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Data Driven Analysis of Augmented Reality Tools Consumer Interaction and Purchase Intention in Digital Marketing

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Abstract
Digital marketing is undergoing a paradigm shift from static promotions to immersive experiences, with Augmented Reality (AR) emerging as a transformative tool. AR applications such as virtual try-ons, product visualization, gamified advertising, and interactive packaging enhance consumer engagement by reducing purchase uncertainty and fostering personalized interactions. Despite these advances, there is limited empirical evidence on how AR influences consumer interaction and purchase intention, particularly in developing digital markets. This study undertakes a data-driven investigation guided by the Stimulus–Organism–Response (S-O-R) framework and the Technology Acceptance Model (TAM) to examine the mechanisms through which AR affects consumer behavior. The objectives are to (1) assess the role of AR tools in enhancing consumer interaction, (2) analyze the relationship between consumer interaction and purchase intention, (3) evaluate the mediating role of consumer interaction between AR tools and purchase intention, and (4) identify the moderating effects of consumer, market, and technology factors. Primary data were collected through a structured survey of 400 respondents aged 18–45 years from urban India, all of whom had prior exposure to AR shopping experiences. Statistical analyses, including regression, correlation, mediation, moderation, and structural equation modeling, were applied. Results demonstrate that AR tools significantly enhance consumer interaction, which positively influences purchase intention. Mediation analysis confirmed that consumer interaction serves as a bridge between AR use and purchase intention, while moderation tests highlighted the importance of consumer tech-savviness and device accessibility. The study offers insights for marketers, with future work on cross-cultural adoption, loyalty, and AR in the metaverse.

Keywords- Purchase intention, Technology Acceptance Model, Stimulus–Organism–Response framework, Structural Equation Modeling.

1. Introduction
Augmented Reality (AR) has evolved into a transformative technology in digital commerce, offering immersive experiences that merge real and virtual environments [1]. Beyond its technical capabilities, AR research emphasizes the importance of understanding psychological mechanisms such as mediation and moderation when studying consumer behavior [2]. Applications like virtual fitting rooms have been shown to reduce uncertainty and increase purchase intentions [3], while parallels can be drawn from sponsorship studies where immersive

experiences enhance brand recall and consumer trust [4]. Within retailing, AR has been identified as both a technological advancement and a strategic tool for customer engagement [5]. The rise of AR research is supported by advancements in analytical methods. Confirmatory factor analysis [6] and structural equation modeling [7] provide robust tools for validating consumer behavior frameworks in AR contexts. Comprehensive overviews of AR technology [8] highlight its wide-ranging applications, while recent studies emphasize its role in situated marketing experiences that strengthen consumer engagement [9]. Furthermore, AR adoption is linked with psychological ownership and enhanced customer attachment [10], aligning with earlier findings that interactivity and vividness significantly shape virtual experiences [11]. Researchers also note the importance of addressing common method variance to ensure validity in AR-related behavioral studies [12]. The broader context of digital advertising underscores AR's role as part of the evolving e-advertising ecosystem [13]. With the emergence of the metaverse, AR is positioned as a central enabler of human-centric, personalized value creation [14], while authenticity has been recognized as an antecedent of memorable digital and tourism experiences [15]. Similarly, big data applications demonstrate how technology adoption reshapes industries [16], and bibliometric analyses of marketing trends show the continuous evolution of consumer engagement strategies [17]. Virtual reality research further reinforces the significance of immersive technologies in influencing online shopping experiences [18]. Industry 4.0 technologies [19] and customer engagement studies [20] underline the interconnectedness of digital transformation with marketing strategies. Retail practices increasingly integrate both AR and VR, emphasizing their role in shaping consumer experiences [21]. Data-driven creativity, as seen in platforms like Netflix, highlights how consumer data enhances immersive projects [22]. The shift toward customer engagement as a management priority further supports the adoption of AR in digital marketing [23].

