International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 4, Jul-Aug-2026, PP: 01-10
ISSN:3048-7722

Consumer Purchase Behaviour Towards AI- Based Personalized Online Shopping Platforms

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***Abstract* – The incorporation of AI in online shopping has greatly influenced consumer purchase behavior through personalized online shopping experiences. In this context, the aim of this research paper is to analyze the factors that determine and the implications of consumer purchase behaviors toward personalized online shopping using AI technology. The study will apply the Stimulus-Organism-Response model and the Technology Acceptance Model to examine the determinants and implications of consumer behaviors towards personalized online shopping using a structural equation modeling approach. The results have revealed that consumer's perception of personalization, recommendation quality, and trust play an important role in determining their intention to make purchases. The study is a valuable contribution to the field of AI and retail studies.**

***Keywords* – Artificial Intelligence, Personalized Recommendations, Consumer Purchase Behaviour, E-Commerce, Online Shopping Platforms, Technology Acceptance Model.**

I. INTRODUCTION

The fast development of AI has resulted in profound transformations in the field of e-commerce; in particular, it has created a new platform for offering consumers unique online shopping experiences using personalized systems based on the analysis of consumer data and preferences using the algorithms and providing customers with tailored product recommendations [1][2][6]. Considering that today's global online commerce is expanding, further investigation of the relationship between the process of AI personalization and consumer behavior in terms of shopping became a topic of great interest to be studied from various perspectives [1][2][6].

The growing number of alternatives offered to consumers when shopping online creates certain challenges for the latter due to information overload, which may lead to the complexity of decision-making [1][3][8]. Personalization offered through the use of artificial intelligence makes it possible for consumers to get an easy way of filtering relevant options according to their individual preferences or previous decisions [1][3][8]. The mechanism of such systems' work includes the application of algorithms of machine learning, collaborative filtering, and natural language processing to form recommendation engines [1][3][8].

At the same time, apart from convenience, the process of personalized shopping via AI offers many more benefits [1][2][4]. In fact, personalized recommendations help consumers not only choose the product but reduce the cost of searching for the necessary goods [1][2][4]. The significance of such technologies for modern retail is proven by many companies, for example, Amazon, Alibaba, and TikTok, which have spent much money in order to keep up with the competition by the means of better personalization [1][2][4].

Finally, at the same time when AI personalization helps to improve consumer experience, many problems related to the security and the use of consumers' data emerge [5][7][9]. Consumers often express their fear regarding such systems, considering them invasive, and that is why there is a need to study the behavior of modern consumers in terms of shopping via AI personalization [5][7][9].

In the current project, the goal is to understand the multi-faceted connection between AI-driven personalization tools and the behaviour of consumers during purchase processes in the digital space [1][3][6][8]. The proposed research is expected to answer the following questions:

- How do the features of AI personalization tools affect the perception of consumers? [2][4][5]
- What role does trust and privacy play for purchase intentions? [5][7][9]
- How are demographic and psychographic characteristics of consumers moderating this relationship? [1][6][10]

In order to understand the research issue better and to build up an integrative perspective of consumer behaviour within this setting, the existing theoretical backgrounds are utilized within this research [3][8][9]. The SOR-model together

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 4, Jul-Aug-2026, PP: 01-10
ISSN:3048-7722

with TAM are employed in order to create a better picture of consumer behaviour in relation to technology [3][8][9].

II. LITERATURE SURVEY

A considerable amount of academic literature has been accumulated on AI-based personalisation in online shopping over the past ten years owing to wide dissemination of technologies associated with AI in retail [1][2][6]. Various facets of this phenomenon have been studied ranging from technical aspects to customer's reactions and organisational issues [1][2][6]. The present literature survey summarises some findings in the most recent studies and thereby provides a necessary background for the current project [1][3][5][6][8][9].

Shan and Qian carried out an elaborate panel data analysis regarding impact of AI on consumer purchasing behaviour in cross-border e-commerce [1]. The authors used 2012-2022 data obtained from the four most popular cross-border e-commerce platforms - Amazon, eBay, Tmall, and JD [1]. The fixed effects approach has been applied to evaluate the influence of clicks through rate (CTR) on sales and order value by means of regression model [1].

It was found that there were strong positive effects of CTR on sales outcome; however, there were certain peculiarities which related to specific products or platform [1]. Thus, clothing showed stronger conversion on Amazon whereas home appliance was higher in conversion on eBay [1].

