www.ijarp.com ISSN 2456-9992 Page: 01-22

International Journal Advanced Research Publications

Research Article

Volume: 02
Issue: 09

EVALUATING CONSUMER TRUST AND BUYING BEHAVIOR IN AUGMENTED E-COMMERCE ENVIRONMENTS

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Article Received: 14 August 2026, Article Revised: 04 September 2026, Published on: 24 September 2026

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Doi: https://doi-doi.org/101555/ijarp.2252

ABSTRACT

Augmented Reality (AR) integration in e-commerce is rapidly transforming how consumers interact with products in digital marketplaces. Despite the growing adoption of AR-enabled shopping features, there remains a significant gap in understanding how these immersive technologies influence consumer trust formation and purchase decision-making. This empirical study investigates the antecedents and consequences of consumer trust in augmented e-commerce environments, drawing on the Technology Acceptance Model (TAM), Trust-Commitment Theory, and Stimulus-Organism-Response (S-O-R) framework. A structured questionnaire was administered to 412 online shoppers across age groups 18-50 who had experience using AR features in e-commerce platforms. Structural Equation Modeling (SEM) using AMOS 24.0 was employed to analyze the relationships among perceived usefulness, perceived ease of use, AR interactivity, information quality, perceived risk, consumer trust, and purchase intention. Results reveal that AR interactivity (β=0.423, $p<0.001$) and information quality (β=0.381, $p<0.001$) are the strongest predictors of consumer trust, which in turn significantly influences purchase intention (β=0.512, $p<0.001$). Perceived risk negatively moderates the trust-purchase intention relationship. The model explains 67.4% variance in purchase intention. This study contributes to digital marketing literature and offers actionable insights for e-commerce practitioners seeking to leverage AR technologies to enhance consumer confidence and conversion rates.

KEYWORDS: *Augmented Reality, E-Commerce, Consumer Trust, Purchase Intention, Technology Acceptance Model, Structural Equation Modelling, Digital Consumer Behavior, Virtual Try-On.*

1. INTRODUCTION

The global e-commerce industry has undergone an unprecedented metamorphosis driven by the convergence of emerging technologies, shifting consumer expectations, and the post-pandemic digital acceleration. Among these technological disruptions, Augmented Reality (AR) stands out as a pivotal innovation that bridges the physical-digital divide by overlaying computer-generated perceptual information onto real-world environments in real time (Azuma, 1997). The integration of AR into e-commerce platforms—often termed 'Augmented E-Commerce'—represents a paradigm shift from information-based to experience-based online shopping.

The global augmented reality in retail market was valued at USD 2 billion in 2021 and is projected to reach USD 61.3 billion by 2031, expanding at a compound annual growth rate of 41.4 per cent between 2022 and 2031 (Allied Market Research, 2023). Leading platforms such as Amazon, IKEA, Sephora, and Warby Parker have deployed AR features including virtual try-on, 3D product visualization, and spatial product placement, fundamentally altering the consumer decision journey. Despite such rapid adoption, the academic understanding of how AR features influence consumer psychological processes—particularly trust formation and purchase behavior—remains nascent and fragmented.

Consumer trust in e-commerce contexts has been extensively studied (McKnight & Chervany, 2002; Gefen et al., 2003); however, the mechanisms through which immersive AR experiences shape trust perceptions differ markedly from conventional web-based interfaces. AR provides enriched sensory information, reduces product uncertainty, and creates a heightened sense of presence that may fundamentally alter cognitive and affective trust antecedents. Simultaneously, concerns around data privacy, technology complexity, and algorithmic accuracy may introduce novel risk dimensions that erode trust.

This research addresses a critical gap by developing and empirically testing an integrated theoretical model that explains consumer trust formation and purchase intention within AR-enhanced e-commerce settings. Specifically, this study examines: (1) how AR-specific attributes influence perceived usefulness, ease of use, and information quality; (2) how these perceptions feed into trust formation; (3) how perceived risk moderates the trust-purchase

intention relationship; and (4) how demographic variables differentially affect AR adoption and trust.