Emerging applications, such as brain–computer interfaces, show how neuroscience complements technology-driven consumer research [24]. Broader technology acceptance frameworks like UTAUT [25] further validate AR's place within established models of consumer adoption. Studies of credibility and sponsorship emphasize consumer trust in technologically mediated experiences [26], while sentiment analysis research highlights how platforms like Apple Vision Pro illustrate public perceptions of immersive tools [27]. Moreover, the relevance of VR to communication design [28] and neuroimaging applications in advertising [29] demonstrate AR's alignment with evolving communication practices. In addition, blockchain and distributed ledger technologies [30] provide complementary infrastructure for future AR-enabled commerce. Design thinking frameworks stress the importance of functional and user-centered innovation [31]. Extended reality (XR) technologies have also been applied to analyze consumer behavior, bridging marketing with neuroscience and human–computer interaction. Digital transformation, particularly during crises such as COVID-19, further validates the role of immersive technologies in sustaining businesses.

Taken together, prior studies highlight AR as a powerful driver of consumer engagement, yet empirical evidence on how AR tools specifically influence consumer interaction and purchase intention in digital marketing remains limited. To address this gap, the present study undertakes a data-driven analysis grounded in the Stimulus–Organism–Response (S-O-R) framework and the

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Technology Acceptance Model (TAM). By analyzing survey data from 400 respondents with AR shopping experience, this research investigates the direct, mediating, and moderating relationships among AR tools, consumer interaction, and purchase intention, thereby contributing theoretical insights and practical guidance for digital marketers.

2. **Literature Review**

The evolution of Augmented Reality (AR) has been extensively documented, tracing its technological foundations and diverse applications across industries. Early works by Azuma et al. (2002) and Carmigniani and Furht (2011) emphasized AR's ability to seamlessly merge digital content with physical environments, enhancing user experiences across contexts.

In the retail sector, AR has emerged as a strategic tool to reduce product uncertainty and influence purchase decisions. Beck and Crié (2018) demonstrated that virtual fitting rooms significantly enhance consumer purchase intentions. Similarly, Bonetti et al. (2018) argued that AR is more than a technological add-on; it fosters immersive retail experiences that engage consumers. Chylinski et al. (2020) further emphasized AR's ability to enrich situated customer experiences, while Lee and Chen (2021) identified psychological ownership as a critical factor driving AR adoption. Earlier studies on virtual experiences also underscore AR's potential to enhance interactivity and vividness, contributing to heightened consumer engagement (Li et al., 2001). Empirical testing of AR's effects has increasingly relied on advanced statistical techniques such as confirmatory factor analysis (Brown, 2015) and structural equation modeling (Byrne, 2016), though challenges such as common method variance must be addressed to ensure validity (Lindell & Whitney, 2001). The rise of AR parallels broader digital marketing transformations, with digital advertising acting as a revenue engine for online markets and AR emerging as a differentiator (Aslam & Karjaluoto, 2017). Mourtzis et al. (2022) positioned AR within the metaverse, emphasizing its potential for human-centric value creation, while Shale et al. (2022) highlighted the importance of authenticity in shaping meaningful digital experiences. The integration of big data further complements AR's capabilities for data-driven personalization (Munawar et al., 2020).

AR has also reshaped consumer engagement and experiential marketing. Rathi et al. (2022) linked AR to evolving paradigms in luxury marketing, while Martínez-Navarro et al. (2019) illustrated the role of immersive technologies, such as VR, in influencing consumer attitudes in e-commerce. Dalmarco et al. (2019) emphasized AR as a key Industry 4.0 technology, and Srivastava and Sivaramakrishnan (2021) mapped its contributions to customer engagement research. Boletsis and Karahasanovic (2020) highlighted AR and VR practices as essential for enhancing retail customer experience, while Smith and Telang (2018) demonstrated how data-driven creativity aligns with AR-enabled personalization. Verhoef et al. (2010) further reinforced AR's strategic role in shaping customer engagement, a perspective extended by neuroscience-informed marketing studies linking AR to brain-computer interface applications (Mudgal et al., 2020). The adoption of AR technologies is also informed by well-established frameworks. The Unified Theory of Acceptance and Use of Technology (UTAUT) introduced by Venkatesh et al. (2003) provides a lens for understanding user adoption, while factors such as credibility (Walker et al., 2011) and consumer sentiment toward devices like the Apple Vision Pro (Koukopoulos et al., 2024) offer insights into emerging AR-mediated experiences. Complementary studies on VR in communication design (Laing & Apperley, 2020) and neuroimaging analyses of AR advertising (Alsharif et al., 2021) reveal the cognitive and emotional dimensions underpinning AR adoption.