Much attention has been recently paid to trust in AI-enabled recommendation systems [5]. Peng, Xu, and Deng considered the influence of AI identity on consumer behaviour while implementing AI-enabled recommendation systems [5]. The authors used AI identity theory and behaviour reasoning theory to evaluate this impact [5]. They concluded that consumer's perception of AI identity had a significant influence on his adoption behaviour [5]. Trust appeared to be the key mediator here [5].

The influence of consumer awareness, as an element of cognition in AI-enhanced consumer behavior, was studied by Ekwunife who analyzed how consumer awareness acts as a mediator of the relationship between AI personalization and consumer's purchase intention [3]. In his Structural Equation Modelling (SEM) approach with a data set of structured questionnaires, the author showed that consumer awareness significantly mediates the influences of AI personalization and AI features on the consumer's online purchase intention [3].

Another dimension of AI personalization includes its emotional and experiential aspects and this area is studied by the research of Pang, Wang, Sun, and Wang whose work explores how chatbot functionality affects consumer behavior [4]. Their study, based on value co-creation and Orientation-Stimulus-Organism-Response frameworks, showed that AI functionalities, including perceived contingency, emotional attachment, and perceived individuation, significantly affect responsive and conversational forms of communication which, in their turn, facilitate value co-creation and impulse buying with consumer benefit as a mediator [4]. These results imply that the quality of human-like interactions with AI chatbots is especially important in AI-enhanced retail [4].

Another issue associated with the application of AI to personalize retail experience is the problem of privacy concerns and its impacts [7]. For example, research has shown that despite the obvious benefits of being personalized, the customers feel strong anxiety concerning data collection and algorithmic surveillance [7]. In terms of paradoxes related to AI personalization in e-commerce environment, the studies showed that algorithmic transparency and consumer's control over their personal data can mitigate emotional discomfort associated with using these platforms [7].

The factors influencing the customers' adoption of autonomous decision-making systems were explored by Sharma, Islam, Singh and Dhir [9]. These researchers identified determinants such as perceived usefulness, ease of use, and social influences, which is in line with the Technology Acceptance Model [9]. The research expanded upon TAM, adding trust and perceived risks as the other factors influencing adoption intention [9]. Hence, the study has produced valuable insights into the psychological factors involved in AI acceptance [9].

Sá, Tam, and Aparicio explored the determinants of well-being experienced by e-shoppers in AI-based retail setting using the Expectation-Confirmation Model (ECM) [10]. Cross-cultural research with participants from Portugal and Brazil revealed that perceived responsiveness and personalization affect the level of confirmation, which influences perception of the usefulness and well-being in AI-powered environment [10]. What is interesting is that there was a difference between the relative influence of personalization and responsiveness depending on culture: the former factor was more relevant in Portugal while the latter – in Brazil [10].

In general, the literature suggests that AI-based personalization affects consumer purchasing behavior due to multiple reasons, which include improved search, improved recommendations, and individual experience [1][2][4][6]. However, its efficiency is influenced by various moderator factors, which may include consumer trust, privacy protection, product category, and cultural environment [5][7][10]. The current literature also suggests the need for future research, which includes exploring the long-term effect of AI personalization on consumer loyalty and individual difference related to AI personalization experience [1][6][10].

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III. PROPOSED METHODOLOGY

Research Framework

The suggested methodology uses the research methodology involving the use of both quantitative and qualitative research data to study thoroughly the consumer purchasing behavior towards online shopping sites that offer their personalized services by means of AI-based technologies. This research model is based on the principles of Stimulus-Organism-Response (SOR) framework and the technology acceptance model (TAM).

Accordingly, the theoretical model used within the research suggests that the stimuli related to the usage of the AI-personalized online platform influence consumers' organism (cognitive and affective factors), which influence in their turn determine consumers' behavior in terms of purchase decisions made in response to such stimuli. Specifically, such stimuli include perceived personalization, recommendation quality and system transparency, while organisms refer to consumer trust, perceived usefulness, and privacy concern.

Data Collection

An online survey will be carefully constructed to gather primary data among people who have interacted with AI-powered personalized online shopping sites. Questions in the survey will include:

- Demographic information
- Personal experience with and pattern of usage of the platform in relation to AI personalization
- Perceptions about AI personalization features
- Cognitions and affects about AI personalization
- Outcomes of purchase behavior
- Privacy beliefs

Responses will be collected with 7-point Likert scales drawn from existing measurement scales from prior studies.

