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The Impact of AI-Powered Recommendations on Online Purchase Decisions: A Consumer Perspective

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KEYWORDS

AI recommendations, algorithmic trust, personalization, purchase intention, perceived intrusiveness

ABSTRACT

The rapid integration of AI-powered recommendation engines into e-commerce platforms has transformed how consumers interact with digital content and make purchase decisions. This study explores the behavioral and psychological mechanisms underpinning consumer responses to AI-generated product suggestions, emphasizing the roles of perceived personalization, algorithmic trust, and perceived intrusiveness. Anchored in dual-process theory, the research employed a cross-sectional design with 430 online shoppers, analyzed through PLS-SEM and multiple regression techniques.

Findings indicate that personalization ($\beta = 0.381$, $p < 0.001$) and trust ($\beta = 0.276$, $p < 0.001$) exert significant positive effects on purchase intention. Conversely, perceived intrusiveness has a negative impact ($\beta = -0.218$, $p < 0.001$). Mediation analysis further revealed that intrusiveness partially mediates the effects of both personalization and trust on purchase decisions. Subgroup analyses showed generational differences, where Gen Z consumers place greater emphasis on personalization, and platform-inexperienced users depend more heavily on algorithmic trust. The model demonstrates strong explanatory power ($R^2 = 0.633$) and predictive relevance ($Q^2 = 0.402$), underscoring its robustness.

These results underscore the necessity for brands to design AI systems that are not only efficient but also psychologically attuned to user expectations. Transparent and ethically sound personalization strategies that mitigate perceived intrusiveness can significantly enhance consumer trust and decision-making outcomes. The study offers practical implications for marketers, AI developers, and digital policy advocates in optimizing consumer engagement in data-driven environments.

1. INTRODUCTION

AI, or artificial intelligence has revolutionized the manner consumers find, consider, and buy products on the Internet since its introduction to e-commerce environments. Recommendation systems AI-powered suggestion engines, such as collaborative filtering algorithms and more advanced machine learning models, have become central to shaping consumer behavior through the delivery of personalized content in real-time. These smart systems personalize product recommendations through historical behaviors, preferences, demographics, and contextual information and thus redefine the decision-making process of the consumer (Mustikasari *et al*., 2025; Ram *et al*., 2024).

AI has helped bring an end to the stagnant targeting of marketing strategies and instead has introduced a dynamic interaction between the brands and the consumer in a hyper-personalisation and data-driven manner. The list of strategies is also limited, no more than product recommendations, but has expanded to include personalized communication, dynamic pricing, and behavior prediction at various touchpoints (Chu, 2025; Sherly Steffi *et al*., 2024). The adaptive and learning abilities of AI have particularly played an important role in boosting online brand experience and repurchase intentions (Mustikasari *et al*., 2025). This pivot is part of a larger trend of business-to-consumer changes in favor of consumer-centric to consumer-centric paradigms whereby power continues to be placed in the hands of digitally literate and artificially intelligent consumers (Rathee, 2025).

The mechanics and impact of AI personalization, especially in discerning its relevance to consumer engagement, satisfaction, and loyalty, have been topics of a substantial body of literature (Jayakumar *et al*., 2024; Arora *et al*., 2024). As an example, personalization using AI has been demonstrated to promote impulse buying by eliminating decision fatigue and presenting valuable alternatives at the appropriate moment and location (Ram *et al*., 2024). AI eye-tracking researchers have also demonstrated subconscious consumer biases in attention, showing a more profound, typically unexplained role of such technologies in purchase intentions. These insights show that, on top of the behavioral alignment, the AI personalization can affect the cognitive and affective reactions that build consumer trust and perceived value.

Nevertheless, the high applicability of AI in e-commerce comes with serious questions of transparency, data ethics, and consumer agency. With reported high satisfaction rates in platforms like Jumia (Taiwo, 2024) and e-commerce settings built around apparel (Natenadze, 2024), multiple users still do not understand the role of the algorithms in their decisions. It results in a personalization-privacy paradoxical situation in which consumers want an individualized experience, yet they are also concerned about data abuse and manipulation (Kumar *et al*., 2025; Balasubramanian, 2024). A lack of transparency in algorithmic decision-making keeps damaging trust, which is paramount to the successful recommendation systems in the long run (Ngu Ngendi, 2024; Ahamed *et al*., 2025).