1.1 Research Motivation

The motivation for this research is twofold. First, from a theoretical standpoint, existing trust models in e-commerce do not account for the unique experiential and cognitive dimensions introduced by AR interfaces. Second, from a managerial standpoint, despite heavy investments in AR technology, conversion rates from AR feature engagement remain suboptimal, suggesting that trust barriers may be impeding purchase completion. This study synthesizes perspectives from information systems, consumer psychology, and digital marketing to provide a holistic understanding of the AR-trust-purchase intention nexus.

1.2 Scope and Contribution

This paper contributes to the existing body of knowledge in three primary ways: (i) it extends the TAM framework by incorporating AR-specific constructs such as AR interactivity and visualization quality; (ii) it empirically validates a comprehensive SEM model using large-scale primary data from Indian e-commerce consumers; and (iii) it provides practical guidelines for AR interface design and trust-building strategies for digital retailers. The study focuses on the Indian context, which represents one of the fastest-growing e-commerce markets globally with over 220 million active online shoppers as of 2024.

2. REVIEW OF LITERATURE

2.1 Augmented Reality in E-Commerce: An Overview

Augmented Reality in e-commerce encompasses a spectrum of applications ranging from marker-based and markerless AR product visualizations to face-tracking virtual try-ons and location-based AR experiences. Scholz and Smith (2016) categorized AR applications in retail into four types: product visualization (seeing products in context), product information (contextual information overlays), brand experience (entertainment and engagement), and co-creation (consumer-generated AR content). Subsequent research has expanded these categories to include social AR experiences and AI-powered personalized AR recommendations.

Yim et al. (2017) conducted one of the earliest empirical investigations into consumer responses to AR, finding that AR's immersive quality—characterized by interactivity and vividness—generates higher consumer engagement compared to static images or videos. Huang and Liao (2017) further demonstrated that AR-based product trial experiences reduce

product uncertainty and enhance purchase confidence in fashion retail contexts. More recently, Smink et al. (2020) provided evidence that AR product visualization in mobile commerce settings positively influences purchase decisions through its impact on self-congruity and psychological ownership.

2.2 Consumer Trust in Digital Commerce

Trust in e-commerce has been conceptualized along multiple dimensions. Mayer et al. (1995) defined trust as 'the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor.' In e-commerce contexts, McKnight et al. (2002) distinguished between trust in the internet as a medium, trust in the e-vendor, and trust in specific platform features. Pavlou and Fygenson (2006) established that e-commerce trust is shaped by perceived competence, benevolence, and integrity of the vendor.

The antecedents of e-commerce trust have been studied extensively. Gefen et al. (2003) applied the TAM to trust, finding that both perceived usefulness and familiarity significantly predict trust in e-vendors. Kim and Park (2013) demonstrated that social presence features in online stores enhance consumer trust by creating human-like interaction cues. More recently, in the context of social commerce, Lu et al. (2016) found that electronic word-of-mouth and user-generated content significantly mediate trust formation. However, the application of these trust frameworks to AR-enhanced commerce remains limited.

2.3 Technology Acceptance Model (TAM) and Extensions

The Technology Acceptance Model, originally proposed by Davis (1989), posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of technology adoption intention. TAM has been widely applied in e-commerce contexts (Venkatesh & Morris, 2000; Pavlou, 2003) and has been extended to incorporate trust as a mediating variable (Gefen et al., 2003). The Extended TAM (TAM2) and Unified Theory of Acceptance and Use of Technology (UTAUT) further incorporated social influence and facilitating conditions as predictors of adoption.