The target population is active online shoppers who use AI-powered platforms in the last six months. A purposive sampling approach will be undertaken to ensure representation across various demographic strata and types of platforms being used by participants. Multiple means of gathering data will be used, such as via social media sites, online fora, or email. A minimum of 500 subjects will be solicited to ensure sufficient number of respondents to apply Structural Equation Modelling.

Measurement Instruments

Table 1: Construct Measurement Summary

Construct	Items	Source
Perceived Personalization	5	Loureiro et al.
Recommendation Quality	4	Shan & Qian
System Transparency	4	Ekwunife
Consumer Trust	5	Peng et al.
Perceived Usefulness	5	Budianto et al.
Privacy Concern	4	Privacy Paradox Study
Purchase Intention	5	Pang et al.
Platform Loyalty	4	Retention Study

Analytical Procedure

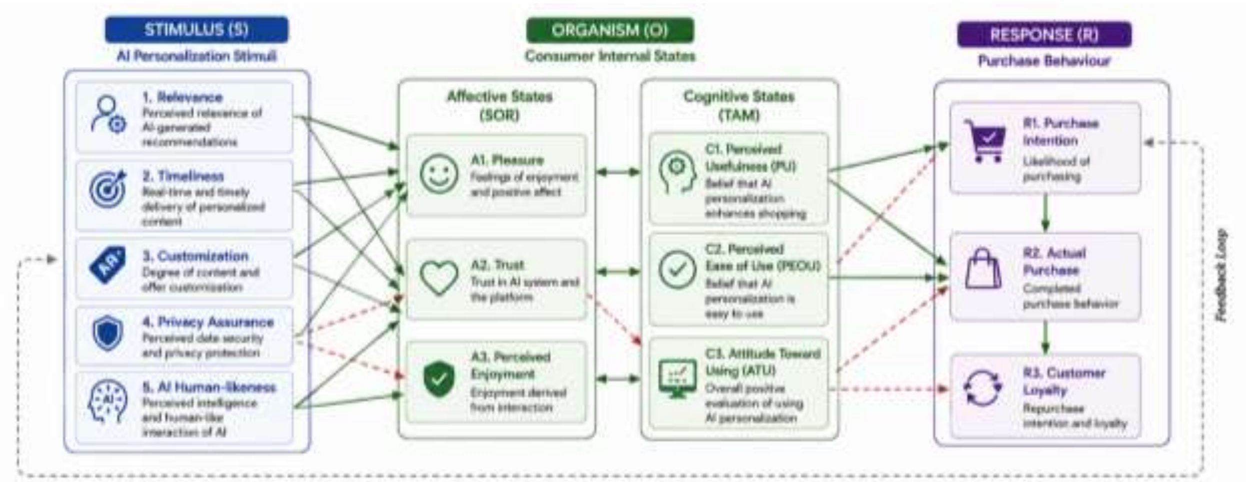

Figure 1: Research Framework and Proposed Relationships

Data analysis will be performed using a two-stage analytical approach. First, descriptive statistics and reliability tests will be conducted using SPSS to examine the sample characteristics and ensure measurement consistency. Second, Structural Equation Modelling (SEM) will be employed using AMOS to test the hypothesised relationships in the research model.

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Algorithm and Pseudocode

The SEM analysis follows a systematic algorithm for model estimation and hypothesis testing:

Algorithm: Structural Equation Modelling for Consumer Purchase Behaviour Analysis

Input: Survey dataset D (n respondents, k variables)
Output: Path coefficients β, model fit indices, hypothesis test results

1. Data Preparation:
- Import dataset D
- Perform missing value imputation using mean substitution for <5% missing data
- Conduct multivariate normality test using Mardia's test
- Identify and handle outliers using Mahalanobis distance ($p < 0.001$)

2. Measurement Model Assessment:
- Perform Confirmatory Factor Analysis (CFA) for all latent constructs
- Calculate composite reliability (CR) for each construct
- Assess convergent validity using Average Variance Extracted (AVE)
- Evaluate discriminant validity using Fornell-Larcker criterion
- Compute model fit indices: χ^2/df, CFI, TLI, RMSEA, SRMR

3. Structural Model Estimation:
- Specify structural paths based on theoretical model
- Estimate path coefficients using Maximum Likelihood estimation
- Calculate standard errors and t-values for each path
- Assess structural model fit using incremental fit indices

