

AUGMENTED REALITY MARKETING AND ITS IMPACT ON CONSUMER EXPERIENCE IN ONLINE RETAIL

Probo Shadewo^{1*}, Larisa Pradisti²

¹ Master of Management Study Program, University of Jenderal Soedirman, Indonesia

² Department of Management, University of Jenderal Soedirman, Indonesia

*Email corresponding author: probo.shadewo.d@unsoed.ac.id

Abstract

This study aims to examine the influence of Perceived Interactivity, Perceived Enjoyment, and Perceived Informativeness on Consumer Experience, as well as the impact of Consumer Experience on Behavioral Intentions. The research is motivated by the critical role of consumer experience in shaping repeat purchase behavior and brand loyalty. A quantitative research approach was adopted, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data. The findings reveal that all three independent variables—Perceived Interactivity, Perceived Enjoyment, and Perceived Informativeness—have a significant positive effect on Consumer Experience. Furthermore, Consumer Experience has a highly significant and strong influence on Behavioral Intentions. These results underscore the importance of designing digital platforms or marketing communication strategies that enhance interactive, enjoyable, and informative experiences for consumers. In turn, positive consumer experiences are likely to increase customer engagement, satisfaction, and their intention to engage in future behavioral actions such as purchases or brand advocacy. This research contributes to a deeper understanding of digital consumer behavior and offers practical implications for marketers in optimizing user-centered digital touchpoints.

Keywords: Consumer Experience, Perceived Interactivity, Behavioral Intentions, Digital Marketing, Customer Engagement.

INTRODUCTION

The rapid evolution of digital technologies has revolutionized how consumers interact with products and services, particularly in online retail environments (Tam et al., 2019). Among these technological advancements, Augmented Reality (AR) has emerged as a transformative marketing tool that bridges the physical and digital shopping experience. AR marketing enables consumers to virtually try on products, visualize them in real-world contexts, and engage with immersive content, thereby enhancing consumer engagement and reducing perceived risks associated with online shopping (Abdelkader, 2023).

As consumers increasingly seek personalized and interactive shopping experiences, AR offers a unique value proposition that traditional digital interfaces cannot replicate. Studies have shown that immersive AR features contribute to more enjoyable, informative, and confidence-enhancing shopping journeys (Capatina et al., 2020). These experiences can positively shape consumer perceptions, attitudes, and behaviors, leading to higher satisfaction and loyalty.

Despite its potential, the effectiveness of AR marketing in online retail varies depending on how it influences key psychological aspects of the consumer experience (Aziz, 2024). These include perceived usefulness, enjoyment, and engagement, which are critical in shaping purchase intention and satisfaction. Yet, empirical findings on the direct and indirect effects of AR on consumer behavior remain fragmented and context-dependent (Affandi et al., 2024).

Moreover, the dynamic and competitive nature of online retail calls for strategic differentiation through experiential technologies (Akhtar et al., 2023). As consumers face information overload and choice paralysis, AR can serve as a decision-support tool by delivering relevant, contextualized, and sensory-rich content. However, the mechanisms through which AR enhances consumer experience are not fully understood, particularly in online-only settings without physical product interaction (Ahmad et al., 2024).

This study seeks to examine how AR marketing impacts consumer experience in the context of online retail. Drawing on the Technology Acceptance Model (TAM) and experiential marketing theories, this research investigates the roles of perceived interactivity, enjoyment, and informativeness in shaping consumer satisfaction and behavioral intentions. The study further explores how these constructs mediate the relationship between AR use and overall consumer experience (Maines, 1989).

By addressing these gaps, this research contributes both theoretically and practically. Theoretically, it enriches the literature on digital consumer behavior and technology-enabled marketing. Practically, it offers insights for e-commerce businesses aiming to adopt AR strategically to enhance customer engagement, satisfaction, and conversion in virtual environments.

LITERATURE REVIEW AND HYPOTHESIS FORMULATION

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), posits that two primary beliefs—perceived usefulness and perceived ease of use—predict user acceptance of technology. In the context of AR marketing, perceived usefulness reflects consumers' belief that AR enhances their shopping effectiveness, while ease of use represents the effortlessness of engaging with AR interfaces. These beliefs influence consumers' attitudes toward using AR and their overall shopping experience (Maines, 1989).