In the context of AR adoption, several studies have extended TAM. Rauschnabel et al. (2019) proposed the AR Value Model, adding enjoyment and social value as AR-specific adoption antecedents. Rese et al. (2017) applied TAM to AR shopping apps, confirming that both PU and PEOU predict AR usage but found that hedonic motivations play a significantly stronger role in AR contexts than in traditional e-commerce. The current study extends this line of inquiry by incorporating AR interactivity and information quality as upstream determinants of TAM constructs.

2.4 Stimulus-Organism-Response (S-O-R) Framework

The S-O-R framework (Mehrabian & Russell, 1974), originally developed in environmental psychology, has been applied in e-commerce to explain how digital environment cues (stimuli) trigger internal consumer states (organism) that drive behavioral outcomes (response). In AR e-commerce, the stimuli consist of AR interface characteristics such as interactivity, vividness, personalization, and ease of navigation. These stimuli influence internal states including cognitive trust, affective trust, perceived risk, and hedonic motivation, which ultimately determine purchase intention and loyalty.

Chang and Chen (2008) applied the S-O-R framework to e-commerce website quality, finding that design and usability cues drive both approach and avoidance behaviors mediated by emotional states. More recently, Parboteeah et al. (2009) extended the framework to include cognitive responses alongside affective ones, establishing that website informativeness and aesthetics influence both cognitive and affective trust. The current study integrates the S-O-R framework with TAM and Trust Theory to provide a comprehensive model of AR e-commerce consumer behavior.

2.5 Perceived Risk and Trust

Perceived risk in e-commerce is a multidimensional construct encompassing financial risk, performance risk, privacy risk, time risk, and psychological risk (Bauer, 1960; Featherman & Pavlou, 2003). In AR-enhanced shopping, novel risk dimensions emerge including concerns about data collection through camera access, accuracy of AR product representations, and device compatibility. Mitchell (1999) found that consumers use trust as a risk-reduction mechanism, a finding corroborated in numerous e-commerce studies (Pavlou, 2003; Kim et al., 2008).

The moderating role of perceived risk on the trust-purchase intention relationship has been established in traditional e-commerce (Kim et al., 2008; Gefen, 2000) but has not been examined in AR contexts. This study posits that while AR features may enhance trust through richer product information and experiential engagement, consumers with high risk perceptions may remain hesitant to complete purchases despite high trust levels, introducing a moderating effect.

2.6 Research Gaps and Theoretical Positioning

Despite the growing body of literature on AR in retail and e-commerce trust, several critical gaps remain. First, existing studies largely treat AR as a single undifferentiated construct, failing to examine how specific AR attributes (interactivity, visualization quality, personalization) differentially contribute to trust formation. Second, the integrative modeling

of AR attributes, TAM constructs, trust, and perceived risk within a single SEM framework is largely absent. Third, the majority of existing AR-trust studies are conducted in Western contexts; Indian consumer behavior in AR commerce remains understudied despite India's significant e-commerce market size. This study addresses all three gaps.

3. STATEMENT OF THE PROBLEM, OBJECTIVES & HYPOTHESES

3.1 Statement of the Problem

Despite significant industry investment in AR features for e-commerce platforms, empirical evidence regarding the psychological mechanisms through which AR influences consumer trust and purchase behavior is limited and fragmented. E-commerce practitioners report that while AR feature engagement rates have increased, conversion rates—the proportion of AR feature users who complete a purchase—remain lower than expected. This suggests the presence of unresolved trust and risk barriers that conventional usability improvements may not adequately address. A rigorous, theory-grounded empirical investigation of the AR-trust-purchase intention nexus is therefore urgently needed to guide both theoretical development and managerial practice.

Furthermore, the Indian e-commerce consumer, characterized by distinct cultural values, price sensitivity, and a rapidly evolving digital literacy landscape, may exhibit trust formation patterns that differ from Western counterparts. The problem thus extends beyond understanding AR's psychological effects in general to understanding them within the specific socio-cultural and economic context of emerging markets.