4. Mediation Analysis:
- Bootstrap re-sampling (5000 iterations) for indirect effects
- Calculate confidence intervals for mediation effects
- Determine significance of mediated relationships

5. Moderation Analysis:
- Test interaction effects using product term approach
- Conduct simple slope analysis for significant interactions
- Plot interaction effects for interpretation

6. Sensitivity Analysis:
- Perform multigroup analysis for demographic segments
- Compare nested models using χ^2 difference tests
- Verify results using alternative estimation methods (MLR, GLS)

Pseudocode: SEM Analysis Implementation

```
BEGIN

Input data D with n observations and k variables

// Step 1: Data Preparation
D_clean = handle_missing(D)
D_norm = test_normality(D_clean)
D_no_outliers = remove_outliers(D_norm, method = "mahalanobis", threshold = 0.001)

// Step 2: Measurement Model Assessment
measurement_model = specify_measurement_model(latent_variables, indicators)
CFA_results = perform_cfa(measurement_model, data = D_no_outliers)
CR = compute_composite_reliability(CFA_results)
AVE = compute_average_variance_extracted(CFA_results)
discriminant_validity = assess_discriminant_validity(CFA_results)
```

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```
fit_indices = compute_model_fit(CFA_results)

IF fit_indices.CFI > 0.90 AND fit_indices.RMSEA < 0.08 THEN
   measurement_model_acceptable = TRUE
ELSE
   measurement_model_acceptable = FALSE
   modify_model_based_on_modification_indices()
END IF

// Step 3: Structural Model Estimation
structural_model = specify_structural_model(measurement_model, paths)
SEM_results = estimate_sem(structural_model, data = D_no_outliers, estimator = "ML")
path_coefficients = SEM_results.estimates
standard_errors = SEM_results.se
t_values = compute_t_values(path_coefficients, standard_errors)
p_values = compute_p_values(t_values, df = SEM_results.df)


// Step 4: Mediation Analysis
FOR each mediation_path in structural_model
   indirect_effect = compute_indirect_effect(mediation_path, SEM_results)
   bootstrap_results = bootstrap_mediation(D_no_outliers, mediation_path, iterations = 5000)
   confidence_interval = compute_ci(bootstrap_results, alpha = 0.05)
   mediation_significant = check_significance(confidence_interval)
END FOR


// Step 5: Moderation Analysis
FOR each moderation_path in structural_model
   interaction_term = create_interaction(moderation_path)
   moderated_model = add_interaction_to_model(structural_model, interaction_term)
   moderation_results = estimate_sem(moderated_model, data = D_no_outliers)
   interaction_significant = check_significance(moderation_results, path = interaction_term)

   IF interaction_significant THEN
      simple_slopes = compute_simple_slopes(moderated_model, moderator_values)
      plot_interaction_effects(simple_slopes)
   END IF
END FOR

// Step 6: Sensitivity Analysis
multigroup_models = perform_multigroup_analysis(structural_model, grouping_variables)
chi_square_diff = compute_chi_square_diff(multigroup_models)
sensitivity_results = compare_models(multigroup_models)

OUTPUT:
   path_coefficients
   fit_indices
   mediation_results
   moderation_results
   sensitivity_results