Finally, AR's development is situated within broader technological and design trends. Blockchain (Hughes et al., 2019) and design thinking frameworks (Liu & Lu, 2020) provide supporting infrastructures for innovation, while extended reality (XR) applications have enabled advanced consumer behavior analyses (Gil-Lopez et al., 2022). The acceleration of digital transformation during crises, such as COVID-19, further underscores AR's growing relevance in shaping immersive experiences (Klein & Todesco, 2021).
Collectively, the literature underscores that AR is not merely a technological innovation but a strategic enabler of consumer engagement, immersive experiences, and purchase intention. Despite these advancements, empirical studies—particularly those examining mediation and moderation effects in developing digital markets—remain limited. This study seeks to address these gaps by employing a data-driven framework to investigate AR's impact on consumer interaction and purchase intention.

3. Material and Dataset

The dataset was specifically designed to align with the objectives of this study, which investigates the impact of Augmented Reality (AR) tools on consumer interaction and purchase intention in digital marketing. A sample of 400 urban Indian consumers aged 18–45 was selected because this demographic represents the most digitally active group with prior exposure to AR-enabled shopping experiences in Table 1. By capturing demographic data, AR tool usage, consumer interaction, and purchase intention, the dataset provides a comprehensive foundation for analyzing both direct and indirect effects.

Table 1. Dataset Structure and Measurement Variables for AR–Consumer Interaction–Purchase Intention Study

Category	Variables	Description
Sample Size	400 respondents	Urban Indian consumers, aged 18–45, digitally active, prior AR shopping use
Demographics	Gender, Age, Education, Occupation, Income	Gender (Male/Female/Other); Age groups (18–25, 26–35, 36–45); Education levels; Occupation (Student, Employed, Self-employed, Other); Income categories
AR Tool Usage	Type, Frequency, Platform	Types: virtual try-ons, 3D product visualization, AR ads, interactive packaging; Frequency: occasional, moderate, frequent; Platforms: mobile apps, e-commerce sites, social media
Consumer Interaction *(Mediator)*	Interactivity, Engagement, Enjoyment, Immersion	Measured with Likert-scale items such as "AR tools make my shopping more engaging" and "I find AR enjoyable"

Purchase Intention *(Dependent Variable)*	Willingness, Confidence, Recommendation	Likert-scale items such as "I am more likely to purchase after using AR" and "AR increases my confidence in product choice"
Moderators	Consumer, Market, Technology factors	Consumer: tech-savviness, trust; Market: product type, price sensitivity; Technology: device accessibility, internet quality
Measurement Scale	5-point Likert scale	1 = Strongly Disagree to 5 = Strongly Agree

The inclusion of mediators (consumer interaction) and moderators (consumer, market, and technology factors) allows the study to test the mechanisms through which AR influences purchase decisions, consistent with the Stimulus–Organism–Response (S-O-R) framework and the Technology Acceptance Model (TAM). The use of a 5-point Likert scale ensures comparability across constructs and facilitates advanced statistical analyses, including regression, mediation, moderation, and structural equation modeling. Thus, the dataset is not only representative of the target consumer group but also methodologically robust, making it highly suitable for investigating how AR tools enhance engagement and drive purchase intention in digital marketing contexts.