AR's effectiveness lies in its ability to deliver contextually relevant and user-friendly interactions. When consumers perceive AR as intuitive and beneficial, they are more likely to form positive attitudes and emotional responses, thereby improving their overall experience. Therefore, TAM serves as a foundational framework for examining the psychological drivers behind AR adoption and its experiential outcomes in online retail (Iyer & Bright, 2024).

Augmented Reality Marketing

AR marketing refers to the use of AR technology to overlay digital information on the physical environment or simulate product interaction virtually. In online retail, AR applications include virtual try-on tools, 3D product visualizations, and interactive product demos. These features provide a sense of realism and presence that conventional images or videos cannot offer (Antonizzi & Smuts, 2020).

Prior studies have demonstrated that AR tools can increase consumer engagement, product confidence, and satisfaction by enhancing sensory stimulation and information richness (Dandis et al., 2023). As such, AR marketing is expected to play a critical role in creating memorable and emotionally resonant shopping experiences, which in turn influence consumer behavior.

Consumer Experience

Consumer experience refers to the holistic perception formed through the cognitive, emotional, sensory, and behavioral responses during the shopping journey (Lemon & Verhoef, 2016). In AR-enabled online retail, consumer experience is shaped by interactive features that simulate touch, proximity, and personalization. Key dimensions include enjoyment, interactivity, informativeness, and control (Waqas et al., 2021).

When AR effectively engages multiple senses and provides control over product interaction, consumers are more likely to experience flow, satisfaction, and brand affinity. These experiences

may also reduce uncertainty and improve decision-making confidence, especially in online settings where physical evaluation is not possible (Kamboj et al., 2016).

Hypothesis Formulation

Based on the literature and theoretical underpinnings, the following hypotheses are proposed:

H1: Perceived interactivity positively influences consumer experience in AR-based online retail.

H2: Perceived enjoyment positively influences consumer experience in AR-based online retail.

H3: Perceived informativeness positively influences consumer experience in AR-based online retail.

H4: Consumer experience positively influences behavioral intentions in online retail.

RESEARCH METHODS

This research employs a quantitative approach with a causal design to examine the influence of AR marketing on consumer experience in online retail settings (J. Hair et al., 2014). The study is structured to test the hypothesized relationships between perceived interactivity, enjoyment, informativeness, and consumer experience, as well as their effects on behavioral intentions. A quantitative method is appropriate for measuring these constructs objectively and validating the theoretical model using statistical tools (Ghozali, 2018).

The target population comprises consumers who have interacted with AR features in online retail platforms within the past 12 months. A purposive sampling method is used to select respondents who meet specific criteria, including familiarity with AR technology and prior online shopping experience involving AR applications. A total of 200 valid responses were collected through an online questionnaire distributed via social media and e-commerce platforms.

The research instrument consists of a structured questionnaire developed from validated scales in previous studies. Items measuring perceived interactivity, enjoyment, informativeness, consumer experience, and behavioral intentions are adapted from existing literature and rated on a 5-point Likert scale. The questionnaire underwent a pilot test with 30 respondents to ensure reliability and validity.

Data analysis is conducted using Structural Equation Modeling with Partial Least Squares (SEM-PLS) via SmartPLS software (J. F. Hair et al., 2022). SEM-PLS is chosen due to its robustness in modeling complex relationships between latent variables, especially with a relatively small to medium sample size. It also supports both measurement model assessment (construct validity and reliability) and structural model testing (hypothesis testing and path analysis).

Through this methodological framework, the study aims to provide empirical insights into how AR marketing contributes to enhancing consumer experience and behavioral outcomes. The results are expected to guide online retailers in designing AR features that effectively align with consumer expectations and drive engagement in digital commerce.

RESULTS AND DISCUSSION

Validity testing in Structural Equation Modeling analysis based on Partial Least Squares (SEM-PLS) aims to measure the extent to which indicators are able to represent the construct being measured (J. Hair et al., 2014). One of the criteria used to assess convergent validity is the outer loading value of each indicator against its construct. In this context, an indicator is said to be valid if its loading factor value is greater than 0.7, which indicates that more than 50% of the indicator's variance is explained by the measured latent construct. Values above 0.7 reflect the indicator's strong and consistent contribution in explaining latent variables, as well as strengthening the reliability and validity of the model as a whole. Thus, when all indicators in the model have loading values above 0.7, it can be concluded that the construct in the model has good convergent validity.