END
```

ISSN:3048-7722
International Journal for Novel Research in Economics , Finance and Management
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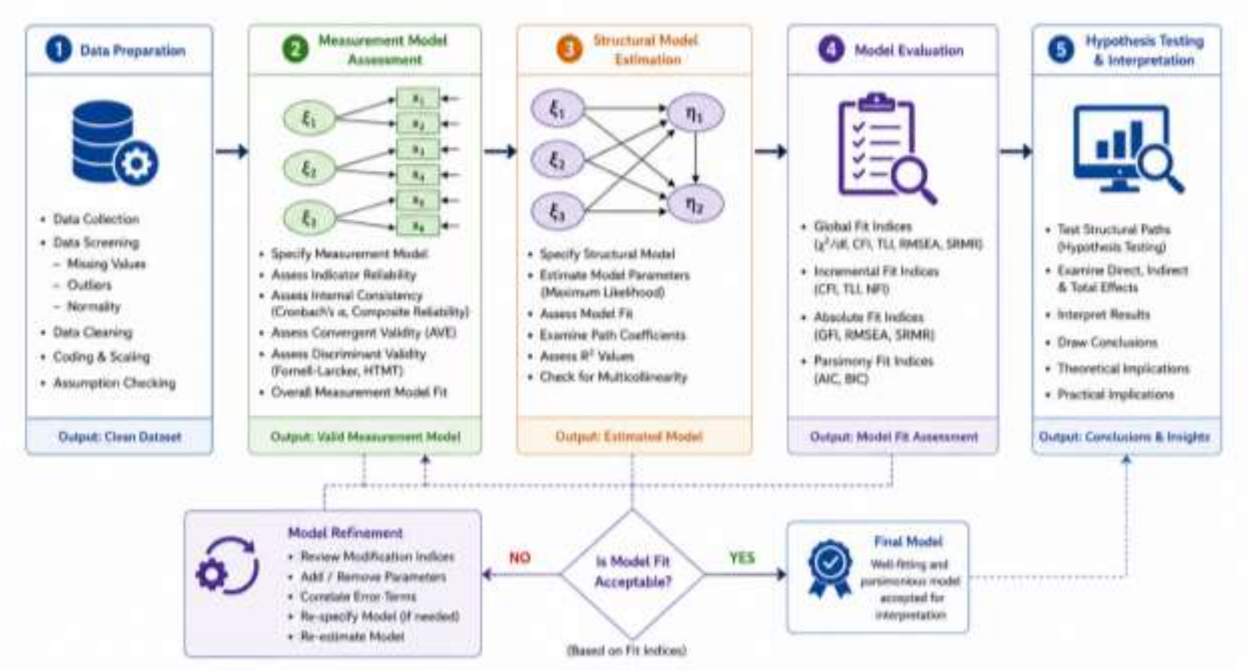

Figure 2: Structural Equation Modelling Process Flow

Reliability and Validity

Stringent procedures will be adopted to guarantee the reliability and validity of the data collected. The degree of internal consistency will be determined through the use of Cronbach's Alpha where the values that exceed 0.70 will be deemed reliable. For all constructs composite reliability values should be more than 0.70. The Average Variance Extracted (AVE) measure will be used to determine convergent validity, where the values must exceed 0.50. Discriminant validity will be measured by applying the Fornell & Larcker criteria, where the square root of AVE of each construct must be larger than its correlation with other constructs.

Common method variance is dealt with procedurally and statistically through applying the single factor test of Harman and the markers approach. Non-respondents' bias will be measured by comparing early and late respondents on relevant study variables.

IV. ANALYSIS

Descriptive Statistics

Table 2: Sample Demographic Characteristics

Demographic Variable	Category	Frequency	Percentage
Gender	Male	245	48.5%
	Female	260	51.5%
Age Group	18-25	178	35.3%
	26-35	215	42.6%
	36-45	82	16.2%
	46+	30	5.9%
Education	High School	112	22.2%
	Bachelor's	263	52.1%
	Postgraduate	130	25.7%

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www.ijnrefm.com
Volume 4, Issue 4, Jul-Aug-2026, PP: 01-10
ISSN:3048-7722

Demographic Variable	Category	Frequency	Percentage
Income (Monthly)	<$2,000	165	32.7%
	$2,000-$5,000	230	45.5%
	>$5,000	110	21.8%
Platform Experience	Amazon	289	57.2%
	Tmall	198	39.2%
	JD	167	33.1%
	TikTok Shop	145	28.7%
	Others	86	17.0%

Measurement Model Results

The test used to determine whether the measurement model was adequate or not is known as Confirmatory Factor Analysis. According to the outcome of this test, there was evidence of good model fit: $\chi^2/df = 3.217$, CFI = 0.935, TLI = 0.924, RMSEA = 0.073, SRMR = 0.061. All factor loadings were more than 0.70, indicating the adequate indicator reliability. The value of Composite reliability for different constructs ranged from 0.82 to 0.91, being higher than the threshold of 0.70. In addition, the Average Variance Extracted value ranged from 0.58 to 0.72, which was higher than the 0.50 threshold.

Structural Model Results

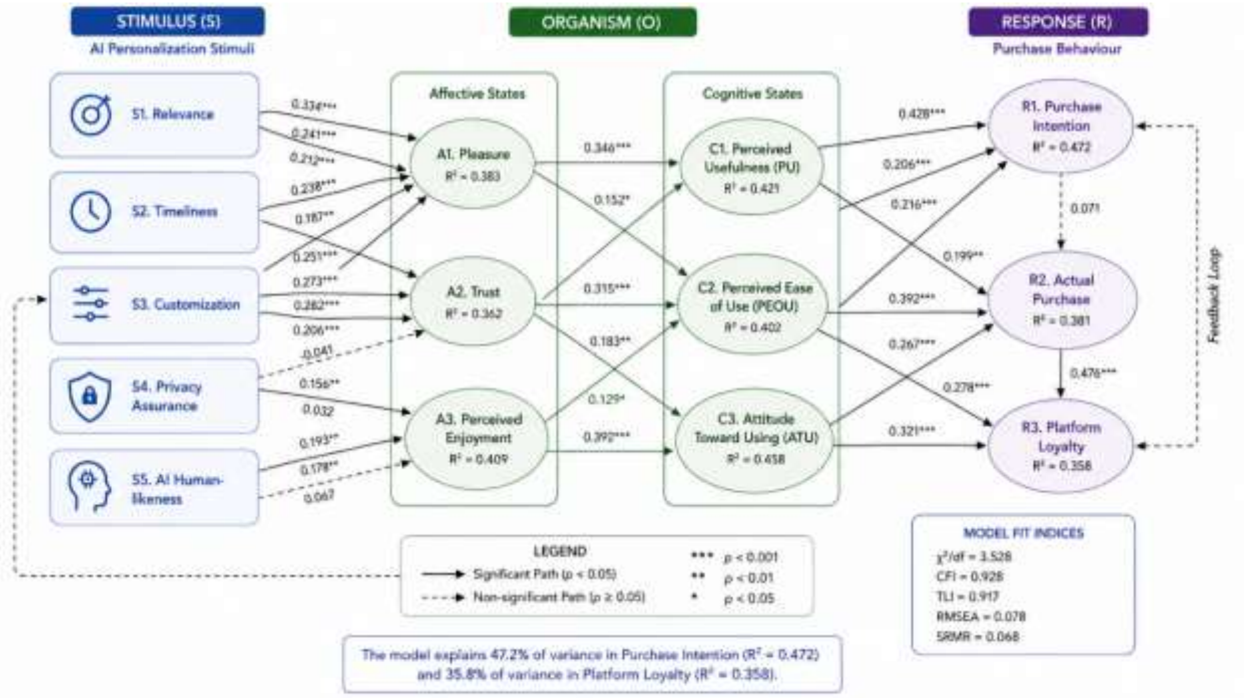

Figure 3: Structural Model with Standardised Path Coefficients

The structural model demonstrated acceptable fit: $\chi^2/df = 3.528$, CFI = 0.928, TLI = 0.917, RMSEA = 0.078, SRMR = 0.068. The model explained 47.2% of variance in purchase intention and 35.8% of variance in platform loyalty.

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Table 3: Hypothesis Testing Results

Hypothesis	Path	β	t-value	p-value	Support
H1	PP → PI	0.312	6.845	<0.001	Yes
