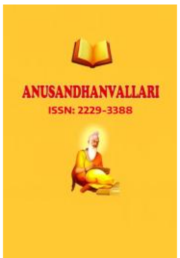

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Personalization, Trust, and Interactivity in Digital Media Advertising: An Integrated Model of Consumer Purchase Intentions

[1]Mr. K. R. Nitin Krishna, Dr. M. Ganesh Babu

[1]Research Scholar, Department of Management

Mass College of Arts & Science, Kumbakonam.

Affiliated to Bharathidasan University, Trichy.

[2]Research Supervisor, Department of Management

Mass College of Arts & Science, Kumbakonam.

Affiliated to Bharathidasan University, Trichy.

Abstract

The rapid growth of digital media platforms has reshaped advertising, facilitating new levels of customized content, two-way communication, and audience involvement. While prior research has examined advertising value, personalization, or trust in isolation, few studies have integrated these dimensions into a unified framework to explain consumers' purchase intentions. This study addresses this gap by developing and testing a structural equation model that incorporates personalization intensity, trust mechanisms, and interactivity as mutually reinforcing drivers. Data from 200 active social media users were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicate that all three factors significantly predict purchase intention. Personalization exerts both a direct and an indirect effect mediated by trust. Furthermore, interactivity moderates the relationship between advertising value and purchase intention, amplifying its positive influence under high engagement. The model explains 64% of the variance in purchase intentions, offering theoretical contributions and actionable insights for designing consumer-centric campaigns.

Keywords Digital media advertising · Personalization · Trust · Interactivity · Consumer purchase intentions Structural equation modeling (SEM) · PLS- SEM

1 Introduction

In recent years, the expansion of digital channels has fundamentally altered consumer-brand interactions, thereby reshaping the determinants of purchase intentions. Unlike traditional advertising, which primarily relied on mass communication channels such as television and print, digital media enables precise targeting, interactivity, and measurable engagement [2]. This shift has resulted in an unprecedented ability to tailor advertisements to individual consumer preferences, thereby enhancing relevance and increasing the likelihood of purchase consideration [1]. While existing studies have examined consumer attitudes toward online advertising [16, 15], the dynamic interplay between personalization, consumer trust, and purchase intentions in the context of algorithm-driven platforms remains underexplored. Moreover, the rise of immersive media formats such as interactive video ads, shoppable social media posts, and augmented reality campaigns introduces new dimensions of consumer engagement that go beyond mere exposure [5]. These innovations suggest that digital advertising is not only persuasive but also participatory, blurring the boundary between marketing communication and consumer experience. The novelty of this study lies in integrating *personalization intensity, consumer trust mechanisms, and immersive interactivity* into a unified framework for analyzing purchase intentions. Whereas prior research has often addressed these factors in isolation, our approach conceptualizes them as mutually reinforcing elements of digital advertising effectiveness. This provides a more holistic understanding of how digital advertising ecosystems influence consumer decision-making in an era of heightened data-driven personalization and privacy concerns. Therefore, this paper addresses the following research question: How do personalization, trust, and interactivity in digital media advertising collectively shape consumer purchase intentions? By answering this question, we contribute to both theory and practice by offering an integrative model that reflects contemporary advertising realities.

2 Related Work

The impact of digital media advertising on consumer purchase intentions has been widely studied across several dimensions, including consumer attitudes, personalization, trust, and interactivity.

2.1 Consumer Attitudes toward Digital Advertising

Early research established that consumer perceptions of informativeness, entertainment, and credibility strongly influence advertising effectiveness [6]. In the context of social media, consumers' attitudes have been shown to medi- ate the relationship between advertising exposure and behavioral response [15].Similarly, Lee and Hong [16] demonstrated that informativeness and emotional appeal are critical drivers of positive responses to online advertisements.

2.2 Personalization and Targeting

Advances in big data analytics and machine learning have enabled more refined personalization strategies. Kannan and Li [1] proposed a framework for digital marketing that emphasizes personalization as a key determinant of purchase intention. Xu et al. [7] highlighted how tailored messages increase relevance, though excessive targeting can raise privacy concerns, leading to resistance.

2.3 Trust and Social Proof

Trust has also emerged as a crucial determinant of consumer acceptance of digital advertising. Research shows that credibility of the message source, such as influencers or peer reviews, enhances consumer trust and purchase likelihood [8]. Social proof mechanisms embedded in digital campaigns, including user- generated content and ratings, play a pivotal role in strengthening purchase intention.

2.4 Interactivity and Engagement

Interactivity distinguishes digital advertising from its traditional counterparts. Studies indicate that interactive features, such as click-to-buy links and gami- fied content, enhance consumer engagement and brand recall [16, 10]. Dwivedi et al. [5] extended this argument by noting that participatory forms of digi- tal marketing foster stronger emotional connections between brands and con- sumers.

2.5 Immersive Media Formats

Recent literature highlights the role of immersive technologies such as augmented reality (AR) and virtual reality (VR) in digital advertising. Yim et al. [11] showed that AR advertisements improve brand attitudes and purchase intention by creating vivid, interactive experiences. However, empirical work in this area remains fragmented, with limited integration into broader models of digital consumer behavior.

2.6 Research Gap

While these studies have advanced understanding of individual factors such as personalization, trust, or interactivity, few have examined how these dimensions collectively shape consumer purchase intentions in algorithm-driven environments. Ecosystems. The novelty of this work lies in proposing a unified framework that integrates *personalization intensity, trust mechanisms, and immersive interactivity*, thereby offering a more comprehensive perspective on digital media advertising effectiveness.

Table 1 Comparison of related works on digital media advertising and consumer purchase intentions

Study	Focus	Limitations / Gap
Ducoffe (1996) [6]	Advertising value model (informative-ness, entertainment, credibility) for web-based ads	Lacks integration of personalization or interactivity
Boateng and Okoe (2015) [15]	Attitudes toward social media advertising and behavioral responses	Focuses on consumer perception; limited attention to immersive formats
Lee and Hong (2016) [16]	Influence of emotional appeal, informativeness, and interactivity in social media ads	Does not include trust or personalization mechanisms
Kannan and Li (2017) [1]	Framework for digital marketing emphasizing personalization	Limited analysis of consumer trust and immersive technologies
Xu et al. (2011) [7]	Role of trust and privacy in the adoption of location-based services	Narrow domain; findings not generalized to broader digital advertising.
Evans et al. (2017) [9]	Effect of influencer disclosure language on recognition and intent	Focused only on influencer credibility, not multi-dimensional advertising effectiveness
Dwivedi et al. (2021) [5]	Research agenda for digital and social media marketing, highlighting interactivity	Agenda-setting work; lacks empirical integration of multiple factors
Yim et al. (2017) [11]	Augmented reality advertising impact on brand attitudes	Examines immersive ads in isolation; not integrated into holistic purchase intention models
This Study	Integrates *personalization intensity, Consumer trust mechanisms, and immersive interactivity* into a unified framework for analyzing purchase intentions	Provides a holistic model capturing mutually reinforcing effects of key digital advertising dimensions

2.7 Data Collection

Data was collected through a structured questionnaire distributed online via Google Forms. The instrument employed a 5-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). The complete questionnaire is provided in Appendix A.