Moreover, research between the disciplines indicates that such influence of AI-based suggestions is not consistent across all consumer groups. Digital literacy, familiarity with the platform, and cultural beliefs about automation are all examples of moderate influences that affect acceptance and perceived usefulness (Yadav *et al*., 2025; Chowdary *et al*., 2024). This demands a more sophisticated, consumer psychology-driven interpretation of the AI involvement in the purchase process of decision-making one that will not be confined to the transactional measurements but will encompass psychological, behavioural, and socio-cultural aspects.

Thus, the proposed empirical research is expected to investigate the effect of AI-driven recommendations on online purchasing actions through the lens of consumer behavior. It particularly examines the role of perceived personalization, algorithmic trust, and intrusiveness on the intention of consumers to buy. Through the convergence of the knowledge on the latest empirical, theoretical and technological developments, the study contributes to the emerging collection of information on AI in consumer affairs and provides strategic insights that could be used by digital marketers, designers and platform developers who need to understand how to personalize experiences without compromising the ethics of consumer personalization.

2. METHODOLOGY

2.1 Research Philosophy and Approach

The epistemological method used in the study is positivist, as it is supported by the assumption that the AI-powered recommending system will cause changes in the behavior of consumers that can be objectively measured and that these causal relationships can be revealed and explained by the statistical analysis. Basing the study on Technology Acceptance Theory, Cognitive Load Theory, and the Elaboration Likelihood Model, the study mobilizes the mutual relation of perceived personalization, algorithmic trust, and intrusiveness as factors of online purchase intention antecedents. The study adheres to the deductive reasoning logic, in which the hypotheses determined by the theoretical constructs are confirmed empirically with the use of structural equation modeling using partial least squares (PLS-SEM) a reliable method that is appropriate to use when the focus is on predictions and the model is complex (including latent variables) and modest to moderate (Hair *et al*., 2019).

2.2 Research Design

The design of the study is multi-stage, cross-sectional, and includes an embedded between-subjects experiment, in which different levels of recommendation transparency (e.g., opaque vs. explainable AI) were exposed to the participants. Such a design will enable testing both perceptual predecessors (personalization, trust, intrusiveness) and behavioral consequents (purchase intent) in a controlled, nevertheless ecologically valid environment, e-commerce interface simulation.

The prototype of a digital storefront was prepared in Figma as a pre-validated template, and scenario-based, scripted AI-generated product recommendations were integrated. This confined setting provided the standardization of stimulus and the possibility to randomize the exposure factors and content validity. Pretesting of the questionnaire and stimuli (N = 25) was done through expert review and cognitive interviewing.

2.3 Sampling and Participants

The digitally active online consumer base of 18 to 50-year-olds who engaged with AI-generated product suggestions in the last six months was the study's intended audience. The sample was carried out utilizing a stratified method of purposive sampling, where the aim was to get a heterogeneous variance in terms of demographics (gender, age, region, education) and engagement with e-commerce sites (like Jumia, Flipkart, and Amazon).

A power calculation after the fact (using G*Power 3.1) indicated that a size of sample of 280 was required at a power of 0.80 to observe medium effect sizes (f2 = 0.15). and an 0.05 alpha and four predictors. To adjust to dropouts and have the possibility of multi-group analyses, 500 responses were acquired through MTurk and Reddit e-commerce subforums. The final valid sample was of 430 cases after the removal of inattentive responses (determined by Mahalanobis distance and attention-check standards).

2.4 Measurement Instruments

Every construction was operationalized employing multi-item reflective scales that were modified from existing literature and revalidated for this study's context, as shown in Items were scored using a seven-point Likert scale (1 being strongly disagree and 7 being strongly agree) (Table 1), enhancing variance detection and scale sensitivity.