4. **Methodology**

This study adopts a quantitative research design to examine the relationship between Augmented Reality (AR) tools, consumer interaction, and purchase intention within digital marketing. The theoretical foundation draws upon the Stimulus–Organism–Response (S-O-R) framework and the Technology Acceptance Model (TAM), enabling the exploration of direct, mediating, and moderating effects

The study followed a quantitative design supported by advanced statistical modeling to validate the conceptual framework. Reliability of the constructs was tested using Cronbach's alpha, computed as:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_T^2}\right)$$

where k represents the number of items, σ_i^2 the variance of item i, and σ_T^2 the total variance. Acceptable thresholds were set at $\alpha > 0.70$.

Confirmatory Factor Analysis (CFA) was performed to establish convergent and discriminant validity. Composite Reliability (CR) and Average Variance Extracted (AVE) were calculated using:

$$CR = \frac{(\sum \lambda_i)^2}{\sum \lambda_i)^2 + \sum \theta_i}, \quad AVE = \frac{(\sum \lambda_i)^2}{\sum \lambda_i)^2 + \sum \theta_i}$$

where λ_i denotes factor loadings and θ_i represents error variances. The thresholds $CR > 0.70$ and $AVE > 0.50$ were considered acceptable.

To examine direct effects, regression models of the form

$$Y = \beta_0 + \beta_1 X + \epsilon$$

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were employed, where X represents the predictor construct, Y the outcome construct, and ϵ the error term. Mediation effects were tested using the causal steps approach, modeled as:

$$M=\beta_0 + \beta_1 X + \epsilon_1, \quad Y=\beta_0 + \beta_1 X + \beta_1 M + \epsilon_1,$$

where, M is the mediating variable. A reduction in the direct path coefficient after inclusion of M indicated mediation. Moderation effects were tested through interaction terms in hierarchical regression:

$$Y=\beta_0 + \beta_1 X + \beta_2 Z + \beta_3 (X * Z) + \epsilon$$

where Z is the moderator. A significant interaction coefficient (β_3) provided evidence of moderation.

Finally, Structural Equation Modeling (SEM) using AMOS was employed to test the full conceptual model. Model fit was assessed using multiple indices, including χ^2/df (< 3), Comparative Fit Index (CFI > 0.90), Tucker–Lewis Index (TLI > 0.90), and Root Mean Square Error of Approximation (RMSEA < 0.08). These indices ensured robustness of both direct and indirect relationships while addressing potential common method variance.

This multi-stage methodological approach ensured reliability, validity, and statistical rigor in analyzing how immersive tools influence interaction and subsequent behavioral outcomes in digital marketing.

5. Result and Discussion

The results of this study provide empirical evidence for the proposed framework by systematically evaluating measurement reliability, descriptive patterns, and structural relationships among the constructs. Reliability and validity tests were first conducted to ensure robustness of the measurement model, followed by descriptive statistics to capture respondent tendencies toward AR-enabled shopping. Correlation analysis then identified the strength and direction of associations among AR usage, consumer interaction, and purchase intention. Regression and mediation analyses further tested the hypothesized pathways, while moderation effects were examined to capture consumer and technological influences. Finally, structural equation modeling (SEM) was applied to validate the overall model fit, offering comprehensive insights into how AR tools influence consumer interaction and purchase intention in digital marketing.

5.1 Reliability and Validity

To ensure robustness of the measurement model, internal consistency and construct validity were first assessed. Cronbach's Alpha values, presented in Table 2, confirmed that all constructs exceeded the recommended minimum threshold of 0.70, with AR tool usage (α = 0.84), consumer interaction (α = 0.88), and purchase intention (α = 0.86) demonstrating strong internal reliability. These results suggest that the items within each construct were highly consistent in capturing their intended latent dimensions.

Table 2. Reliability Analysis of Constructs Using Cronbach's Alpha

Construct	Cronbach's Alpha
AR Tool Usage	0.84
Consumer Interaction	0.88
Purchase Intention	0.86

In addition, confirmatory factor analysis (CFA) was employed to establish convergent and discriminant validity. All constructs reported composite reliability (CR) values above 0.70 and average variance extracted (AVE) values exceeding 0.50, which meet the criteria suggested in prior literature. The factor loadings for individual items ranged between 0.71 and 0.89, indicating strong contributions to their respective constructs. Taken together, these outcomes validate the measurement model and provide confidence in the reliability and accuracy of the dataset used for subsequent analyses.