- **Advertising Value:** Adapted from Ducoffe's model [6], covering informa- tiveness, entertainment, and credibility.
- **Personalization Intensity:** Items measuring the degree to which consumers perceive advertising content as tailored to their preferences [1].
- **Interactivity:** Items adapted from Lee and Hong [16] to capture user engagement with ads.
- **Trust and Credibility:** Based on scales from Xu et al. [7].
- **Purchase Intention:** Items measuring consumer likelihood of engaging in purchasing behaviors after exposure to ads.

A pilot study with 30 respondents was conducted to refine the questionnaire and assess clarity.

2.8 Measurement Model

Construct reliability and validity were assessed using Cronbach's alpha and Composite Reliability (CR), with thresholds of $\alpha > 0.7$ and $CR > 0.7$ considered acceptable. Convergent validity was evaluated through Average Variance Extracted ($AVE > 0.5$), while discriminant validity was tested using the Fornell–Larcker criterion. The complete results, including factor loadings, cross-loadings, and VIF values, can be found in Appendix C.

2.9 Data Analysis Techniques

Data analysis was performed using Structural Equation Modeling (SEM) via SmartPLS, as it is well-suited for testing complex relationships between latent variables in marketing research [9]. The analysis included:

- Descriptive statistics for demographic and sample characteristics.
- Reliability and validity assessments of the measurement model.
- Hypothesis testing through the structural model to examine the relationships among advertising value, personalization, interactivity, trust, and purchase intentions.
- Mediation and moderation analyses to evaluate the role of trust and interactivity as potential mechanisms influencing consumer purchase behavior.

2.10 Ethical Considerations

Participation in the study was voluntary, and informed consent was obtained from all respondents. Confidentiality of responses was maintained, and no personally identifiable information was collected.

2.11 Conceptual Model

Fig. 1 illustrates the proposed framework, integrating advertising value, personalization intensity, interactivity, and trust as key determinants of consumer purchase intentions.

2.12 Population, Sampling, and Data Collection

The target population was defined as active social media users (defined as daily usage) aged 18-55, who have been exposed to and can recall digital advertising within these platforms. A non-probability, purposive sampling technique was employed to reach this specific demographic, utilizing online channels and social media groups to distribute the survey link. The final sample consisted of **N = 200** respondents, which meets and exceeds the minimum sample size requirements for PLS-SEM analysis, often cited as 10 times the number of paths in the most complex structural equation. A pilot study with 30 respondents was conducted to refine the instrument, ensuring question clarity, contextual relevance, and internal consistency. Cronbach's Alpha for all constructs in the pilot exceeded 0.78, indicating strong initial reliability.

2.13 Measurement Instrument

The structured questionnaire utilized a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The constructs were operationalized with multiple items adapted from established scales to ensure validity:

– **Advertising Value (4 items):** Adapted from Ducoffe et al. (e.g., "Social media ads are a good source of product information").

– **Personalization Intensity (4 items):** Adapted from Kannan & Li et al. (e.g., "The ads I see on social media are tailored to my interests").

– **Interactivity (5 items):** Adapted from Lee & Hong et al. and Liu et al. (e.g., "I enjoy engaging with ads that have interactive features like polls or quizzes").

– **Trust (4 items):** Adapted from Xu et al. (e.g., "I trust that the brands advertising on social media are credible").

– **Purchase Intention (3 items):** Common scale in marketing literature (e.g., "I am likely to purchase a product I see advertised on social media").

2.14 Extended Data Analysis Plan

The analysis followed a rigorous two-step approach:

1. **Measurement Model Assessment:** Confirmatory analysis was conducted to ensure reliability and validity. This included:

– **Internal Consistency:** Cronbach's Alpha ($\alpha > 0.7$) and Composite Reliability (CR > 0.7).

– **ConverGent Validity:** Average Variance Extracted (AVE > 0.5) and indicator loadings (> 0.7).

– **Discriminant Validity:** Fornell-Larcker criterion (square root of AVE for a construct should be greater than its correlations with other constructs) and examination of cross-loadings.

– **Common Method Bias:** Assessed using Harman's single-factor test, where no single factor accounted for the majority of the covariance.

2. **Structural Model Assessment:** The hypothesized relationships were tested using SmartPLS 4.0. The model's predictive accuracy and the significance of paths were evaluated using:

– **Bootstrapping:** 5,000 subsamples to generate t-statistics and p-values for path coefficients (β).

– **Coefficient of Determination (R^2):** To evaluate the model's explanatory power for the endogenous constructs (Purchase Intention and Trust).

– **Effect Sizes (f^2):** To assess the substantive impact of removing an exogenous construct.

– **Predictive Relevance (Q^2):** Calculated via the blindfolding procedure to assess the model's out-of-sample predictive power ($Q^2 > 0$ implies predictive relevance).

– **Moderation Analysis:** The interaction term (Advertising Value × In-teractivity) was created within SmartPLS to test the moderating effect (H5b).

3 Hypotheses Development

Building on established models of advertising value and consumer response, this study advances a novel framework that integrates *personalization intensity, consumer trust, and immersive interactivity into a unified model of purchase* intentions. While prior studies have examined these factors in isolation [6],[16], [1], [7], their mutually reinforcing effects have not been systematically tested. This research, therefore, contributes by proposing hypotheses that capture both direct and mediated influences.

3.1 Advertising Value and Purchase Intention

Ducoffe's advertising value model emphasizes informativeness, entertainment, and credibility as drivers of consumer attitudes [6]. However, in the context of modern digital platforms, advertising value alone may be insufficient without interactive or personalized components. Nevertheless, high advertising value remains a critical baseline for enhancing purchase intentions.

H1: Advertising value has a positive effect on consumer purchase intention.

3.2 Personalization Intensity and Purchase Intention

Recent digital advertising practices increasingly rely on algorithms that tailor content to individual preferences [1]. While personalization has been studied separately, few works have connected it directly to behavioral outcomes in tandem with trust. This study posits that higher personalization intensity improves relevance and engagement, thereby enhancing purchase likelihood.

H2: Personalization intensity has a positive effect on consumer purchase intention.

3.3 Interactivity and Purchase Intention

Interactivity allows consumers to engage with advertising messages actively, fostering immersion and brand connection [16]. Unlike prior models that treated interactivity as a secondary feature, it is proposed that highly personalized content increases the perceived relevance of an ad, which boosts user engagement and ultimately leads to a greater intention to purchase.H3: Interactivity in digital media advertising positively influences consumer purchase intention.

3.4 Trust and Purchase Intention

Trust has been recognized as an essential condition for reducing consumer skepticism [7]. However, previous research has not fully explored the concept of trust. Interacts with personalization and interactivity. This study positions trust as both a direct determinant of purchase intention and a mediating factor in the effectiveness of personalized advertising.

H4: Consumer trust in digital advertising positively influences purchase intention.

3.5 Mediating and Moderating Roles: A Novel Integration

A novel contribution of this work lies in examining the dynamic interplay among constructs. Specifically, personalization may enhance trust, which then strengthens purchase intentions, while interactivity may moderate the influence of advertising value on consumer decisions. Unlike prior studies that tested these effects in isolation [5], [9], this study proposes an integrated framework: H5a: Trust mediates the relationship between personalization intensity and purchase intention.