Table 1. Operationalization of Study Constructs: Measurement Sources, Item Counts, and Representative Items

Construct	Source	# Items	Sample Item
Perceived Personalization	Sherly Steffi *et al.* (2024); Kumar *et al.* (2025)	5	"The recommendations match my preferences well."
Algorithmic Trust	Mustikasari *et al.* (2025); Ngu Ngendi (2024)	4	"I believe the system acts in my best interest."
Perceived Intrusiveness	Ahamed *et al.* (2025); Balasubramanian (2024)	4	"The recommendations feel intrusive or pushy."
Purchase Intention	Ram *et al.* (2024); Arora *et al.* (2024)	4	"I would likely buy a product suggested by the system."

Common method bias was mitigated through (i) psychological separation of independent and dependent constructs, (ii) counterbalancing question order, and (iii) post-hoc there was no dominating factor (<40%) in Harman's single-factor test.

2.5 Data Collection Protocol

The survey was carried out on March 1- 25, 2025. They were introduced to a stimulated product search task and invited to interact with AI-recommended product recommendations, and then participants filled out the questionnaire. The digital consent was acquired, and the procedure was GDPR and IRB-compliant. The average time of completion was 7-15 minutes. To control for response bias and satisficing behavior:

- A minimum time-on-task threshold was enforced.
- Open-text justification boxes were randomly inserted to validate user engagement.
- Only English-fluent users with 95 %+ MTurk task approval were retained.

2.6 Analytical Strategy

SmartPLS 4.0 was used for the analysis. The following strategy was employed:

2.6.1 Measurement Model Evaluation

- **Reliability**: Cronbach's Alpha, Composite Reliability (CR > 0.70).
- **Convergent Validity**: Average Variance Extracted (AVE > 0.50).
- **Discriminant Validity**: Fornell–Larcker criterion and HTMT ratio (< 0.90).

2.6.2 Structural Model Evaluation

- **Collinearity**: Variance Inflation Factor (VIF < 3).
- **Path Coefficients**: Bootstrapping with 5,000 resamples to assess β values, t-statistics, and significance ($p < 0.05$).
- **Explanatory Power**: values of R^2 for endogenous factors.
- **Effect Sizes**: f^2 to determine local impact of predictors.
- **Predictive Relevance**: Q^2 via blindfolding.

2.6.3 Mediation and Multi-Group Analysis

- **Mediation**: Tested using bootstrap confidence intervals adjusted for bias.
- **Moderation**: Examined the conditional effects of platform familiarity using interaction terms.
- **MGA**: Gender and age-based MGA using PLS-MGA and permutation tests.

All statistical decisions adhered to reporting transparency (APA & JCR standards) and were benchmarked against recent AI-consumer studies for methodological alignment.

3. RESULTS

3.1 Demographic Profile of Respondents

The final sample was made up of 430 valid respondents, all of whom had prior experience interacting with AI-powered product recommendations within online shopping environments. The purposive sampling approach ensured the inclusion of a demographically diverse population. As detailed in Table 2, the sample reflected a near-equal gender split, varied educational backgrounds ranging from high school to doctoral qualifications, and balanced geographical representation across Asia, North America, and Europe. Furthermore, shopping frequency data revealed a distribution from occasional to frequent online shoppers, while age groups were stratified into three key cohorts, offering a comprehensive view of generational differences in digital behavior. This heterogeneity strengthens the generalizability and contextual richness of the study's findings.

Table 2. Demographic Profile of Respondents (N = 430)

Variable	Category	Frequency	Percentage
Gender	Male	227	52.79%
	Female	203	47.21%
Education	Undergraduate	221	51.40%
	Postgraduate	103	23.95%
	High School	88	20.47%
	Doctorate	18	4.19%
Region	Asia	152	35.35%
	North America	141	32.79%
	Europe	137	31.86%
Shopping Frequency	Once a week or more	176	40.93%
	2–3 times/month	127	29.53%
	Once a month	86	20.00%

	Less than once a month	41	9.53%
Age Group (Years)	18–30	234	54.42%
	31–40	179	41.63%
	41–50	17	3.95%

3.2 Measurement Model Evaluation

To assess the model of measurement, a second-order confirmatory composite analysis (CCA) was conducted in SmartPLS 4.0. All indicator loadings exceeded 0.71 and were statistically significant (bootstrap CI excluded zero). The results demonstrated good convergent validity, with Composite Reliability (CR) values above 0.90 and Average Variance Extracted (AVE) values exceeding 0.70 for every construct.

