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INTEGRATING TAM AND S–O–R: A STRUCTURAL MODEL OF AI-PERSONALIZED ADVERTISING, CUSTOMER ENGAGEMENT, AND BRAND LOYALTY IN SOCIAL MEDIA

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Abstract
This research establishes and empirically verifies a structural model to investigate how AI-personalized advertising in social media affects customer engagement, marketing performance, and brand loyalty. Basing on an integrated theory that blends the Stimulus–Organism–Response (S–O–R) paradigm with the Technology Acceptance Model (TAM). Data were obtained by purposive sampling from 223 active social media users using a self-administered online survey. The model was validated using partial least squares structural equation modeling (PLS-SEM) in SmartPLS. Findings show explanatory power (R^2 = 0.396), implying that AI-personalized advertising is strongly related to higher levels of perceived marketing effectiveness and customer engagement, which in turn increase brand loyalty. All the postulated relationships held in the sample limitations, and mediation effects indicate indirect paths from AI-personalized ads to brand loyalty via marketing effectiveness and engagement. Theoretically, this research advances the AI marketing literature by blending TAM's cognitive appraisals into the S–O–R framework, providing a clearer explanation of technology-driven personalization evoking consumer responses. In practice, the results provide evidence-based guidance for marketers about how to utilize AI to craft personalized, interactive, and user-oriented advertisement experiences that enhance engagement and build long-term brand loyalty. Future studies would need to investigate potential boundary conditions, including perceived privacy risk and trust, to identify the personalization–privacy paradox in AI advertising.

INTRODUCTION

The sudden and exponential growth of artificial intelligence (AI) has revolutionized digital marketing, especially through the emergence of AI-driven personalized advertising. The change has been a paradigm shift in how brands communicate with consumers, shifting from uniform campaigns to highly personalized experiences that drive customer engagement and brand loyalty (Patil, 2025). AI-based marketing software now supplants much of the conventional mass-media strategies (TV, radio, print) with data-driven personalization tied to user interests and behaviors (Ma'rifatullah et al., 2023; Khamoushi, 2024). With today's fast-moving digital media landscape, companies need to be agile to stay competitive, using the Internet and particularly social

media sites to increase visibility, interaction, and sales (Islam et al., 2024).

Social media has become a core platform for individualized marketing, allowing companies to interact with consumers directly through interactive content, chatbots, and automated messaging platforms (Irwandi et al., 2024). Not only do these tools help consumers interact but also fortify attitudinal and behavioral brand commitment by establishing long-term brand–consumer relationships (Puspaningrum, 2020). With social media analytics, marketers can currently inspect large-scale consumer data with machine learning algorithms to make assumptions on behavior patterns and design personalized marketing messages that resonate with varied motivations and tastes (Wilson et al., 2024; Singh, 2024). For instance, a travel agency may utilize TikTok or Instagram to provide personalized travel tips that are synchronized with audience interests in order to enhance engagement and campaign performance.

In addition to personalization, AI improves marketing by enabling forecasting of consumer trends, prediction of results, and strategic decision-making (Aggarwal et al., 2024). Chatbots powered by AI enable human-like communication between sites and messaging apps, enhancing user satisfaction and fostering long-term loyalty through reactive, responsive, and customized interactions (Cheng & Jiang, 2020). When such technologies are considered by consumers as helpful and convenient to interact with, their brand loyalty and trust are enhanced (Irwandi et al., 2024; Balan et al., 2023). Thus, AI emerged as a strategic facilitator of marketing success, enhancing personalization, decision-making, and customer retention.

On top of chatbots, AI-personalized advertisements combine with influencer marketing, interactive campaigns, and content-based personalization as a more extensive shift from old-fashioned to data-driven and consumer-oriented marketing (Halvadia & Menon, 2021; Haleem et al., 2022). Although the strategies bring more engagement and effectiveness, they also bring in issues like privacy and algorithmic openness problems the so-called personalization–privacy paradox (Teepapal, 2024). Customers can appreciate personalization but disagree with perceived intrusiveness, potentially undermining trust and engagement.