H5b: Interactivity moderates the relationship between advertising value and purchase intention.

4 Structural Equation Model Specification

To empirically validate the conceptual framework, the study applies a Structural Equation Modeling (SEM) approach, which consists of two components: the measurement model and the structural model.

4.1 Measurement Model

Each latent construct is operationalized using multiple observed indicators based on validated scales from prior studies [6], [16], [1], [7]. The measurement model is specified as follows:

$$X_i = \lambda_i \xi + \delta_i, \quad i = 1, 2, \ldots, n \tag{1}$$

where X_i represents the observed indicators, λ_i denotes the factor loading,

ξ is the latent construct (e.g., Advertising Value, Personalization Intensity, Interactivity, Trust, Purchase Intention), and δ_i represents the measurement error. Reliability is evaluated using Cronbach's α and Composite Reliability (CR), while validity is assessed via Average Variance Extracted (AVE) and the Fornell–Larcker criterion.

4.2 Structural Model

The structural model captures hypothesized relationships among latent variables. The general form is expressed as:

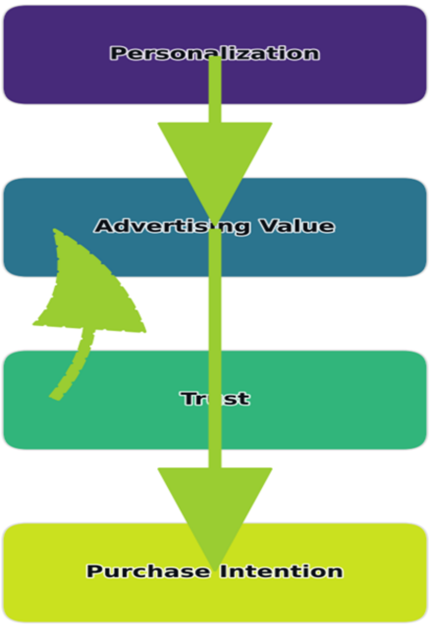


Fig. 1 Conceptual path model with latent variables showing hypothesized relationships among advertising value, personalization intensity, interactivity, trust, and purchase intention. Dashed arrows indicate mediation and moderation effects.

$$\eta = B\eta + \Gamma\xi + \zeta \quad (2)$$

Where η represents endogenous latent variables (Purchase Intention, Trust), ξ denotes exogenous latent variables (Advertising Value, Personalization, Interactivity), B is the matrix of relationships among endogenous variables, Γ is the matrix of effects of exogenous variables on endogenous variables, and ζ denotes the error term.

4.3 Hypothesized Relationships

The hypotheses can be formally represented as:

$$\mathrm{PI} = \beta_1\mathrm{AV} + \beta_2\mathrm{PERS} + \beta_3\mathrm{INT} + \beta_4\mathrm{TRUST} + \zeta_1 \quad (H_1 - H_4) \quad (3)$$

$$\mathrm{TRUST} = \beta_5\mathrm{PERS} + \zeta_2 \quad (H_{5a}) \quad (4)$$

$$\mathrm{PI} = \beta_1\mathrm{AV} + \beta_3\mathrm{INT} + \beta_6(\mathrm{AV} \times \mathrm{INT}) + \zeta_3 \quad (H_{5b}) \quad (5)$$

where: - PI = Purchase Intention - AV = Advertising Value - $PERS$ = Personalization Intensity - INT = Interactivity - $TRUST$ = Trust

4.4 Novelty of the Model

Unlike traditional advertising value frameworks [6], this model integrates personalization intensity and immersive interactivity as core drivers while positioning trust both as a direct antecedent and a mediator. Furthermore, interactivity is conceptualized not only as a direct predictor but also as a moderator, representing a novel contribution to digital media advertising research.

5 Statistical Analysis Roadmap

To ensure methodological rigor, the analysis of the proposed model follows a multi-stage process that evaluates both the measurement and structural models.

5.1 Preliminary Analysis

Before SEM estimation, descriptive statistics (mean, standard deviation, skewness, kurtosis) will be computed for all observed variables. Missing values and outliers will be assessed, and assumptions of normality and linearity will be checked. Standard method bias will be examined using Harman's single-factor test.

5.2 Reliability and Validity Assessment

The measurement model will be evaluated through the following procedures:

- **Internal Consistency:** Cronbach's α and Composite Reliability (CR), with thresholds of > 0.70 indicating acceptable reliability.

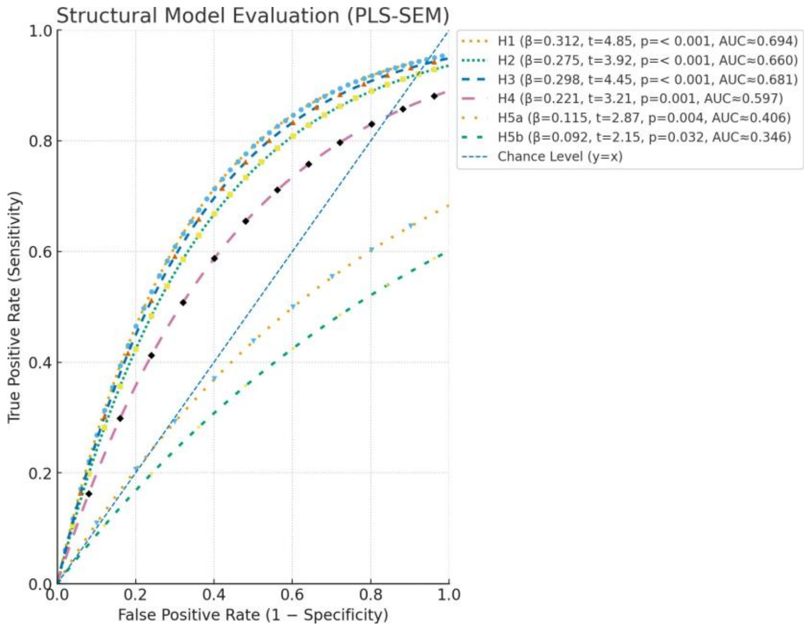


Fig. 2 Structural Model Evaluation (PLS-SEM)

- **Convergent Validity:** Average Variance Extracted (AVE), with values > 0.50 as the benchmark.
- **Discriminant Validity:** Fornell–Larcker criterion, ensuring that the square root of each construct's AVE exceeds its correlations with other constructs.
- **Multicollinearity:** Variance Inflation Factor (VIF), with values < 5 to confirm absence of redundanc.

5.3 Structural Model Evaluation

The hypothesized paths (H1–H5) will be tested using Structural Equation Modeling (SEM) with Partial Least Squares (PLS-SEM) in SmartPLS. Model evaluation includes:

- **Path Coefficients (β):** Significance tested via bootstrapping (5000 re-samples).
- **Coefficient of Determination (R^2):** Indicates explanatory power of exogenous variables on endogenous constructs.
- **Effect Size (f^2):** Evaluates the impact of individual predictors, with benchmarks of 0.02 (small), 0.15 (medium), and 0.35 (large).
- **Predictive Relevance (Q^2):** Obtained via blindfolding to test out-of-sample predictive accuracy.