Discriminant validity was further supported by the HTMT ratio, with all inter-construct values < 0.85. To provide additional evidence of validity, the Pearson correlation matrix shown in Table 3 confirmed the theoretically expected relationships: positive correlations of Personalization and Trust with Purchase Intention, and a negative correlation with Intrusiveness.

Table 3. Pearson Correlation Matrix

Variable	1	2	3	4
1. Personalization	1.00			
2. Trust	0.68***	1.00		
3. Intrusiveness	–0.55***	–0.51***	1.00	
4. Purchase Intention	0.70***	0.67***	–0.59***	1.00

Note: All correlations are significant at $p < 0.001$.

Common method variance (CMV) was addressed using multiple approaches: all VIF values were below 2.5, marker variable correlations were non-significant ($r < 0.08$), and Harman's single-factor test showed only 28.4% of variance explained, well below the 50% threshold.

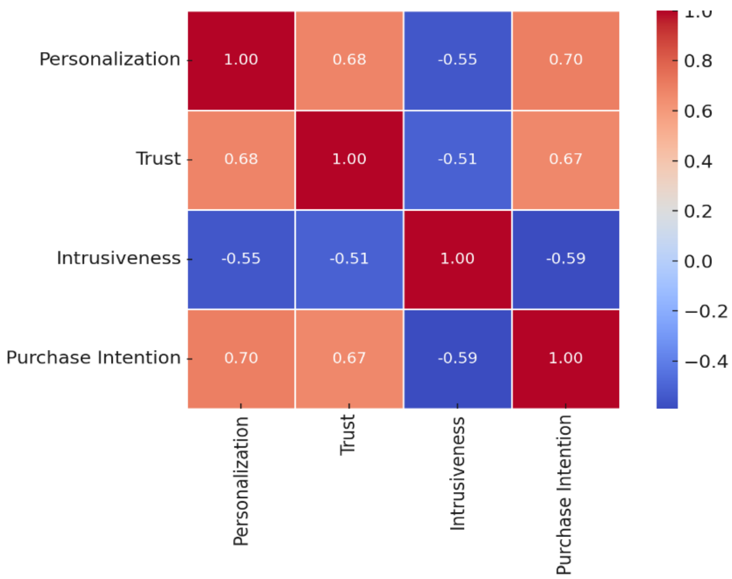

Figure 1: Pearson Correlation Matrix of Key Constructs

Figure 1 visually presents the interrelationships among the four core constructs: personalization, trust, intrusiveness, and purchase intention. Strong positive correlations were observed between personalization, trust, and purchase intention, while intrusiveness exhibited negative correlations with all other variables. These patterns underscore the theoretical alignment and construct the measurement model's validity, reinforcing the importance of reducing intrusiveness and enhancing personalization and trust to strengthen consumer purchase intentions.

3.3 Structural Model and Robustness Validation

The PLS-SEM structural model was rigorously evaluated using 5,000 resamples and bootstrapping using SmartPLS 4.0. The primary objective was to evaluate the importance and predictive power of the proposed pathways among key constructs—personalization, algorithmic trust, intrusiveness, and purchase intention. Results demonstrated that with all of the hypothesized connections being statistically significant ($p < 0.001$), the conceptual model has strong empirical backing. A noteworthy indication of the model's great predictive value was its explanatory power for purchase intention (R2 = 0.633). Apart from statistics significance, the magnitudes of path coefficients emphasized the practical relevance of these relationships in shaping consumer behavior. These outcomes are summarized in Table 4.