Table 1. Loading Factor

Indicator	Consumer Experience	Influences Behavioral Intentions	Perceived Enjoyment	Perceived Informativeness	Perceived Interactivity
CE1	0,806				
CE2	0,867				
CE3	0,863				
CE4	0,794				
IBI1		0,892			
IBI2		0,869			
IBI3		0,862			
IBI4		0,836			
PE1			0,877		
PE2			0,849		
PE3			0,887		
PE4			0,826		
PE5			0,767		
PI2					0,932
PI3					0,926
PI4					0,892
PIN1				0,842	
PIN2				0,891	
PIN3				0,818	
PIN4				0,850	
PI1					0,781

Source: Data processing results, 2025

This table demonstrates that all indicators for the five constructs — Consumer Experience, Influences Behavioral Intentions, Perceived Enjoyment, Perceived Informativeness, and Perceived Interactivity — have loading values above 0.70. This confirms that all indicators possess strong convergent validity. For instance, indicators CE2 and CE3 for Consumer Experience have loadings of 0.867 and 0.863 respectively, indicating a strong relationship with their construct. Similarly, the indicators for Influences Behavioral Intentions (IBI1–IBI4) all exceed 0.83 in loading, reflecting solid measurement reliability. Other indicators such as PE3 (0.887), PIN2 (0.891), and PI2 (0.932) further reinforce the robustness of the construct measurements.

The Construct Reliability and Validity test in SEM-PLS aims to assess the extent to which the constructs in the research model show internal consistency and convergent validity. There are several indicators used in this test, namely Cronbach's Alpha, rho_A, Composite Reliability, and Average Variance Extracted (AVE). Cronbach's Alpha and Composite Reliability are used to measure construct reliability, where the recommended value is at least 0.7. Meanwhile, the AVE value is used to measure convergent validity, with a minimum threshold of 0.5. If all indicator values meet the criteria, then the construct is considered reliable and valid, so it is suitable for use in the structural model.

Table 2. Construct Reliability and Validity

Variable	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Consumer Experience	0,852	0,853	0,901	0,694

Influences Behavioral Intentions	0,888	0,888	0,922	0,748
Perceived Enjoyment	0,897	0,898	0,924	0,710
Perceived Informativeness	0,873	0,879	0,913	0,724
Perceived Interactivity	0,906	0,918	0,935	0,783

Source: Data processing results, 2025

All constructs meet the reliability and convergent validity criteria. Cronbach's Alpha values are all above 0.85, indicating high internal consistency. The Composite Reliability (CR) values range from 0.901 to 0.935, significantly above the minimum threshold of 0.70, demonstrating strong construct reliability. The Average Variance Extracted (AVE) values are all above 0.694, meaning that more than 50% of the variance in the indicators is explained by the constructs. This further confirms that the instrument is both reliable and valid for measurement.

The Discriminant Validity test in SEM-PLS aims to ensure that each construct in the model actually measures different concepts from each other. One of the commonly used methods is the Fornell-Larcker Criterion, which compares the square root of the Average Variance Extracted (AVE) value of each construct with the correlation between other constructs (Fornell & Larcker, 1981). Discriminant validity is declared fulfilled if the square root value of AVE (shown on the diagonal of the table) is higher than the correlation between constructs (values outside the diagonal). This indicates that the construct is more highly correlated with its own indicators compared to other constructs, thus confirming that each construct is unique and does not overlap with other constructs in the model.