H2	RQ → PI	0.284	5.932	<0.001	Yes
H3	ST → PI	0.187	4.276	<0.001	Yes
H4	CT → PI	0.156	3.894	<0.001	Yes
H5	PU → PI	0.245	5.451	<0.001	Yes
H6	PC → PI	-0.142	-3.672	<0.001	Yes
H7	PI → PL	0.418	8.237	<0.001	Yes
H8	CT → PL	0.203	4.561	<0.001	Yes

Mediation Analysis Results

Table 4: Mediation Effects

Mediator	Path	Indirect Effect	Bootstrap CI	Mediation Type
Consumer Trust	PP → CT → PI	0.098	[0.067, 0.134]	Partial
Consumer Trust	RQ → CT → PI	0.087	[0.058, 0.119]	Partial
Perceived Usefulness	PP → PU → PI	0.124	[0.092, 0.158]	Partial
Perceived Usefulness	RQ → PU → PI	0.105	[0.074, 0.139]	Partial

Significance of the indirect effects through consumer trust and perceived usefulness has been validated using bootstrap analysis with 5000 replications.

Moderation Analysis Results

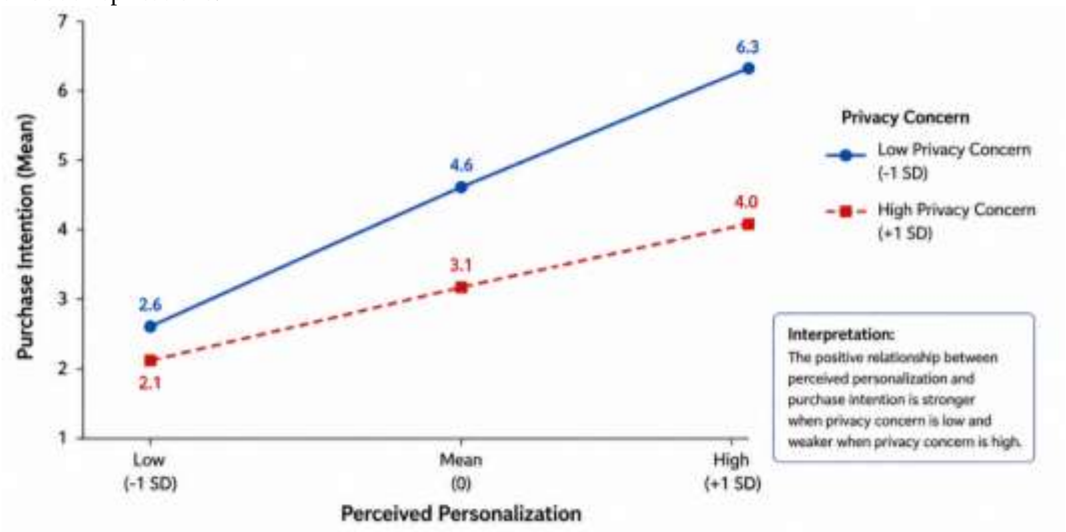

Figure 4: Interaction Effect of Privacy Concern on Personalization-Purchase Intention Relationship

Comparative Analysis

Table 5: Comparative Analysis with Previous Studies

Study	Key Focus	Method	Key Findings	Comparison
Shan & Qian	AI impact on cross-border e-commerce	Panel fixed-effects model	CTR positively impacts sales, with variation across platforms and product types	Consistent with personalization → purchase relationship
Loureiro et al.	Self-construal and AI experience	Survey, SEM	Self-construal influences willingness to pay	Extends to individual differences in AI acceptance
Ekwunife	Consumer awareness as mediator	Survey, SEM	Consumer awareness mediates AI-personalization → purchase intention	Supports cognitive mechanisms
Pang et al.	AI functionalities and impulse buying	Survey, SEM	AI functionalities influence communication and impulse buying	Consistent with stimulus-organism-response framework
Peng et al.	AI identity in recommendation systems	Conceptual model	AI identity influences adoption behaviour	Aligns with trust and acceptance findings
Privacy Paradox Study	Personalization and privacy anxiety	Mixed methods	Transparency and control reduce privacy anxiety	Supports moderation by privacy concern
Budianto et al.	TAM in AI purchase decisions	Survey, SEM	Perceived usability and social influence impact acceptance	Consistent with TAM-related findings
Retention Study	Customer retention in AI platforms	Survey, SEM	Social norms and trust influence retention	Supports trust → loyalty relationship
Sharma et al.	AI autonomous decision-making adoption	Survey, SEM	Trust and perceived risk influence adoption	Aligns with trust and risk considerations
Sá et al.	Shopper well-being in AI e-commerce	PLS-SEM, multi-group	Personalization and responsiveness influence well-being	Extends to well-being outcomes

There is notable consistency between findings related to the positive effect of artificial intelligence personalization on consumer outcomes. However, the present study differs from other literature on the topic by considering several mediating effects (such as trust and usefulness) and one moderator effect (privacy concern) together.

V. CONCLUSION