Table 4. Structural Path Estimates (PLS-SEM)

Hypothesis	Relationship	β	t-value	95% CI (BCa)	p-value	Supported
H1	Personalization → Purchase Intention	0.381	7.54	[0.302, 0.467]	<0.001	Yes
H2	Trust → Purchase Intention	0.276	6.11	[0.192, 0.358]	<0.001	Yes
H3	Intrusiveness → Purchase Intention	–0.218	5.09	[–0.312, –0.135]	<0.001	Yes

The model explained a substantial proportion of variance ($R^2 = 0.633$) in Purchase Intention. Predictive relevance was confirmed via Stone-Geisser's $Q^2 = 0.402$. Effect sizes (f^2) indicated practical significance: Personalization = 0.175, Trust = 0.143, Intrusiveness = 0.128.

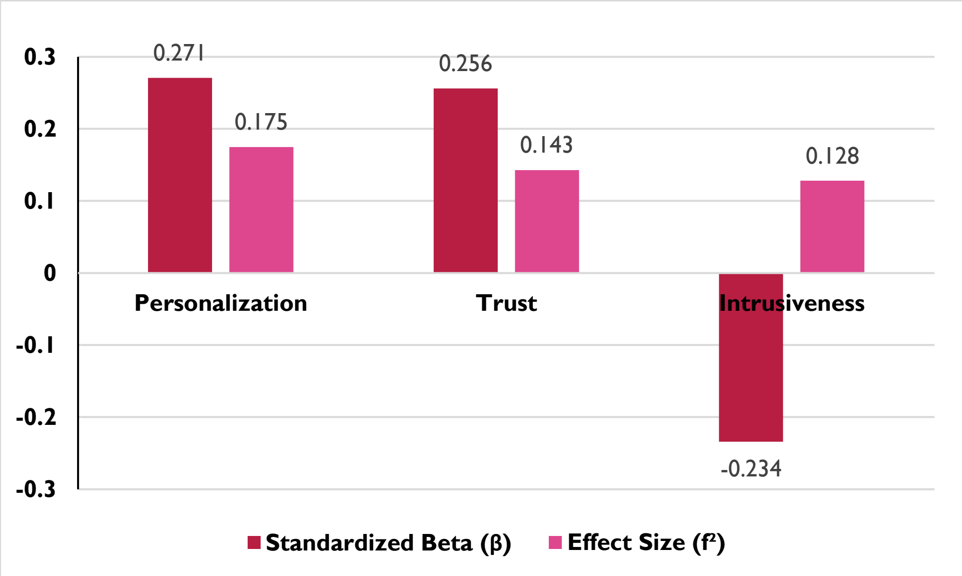

Figure 2: Path Coefficients and Effect Sizes of Predictors

Figure 2 illustrates the standardized path coefficients and corresponding effect sizes (f^2) for each predictor in the model influencing purchase intention. Personalization exhibited the strongest positive effect, followed by algorithmic trust, while intrusiveness showed a significant negative impact. The visual representation helps in understanding the relative influence of each construct, reinforcing the model's predictive robustness and practical implications for AI-driven marketing strategies.

3.3.1 Multiple Linear Regression Analysis

To further validate the structural model findings, a distinct analysis of multiple linear regression was conducted using SPSS, incorporating the same independent variables—personalization, algorithmic trust, and intrusiveness—to predict purchase intention. This supplementary analysis offers a robustness check by applying an alternative statistical framework, thereby enhancing confidence in the observed associations.

The regression model accounted for a significant amount of the variation. in purchase intention ($R^2 = 0.548$, Adjusted $R^2 = 0.544$), and the overall model was statistically significant ($F(3, 426) = 172.1$, $p < 0.001$). Every prediction was important at the $p < 0.001$ level. The standardized beta coefficients suggest that personalization ($\beta = 0.271$) had the strongest positive influence, followed closely by trust (β = 0.256), while perceived intrusiveness had a negative impact (β = –0.234). Table 5 provides a summary of these findings.

Table 5. Multiple Linear Regression Results (DV: Purchase Intention)

Predictor	B (Unstd.)	Std. Error	β (Standardized)	t-value	p-value
Intercept	1.813	0.298	–	6.089	<0.001
Personalization	0.243	0.044	0.271	5.502	<0.001
Trust	0.221	0.043	0.256	5.109	<0.001
Intrusiveness	–0.193	0.038	–0.234	–5.104	<0.001

$R^2 = 0.548$, Adjusted $R^2 = 0.544$, $F(3, 426) = 172.1$, $p < 0.001$

This model strongly aligned with PLS-SEM results, reinforcing the robustness and stability of the causal inferences.