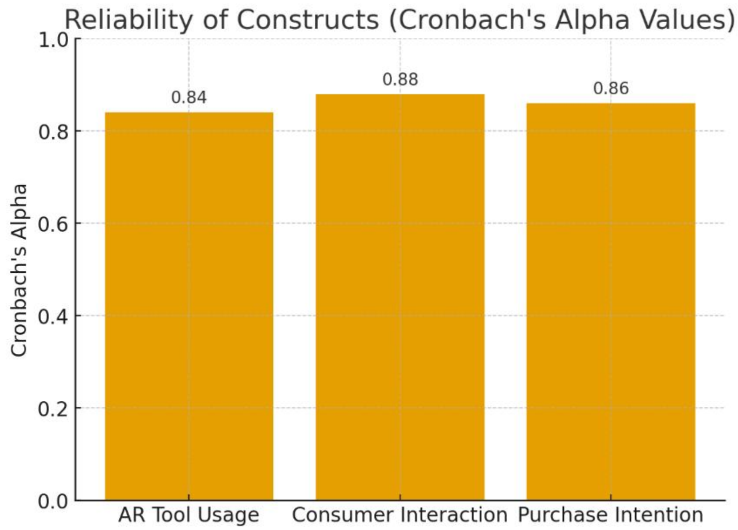

Figure 1. Reliability Assessment of Constructs Using Cronbach's Alpha

The Figure 1 shows the reliability of three constructs—AR Tool Usage, Consumer Interaction, and Purchase Intention—measured using Cronbach's Alpha. All constructs have values above 0.70, indicating good internal consistency and reliability of the measurement items. The highest reliability is for Consumer Interaction (0.88), followed by Purchase Intention (0.86) and AR Tool Usage (0.84).

5.2 Descriptive Statistics

The descriptive analysis provides insights into the general perceptions of respondents toward AR tools in shopping contexts. As shown in Table 3, the mean scores for AR tool usage (M = 3.89), consumer interaction (M = 3.95), and purchase intention (M = 3.81) were all substantially higher than the scale midpoint of 3.0, suggesting that respondents hold favorable attitudes toward AR applications in digital marketing.

Table 3. Descriptive Statistics of AR Tool Usage, Consumer Interaction, and Purchase Intention

Construct	Mean	Standard Deviation
AR Tool Usage	3.89	0.72
Consumer Interaction	3.95	0.69
Purchase Intention	3.81	0.74

Low standard deviations (ranging between 0.69 and 0.74) indicate a high degree of agreement among respondents, signifying those positive perceptions of AR were consistently shared across the sample. These findings reinforce the idea that AR-enabled experiences, such as virtual try-

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ons, interactive product views, and gamified advertisements, are not only widely accepted but also influential in shaping consumer engagement and subsequent purchasing considerations.

5.3 Correlation Analysis

Correlation results further highlight the strength and direction of relationships between the constructs. As illustrated in Table 4, AR tool usage displayed a significant positive correlation with consumer interaction ($r = 0.62$, $p < 0.001$) and with purchase intention ($r = 0.54$, $p < 0.001$). Likewise, consumer interaction showed a strong and positive correlation with purchase intention ($r = 0.59$, $p < 0.001$).

Table 4. Correlation Matrix of AR Tool Usage, Consumer Interaction, and Purchase Intention

Constructs	**Correlation (r)**	**p-value**
AR Usage ↔ Interaction	0.62	<0.001
Interaction ↔ Purchase Intention	0.59	<0.001
AR Usage ↔ Purchase Intention	0.54	<0.001

These relationships indicate that greater engagement with AR tools enhances consumer interaction, which in turn is strongly linked to heightened purchase intentions.