Table 3. Discriminant Validity

Variable	Consumer Experience	Influences Behavioral Intentions	Perceived Enjoyment	Perceived Informativeness	Perceived Interactivity
Consumer Experience	0,833				
Influences Behavioral Intentions	0,900	0,865			
Perceived Enjoyment	0,815	0,806	0,843		
Perceived Informativeness	0,818	0,816	0,826	0,851	
Perceived Interactivity	0,799	0,766	0,813	0,787	0,885

Source: Data processing results, 2025

This table shows that the square root of the AVE (diagonal values) for each construct is higher than its correlations with any other construct. For example, the AVE square root for *Consumer Experience* is 0.833, which is higher than its correlation with *Perceived Enjoyment* (0.815) and *Perceived Interactivity* (0.799). This indicates that each construct is distinct and measures a different concept, fulfilling the requirement for discriminant validity. It confirms that there is no conceptual overlap between constructs in the model.

The F-Square test in the SEM-PLS approach is used to measure the magnitude of the exogenous influence on the endogenous by looking at how much a variable contributes to increasing the R-Square value of the endogenous construct. The F-Square value provides an indication of whether a construct has a small (≥ 0.02), medium (≥ 0.15), or large (≥ 0.35) effect on other constructs in the structural model. Thus, this test is important to evaluate the predictive power of the relationship between variables in the research model.

Table 4. F-Square

Variable	Consumer Experience	Influences Behavioral Intentions	Perceived Enjoyment	Perceived Informativeness	Perceived Interactivity
Consumer Experience		4,282			
Influences Behavioral Intentions	0,086				
Perceived Enjoyment	0,142				
Perceived Informativeness	0,097				

Source: Data processing results, 2025

According to this table, the path coefficient from Consumer Experience to Influences Behavioral Intentions is the strongest and statistically significant, with a value of 4.282. This reveals a very strong direct effect of consumer experience on behavioral intentions. However, the path coefficients from Perceived Enjoyment (0.086), Perceived Informativeness (0.142), and Perceived Interactivity (0.097) to Consumer Experience are lower and less significant. This implies that while these variables are conceptually relevant, their direct impact on Consumer Experience is not statistically strong in this particular model.

The R-Square test in Structural Equation Modeling Partial Least Squares (SEM-PLS) is used to measure the magnitude of the ability of the independent variables to explain the dependent variable. A high R-Square value indicates that the model has good predictive power. In general, an R-Square value of 0.25 is considered weak, 0.50 moderate, and 0.75 strong. While R-Square Adjusted takes into account the number of indicators and variables in the model, thus providing a more conservative measure of the predictive power of the model.

Table 5. R-Square

Variable	R Square	R Square Adjusted
Consumer Experience	0,755	0,747
Influences Behavioral Intentions	0,811	0,809

Source: Data processing results, 2025

The R Square value shows that 75.5% of the variance in Consumer Experience is explained by its predictors, and 81.1% of the variance in Influences Behavioral Intentions is explained by Consumer Experience. The adjusted R Square values (0.747 and 0.809) are close to their respective R Square values, indicating a stable model with strong predictive power. This suggests that the structural model in this study has a high level of explanatory strength for the endogenous variables.

Hypothesis testing in Structural Equation Modeling Partial Least Squares (SEM-PLS) is carried out to test the influence between latent variables in the research model. This process involves analyzing the path coefficient, t-statistic, and p-value values to determine whether the relationship between variables is statistically significant. A t-statistic value above 1.96 (at a significance level of 5%) indicates that the hypothesis is accepted, meaning that there is a significant influence between the independent variables on the dependent variable. In addition, the direction of the coefficient (positive or negative) indicates the type of relationship that occurs. This hypothesis test is crucial in empirically proving the causal relationship that has been formulated in the conceptual framework of the study. The validity of the results of this test provides a strong basis for drawing conclusions about the influences tested in the SEM-PLS model.

Table 6. Hypothesis Test

Hypothesis	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
Perceived Interactivity to Consumer Experience	0,132	2,137	0,033
Perceived Enjoyment to Consumer Experience	0,137	2,139	0,033
Perceived Informativeness to Consumer Experience	0,119	2,986	0,003
Consumer Experience to Influences Behavioral Intentions	0,029	31,314	0,000

Source: Data processing results, 2025

Discussion

Perceived Interactivity to Consumer Experience

The hypothesis testing reveals that Perceived Interactivity has a statistically significant effect on Consumer Experience, with a T-statistic of 2.137 and a p-value of 0.033, which is below the 0.05 significance threshold. This suggests that consumers who perceive a high level of interactivity in digital platforms or brand touchpoints tend to have a better overall experience. Interactivity may involve real-time responses, customizable features, or engaging interfaces that allow users to feel more involved in the process.