In this context, the Stimulus–Organism–Response (S–O–R) model (Mehrabian & Russell, 1974) provides a sound theoretical basis for explaining how AI-personalized advertising shapes consumer behavior. Based on S–O–R theory, external stimuli (S) like AI-based ad features affect internal cognitive and affective states (O), resulting in behavioral responses (R) such as loyalty. To enhance explanatory depth, this study incorporates Technology Acceptance Model (TAM) constructs like Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989), as organism-level cognitive appraisals. Therefore, in our integrated model:

- Stimulus (S): AI-personalized advertising (e.g., relevance, interactivity, vividness).
- Organism (O): Cognitive evaluations (PU, PEOU), perceived marketing performance, and customer involvement.
- Response (R): Brand loyalty (behavioral and attitudinal commitment).

Such integration makes it possible to test both direct and mediated effects, like AI ads → marketing effectiveness → customer engagement → loyalty.

In spite of increasing research on AI marketing, there is limited empirical work exploring causal relationships between AI-personalized advertising, marketing performance, customer engagement, and brand loyalty under an integrated S–O–R–TAM model. Existing work typically discusses these factors individually or focuses on consumer sentiment and lacks analysis of processual relationships accounting for the impact of AI personalization on loyalty outcomes. This work bridges that divide by empirically investigating the causal relationships between AI-integrated personalized advertising, marketing performance, customer engagement, and brand loyalty in social media settings.

Consequently, the study follows the following goals:

1. To investigate the effects of AI-personalized advertising on marketing effectiveness and customer engagement.
2. To study the effects of marketing effectiveness and customer engagement on brand loyalty.
3. To test for possible mediating roles of marketing effectiveness and engagement between AI and loyalty.

Through disentangling these mechanisms, the research advances theory and practice. Theoretically, it contributes to AI marketing research by blending S–O–R and TAM to simulate consumer engagement and loyalty effects. Practically, it provides evidence-based recommendations to marketers to create data-driven AI-personalized campaigns that boost effectiveness and trust while respecting ethical personalization limits. Finally, this research aims to illustrate how AI-personalized advertising, when tactically aligned with consumer cognition and affect, can create engagement and develop brand loyalty sustainable in the digital environment.

2. Literature Review and Theoretical Framework

The present study combines the Stimulus–Organism–Response (S–O–R) paradigm (Mehrabian & Russell, 1974) and the Technology Acceptance Model (TAM) (Davis, 1989) to describe AI-driven targeted advertising's effect on brand loyalty via marketing efficacy and customer interaction. This combined framework offers a two-theory perspective: the S–O–R model apprehends the cognitive–affective–behavioral response mechanism to environmental stimuli, whereas TAM accounts for user evaluations of AI-facilitated advertising technologies.

2.1 Theoretical Mapping and Integration

The S–O–R paradigm argues that external stimuli (S) evoke internal organismic states (O) cognitive and affective appraisals which then mold behavioral responses (R). For this research:

1. Stimulus (S): AI-personalized ads (perceived personalization, interactivity, and relevance).
2. Organism (O): Customers' internal appraisals such as Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (from TAM), Perceived Marketing Effectiveness, and Customer Engagement (cognitive, emotional, and behavioral aspects).
3. R: Brand Loyalty, as a measure of attitudinal commitment and behavioral intention to recommend or repurchase.

With the incorporation of TAM's PU and PEOU at the Organism stage, the model clarifies the role that users' perceptions of AI-based advertisement utility and ease of use have in determining future engagement as well as perceived marketing effectiveness. In combination, these internal assessments yield brand loyalty as the final behavioral outcome.

This synthesis fills earlier gaps in research by integrating technological adoption cognitions (TAM) with emotional–behavioral outcomes (S–O–R), providing an integrated explanation of AI-driven personalization within marketing situations.