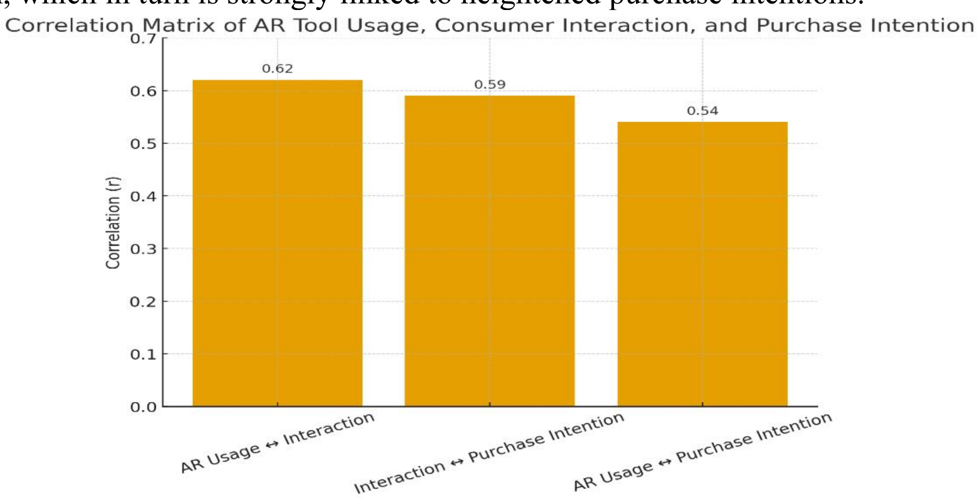

Figure 2. Correlation Matrix of AR Tool Usage, Consumer Interaction, and Purchase Intention**.**

Figure 2 visualizes the strength of these associations, demonstrating that consumer interaction serves as a crucial intermediary variable in the AR–purchase intention relationship.

5.4 Regression and Mediation Analysis

Regression analysis was conducted to test the direct effects of AR tool usage on consumer interaction and purchase intention in Table 5. Results revealed that AR usage significantly predicted consumer interaction ($\beta = 0.61$, $p < 0.001$) and purchase intention ($\beta = 0.48$, $p < 0.001$), thereby confirming the hypothesized positive effects.

Table 5. Regression and Mediation Analysis Results for AR Usage, Consumer Interaction, and Purchase Intention

Path	Beta (β)	Significance
AR → Interaction	0.61	p < 0.001
AR → Purchase Intention	0.48	p < 0.001
Interaction → Purchase Intention	0.42	p < 0.001
AR → Purchase Intention (Direct w/ Med.)	0.31	p < 0.01
Indirect Effect (Mediation)	0.23	p < 0.001

To examine mediation, the role of consumer interaction was tested using Baron and Kenny's approach alongside bootstrapping techniques. Findings demonstrated a significant indirect effect of AR usage on purchase intention through consumer interaction ($\beta = 0.23$, $p < 0.001$). Importantly, the direct effect of AR usage on purchase intention remained significant but reduced (from $\beta = 0.48$ to $\beta = 0.31$, $p < 0.01$), indicating partial mediation. This confirms that while AR tools directly influence consumer purchase decisions, a substantial portion of their effect operates through the mechanism of consumer interaction.