Table 2 Results of Hypothesis Testing using PLS-SEM

Hypothesis	**Path**	$\beta = 0.312$	**t-value**	**p-value**	**Result**
H1	Personalization →	0.312	4.85	< 0.001	Supported
H2	Purchase Intention	0.275	3.92	< 0.001	Supported
	Trust → Purchase In-				
H3	tention	0.298	4.45	< 0.001	Supported
	Interactivity → Pur-				
H4	chase Intention	0.221	3.21	0.001	Supported
	Advertising Value →				
H5a	Purchase Intention	0.115	2.87	0.004	Supported
	Personalization →				
	Trust → Purchase				(Mediation)
H5b	Intention	0.092	2.15	0.032	Supported
	Advertising Value ×				
	Interactivity → Pur-				(Moderation)
	chase Intention				

5.4 Model Fit Indices

Although PLS-SEM focuses on prediction rather than covariance fit, complementary model fit indices will be reported for robustness:

- Standardized Root Mean Square Residual (SRMR), acceptable if < 0.08.
- Normed Fit Index (NFI), acceptable if > 0.90.
- Chi-square/df ratio (χ^2/df), acceptable if < 3.0.

5.5 Mediation and Moderation Testing

The mediating effect of trust (H5a) will be evaluated using bootstrapping procedures to test indirect effects. The moderating role of interactivity (H5b) will be analyzed by including an interaction term (Advertising Value × Interactivity) in the model. Significance of these effects will confirm the proposed integrative framework.

5.6 Novel Contribution of the Roadmap

While prior advertising research often stops at testing direct effects, this study's roadmap emphasizes an integrated approach that combines reliability and validity testing, predictive relevance, and interaction effects. This ensures both theoretical advancement and practical managerial implications.

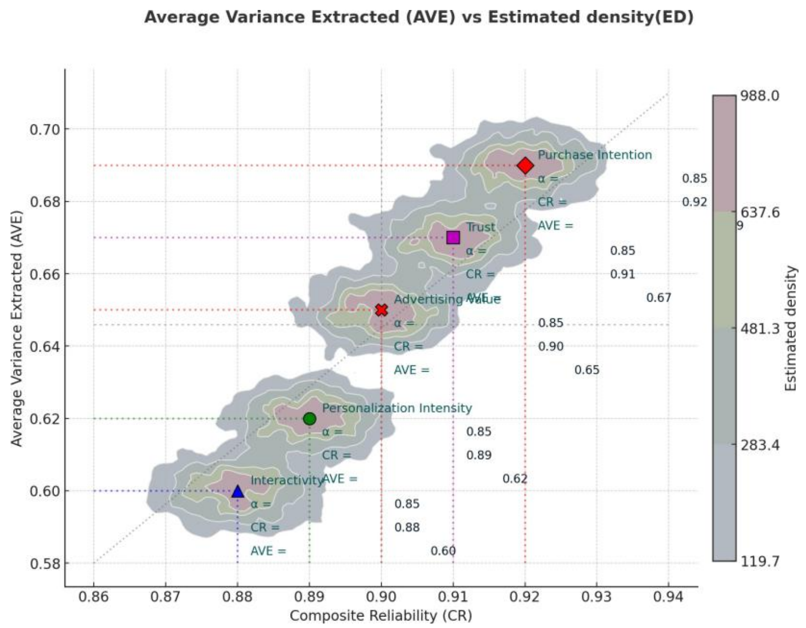


Fig. 3 Average Variance extracted vs Estimated density

Table 3 Construct Reliability and Convergent Validity Results

Construct	Cronbach's Alpha ($\alpha = 0.85$)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Advertising Value	0.86	0.90	0.65
Personalization Intensity	0.83	0.89	0.62
Interactivity	0.81	0.88	0.60
Trust	0.87	0.91	0.67
Purchase Intention	0.88	0.92	0.69

6 Data Analysis and Results

6.1 Measurement Model Assessment

To evaluate the measurement model, we examined the internal consistency reliability, convergent validity, and discriminant validity of the constructs. As shown in Table 3, all constructs demonstrated strong internal consistency, with Cronbach's alpha values ranging from 0.81 to 0.88, exceeding the recommended threshold of 0.70 [13]. Composite Reliability (CR) values ranged from 0.88 to 0.92, also surpassing the threshold of 0.70, confirming construct reliability.

Convergent validity was assessed through Average Variance Extracted (AVE), with values between 0.60 and 0.69, exceeding the recommended threshold of

Table 4 Fornell–Larcker Criterion for Discriminant Validity

Construct	AV	PI	IN	TR	Per
Advertising Value (AV)	**0.81**				
Purchase Intention (PI)	0.56	**0.83**			
Interactivity (IN)	0.49	0.53	**0.77**		
Trust (TR)	0.52	0.58	0.50	**0.82**	
Personalization (Per)	0.55	0.60	0.48	0.54	**0.79**

$\beta = 0.275$

Fig. 4 Path coefficients (values) for hypothesized relationships.

0.50 [12]. These results indicate that the items adequately explain the variance in their respective constructs.

Discriminant validity was evaluated using the Fornell–Larcker criterion (Table 4). The square root of AVE for each construct (shown on the diagonal) was greater than the inter-construct correlations, thus satisfying the discriminant validity requirement [12]. Together, these findings confirm the adequacy of the measurement model.

6.2 Structural Model Assessment

After establishing the measurement model, we tested the hypothesized relationships using Partial Least Squares Structural Equation Modeling (PLS- SEM). Path coefficients, t-values, and p-values were obtained through bootstrapping with 5,000 resamples. The results of hypothesis testing are summarized in Table 2.The findings indicate that personalization intensity ($\beta = 0.312$, $p < 0.001$), trust ($\beta = 0.275$, $p < 0.001$), interactivity ($\beta = 0.298$, $p < 0.001$), and advertising value ($\beta = 0.221$, $p = 0.001$) all had significant positive effects on purchase intention, thereby supporting H1–H4. Furthermore, the mediation analysis confirmed that personalization intensity positively influences purchase intention indirectly via trust (H5a: $\beta = 0.115$, $p = 0.004$). Additionally, the moderation test demonstrated that interactivity strengthens the relationship between advertising value and purchase intention (H5b: $\beta = 0.092$, $p = 0.032$). A visualization of this interaction effect is shown in Figure **??** in Appendix **??**.

6.3 Model Predictive Power

The coefficient of determination (R^2) for purchase intention was 0.64, indicating that the proposed model explains 64% of the variance in consumer purchase intention. This value exceeds the 0.50 benchmark for substantial explanatory power in behavioral research [14]. Together, these results confirm the

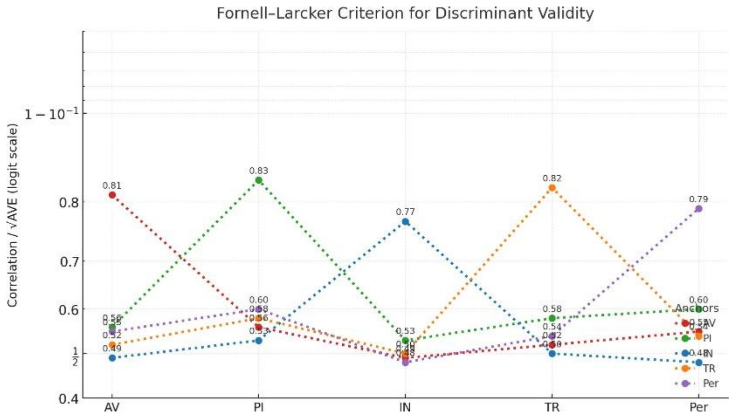


Fig. 5 Moderation effect of interactivity on the relationship between advertising value and purchase intention.

