingency model. The model makes three moves that distinguish it from prior work. It decomposes the personalization-to-purchase mechanism into parallel cognitive- and affective-trust pathways; it specifies perceived AI capability and privacy risk perception as theoretically targeted moderators of distinct paths, yielding a moderated-mediation structure rather than an undifferentiated main effect; and it relocates the inquiry to an emerging-market setting where the institutional preconditions of trust differ in kind. In doing so, the study advances consumer AI theory from a question of average effects toward a contingency account of when and why algorithmic personalization converts attention into commitment.

2. Theoretical Background and Hypothesis Development

2.1. AI-Powered Personalization as a Double-Edged Stimulus

AI-powered personalization differs from earlier rule-based personalization in degree and in kind. Where legacy systems matched offers to declared preferences, contemporary systems infer latent intentions from behavioural traces, continuously updating their models without explicit consumer input (Davenport *et al.* [1]; De Bruyn *et al.* [2]). Kumar *et al.* [9] describe this capability as the foundation of personalized engagement marketing and Shankar [10] traces its diffusion through retailing, while Xiao and Benbasat [25] provide the foundational account of how recommendation agents reshape consumer decision processes. This inferential opacity is the source of both the value and the threat that personalization carries. On one side, relevance reduces search costs and signals that the firm understands the consumer, mechanisms long argued to lift adoption and engagement (Aguirre *et al.* [11]; Chandra *et al.* [26]) and echoed in evidence that richer, more immersive digital presentation formats raise perceived usefulness and purchase intention (Yim *et al.* [27]). On the other, the covert character of behavioural inference can heighten perceived vulnerability, an affective state that depresses click-through and purchase responses even when relevance is objectively high (Aguirre *et al.* [11]; Bleier and Eisenbeiss [12]). The demonstration by Aguirre *et al.* [11] that covert data collection inverts the benefit of personalization established the empirical core of the personalization privacy paradox and, together with its extension in Aguirre *et al.* [13], remains the reference point against which subsequent boundary-condition research is evaluated. We retain a baseline expectation that, on average, personalization raises purchase intention, while treating that main effect as theoretically incomplete until its mediating and moderating structure is specified.

H1. AI-powered personalization is positively associated with consumers' purchase intention.

2.2. Decomposing the Trust Mechanism: Cognitive and Affective Pathways

Initial trust theory holds that, when transacting with an unfamiliar online actor, consumers form trusting beliefs that allow them to overcome uncertainty and risk and to act by following advice, disclosing information, and purchasing (McKnight *et al.* [15] [16]; Gefen *et al.* [28]). Critically, these beliefs are not monolithic. Cognitive trust is a calculative judgement grounded in competence and reliability cues, whereas affective trust is an emotional bond grounded in perceived benevolence and goodwill (McKnight *et al.* [15] [16]; Mayer *et al.* [17]; Johnson and Grayson [18]). Although our respondents had a recent personalized-purchase experience with a platform, initial trust theory remains the appropriate lens here because the object of trust is the AI recommender agent rather than the retail platform as a whole. Even experienced online shoppers encounter each algorithmic recommendation as an interaction with an opaque, non-human actor whose inference process is unobservable and whose "intentions" cannot be verified from prior familiarity; every new recommendation reactivates the same competence- and benevolence-based judgments that initial trust theory describes, because the machine unlike a human counterpart accrues limited relational history and is continually re-evaluated against fresh performance cues. In this sense the construct we model is best understood as the ongoing, repeatedly re-formed trust that consumers extend to AI-enabled recommendation systems, for which the cognitive and affective distinction of initial trust theory provides the operative structure; we therefore retain its two-component architecture while framing trust as recurrently negotiated across encounters rather than formed only at first contact. AI-powered personalization speaks to both, but through different channels. Accurate, well-targeted recommendations function as competence signals: they provide ongoing evidence that the system reliably models the consumer's needs, supplying precisely the kind of performance information on which cognitive trust is calibrated (Dietvorst *et al.* [20]; Castelo *et al.* [21]), a mechanism Komiak and Benbasat [29] document directly for recommendation agents, whose personalization and familiarity raise both cognitive and emotional trust. Personalization also carries relational meaning being recognized and anticipated can be experienced as a form of attentiveness thereby feeding the affective component, though this channel is more fragile because the same recognition can be reinterpreted as intrusion (Bleier and Eisenbeiss [12]; Aguirre *et al.* [13]).