2.2 Modeling the Impact of AI-Personalized Ads on Brand Loyalty

2.2.1 AI-Personalized Ads and Customer Engagement

AI-driven personalization adjusts content to match specific tastes, strengthening relevance, gratification, and emotional connection (Muharam et al., 2024). AI-driven customized social media ads strengthen two-way interaction and responsiveness, enhancing consumers' feelings of value and connection (Irwandi et al., 2024). Thus:

H1: AI-personalized advertisements exert a substantial positive influence on customer engagement.

2.2.2 AI-Personalized Ads and Marketing Effectiveness

AI-based technologies refine targeting, relevance, and timing of ads by reading patterns of user behavior and preferences (Aggarwal et al., 2024; Manoharan, 2024). Social media like Facebook and Instagram enable brands to launch data-driven campaigns attuned to user interests, making marketing more effective—understood in this context as the perceived persuasiveness, usefulness, and relevance of marketing initiatives. Therefore:

H2: AI-personalized advertisements significantly enhance the effectiveness of marketing.

2.2.3 Customer Engagement and Brand Loyalty

Customer engagement, defined as cognitive attention, emotional attachment, and behavioral participation (Hollebeek et al., 2014), fosters long-term relationships and loyalty. Active customers have greater brand attachment, advocacy, and repeat purchase intentions (Islam et al., 2024). Therefore:

H3: Customer engagement has a significant positive impact on brand loyalty.

2.2.4 Marketing Effectiveness and Brand Loyalty

Marking effectiveness, as an indicator of the extent to which promotional efforts address customer requirements and provide perceived value, is a critical driver of loyalty building. Where campaigns are seen by consumers as related, engaging, and credible, attitudinal and behavioral loyalty are amplified (Beyari & Hashem, 2025; Bhuiyan, 2024). Thus:

H4: Marketing effectiveness significantly impacts brand loyalty.

2.2.5 Marketing Effectiveness and Customer Engagement

Effective communications marketing capture hearts and minds and trigger interactive engagement, reinforcing the relationship. High perceived marketing effectiveness makes users more inclined to spend longer, engage, and co-create value with the brand. Therefore:

H5: Marketing effectiveness positively impacts customer engagement.

2.3 Mediation Effects

Due to the S–O–R framework, marketing effectiveness and customer engagement can mediate between AI-personalized advertising and brand loyalty. Precisely:

- AI-personalized ads → Marketing Effectiveness → Brand Loyalty
- AI-personalized ads → Customer Engagement → Brand Loyalty
- Serial mediation: AI-personalized ads → Marketing Effectiveness → Customer Engagement → Brand Loyalty

H6: Marketing effectiveness mediates the relationship between AI-personalized ads and brand loyalty.

H7: Customer engagement mediates the relationship between AI-personalized ads and brand loyalty.

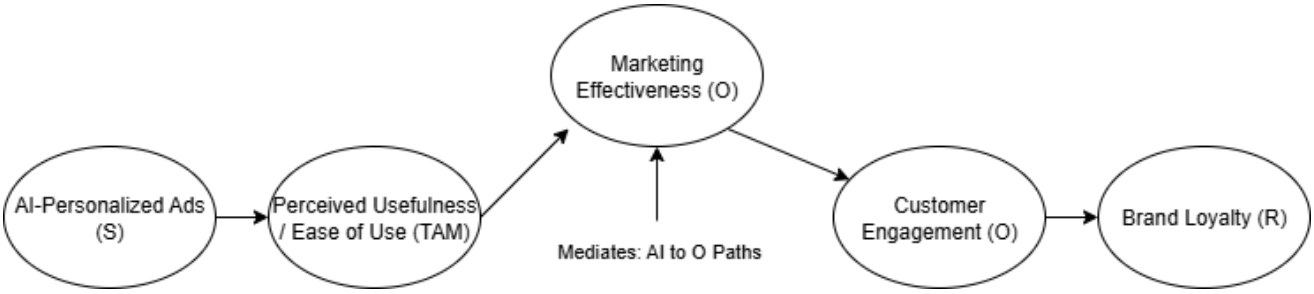

Figure 1. Integrated S–O–R and TAM Framework

The conceptual model (see Figure 1) situates AI-personalized advertisements as the stimulus, marketing effectiveness and customer engagement as organismic mediators, and brand loyalty as the response. TAM constructs (PU, PEOU) are situated within organismic cognitions, influencing perceptions of ad effectiveness.