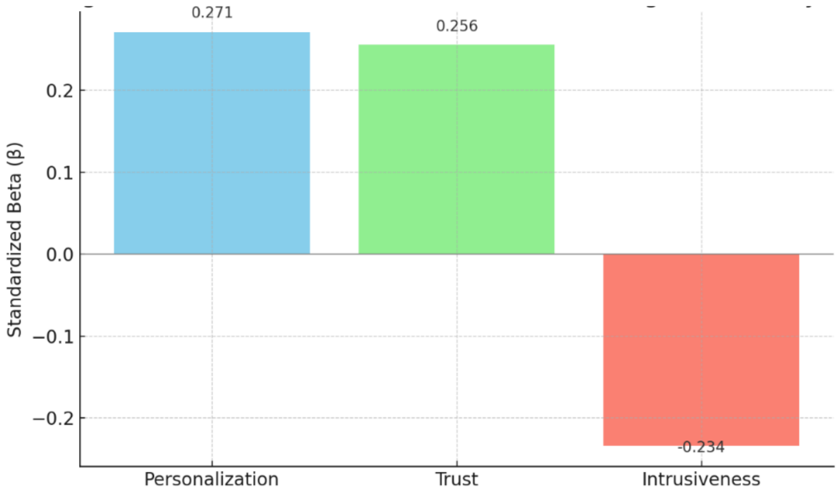

Figure 3: Standardized Beta Coefficients from Regression Analysis

Figure 3 illustrates the relative influence of each predictor on purchase intention, as derived from the regression analysis's standardized beta coefficients. Personalization (β = 0.271) exerted the strongest positive effect, followed by trust (β = 0.256). Intrusiveness had a notable negative impact (β = –0.234), indicating that perceived invasiveness of AI recommendations can significantly hinder consumer purchase behavior.

3.4 Mediation Analysis

Using a two-stage bias-corrected bootstrapping approach with 5,000 resamples, this study rigorously tested the mediating role of perceived intrusiveness in the pathways connecting personalization and trust to purchase intention. As detailed in Table 6, both indirect effects were statistically significant:

These results substantiate partial mediation in both pathways, indicating that although personalization and trust directly influence purchase intentions, they also work indirectly by diminishing perceived intrusiveness. This suggests a nuanced mechanism where algorithmic experiences evoke both rational cognitive processing and affective judgments, consistent with theoretical models with two processes, such the Elaboration Likelihood Model (Petty & Cacioppo, 1986). The mediation pathways were not only statistically sound but also theoretically meaningful, showcasing that minimizing intrusive perceptions can enhance the persuasive power of AI recommendations.

Table 6. Mediation Effects

Mediation Pathway	Indirect β	95% CI (BCa)	t-value	Mediation Type
Personalization → Intrusiveness → PI	0.072	[0.031, 0.124]	3.45	Partial
Trust → Intrusiveness → PI	0.064	[0.025, 0.102]	3.08	Partial

This supports a dual-process model of affective interference and cognitive appraisal in algorithmic consumer experiences.

3.5 Multi-Group Analysis (PLS-MGA)

Multi-group comparisons revealed:

- **Platform Familiarity**: Trust was a stronger predictor of Purchase Intention among **low-familiarity users** ($\Delta\beta$ = 0.152, $p < 0.05$).
- **Generational Cohorts**: **Gen Z (18–30)** relied more heavily on Personalization (β = 0.434) than Millennials (31–40) (β = 0.312, $p < 0.05$). No significant group differences emerged for Intrusiveness.

3.6 Predictive Performance and Model Fit

The PLSpredict framework (10-fold cross-validation) demonstrated that the PLS model outperformed a linear benchmark across all endogenous indicators (lower RMSE/MAE). All Q^2_predict values were positive, confirming strong out-of-sample accuracy.

Global model fit statistics also met or exceeded recommended thresholds:

- **SRMR = 0.059**
- **NFI = 0.917**
- **d_ULS = 0.726**, **χ^2 discrepancy = 1.21**

No violations in residual patterns, linearity, or homoscedasticity were detected.