Because cognitive and affective trust are themselves established antecedents of behavioural intention in online exchange (McKnight *et al.* [15] [16]; Pavlou [30]; Bart *et al.* [31]), we model them as parallel mediators linking personalization to purchase intention. Distinguishing them is not a psychometric nicety: it is the analytical precondition for detecting the divergent boundary conditions developed below, which an undifferentiated trust construct would average away.

H2a. AI-powered personalization is positively associated with cognitive trust in the AI agent.

H2b. AI-powered personalization is positively associated with affective trust in the AI agent.

H3a. Cognitive trust mediates the relationship between AI-powered personalization and purchase intention.

H3b. Affective trust mediates the relationship between AI-powered personalization and purchase intention.

2.3. Perceived AI Capability as a Contingency on the Cognitive Pathway

If cognitive trust is calibrated on competence evidence, then the diagnostic value of any given personalization cue depends on the consumer's prior belief about whether the system is capable of competent inference at all. The algorithm-appreciation literature shows that, absent disconfirming experience, individuals often prefer algorithmic to human judgement, but that this appreciation is conditional and collapses when competence is in doubt (Logg *et al.* [19]; Dietvorst *et al.* [20]). Conversely, the algorithm-aversion literature documents a steep penalty for perceived machine error and a reluctance to rely on systems judged incompetent (Dietvorst *et al.* [20]; Castelo *et al.* [21]), an aversion that Longoni *et al.* [22] find to be sharpest where consumers doubt that a machine can accommodate their individuality. Evidence from service settings converges on the same conclusion: acceptance of AI-enabled and robotic frontline agents is governed principally by beliefs about what the technology can competently do (Wirtz *et al.* [32]; Ostrom *et al.* [33]; Belanche *et al.* [34]), and comparable capability assessments drive AI adoption at the organizational level (Chatterjee *et al.* [35]), while Hermann [36] argues that the visible ethical conduct of firms deploying AI further shapes the credibility consumers assign to it. Perceived AI capability the consumer's general belief in the system's competence to understand and serve them should therefore act as an interpretive lens. When capability beliefs are high, personalization cues are read as confirmation of competence and translate efficiently into cognitive trust; when they are low, the same cues are discounted as noise or coincidence. The personalization-to-cognitive-trust relationship is thus expected to strengthen as perceived AI capability rises.

H4. Perceived AI capability moderates the relationship between AI-powered personalization and cognitive trust, such that the relationship is stronger when perceived AI capability is high.

2.4. Privacy Risk Perception as a Contingency on the Affective Pathway

The affective pathway is governed by a different boundary condition. The personalization-privacy paradox locates the threat of personalization not in competence but in vulnerability the felt exposure that arises when a firm appears to know more than the consumer disclosed (Aguirre *et al.* [11]; Bleier and Eisenbeiss [12]; Aguirre *et al.* [13]). Privacy risk perception, the consumer's expectation that personal data may be misused, sits at the centre of the privacy calculus through which consumers weigh disclosure against benefit (Dinev and Hart [37]), and firm-level evidence confirms that mishandled data carries measurable performance costs (Martin *et al.* [38]); it should therefore condition the emotional, benevolence-based response to personalization rather than the competence-based one. In emerging-market settings where institutional data protection is weak, this perception is unlikely to be offset by structural assurance, intensifying its relevance (Sheth [23]; McKnight *et al.* [16]). When privacy risk perception is high, the relational warmth that personalization might otherwise generate is overwritten by suspicion of opportunism, weakening the personalization-to-affective-trust link; when it is low, personalization is freer to register as attentiveness.

H5. Privacy risk perception moderates the relationship between AI-powered personalization and affective trust, such that the relationship is weaker when privacy risk perception is high.