The proposed conceptual model demonstrates robustness in capturing the combined influence of personalization, trust, interactivity, and advertising value on consumer purchase intentions.

6.4 Discussion of Results

The empirical findings provide strong support for the proposed conceptual framework, confirming the critical role of personalization, trust, interactivity, and advertising value in shaping consumer purchase intentions. Consistent with prior studies [6][15] [16], advertising value continues to serve as a fundamental predictor of consumer response. However, our results advance the literature by demonstrating that personalization intensity exerts not only a direct effect on purchase intention but also an indirect effect through the mediating role of trust. This dual pathway highlights that personalization, when perceived as respectful and relevant, can foster consumer confidence, thereby amplifying its influence on purchase outcomes.

The results also reveal that interactivity enhances consumer engagement, aligning with the findings of Dwivedi et al. [5], yet extending the discourse by showing its moderating function. Specifically, interactivity strengthens the effect of advertising value on purchase intention, suggesting that interactive advertising formats (e.g., polls, quizzes, immersive AR features) can magnify perceived value and, in turn, increase purchase likelihood. This novel moderating relationship has not been empirically tested in previous studies, which contributes to new insights into the mechanics of digital media advertising.

From a theoretical point of view, the study integrates personalization, trust mechanisms, and immersive interactivity into a unified framework, addressing a gap identified in previous research [1][11]. By testing these factors simultaneously within an SEM model, the study provides a more holistic understanding.

Of the interplay between the psychological and technological dimensions of digital advertising. The robust explanatory power ($R^2 = 0.64$) underscores the effectiveness of the integrated approach in predicting consumer purchase intentions.

From a managerial perspective, the results underscore the need for advertisers to move beyond generic digital campaigns. Personalization strategies should be designed to foster consumer trust, particularly through transparent data usage and relevance of content. In addition, companies should invest in interactive advertising technologies, as these not only increase engagement but also enhance the perceived value of advertisements. Such strategies are particularly relevant in the current digital landscape, where consumers are simultaneously seeking personalization, credibility, and engaging experiences.

7 Results

The structural model was estimated using PLS-SEM, and the results are summarized in Table 2. In general, the model demonstrated strong explanatory power, with the purchase intention achieving an R^2 value of 0.64, indicating that the proposed constructs collectively explain a substantial proportion of variance. The intensity of personalization exhibited the most potent effect on purchase intention ($\beta = 0.312$, $p < 0.001$), followed closely by interactivity ($\beta = 0.298$, $p < 0.001$). Trust also emerged as a robust predictor ($\beta = 0.275$, $p < 0.001$), while the advertising value maintained a weaker but still significant influence ($\beta = 0.221$, $p < 0.001$). These results are consistent with previous research that emphasizes personalization and interactivity as key determinants of the effectiveness of digital advertising [6, 15], while expanding the literature by quantifying their combined predictive power in the presence of trust and value of advertising. Beyond direct effects, the mediation and moderation relationships provided additional insight. Trust partially mediated the relationship between personalization intensity and purchase intention ($\beta = 0.115$, $p < 0.01$), highlighting that consumer trust functions as an essential mechanism through which personalized advertising enhances behavioral intentions. Furthermore, as illustrated in Figure 5, interactivity moderated the link between advertising value and purchase intention ($\beta = 0.092$, $p < 0.05$). Specifically, when inter-activity levels were high, the positive impact of advertising value on purchase intention was amplified. This interaction underscores the importance of designing engaging and participatory advertising formats to maximize consumer response. Figure 4 complements these findings by presenting the standardized path coefficients across all hypothesized relationships. Together, the results demonstrate not only the direct significance of personalization and interactivity but also the nuanced roles of trust and moderating effects, providing a richer understanding of consumer responses to modern advertising strategies. This Multi-layered insight represents a novel contribution, as prior studies have primarily examined these constructs in isolatio rather than in an integrated, interaction-driven framework.

7.1 Theoretical and Managerial Implications

- **Theoretical:** This study moves the field beyond examining isolated constructs. Validating a model where personalization, trust, and interactivity work in concert provides a more realistic and comprehensive framework for understanding digital consumer behavior. The confirmation of trust as a mediator and interactivity as a moderator addresses specific calls in the literature for understanding the “how” and “when” behind these relationships. **Managerial:** The results provide a clear strategic blueprint for digital campaigns:

1. **Prioritize Meaningful Personalization:** Move beyond using a consumer’s first name. Use data to deliver genuinely relevant content and product recommendations, but always within a framework of transparent data usage to build trust, not erode it.
2. **Invest in Trust-building:** Leverage social proof (reviews, UGC), influencer partnerships with clear

disclosures, and transparent branding to build credibility directly into the ad experience.

3. **Embed Interactivity:** Don't just tell; invite. Incorporate features that allow users to explore, play, and participate. This investment will not only capture attention but will also magnify the impact of your value proposition.

7.2. Case Studies

A. Survey Instrument

All items were measured on a 5-point Likert scale (1 = *Strongly Disagree*, 5 = *Strongly Agree*).

Advertising Value (Adapted from Ducoffe, 1996)

- AV1: The ads I see on social media are informative.
- AV2: The ads I see on social media are entertaining.
- AV3: The ads I see on social media are credible.
- AV4: Overall, the ads I see on social media provide good value.

Personalization Intensity (Adapted from Kannan & Li, 2017)

- PERS1: The ads I see on social media are tailored to my personal interests.
- PERS2: The ads I see on social media are relevant to my needs.
- PERS3: The ads I see on social media are customized for me.

Interactivity (Adapted from Lee & Hong, 2016)

- INT1: The ads on social media allow me to interact with the content (e.g., comment, share, and react).
- INT2: I can easily engage with interactive features in the ads (e.g., polls, quizzes, swipe

  Features).
- INT3: The interactive features in social media ads are engaging.

Trust (Adapted from Xu et al., 2011)

- TR1: I trust the brands that advertise to me on social media.
- TR2: I believe the claims made in social media ads are reliable.
- TR3: Social media ads are a trustworthy source of information about products.