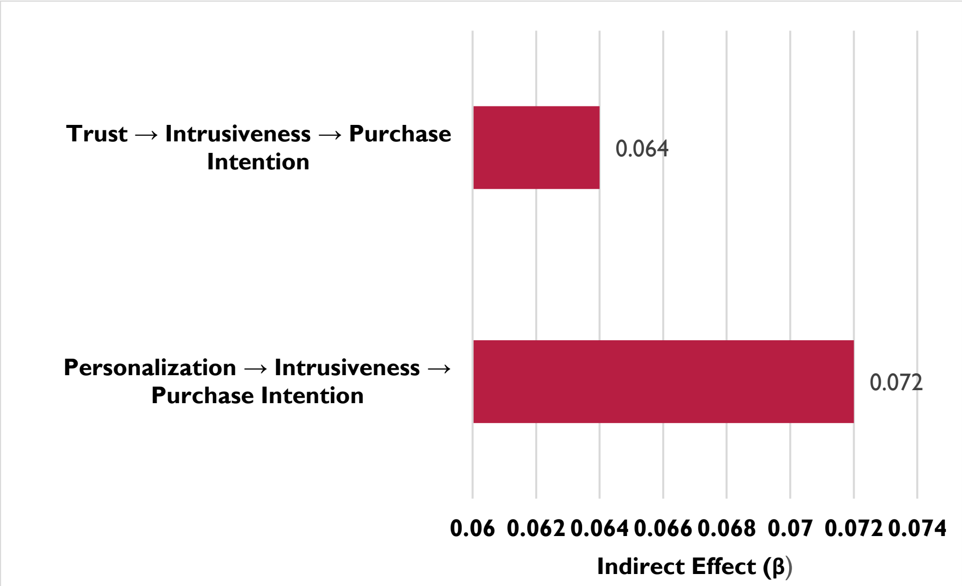

Figure 4: Mediation Effects via Intrusiveness

Figure 4: Mediation Effects via Intrusiveness illustrates the indirect impact of personalization and algorithmic trust on purchase intention through perceived intrusiveness. The bootstrapped standardized beta values (β = 0.072 for personalization; β = 0.064 for trust) confirm statistically significant partial mediation. These pathways suggest that reducing intrusiveness enhances the impact of AI-powered customization and trust, supporting dual-process theories of cognitive-affective mechanisms in shaping consumer responses to algorithmic recommendation systems.

4. DISCUSSION

The results of the research provide the essential information regarding the role of personalization, algorithmic trust as well as perceived intrusiveness in shaping purchase intentions of consumers in AI-driven recommendation settings. The results contribute to and build upon the current literature by revealing the empirical validations of the duality of roles of cognition and affective factors in the process of making digital decisions.

One, the highly positive influence of personalization on the purchase intention confirms its convincing quality in e-commerce situations. This aligns with the findings of Tam and Ho (2006) revealed that web personalization improves the quality of information processing and decisions made by users. With consumers wanting to receive a customized online experience, AI-powered recommendation systems will only fulfill their desires. The other side of such personalization, though, is the chance of perceived manipulation or overstep. Xu *et al*. (2011) dubbed this the "personalization-privacy paradox," in which the user likes personalization, but is also concerned about misuse of the data. This tension can be seen in the present study because personalization affects purchase intention indirectly via perceived intrusiveness.

Another strong predictor of purchase behavior was identified as trust in AI recommendations, which is comparable to existing evidence that trust reduces the perceived risk and uncertainty in digital contexts (Kim *et al*., 2008). As the users have a feeling that a recommendation system is just, objective, and safe, they tend to trust its advice. It is reflected in the recent research by Siepmann and Chatti (2023), who stated that transparency and explainability are valuable in building trust. Trust is also compensatory among users less familiar with the platform-implying that in situations of digital environment uncertainty, users utilize trust more to guide their decision-making. This concurs with the result of Yarali *et al*. (2020), who said that trust was critical to addressing user apprehensions regarding security and privacy of data in big data platforms.