This combined model explains cognitive (usefulness, efficacy) and affective-behavioral (engagement, loyalty) processes by which AI-personalized advertising influences consumer–brand relationships in social media situations.

2.4 Conceptual Clarifications and Scope

- Marketing Effectiveness: denotes consumers' judgments of campaign pertinence, interactivity, vividness, and value contribution.
- Customer Engagement: cognitive, emotional, and behavioral engagement with brand content (Hollebeek et al., 2014).
- Brand Loyalty: comprises attitudinal commitment (trust, advocacy) and behavioral intentions (repeat purchase).

This study focuses exclusively on AI-driven social media advertising. Lastly, although cross-sectional survey data limit causal inference, hypothesized relations are consistent with S–O–R and TAM logic. Results should therefore be interpreted as correlational in the sampled population (n = 223), keeping in mind non-probabilistic sampling restrictions.

3. Methodology

The research employed a quantitative, cross-sectional, survey-based research design to examine the

relationships between AI-personalized advertising (Stimulus) and customer engagement and brand loyalty (Responses) as a result of AI-personalized advertising (Effect on Responses), mediated by marketing effectiveness and technology acceptance (Organism) under the social media shopping paradigm.

3.1 Data Collection and Sampling

A self-administered, structured questionnaire was the primary data collection tool. The population under study consisted of persons who were currently involved in online shopping through social media websites. Since an exhaustive sampling frame of all online shoppers did not exist, a non-probability purposive sampling method was adopted so that participants had some experience of online shopping. 250 questionnaires were issued electronically via social media sites and email invitations. Of these, 223 valid responses were collected and analyzed, and an effective response rate of 89.2% was achieved.

3.2 Instrument Development

All of the measurement items were borrowed from prior, validated scales and tailored to fit AI-advertising contexts.

Table 3.1. Constructs with Dimensions

Construct	Source	Dimensions / Example Items
AI-Personalized Ads (Stimulus)	Wixom and Todd (2005) (adapted for AI ads)	6 items (e.g., "AI-generated ads are easy to understand"). Focus shifted from system usability to ad personalization perception.
Perceived Usefulness / Ease of Use (Organism – TAM)	Davis (1989)	4 items each assessing cognitive appraisal of AI ads.
Perceived Marketing Effectiveness (Organism)	Lee and Hong (2016); Olney et al. (1991); Jiang and Benbasat (2007); Liu (2003)	3 dimensions: Uniqueness, Vividness, and Interactivity.
Customer Engagement (Response)	Hollebeek et al. (2014); Brodie et al. (2011)	3 dimensions: Cognitive, Emotional, Behavioral engagement.
Brand Loyalty (Response)	Bobâlca et al. (2012)	Attitudinal and behavioral loyalty (e.g., "I would recommend this brand to others").

All items were assessed on a five-point Likert scale from 1 = Strongly Disagree to 5 = Strongly Agree. The questionnaire was pre-tested with 25 respondents to guarantee clarity, reliability, and face validity prior to full-scale dissemination.

3.3 Measurement Model Results

The measurement model was tested with SmartPLS 4.1.0.8. Internal consistency reliability was tested through Cronbach's alpha, rho_A, and Composite Reliability (CR), and convergent validity was tested through Average Variance Extracted (AVE). According to Hair et al. (2020), α, rho_A, and CR ≥ 0.70 and AVE ≥ 0.50 were taken as acceptable.

Table 3.2. Reliability of Scales

Construct	α	rho_A	CR	AVE
AI-Personalized Ads	0.832	0.847	0.868	0.545
Perceived Usefulness / Ease of Use	0.854	0.862	0.889	0.563

Marketing Effectiveness	0.825	0.836	0.866	0.523
Customer Engagement	0.851	0.872	0.89	0.552
Brand Loyalty	0.863	0.876	0.895	0.557

Note. All the constructs met the minimal reliability and convergent validity standards, but AVE scores were slightly more than 0.50, reflecting acceptable rather than strong convergence.