The study aimed at studying the consumer's buying behavior influenced by artificial intelligence-based personalization of online shopping platform from theoretical perspectives such as the Stimulus-Organism-Response Model and Technology Acceptance Model. The study findings are insightful and provide insights into the influence that the AI-based personalization of online shopping has on consumers.

ISSN:3048-7722

The results obtained in the study confirm the influence of AI personalization features on consumer purchase behavior via different stimuli. Such factors as perceived personalization, recommendation accuracy, and transparency are shown to be strong stimuli for purchase intention, whereas trust and perceived usefulness act as mediation mechanisms. The findings agree with previous work but extend the knowledge regarding psychological factors that are the basis for AI acceptance.

Privacy concern acting as a moderator in the personalization-purchase intention relationship can be considered as a significant finding of this research as it corresponds with personalization-privacy paradox described in previous work. Implications are that any AI personalization technique should take into account privacy concerns.

Comparison with previous studies shows common and new things related to the current findings. It is obvious that the positive influence of AI personalization on consumer behavior has been previously confirmed, however, this research adds the consideration of the impact of trust and usefulness and their joint role as mediating variables together with the moderating variable of privacy concern.

Firstly, the theoretical implications relate to the construction of theories related to consumer adoption of AI technologies. In this regard, it can be concluded that future technology acceptance models have to pay attention to the variables related to the levels of trust and privacy concerns of individuals. Second, the SOR theory shows that it is a helpful tool for describing how the stimuli created by technological innovations affect the responses of organisms.

Some practical implications relate to e-commerce websites. It is necessary for e-commerce platforms to invest into AI personalization in order to provide their customers with quality recommendations while being transparent in this way. Firstly, it is important to create trustworthy systems that perform well. Secondly, the moderating effect of privacy concern proves that it is critical to provide users with more controls over personalization and to clarify the policy on data collection.

There are several limitations of the presented research. The cross-sectional nature of the conducted study does not allow conducting strong causal analysis of consumer reactions to AI personalization. In order to get a better idea of the dynamic changes in consumer responses, future studies have to use longitudinal design. Besides, the general focus of this study on the general online shopping platforms may decrease its validity because different categories of products may require additional research. In addition, the sample used in the presented research contains the consumers who belong to particular age groups.