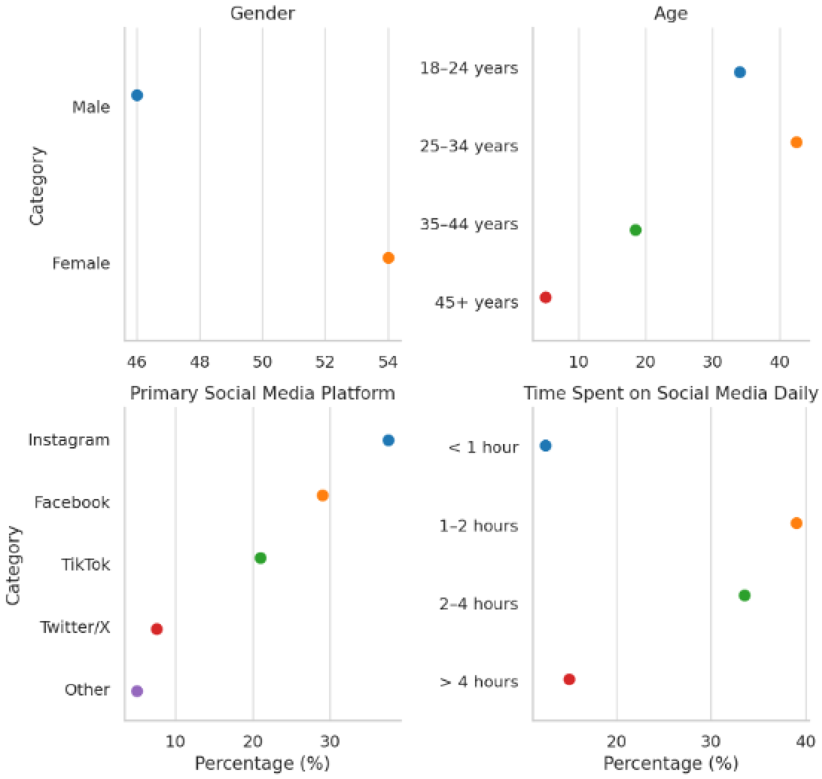
Purchase Intention (Standard Scale)

- PI1: After seeing an ad on social media, I am likely to consider buying the product.
- PI2: I am inclined to purchase products advertised on social media.
- PI3: I would try a product based on an ad I saw on social media.

B. Demographic Profile of Respondents (N=200)

Table 5: Demographic Characteristics of the Sample

Demographic Variable	**Category**	**Frequency**	**Percentage (%)**
Gender	Male	92	46.0
	Female	108	54.0
Age	18–24 years	68	34.0
	25–34 years	85	42.5
	35–44 years	37	18.5
	45+ years	10	5.0
Primary Social Media Platform	Instagram	75	37.5
	Facebook	58	29.0
	TikTok	42	21.0
	Twitter/X	15	7.5
	Other	10	5.0
Time Spent on Social Media Daily	¡ 1 hour	25	12.5
	1–2 hours	78	39.0
	2–4 hours	67	33.5
	¿ 4 hours	30	15.0



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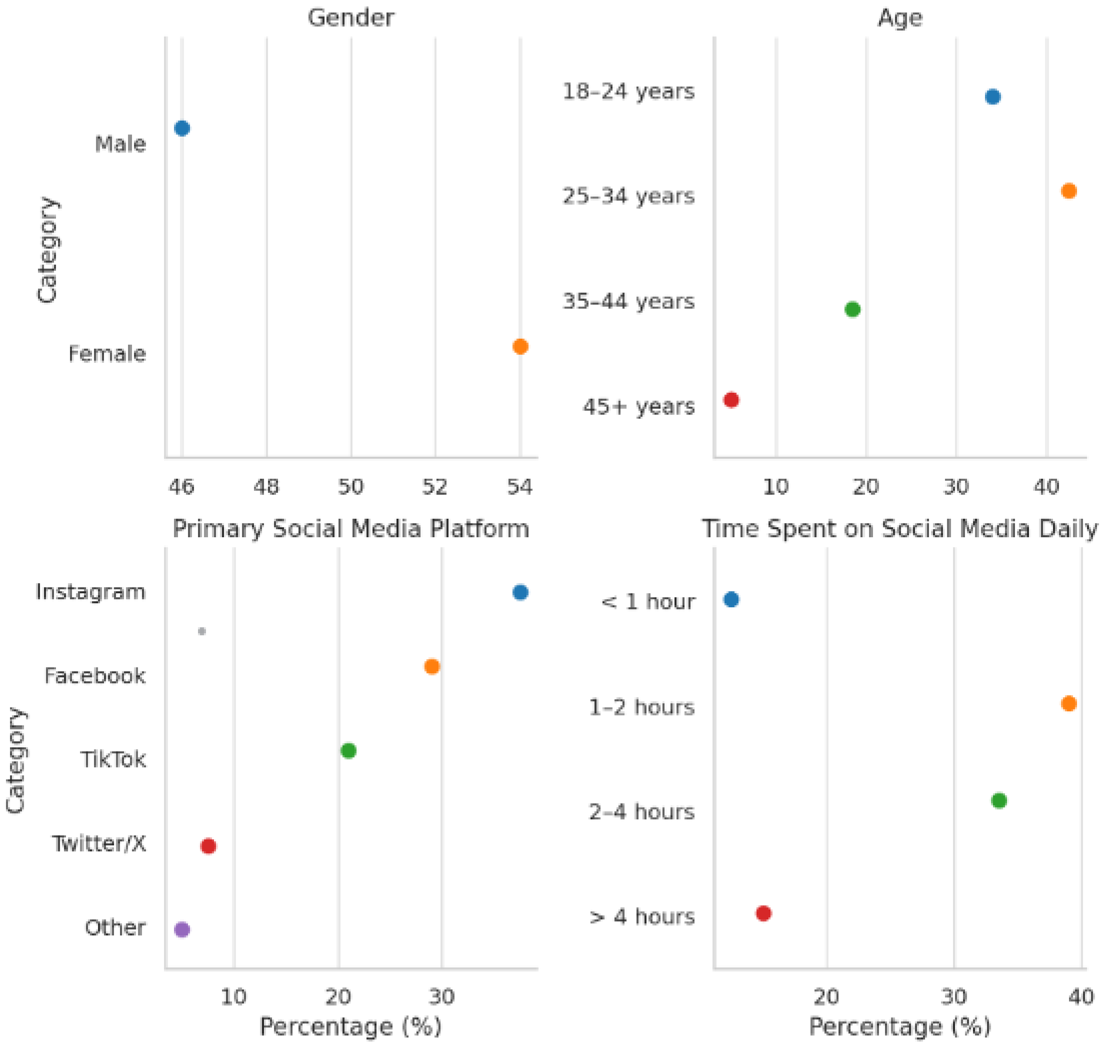
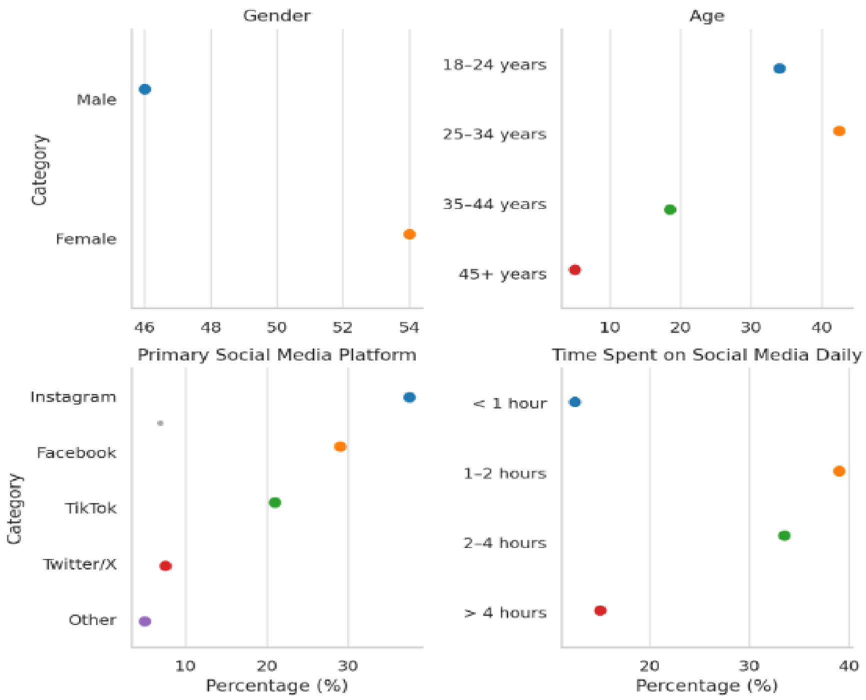