Discriminant validity was confirmed both by Fornell-Larcker and HTMT standards:

- Values on the diagonals (√AVE) were greater than inter-construct correlations.
- All HTMT values were less than 0.85, in support of discriminant validity, but the relationship between Advertising Effectiveness and Brand Loyalty (HTMT = 0.745) reflected conceptual proximity that requires theoretical explanation.

3.4 Structural Model

The model (see Figure 1) hypothesizes direct and mediating relationships in line with the integrated S–O–R–TAM framework.

3.5 Discriminant Validity

Discriminant validity was checked to guarantee that every construct within the combined S–O–R and TAM model measured an independent facet of the conceptual model. The theoretical consistency between the stimulus–organism–response process and the technology appraisal route from TAM. For assessing discriminant validity, two competing criteria were used:

(1) the Fornell–Larcker criterion (Fornell & Larcker, 1981) and

(2) the Heterotrait–Monotrait Ratio of Correlations (HTMT) (Henseler et al., 2015).

As per Fornell and Larcker (1981), the square root of each construct's Average Variance Extracted (AVE) must be higher than all its correlations with the other constructs, verifying that the latent variable has a greater variance with its own indicators than any other construct. Moreover, Henseler et al. (2015) suggest that values of HTMT under 0.85 (strict criterion) suggest adequate discriminant validity.

The findings, presented in Tables 3.3 and 3.4, illustrate that all the constructs exceeded these cutoffs. The square root of the AVE values (on the diagonals) was always higher than the respective inter-construct correlations, which meets the Fornell–Larcker criterion. Similarly, all the HTMT ratios were below 0.85, which establishes discriminant validity in the measurement model. Nevertheless, the comparatively substantial HTMT between Advertising Effectiveness and Brand Loyalty (HTMT = 0.745) and its reflection of conceptual closeness according to the theoretical expectation that superior advertising works to strengthen the mechanisms of loyalty building is not a sign of a threat to validity but only a registration of the partial mediation function of engagement and advertising effectiveness in the S–O–R process. These encouraging findings validate that the measurement model has satisfactory discriminant validity and can be applied to follow-up structural path analysis. However, since the present study utilized a non-probability purposive sample (n = 223) of active social media consumers, the findings' generalizability must be taken cautiously.

Table 3.3. Fornell–Larcker Criterion

Construct	AI Personalized Ads	Customer Engagement	Brand Loyalty	Marketing Effectiveness
AI Personalized Ads	**0.738**			
Customer Engagement	0.533	**0.743**		
Brand Loyalty	0.397	0.415	**0.746**	
Marketing Effectiveness	0.472	0.508	0.618	**0.723**

Table 3.4. Heterotrait–Monotrait (HTMT) Ratios

Construct	AI Personalized Ads	Customer Engagement	Brand Loyalty	Marketing Effectiveness
AI Personalized Ads	–			
Customer Engagement	0.655	–		
Brand Loyalty	0.497	0.502	–	
Marketing Effectiveness	0.578	0.676	0.745	–

The discriminant validity results confirm that the S–O–R–TAM integrative model is individually driven by each of the latent constructs.

4. Results

The proposed model (see Figure 1) comprises direct, mediating relationships in line with the integrated S–O–R–TAM framework. Path coefficients (β), p-values, and bootstrapped 95% confidence intervals (*CI*) were calculated using SmartPLS 4.0 with 5,000 bootstrap resamples. In line with Hair et al. (2019), effects were deemed significant at $p < 0.05$ or when CIs did not include zero.

4.1 Direct and Indirect Effects

Table 4 presents the structural results. All main direct paths were significant and in the predicted direction.