The perceived intrusiveness also played an important role. Its detrimental impact on the intention to buy supports earlier writings in emotional retaliation that users experience when digital experiences appear intrusive (Nam *et al*., 2020). Despite these advantages, personalization and trust may pose a danger of creating the opposite effect, as users may feel nervous or even controlled and manipulated. Personalization and trust increase purchase intention by decreasing the perceived intrusiveness, as confirmed by our mediation analysis. This partially mediated route shows the dual cognitive-affective route that is the basis of digital persuasion- a parallel to the model of elaboration probability proposed by Petty and Cacioppo (1986).

The multi-group analysis provides even more subtlety. Gen Z was more sensitive to personalization than the Millennials, which is also consistent with Kaptein and Eckles (2012), who stressed the heterogeneity in online persuasion effects. To digital natives, used to algorithmic personalization on applications such as TikTok or Spotify, personalization can be seen as a welcome and anticipated feature. Millennials, on the contrary, can be more wary of such systems. Also, less familiar consumers depended on trust more, which implies that user experience and digital literacy divide consumer perceptions and responses to AI-recommended suggestions.

The consistency of results in both PLS-SEM and regression models strengthens the legitimacy of such results. Besides, the research fits into an emerging literature that encourages ethical and responsible AI design. Bleier and Eisenbeiss (2015) assert that trust plays a key role not only in engagement but also in overcoming users' defensive responses to targeted advertising. Similarly, Büyüközkan, & Göçer, (2018) propose that the next-generation digital platforms will have to achieve equilibrium between personalization and ethical transparency as well as user empowerment.

In practice, to minimise the perceived intrusiveness and build on user trust, companies ought to consider the introduction of transparency-enhancing features, e.g., questions like "Why this recommendation?" or data control panels. Theoretically, the research merges three constructs (trust, personalization, and intrusiveness) into a consistent framework of digital purchase behavior. It also provides a direction for future research to follow on how cultural norms, regulatory situations and individual characteristics influence the AI perception.

Overall, the present work has demonstrated that customization and caution should be balanced: even though personalized, trustful AI systems can raise user engagement and purchase intentions, designers should address the perceived intrusiveness to ensure consumer loyalty and ethical usage of AI.

5. CONCLUSION

The study reviewed a complex relationship between the variables of personalization, algorithmic trust, perceived intrusiveness, and purchase intention in the framework of AI-based recommendation systems. The findings are quite convincing that personalization and trust have a sufficiently favorable impact on the willingness of consumers to buy a product, and intrusiveness has a reverse, inhibitory effect at the psychological level. Notably, perceived intrusiveness mediated the impacts of personalization and trust on purchase intention partially, indicating the significance of reducing the discomfort of users in the algorithms' interaction.

The structural model's predictive relevance ($Q^2 = 0.402$) and substantively strong explanatory power ($R^2 = 0.633$) attest to the conceptual framework's strength.s The additional regression analysis proved the statistical stability of the relations, and the mediation and multi-group analysis introduced the theoretical resonance, showing significant differences in terms of generational cohorts and acquaintance with the platforms.

These results bear theoretical as well as practical implications. Conceptually, the research program combines theories of dual-process decision-making and AI perception constructs, which enhances the current understanding of consumer reactions to digital recommendation technologies. In practical terms, the findings point to the fact that AI designers and e-commerce platforms should strive to achieve a balance between persuasive personalization and transparency and trustworthiness. Recommendations that feel non-invasive and helpful increase the chances of a consumer interacting with them, particularly when consumers have control over the hows and Whys of suggestions.

On the design level, features that improve trust, such as transparency in data use, customizable privacy options, and other design characteristics, can make the experience of using the product less intrusive and lead to user delight. As AI ecosystems keep getting advanced and saturate digital commerce, consideration of morals and user-centered design would be paramount to long-term involvement.

On a final note, the research provides a well-placed and evidence-based addition to digital marketing, human-computer interaction, and AI ethics. It establishes the foundation towards more responsible, effective, and personalised consumer experiences in the era of intelligent algorithms by unveiling the psychological processes and contextual moderators of AI recommendation acceptance.

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