Interactive features encourage two-way communication, giving consumers a sense of agency and involvement. This sense of control and participation positively affects their perception of the brand and increases engagement. In many cases, interactivity leads to increased satisfaction because consumers feel their input or actions shape the experience.

Practically, businesses should prioritize interactive components in digital interfaces, such as live chat, product customization, and interactive tutorials, to improve consumer experiences. These features not only enhance usability but also create emotional connections by making consumers feel valued. Therefore, enhancing perceived interactivity is a strategic tool for improving consumer relationships and satisfaction.

Perceived Enjoyment to Consumer Experience

The path from Perceived Enjoyment to Consumer Experience is also statistically significant, with a T-statistic of 2.139 and a p-value of 0.033. This indicates that consumers who find the interaction with a brand enjoyable are more likely to report positive experiences. Enjoyment captures the emotional response and intrinsic pleasure derived from using a product or service, which plays a vital role in shaping consumer evaluations.

An enjoyable experience typically elicits positive emotions such as fun, excitement, or relaxation, which can enhance memory and brand associations. This emotional dimension often outweighs

functional benefits in influencing consumer behavior, especially in lifestyle and entertainment-related industries.

In real-world application, companies should design their offerings to be not only functional but also emotionally satisfying. This can include gamified interfaces, aesthetic design, or playful content. By making the experience enjoyable, firms can improve customer retention, word-of-mouth referrals, and brand loyalty.

Perceived Informativeness to Consumer Experience

The hypothesis that Perceived Informativeness affects Consumer Experience is strongly supported by the results, with a T-statistic of 2.986 and a p-value of 0.003. This demonstrates that the more informative the content provided by a company, the more positive the consumer experience. Informativeness refers to the perceived value and usefulness of the information offered during the consumer journey.

High informativeness reduces uncertainty, assists in decision-making, and builds trust in the brand. When consumers feel well-informed, they are more confident in their choices and more likely to perceive the brand as transparent and credible.

In practice, businesses should focus on delivering clear, relevant, and comprehensive information across all touchpoints, including websites, product descriptions, FAQs, and customer support. Educational content, such as how-to videos and product comparisons, can further enhance perceived informativeness.

Consumer Experience to Influences Behavioral Intentions

The relationship between Consumer Experience and Behavioral Intentions is highly significant, with a T-statistic of 31.314 and a p-value of 0.000. This confirms that a positive consumer experience directly contributes to favorable behavioral intentions, such as repeat purchases, positive word-of-mouth, and brand advocacy.

This result is aligned with consumer behavior theory, which suggests that experiences shape future behaviors. A satisfying experience fosters emotional bonds, reinforces trust, and lowers the perceived risk of future transactions, making consumers more likely to engage with the brand again. Companies that deliver superior consumer experiences often enjoy sustainable competitive advantages. By focusing on consistency, personalization, and emotional resonance throughout the customer journey, they can turn one-time buyers into loyal advocates. Thus, enhancing consumer experience is not just about satisfaction but also about cultivating long-term behavioral commitment.

CONCLUSION

The findings confirm that Perceived Interactivity, Perceived Enjoyment, and Perceived Informativeness all significantly influence Consumer Experience. These dimensions contribute uniquely to how consumers perceive and respond to brand interactions. Interactivity empowers users, enjoyment stimulates emotional engagement, and informativeness reduces uncertainty—each playing a critical role in crafting valuable consumer experiences.

Furthermore, Consumer Experience itself exerts a strong positive influence on Behavioral Intentions. This underscores the strategic importance of experience management in shaping customer actions and building brand loyalty. Together, the results highlight a holistic pathway where digital and emotional elements enhance experience, which in turn drives meaningful consumer behavior.

In practice, firms should develop integrated strategies that simultaneously address functional and emotional needs. Enhancing interactivity, delivering enjoyable and informative content, and maintaining consistent consumer satisfaction are essential pillars of sustainable success in today's competitive landscape. Future research may explore these dynamics in varying cultural or industry contexts to expand understanding and application.

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