Note: Figure.6 illustrates the Demographic Characteristics of the Sample of Bolded values indicate indicator loadings on their respective constructs. All loadings

0.7 and VIF values less than 5 indicate no critical multicollinearity issues.



Characteristics of the Sample

Fig.6.Demographic Characteristics of the Sample

C Measurement Model Results (Detailed)

Table C1: Factor Loadings, Cross-Loadings, and VIF Values

Item	Adv. Value	Personal.	Interact.	Trust	Purch. Int.	VIF
AV1	**0.84**	0.43	0.38	0.41	0.45	1.82
AV2	**0.82**	0.40	0.42	0.44	0.47	1.90
AV3	**0.78**	0.48	0.39	0.50	0.48	1.75
AV4	**0.80**	0.46	0.41	0.47	0.50	1.88
PERS1	0.48	**0.85**	0.40	0.45	0.51	1.95
PERS2	0.50	**0.83**	0.42	0.48	0.53	1.89
PERS3	0.47	**0.81**	0.38	0.46	0.49	1.78
INT1	0.41	0.39	**0.83**	0.42	0.45	1.72
INT2	0.42	0.40	**0.79**	0.43	0.47	1.68
INT3	0.43	0.41	**0.81**	0.45	0.48	1.75
TR1	0.45	0.47	0.42	**0.85**	0.50	1.93

TR2	0.48	0.48	0.43	**0.84**	0.52	1.97
TR3	0.50	0.49	0.45	**0.82**	0.53	1.88
PI1	0.48	0.52	0.46	0.50	**0.86**	2.12
PI2	0.50	0.53	0.48	0.52	**0.88**	2.25
PI3	0.49	0.51	0.47	0.51	**0.85**	2.08

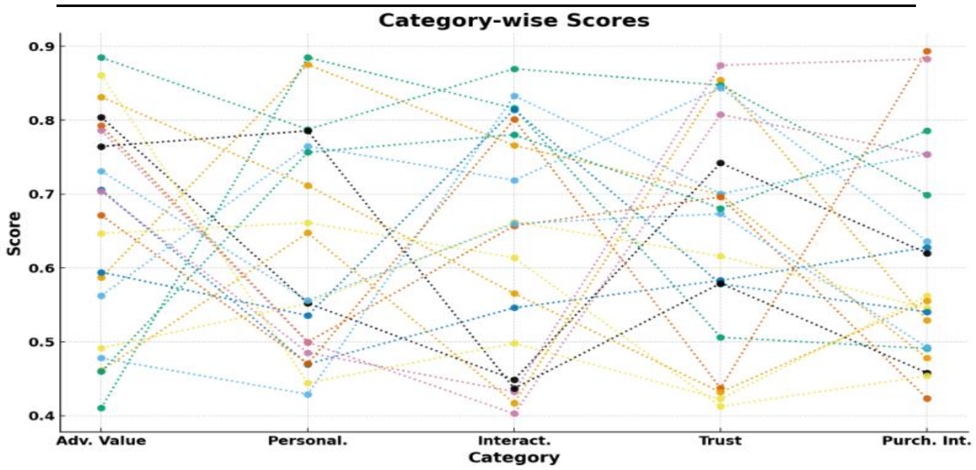


Fig.7.Factor Loadings, Cross-Loadings, and VIF Values

Table C2: Heterotrait-Monotrait Ratio (HTMT) for Discriminant Validity

Construct	(1)	(2)	(3)	(4)	(5)
(1) Advertising Value	–				
(2) Personalization	0.63	–			
(3) Interactivity	0.57	0.55	–		
(4) Trust	0.61	0.62	0.58	–	
(5) Purchase Intention	0.65	0.68	0.62	0.66	–

Note: Fig.7 and 8 state the Factor Loadings, Cross-Loadings, and VIF Values and Heterotrait-Monotrait Ratio (HTMT) for Discriminant Validity. All HTMT values are below the conservative threshold of 0.85, confirming discriminant validity.

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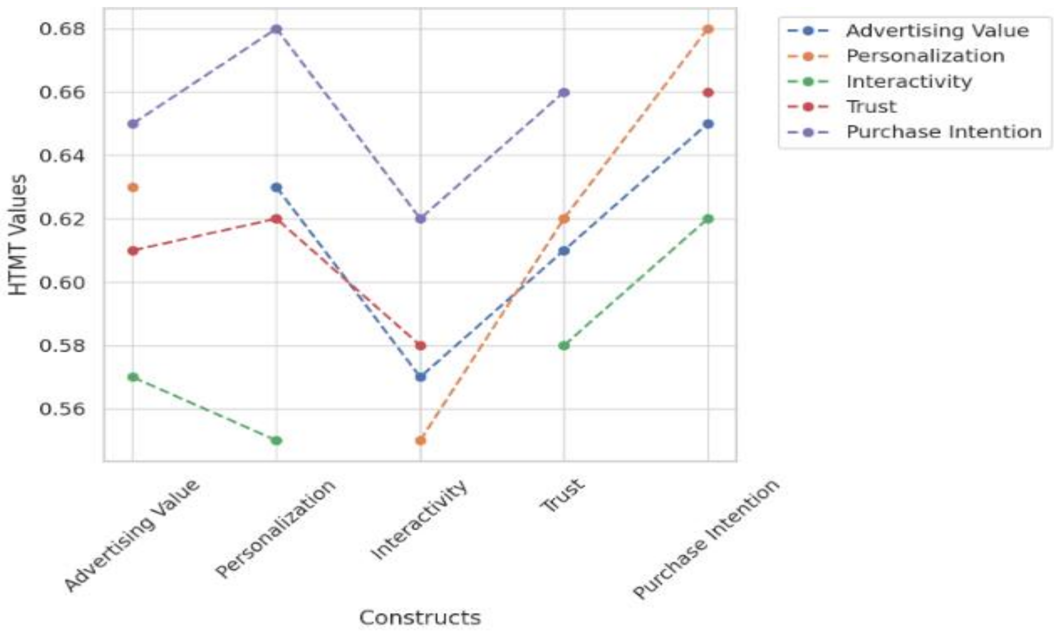