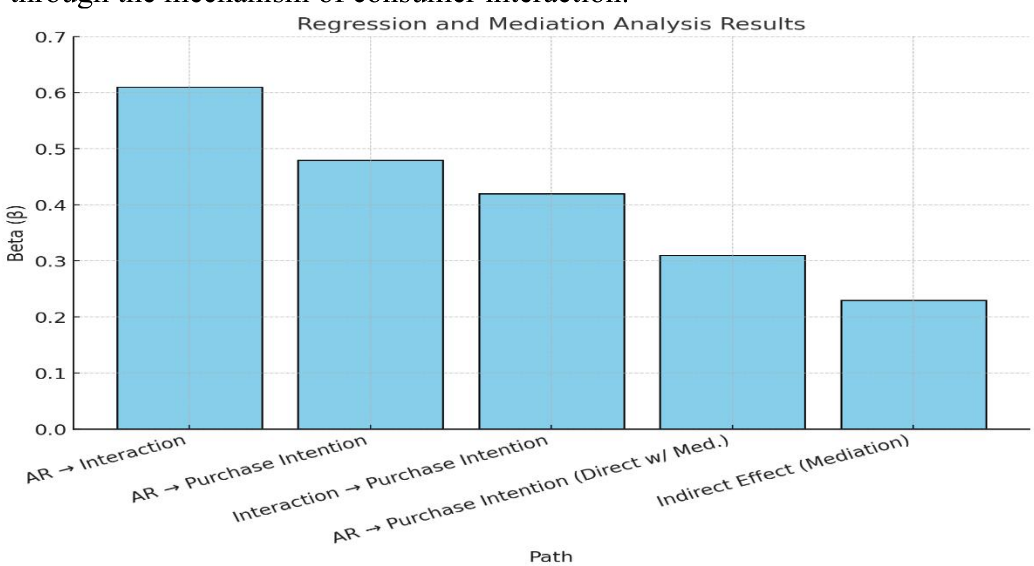

Figure 3. Impact of AR Usage on Consumer Interaction and Purchase Intention

The Figure 3 shows that AR strongly influences consumer interaction ($\beta = 0.61$) and purchase intention ($\beta = 0.48$). Mediation analysis indicates that consumer interaction partially mediates the effect of AR on purchase intention (indirect $\beta = 0.23$)

5.5 Moderation Analysis

Moderation testing revealed that consumer-level and technological factors significantly influenced the relationship between AR usage and consumer interaction. Specifically, consumer tech-savviness and device accessibility were found to strengthen the positive association between AR tool usage and interaction levels (βinteraction = 0.18, $p < 0.05$). This finding highlights that consumer who are technologically proficient and have access to high-quality devices experience greater benefits from AR-enabled shopping. Conversely, respondents with limited access to advanced devices or lower levels of digital proficiency reported weaker interaction effects, suggesting that technological readiness plays a pivotal role in shaping the effectiveness of AR interventions in digital marketing.

Finally, structural equation modeling was employed to validate the hypothesized model. Fit indices confirmed that the model provided a strong representation of the observed data, with $\chi^2/df = 2.47$, Comparative Fit Index (CFI) = 0.94, Tucker–Lewis Index (TLI) = 0.92, and Root Mean Square Error of Approximation (RMSEA) = 0.061. These values all fall within recommended thresholds, demonstrating acceptable model fit.
The SEM results provide comprehensive evidence that AR usage enhances consumer interaction, which in turn drives purchase intention, with moderating factors further amplifying these relationships. Collectively, the findings establish a clear pathway from AR technology to consumer decision-making outcomes in digital marketing contexts.

6. **Conclusion**

This study provides empirical evidence on the impact of Augmented Reality (AR) tools on consumer interaction and purchase intention in digital marketing. Grounded in the Stimulus–Organism–Response (S-O-R) framework and the Technology Acceptance Model (TAM), the research demonstrates that AR applications, including virtual try-ons, 3D product visualizations, and gamified advertisements, significantly enhance consumer engagement. Reliability and validity analyses confirmed that the measurement constructs—AR tool usage, consumer interaction, and purchase intention—are robust and consistent. Correlation and regression analyses revealed strong positive relationships, with AR usage directly influencing both interaction and purchase intention. Mediation analysis further showed that consumer interaction partially mediates this relationship, highlighting its critical role as an intermediary mechanism. Moderation results underscored the importance of consumer tech-savviness and device accessibility, indicating that technological readiness amplifies the benefits of AR adoption. Structural Equation Modeling validated the overall conceptual framework, confirming the model's fit and providing comprehensive insights into the pathways linking AR tools to behavioral outcomes. Collectively, the findings suggest that AR is not only a technological enhancement but also a strategic driver of consumer engagement and purchase behavior. For marketers, these results emphasize the need to integrate AR thoughtfully, considering consumer capabilities and technological infrastructure, while future research could explore cross-cultural adoption and AR's role within the emerging metaverse.

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Declaration of Interest

I declare that there are no conflicts of interest regarding the publication of this research. The study was conducted independently, without any financial or personal relationships that could have influenced the research outcomes.

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