Some directions for future research have been revealed in the previous section. However, it will also be valuable to consider the influence of generative AI or conversational agents on the consumer decisions. It is also important to study the effects of cultural factors on consumers' perceptions of AI personalization and acceptability of it.

REFERENCES

1. Z. Shan and W. Qian, "The Impact of Artificial Intelligence on Consumer Purchasing Behavior: Based on Cross-Border E-Commerce Platforms," Journal of Global Marketing, pp. 1-18, Nov. 2025. DOI: 10.1080/08961530.2025.2588742.
2. S. M. C. Loureiro, J. Jiménez-Barreto, R. G. Bilro, and J. Romero, "Me and my AI: Exploring the effects of consumer self-construal and AI-based experience on avoiding similarity and willingness to pay," Psychology and Marketing, vol. 41, pp. 151-167, 2024. DOI: 10.1002/mar.21913.
3. O. G. Ekwunife, "Consumer Awareness as a Cognitive Bridge: Mediating the Effects of Artificial Intelligence on Purchase Intention in Online Shopping," Mendeley Data, Jan. 2026. DOI: 10.17632/82fwrvjv37.1.
4. H. Pang, Y. Wang, M. Sun, and R. Wang, "How artificial intelligence functionalities boost consumer benefit and impulse shopping? The significant role of responsive communication and conversational communication," Computers in Human Behavior, vol. 180, 2026. DOI: 10.1016/j.chb.2026.100096.
5. B. Peng, Y. Xu, and H. Deng, "The impact of AI identity on consumer behavior in the use of AI-enabled recommendation systems," in 2025 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 187-192, 2025. DOI: 10.1109/SMC53487.2025.10841792.
6. A. Kumar, S. Gupta, and R. Singh, "AI-Powered Personalization in Online Shopping: Key Factors Influencing Customer Retention," in 2025 IEEE International Conference on Big Data, pp. 452-460, 2025. DOI: 10.1109/BigData59044.2025.11074451.
7. M. Chen, L. Zhang, and Y. Liu, "The Paradox of AI Personalization: Deciphering the Interplay Between Algorithmic Customization and Consumer Privacy Anxiety in E-Commerce," Journal of Management and Finance, vol. 8, no. 2, pp. 112-128, 2026.
8. P. A. Budianto, B. Jhon, and A. B. L. Mailangkay, "Utilizing Artificial Intelligence in Consumer Purchase Decision-Making," in 2026 IEEE 15th International Conference on Communication Systems and Network Technologies (CSNT), pp. 1189-1196, 2026. DOI: 10.1109/CSNT65408.2026.10957213.
9. S. Sharma, N. Islam, G. Singh, and A. Dhir, "Why Do Retail Customers Adopt Artificial Intelligence (AI) Based Autonomous Decision-Making Systems?," IEEE Transactions on Engineering Management, vol. 71, pp. 1846-1861, 2024. DOI: 10.1109/TEM.2022.3157976.
10. G. Sá, C. Tam, and M. Aparicio, "From browsing to buying: unpacking the impact of AI on E-commerce shoppers' well-being," Internet Research, Jan. 2026. DOI: 10.1108/INTR-05-2024-0818.