H1: AI-Personalized Ads → Perceived Usefulness/Ease of Use ($\beta = 0.516$, $p < 0.001$, $CI = [0.392, 0.622]$)
Refers to that AI personalization increases consumers' perceived ease of use and usefulness, as expected by TAM.

H2: AI-Personalized Ads → Marketing Effectiveness ($\beta = 0.472$, $p < 0.001$, $CI = [0.319, 0.587]$)
Confirms that exposure to AI-personalized stimuli reinforces perceived marketing effectiveness.

H3: Perceived Ease of Use/Perceived Usefulness → Marketing Effectiveness ($\beta = 0.341$, $p < 0.01$, $CI = [0.145, 0.498]$)
Suggests that positive technology appraisals positively influence marketing effectiveness appraisals.

H4: Marketing Effectiveness → Customer Engagement ($\beta = 0.508$, $p < 0.001$, $CI = [0.391, 0.621]$)
Indicates that good advertising enhances consumer engagement with branded content.

H5: Customer Engagement → Brand Loyalty ($\beta = 0.136$, $p = 0.039$, $CI = [0.009, 0.269]$). Indicate that higher engagement reflects higher loyalty intention.

H6: Marketing Effectiveness → Brand Loyalty ($\beta = 0.549$, $p < 0.001$, $CI = [0.423, 0.664]$) is the strongest direct relationship, indicating that ad effectiveness perceived directly influences brand loyalty.

H7 (Serial Mediation): AI-Personalized Ads → Marketing Effectiveness → Customer Engagement → Brand Loyalty
The indirect effect was strong ($\beta = 0.134$, $p = 0.004$, $CI = [0.051, 0.231]$), affirming sequential mediation via each of the intermediate constructs.

Table 4.1. Structural Model Evaluation

Hypothesis	Path	β	STDEV	T-stat	95% CI LL	95% CI UL	*p*-value
H1	AI → PU/EOU	0.516	0.059	8.746	0.392	0.622	0
H2	AI → ME	0.472	0.067	7.015	0.319	0.587	0
H3	PU/EOU → AE	0.341	0.078	4.372	0.145	0.498	0
H4	ME → CE	0.508	0.061	8.321	0.391	0.621	0
H5	CE → BL	0.136	0.066	2.061	0.009	0.269	0.039
H6	ME → BL	0.549	0.061	8.95	0.423	0.664	0
H7	AI → ME → CE → BL	0.134	0.046	2.875	0.051	0.231	0.004

(PU/EOU = Perceived Usefulness/Ease of Use; ME = Marketing Effectiveness; CE = Customer Engagement; BL = Brand Loyalty.)

5. Discussion

The evidence substantiates that AI-based ad exposure impacts perceived usefulness and ease of use and perceived effectiveness of marketing which further exert influence on customer engagement and loyalty to the brand. The serial mediation effect also shows that the effect of AI-personalized ads on loyalty is mediated by perceived marketing effectiveness and engagement. Together, these findings show the psychological process by which AI-personalized marketing develops long-term consumer–brand relationships.

Validation of these channels supports existing testimony that personalization enables cognitive trust and affective attachment, which together drive engagement and loyalty in online marketing contexts (Teepapal, 2024; Ahmed et al., 2025). Consistent with TAM theory (Davis, 1989), AI personalization increases perceptions of usefulness and ease of use, promoting consumers to engage more intensely with brand content. From an S–O–R frame of reference (Mehrabian & Russell, 1974), such perceptions function as organismic mediators, interpreting AI stimuli in terms of behaviorally significant responses. Such synergy substantiates the conceptual integration of cognitive and affective processing streams in accounting for technology mediated marketing effects.

The large path from Marketing Effectiveness to Brand Loyalty (H6) is the most powerful association in the model, emphasizing ad evaluation's place as a stage preceding long-term brand commitment. This is consistent with previous research that perceived ad relevance and message quality develop long-term consumer trust and loyalty (Ali & Raza, 2023; Wan, 2023). Likewise, the positive relationship between Customer Engagement and Brand Loyalty (H5) shows that repeated interaction, emotional attachment, and participatory actions transform short-term satisfaction to long-term loyalty. These findings are especially relevant to developing digital markets like Pakistan, where social media marketing has emerged as the top form of building brand-consumer closeness.