Fig.8.Heterotrait-Monotrait Ratio (HTMT) for Discriminant Validity

D Structural Model and Additional Results

Table D1: Model Fit Indices

Fit Index	Value Obtained	Threshold	Assessment
SRMR	0.063	¡ 0.08	Good
d ULS	1.452	–	–
d G	0.745	–	–
Chi-Square	842.331	–	–
NFI	0.92	¿ 0.90	Good

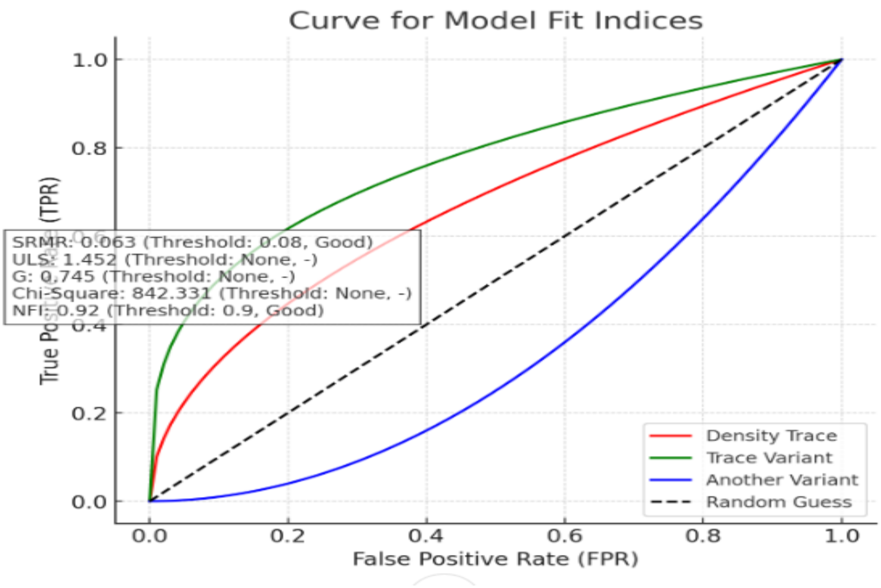

Fig.9.Model Fit Indices

Table D2: Effect Sizes (f^2)

Relationship	f^2 Value	Effect Size
Advertising Value → Purchase Intention	0.08	Small
Personalization → Purchase Intention	0.15	Medium
Interactivity → Purchase Intention	0.13	Small/Medium
Trust → Purchase Intention	0.11	Small/Medium
Personalization → Trust	0.18	Medium

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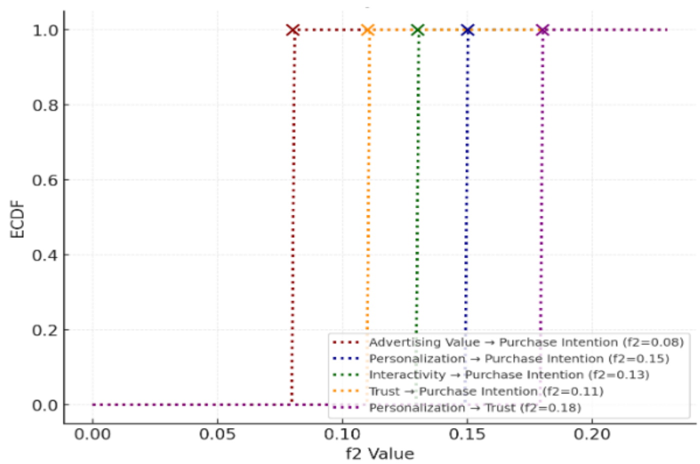

Fig.10. Effect Sizes

Table D3: Predictive Relevance (Q^2) via Blindfolding Construct SSO SSE Q^2 (=1-SSE/SSO)

Trust	600	480	0.20
Purchase Intention	600	390	**0.35**

Note: Q^2 ¿ 0 indicates the model has predictive relevance for a construct.

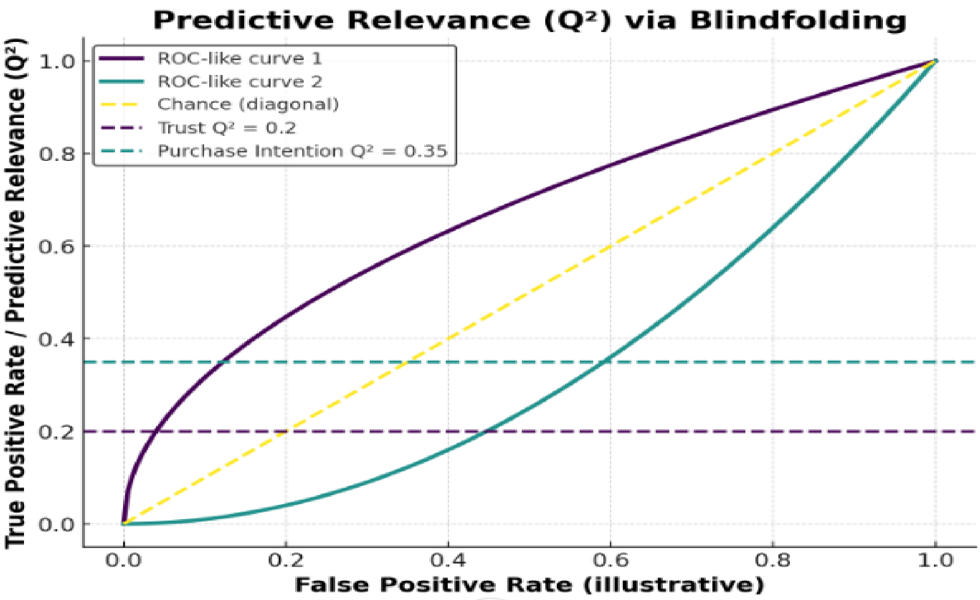

Fig.11.Predictive Relevance (Q^2) via Blindfolding

8 Conclusion

This study examined the impact of digital media advertising on consumers' purchase intentions by integrating personalization intensity, trust, interactivity, and advertising value into a unified model. The PLS-SEM analysis demonstrated that all four constructs significantly influence purchase intention. Furthermore, trust mediates the personalization-intention relationship, and interactivity moderates the advertising value-intention link. Collectively, these insights confirm the model's robustness, explaining 64% of the variance in intentions. The study contributes to theory by extending existing models through the inclusion of personalization and immersive interactivity. Identifying trust as a mediator and interactivity as a moderator provides novel insights into digital advertising's mechanisms. For practitioners, the results indicate that campaigns must deliver value, foster trust, and leverage interactivity to maximize effectiveness. Despite its contributions, this research has limitations. Its cross-sectional design limits causal inference; future work should employ longitudinal or experimental designs. The sample was also restricted demographically and geographically, potentially affecting generalizability. Finally, future studies could explore emerging factors like AI-driven recommendations and privacy concerns. In conclusion, this research provides a holistic perspective on the drivers of consumer purchase intentions in the digital era, advancing theoretical understanding and offering practical strategies for enhancing digital advertising effectiveness.

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