Taken together, H1 - H5 constitute a moderated-mediation system in which the indirect effect of personalization on purchase intention is conditional on perceived AI capability (through cognitive trust) and on privacy risk perception (through affective trust). **Figure 1** presents the model.

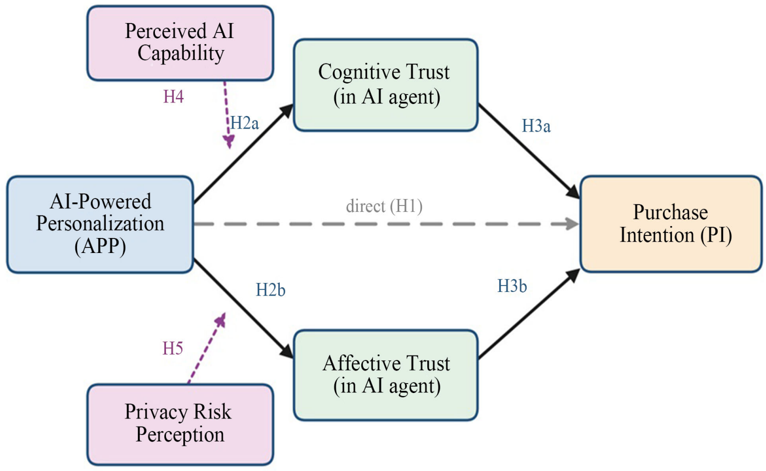

Figure 1. Capability trust contingency model of AI personalization and purchase intention.

3. Method

3.1. Sample and Procedure

Data were collected from active online consumers in Nigeria through a structured self-administered questionnaire distributed across major commercial centres and online shopping communities. Respondents were recruited through non-probability purposive and snowball sampling between March and May 2024. The questionnaire, administered online via Google Forms, was circulated through three channels: 1) e-commerce and online-shopping interest groups on WhatsApp, Facebook, and Telegram; 2) targeted social-media posts on Instagram and X (formerly Twitter) using shopping-related hashtags; and 3) intercept referrals in high-footfall commercial areas of Lagos, Abuja, and Port Harcourt. Participation was voluntary; on completion, respondents could enter a raffle for one of twenty ₦2000 mobile-airtime vouchers as a modest incentive. To ensure a common referent, each respondent was asked before answering the focal items to recall one specific, recent personalized online-shopping experience, prompted as follows: Please think of the most recent occasion, within the past three months, on which an online shopping app or website showed you personalized product recommendations chosen for you by its system. Keep that specific experience and that platform in mind as you answer the following questions. Respondents also named the platform they had in mind; the responses spanned Jumia, Konga, Amazon, AliExpress, Temu, and Instagram and Facebook Shops, with no single platform exceeding 40% of cases. Eligibility required at least one personalized online purchase in the preceding three months, ensuring that respondents could meaningfully evaluate AI-driven recommendation experiences. Of 561 questionnaires initiated, 512 were submitted 49 abandoned before submission. Screening then removed cases sequentially: 38 for failing the eligibility no personalized purchase in the past three months, 21 for incomplete responses on focal items, 25 for failing at least one of two embedded attention checks, and 16 for straight-line or near-zero-variance response patterns, leaving an analytic sample of 412 73.4% of submitted questionnaires. After screening for incomplete responses, attentiveness-check failures, and straight-line patterns, the analytic sample comprised 412 respondents. The sample skewed toward younger, mobile-first consumers consistent with the demographic profile of Nigerian e-commerce, with balanced gender representation and variation across income and education strata. Table 1 summarizes respondent characteristics.

Table 1. Sample characteristics (N = 412).