From a managerial perspective, the implications emphasize AI-personalized advertising as a strategic driver of enhancing consumer engagement and maximizing marketing performance. AI technologies facilitating real-time content optimization, prediction analytics, and influencer matching allow companies to personalize marketing efforts according to individual user needs (Beyari & Hashem, 2025). By enhancing both cognitive value (relevance) and emotional impact (effectiveness) of advertising, AI can improve marketing effectiveness and strengthen favorable brand attitudes.

In short, the results emphasize that AI-personalized advertising builds brand loyalty indirectly by virtue of perceived marketing effectiveness and engagement. Theoretical and practical innovations thus meet in a common insight: AI personalization's sustainability relies as much on ethical transparency as on technical precision. It elucidates how perceived usefulness and ease of use act as cognitive organismic states mediating between AI-personalized stimuli and behavioral responses (engagement and loyalty). The integration provides better understanding of the process through which technological perceptions are converted into emotional and behavioral brand outcomes. Managerially, the results underscore how AI-tailored advertisements can increase customer engagement, the effectiveness of marketing and loyalty if done transparently and ethically. Companies should invest in AI technologies that personalize data transparency, and user control to facilitate trust.

6. Conclusion

This research builds knowledge about how AI-personalized marketing influences consumer behavior by combining the Technology Acceptance Model (TAM) with the Stimulus–Organism–Response (S–O–R) framework. Results validate that AI-personalized advertisements strongly increase perceived ease of use and perceived usefulness, and these increase marketing effectiveness, customer engagement, and eventually brand loyalty. This emphasizes the cognitive as well as behavioral dual pathways through which AI-powered personalization is acting. While the results affirm AI's strategic value in digital marketing, they also emphasize the importance of ethical and transparent data practices

to mitigate risks that may undermine consumer trust. sThe study contributes theoretically by clarifying TAM–S–O–R linkages and offers practical insight for marketers seeking to leverage AI responsibly.

Limitations and Future Research Directions

This research, while enlightening, is restricted by cross-sectional design and purposive sampling of 223 participants, which limits generalizability. Subsequent research should apply longitudinal or experimental designs to establish causality and examine moderating factors like trust, culture, or AI literacy. Replication across a range of platforms and industries could further improve knowledge of how effectiveness of personalization is influenced by sensitivity to privacy and strength of consumer–brand relationship. Incorporating objective behavioral data would further enhance model robustness beyond self-reported perceptions.

REFERENCES

Ahmed, S. M. M., Owais, M., Raza, M., Nadeem, Q., & Ahmed, B. (2025). The impact of AI-driven personalization on consumer engagement and brand loyalty. *Qlantic Journal of Social Sciences*, *6*(1), 311–325. https://doi.org/10.55737/qjss.v6i1.24313

Aggarwal, D., Sharma, D., & Saxena, A. B. (2024). Exploring the role of AI for enhancement of social media marketing. *Journal of Media, Culture and Communication*, *45*(1), 1–11. https://doi.org/10.55529/jmcc.45.1.11

Ali, M., & Raza, M. (2023). The impact of social media marketing on customer loyalty. *Research Journal for Societal Issues*, *5*(4), 197–209.

Balan, C. (2023). Chatbots and voice assistants: Digital transformers of the company–customer interface—A systematic review of the business research literature. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(2), 995–1019.