Characteristic	Category	n	%
Gender	Female	201	48.8
	Male	211	51.2
Age	18 - 24	148	35.9
	25 - 34	169	41.0
	35 - 44	71	17.2
	45+	24	5.8
Monthly online spend	Low	139	33.7
	Medium	186	45.1
	High	87	21.1
Primary device	Smartphone	357	86.7
	Desktop/Other	55	13.3

3.2. Measures

Respondents evaluated an AI-powered recommender system the personalized product-recommendation engine of a consumer e-commerce platform or online marketplace (e.g., recommendation feeds, recommended for you and because you viewed modules on shopping apps and websites) and not a customer-service chatbot, a social-media feed algorithm, or a retailer's human-curated promotions. All focal constructs were measured with multi-item, seven-point Likert scales adapted from validated instruments and contextualized to AI-powered shopping in Nigeria. AI-powered personalization was operationalized through perceived recommendation relevance and adaptivity, building on the personalization-effectiveness scales of Aguirre *et al.* [11] and Chandra *et al.* [26] and on the recommendation-agent measures of Komiak and Benbasat [29]. Cognitive and affective trust were measured using items reflecting the competence/reliability and benevolence and goodwill distinction central to initial trust theory (McKnight *et al.* [15] [16]), with wording informed by the credibility-based trust scales of Lou and Yuan [39]. Perceived AI capability captured beliefs about the system's competence to understand consumer needs (Logg *et al.* [19]; Dietvorst *et al.* [20]). Privacy risk perception was assessed with items reflecting expected likelihood and severity of data misuse (Bleier and Eisenbeiss [12]; Aguirre *et al.* [13]; Dinev and Hart [37]). Purchase intention was measured with established behavioural-intention items (McKnight *et al.* [15]; Venkatesh *et al.* [40]). Age, gender, income, prior online-purchase frequency, and product category were retained as covariates. **Table 2** reports the measurement model.

Table 2. Measurement model: reliability and convergent validity.

Construct	Items	α	CR	AVE
AI-powered personalization (APP)	4	0.89	0.91	0.72
Cognitive trust	4	0.91	0.93	0.77
Affective trust	4	0.88	0.91	0.71
Perceived AI capability	3	0.86	0.91	0.78
Privacy risk perception	4	0.90	0.92	0.74
Purchase intention (PI)	3	0.92	0.95	0.86

All standardized item loadings were significant ($p < 0.001$) and ranged from 0.71 to 0.92, exceeding the 0.70 threshold. The measurement model demonstrated good fit: $\chi^2(174) = 312.6$, $\chi^2/df = 1.80$, CFI = 0.968, TLI = 0.961, RMSEA = 0.044 (90% CI [0.037, 0.051]), and SRMR = 0.038. Internal consistency and composite reliability exceeded conventional thresholds, and average variance extracted (AVE) exceeded 0.50 for every construct, supporting convergent validity. Discriminant validity was satisfied under the Fornell-Larcker criterion (Fornell and Larcker [41]), with the square root of each construct's AVE exceeding its inter-construct correlations, and corroborated by heterotrait-monotrait ratios below the 0.85 benchmark recommended by Henseler *et al.* [42]. Because all data were self-reported, common-method bias was assessed following the guidance of Podsakoff *et al.* [43]: Harman's single-factor test returned a first factor accounting for less than half of total variance, and a marker-variable adjustment left the structural estimates substantively unchanged.

3.3. Analytic Strategy

Hypotheses were tested using covariance-based structural equation modelling for the measurement and direct-path estimates, complemented by bias-corrected bootstrap moderated-mediation analysis (5000 resamples) to estimate conditional indirect effects and indices of moderated mediation following Hayes [44]. Predictors entering interaction terms were mean-centred. This combined strategy directly tests whether the indirect effects of personalization on purchase intention vary across levels of perceived AI capability and privacy risk perception, which is the empirical crux of the contingency argument.

4. Results

4.1. Descriptive Statistics and Correlations

Table 3 presents means, standard deviations, and bivariate correlations. Personalization correlated positively with cognitive trust, affective trust, and purchase intention; privacy risk perception correlated negatively with affective trust and purchase intention. The pattern is consistent with the proposed dual-pathway structure and provides preliminary support for the moderating roles developed in the model.

Table 3. Means, standard deviations, and correlations.

Variable	M	SD	1	2	3	4	5	6
1. APP	4.92	1.18	—					
2. Cognitive trust	4.71	1.24	0.58	—				
3. Affective trust	4.38	1.31	0.46	0.61	—			
4. Perceived AI capability	4.85	1.22	0.49	0.55	0.41	—		
5. Privacy risk perception	4.63	1.40	0.12	−0.18	−0.34	−0.09	—	
6. Purchase intention	4.80	1.29	0.55	0.64	0.52	0.48	−0.27	—

Correlations $|r| \geq 0.12$ are significant at $p < 0.05$; $|r| \geq 0.16$ at $p < 0.01$. APP = AI-powered personalization.

4.2. Direct Effects and Mediation

Table 4. Structural path estimates.

Path	β	SE	t	Result
APP → Purchase intention (H1, direct effect; total effect $\beta = 0.55$)	0.21	0.05	4.20	Supported
APP → Cognitive trust (H2a)	0.54	0.04	13.50	Supported
APP → Affective trust (H2b)	0.39	0.05	7.80	Supported
Cognitive trust → Purchase intention	0.42	0.05	8.40	Supported
Affective trust → Purchase intention	0.24	0.05	4.80	Supported
APP → Cognitive trust → PI (H3a)	0.23	0.03	—	Supported
APP → Affective trust → PI (H3b)	0.09	0.02	—	Supported

All coefficients significant at $p < 0.01$. Indirect effects estimated via 5000 bias-corrected bootstrap resamples; 95% CIs excluded zero.

The structural model fit the data well by conventional indices ($\chi^2(179) = 331.4$, $\chi^2/df = 1.85$, CFI = 0.965, TLI = 0.959, RMSEA = 0.045 [90% CI 0.038 - 0.052], SRMR = 0.041). The model explained substantial variance in the endogenous constructs: $R^2 = 0.34$ for cognitive trust, $R^2 = 0.19$ for affective trust, and $R^2 = 0.52$ for purchase intention. Supporting H1, personalization exhibited a positive total effect ($\beta = 0.55$) on purchase intention, of which the direct effect ($\beta = 0.21$) net of the cognitive- and affective-trust mediators was smaller; H1 is thus supported as a total-effect hypothesis, and the direct path in Table 4 is labelled accordingly so that its interpretation matches the partially mediated model. Supporting H2a and H2b, personalization significantly predicted both cognitive trust and affective trust, with the standardized coefficient larger on the cognitive path. Both trust dimensions in turn predicted purchase intention, with cognitive trust the stronger proximal driver. Bootstrap mediation analysis confirmed significant indirect effects through both pathways, supporting H3a and H3b; the cognitive-trust pathway carried the larger share of the total indirect effect, indicating that, in this market, personalization persuades primarily by demonstrating competence rather than by cultivating warmth. Table 4 reports the structural estimates.

4.3. Moderation and Conditional Indirect Effects

Supporting H4, the interaction of personalization and perceived AI capability on cognitive trust was positive and significant ($\beta = 0.19$, SE = 0.05, t = 3.80, $p < 0.001$, 95% CI [0.09, 0.29]): the slope of personalization on cognitive trust was substantially steeper for consumers high in capability beliefs than for those low in them, as depicted in the simple-slopes plot in Figure 2. The diagnostic value of a personalization cue, in other words, depends on whether the consumer already credits the system with competence.

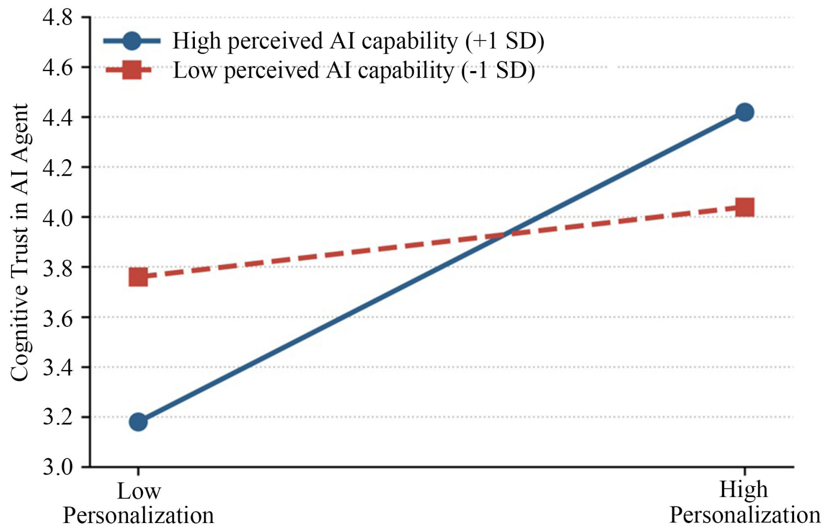

Figure 2. Interaction of personalization and perceived AI capability on cognitive trust.