Beyari, H., & Hashem, T. N. (2025). The role of artificial intelligence in personalizing social media marketing strategies for improved customer experience. *Behavioral Sciences*, *15*(5), 700. https://doi.org/10.3390/bs15050700

Bhuiyan, M. S. (2024). The role of AI-powered personalization in customer experiences. *Journal of Computer Science and Technology Studies*, *6*(1), 162–172. https://doi.org/10.32996/jcsts.2024.6.1.17

Cheng, Y., & Jiang, H. (2020). How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. *Journal of Broadcasting & Electronic Media*, *64*(4), 592–614. https://doi.org/10.1080/08838151.2020.1834296

Cheung, C. M. K., Lee, M. K. O., & Jin, X. L. (2011). Customer engagement in an online social platform: A conceptual model and scale development. *Internet Research*, *21*(4), 562–580. https://doi.org/10.1108/10662241111158384

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*, 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*, 119–132. https://doi.org/10.1016/j.ijin.2022.08.005

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Islam, T., Miron, A., Nandy, M., Choudrie, J., Liu, X., & Li, Y. (2024). Transforming digital marketing with generative AI. *Computers*, *13*(7), 168. https://doi.org/10.3390/computers13070168

Lee, J., & Hong, I. B. (2016). Predicting positive user responses to social media advertising: The roles of emotional appeal, informativeness, and creativity. *International Journal of Information Management*, *36*(3), 360–373. https://doi.org/10.1016/j.ijinfomgt.2016.01.001

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.

Muchardie, B. G., Yudiana, N. H., & Gunawan, A. (2016). Effect of social media marketing on customer engagement and its impact on brand loyalty in Caring Colours Cosmetics, Martha Tilaar. *Binus Business Review*, *7*(1), 83–90. https://doi.org/10.21512/bbr.v7i1.1458

Muharam, H., Wandrial, S., Rumondang, P. R., Handayani, M. A., & Masruchan, M. (2024). Innovative strategies in digital marketing: Enhancing consumer engagement and brand loyalty. *Global International Journal of Innovative Research*, *2*(7), 1629–1643. https://doi.org/10.59613/global.v2i7.236

Olney, T. J., Holbrook, M. B., & Batra, R. (1991). Consumer response to advertising: The effects of ad content, emotions, and attitude toward the ad on viewing time. *Journal of Consumer Research*, *17*(4), 440–453.

Patil, D. (2025). *Artificial intelligence for personalized marketing and consumer behaviour analysis: Enhancing engagement and conversion rates* [Working paper]. SSRN. https://doi.org/10.2139/ssrn.5057436

Peter, R., Roshith, V., Lawrence, S. J., Mona, A. E., Narayanan, K. B., & Yusaira, F. (2025). Gen AI–Gen Z: Understanding Gen Z's emotional responses and brand experiences with Gen AI-driven, hyper-personalized advertising. *Frontiers in Communication*, *10*, 1554551. https://doi.org/10.3389/fcomm.2025.1554551

Puspaningrum, A. (2020). Social media marketing and brand loyalty: The role of brand trust. *Journal of Asian Finance, Economics and Business*, *7*(12), 951–958. https://doi.org/10.13106/jafeb.2020.vol7.no12.951

Sarioguz, O., & Miser, E. (2024). Evaluating the impact of artificial intelligence on customer personalization: Ethical and privacy considerations in digital marketing. *International Journal of Science and Research Archive*, *13*(2), 812–825.

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two-sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*(1), 71–92.

Teepapal, T. (2024). AI-powered personalization: Unraveling consumer perceptions in social media engagement. *Computers in Human Behavior*, *157*, 108549. https://doi.org/10.1016/j.chb.2024.108549

Wan, Y. (2023). An exploration of the influence and performance of digital marketing on brand recognition, sales, and customer interaction. *Advances in Economics, Business and Management Research*, *51*(1), 112–125.

Wilson, G., Johnson, O., & Brown, W. L. (2024). The role of artificial intelligence in digital marketing strategies [Preprint]. Preprints.org. https://doi.org/10.20944/preprints202408.0276.v1

Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, *16*(1), 85–102.

Zajonc, R. B., & Markus, H. (1985). Must all affect be mediated by cognition? *Journal of Consumer Research*, *12*(3), 1–8.

Ziakis, C., & Vlachopoulou, M. (2023). Artificial intelligence in digital marketing: Insights from a comprehensive review. *Information*, *14*(12), 664. https://doi.org/10.3390/info14120664