Supporting H5, the interaction of personalization and privacy risk perception on affective trust was negative and significant ($\beta = -0.16$, SE = 0.05, t = −3.20, p = 0.001, 95% CI [−0.26, −0.06]): under high privacy risk perception, the affective benefit of personalization was attenuated, consistent with the vulnerability logic of the personalization-privacy paradox. The index of moderated mediation was significant for the cognitive pathway moderated by perceived AI capability, confirming that the indirect effect of personalization on purchase intention through cognitive trust is conditional on capability beliefs. Figure 3 plots the conditional indirect effects, which rise monotonically from a non-significant effect at low capability to a strong, significant effect at high capability.

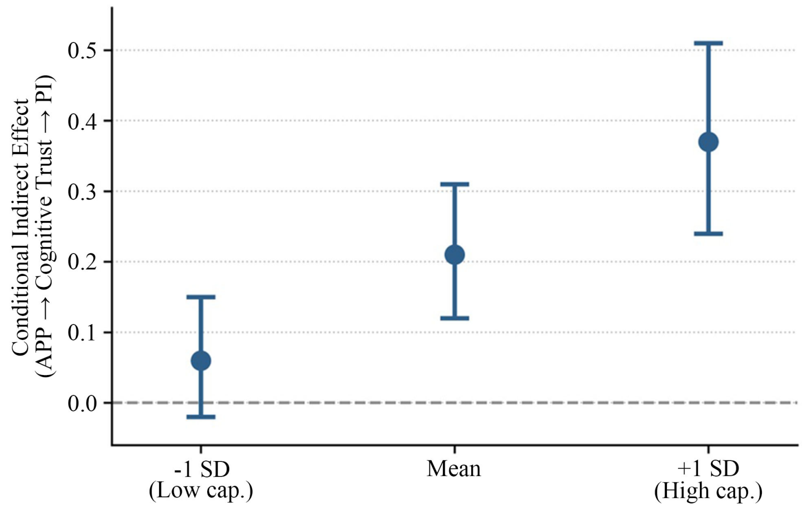

Figure 3. Conditional indirect effects at levels of perceived AI capability 95% (Bias corrected bootstrap CIs).

Table 5 summarizes the conditional indirect effects and the indices of moderated mediation, providing the formal test of the contingency structure.

Table 5. Conditional indirect effects and indices of moderated mediation.

Pathway/moderator level	Indirect effect	95% CI	Significant
Cognitive trust @ low capability (−1 SD)	0.06	[−0.02, 0.15]	No
Cognitive trust @ mean capability	0.21	[0.12, 0.31]	Yes
Cognitive trust @ high capability (+1 SD)	0.37	[0.24, 0.51]	Yes
Index of moderated mediation (capability)	0.15	[0.07, 0.24]	Yes
Affective trust @ low privacy risk (−1 SD)	0.14	[0.07, 0.22]	Yes
Affective trust @ high privacy risk (+1 SD)	0.04	[−0.01, 0.10]	No
Index of moderated mediation (privacy risk)	−0.05	[−0.10, −0.01]	Yes

5. Discussion

5.1. Theoretical Contributions

This study reframes AI-powered personalization from a uniform persuasion lever into a contingent, mechanism-specific process, and in doing so makes three contributions. First, by decomposing the trust mediator into cognitive and affective components, it resolves an aggregation problem that has masked how personalization actually operates. The finding that the cognitive pathway dominates the affective pathway in this market indicates that, where institutional assurance is scarce, consumers lean on demonstrated competence rather than inferred goodwill when deciding to act on algorithmic recommendations an insight unavailable to models that treat trust as a single construct (McKnight *et al.* [15] [16]; Johnson and Grayson [18]). Second, by specifying perceived AI capability and privacy risk perception as moderators of distinct paths, the study converts the personalization-privacy paradox from a static tension into a structured contingency: capability beliefs govern when competence signals translate into trust, while privacy risk governs when relational warmth survives (Aguirre *et al.* [11]; Aguirre *et al.* [13]; Logg *et al.* [19]). The significant index of moderated mediation for the capability pathway is, to our knowledge, a novel demonstration that the persuasive power of personalization is conditional on the consumer's prior theory of the machine's competence. Third, by situating the model in Nigeria, the study extends consumer AI theory beyond the high-institutional-trust settings that dominate the literature and shows that the scope conditions of trust formation differ where structural assurance is weak (Sheth [23]; McKnight *et al.* [16]; Hoffman and Novak [24]).

5.2. What Is New

Prior work has established that personalization can both attract and repel, that trust mediates digital-commerce outcomes, and that algorithm appreciation is conditional. What has been missing is an integrated account specifying which trust mechanism each force operates through and which consumer belief switches it on or off. The capability-trust contingency model supplies that account and tests it as a moderated-mediation system rather than as a set of disconnected main effects. The relocation to an emerging African market is not incidental: it is the condition under which the dominance of the cognitive pathway and the salience of privacy risk become observable, because the institutional buffers that would otherwise obscure them are absent.

5.3. Managerial Implications

For firms personalizing at scale in emerging markets, the results counsel against treating personalization intensity as a monotonic good. Because the cognitive pathway dominates and is gated by capability beliefs, returns to personalization are largest among consumers who already credit the system with competence; for sceptical segments, investments in visible competence signalling explainable recommendations, accuracy cues, and transparent rationale are prerequisites rather than embellishments (Castelo *et al.* [21]). Because the affective pathway is suppressed by privacy risk, firms operating where data-protection enforcement is weak cannot rely on relational warmth to carry conversion and should instead reduce perceived vulnerability through overt, consent-based data practices that substitute for absent structural assurance (Aguirre *et al.* [11]; Aguirre *et al.* [13]; Martin *et al.* [38]). Strategically, this implies adaptive personalization: calibrating intensity and transparency to inferred capability and privacy-risk profiles rather than applying a uniform policy.

5.4. Limitations and Future Research

The cross-sectional design limits causal inference; longitudinal and experimental replications would strengthen the temporal ordering of personalization, trust, and intention. The focus on a single national market, chosen for its theoretical lever-age, invites comparative replication across African and other emerging economies to test the generalizability of the cognitive-pathway dominance. Future work might also incorporate behavioural outcomes beyond stated intention, examine the dynamics of trust repair following algorithmic error, and test whether explainable-AI interventions can shift capability beliefs and thereby unlock the conditional indirect effect among currently sceptical consumers.

6. Conclusion

AI-powered personalization does not persuade uniformly; it persuades conditionally, through separable trust mechanisms whose activation depends on what consumers believe about machine competence and data exposure. By decomposing the trust mediator, specifying targeted moderators, and testing the resulting moderated-mediation system in an under-studied emerging market, this study replaces the prevailing average-effect view with a contingency account of when algorithmic personalization converts attention into commitment. For theory, it clarifies the architecture of trust in consumer-AI interaction; for practice, it reframes personalization strategy as an exercise in trust calibration rather than relevance maximization.

Author Contributions

Conceptualization, N.U.G.O.; methodology, N.U.G.O.; software, N.U.G.O.; validation, N.U.G.O. and Y.Y.; formal analysis, N.U.G.O.; investigation, N.U.G.O.; resources, N.U.G.O. and Y.Y.; data curation, N.U.G.O.; writing original draft preparation, N.U.G.O.; writing review and editing, N.U.G.O. and Y.Y.; visualization, N.U.G.O.; supervision, Y.Y.; project administration, N.U.G.O.; funding acquisition, N.U.G.O. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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