3.2 Research Objectives

This study is guided by the following specific research objectives:

1. To examine the influence of AR-specific attributes (AR interactivity, visualization quality, and personalization) on perceived usefulness, perceived ease of use, and information quality.
2. To assess the impact of perceived usefulness, perceived ease of use, and information quality on consumer trust in AR-enhanced e-commerce platforms.
3. To evaluate the relationship between consumer trust and purchase intention in augmented e-commerce environments.
4. To investigate the moderating role of perceived risk on the trust-purchase intention relationship.

5. To analyze the demographic variations in AR adoption, trust perceptions, and purchase behavior among Indian online shoppers.
6. To develop and validate a comprehensive structural model of consumer trust and buying behavior in augmented e-commerce environments.

3.3 Research Hypotheses

Based on the theoretical review, the following hypotheses are proposed:

H1: AR Attributes → TAM Constructs

- H1a: AR Interactivity is positively associated with Perceived Usefulness.
- H1b: AR Interactivity is positively associated with Perceived Ease of Use.
- H1c: Visualization Quality is positively associated with Information Quality.
- H1d: Personalization is positively associated with Perceived Usefulness.

H2: TAM Constructs → Consumer Trust

- H2a: Perceived Usefulness is positively associated with Consumer Trust.
- H2b: Perceived Ease of Use is positively associated with Consumer Trust.
- H2c: Information Quality is positively associated with Consumer Trust.

H3: Consumer Trust → Purchase Intention

- H3: Consumer Trust is positively associated with Purchase Intention.

H4: Moderation Hypothesis

- H4: Perceived Risk negatively moderates the relationship between Consumer Trust and Purchase Intention.

H5: Demographic Hypotheses

- H5a: Age significantly differentiates AR adoption and trust perceptions among consumers.
- H5b: Prior online shopping experience positively moderates the trust formation process in AR environments.

4. RESEARCH DESIGN

4.1 Research Philosophy and Approach

This study adopts a positivist research philosophy, assuming that social reality is objective and can be measured through quantitative methods. A deductive approach was employed, wherein hypotheses derived from established theories were empirically tested using primary

survey data. The study follows a cross-sectional research design, which is appropriate for capturing consumer perceptions and attitudes at a specific point in time (Bryman, 2016). While cross-sectional designs preclude causal inferences, the use of SEM allows for the examination of directional relationships among latent constructs.

4.2 Target Population and Sampling

The target population comprised adult online shoppers in India who had used AR features (virtual try-on, 3D product visualization, or room placement tools) on at least one e-commerce platform in the six months preceding the survey. This criterion ensures that respondents have direct experiential knowledge of the phenomenon under investigation, enhancing construct validity.

A multi-stage sampling strategy was employed. First, purposive sampling was used to identify online shoppers with AR experience through social media communities, e-commerce platform user forums, and university campus networks. Second, snowball sampling was employed to expand the sample. The final usable sample comprised 412 respondents, exceeding the recommended minimum of 200 for SEM analysis (Hair et al., 2019) and satisfying the 10-times rule (each indicator should have at least 10 respondents).

4.3 Instrument Development

A structured questionnaire was developed through a systematic process. All measurement items were adapted from validated scales in the existing literature to ensure content validity. Perceived Usefulness (4 items) and Perceived Ease of Use (4 items) were adapted from Davis (1989) and Venkatesh et al. (2003). Consumer Trust (5 items) was measured using McKnight et al.'s (2002) multidimensional trust scale. AR Interactivity (4 items) was adapted from Liu and Shrum (2002). Visualization Quality (3 items) was adapted from Yim et al. (2017). Information Quality (4 items) was drawn from Wang and Strong (1996). Perceived Risk (4 items) was measured using Featherman and Pavlou's (2003) scale. Purchase Intention (3 items) was adapted from Pavlou (2003).

All items were measured on a 5-point Likert scale anchored at 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was administered in English with Hindi translation available. A pilot study was conducted with 40 respondents to refine item wording, assess initial reliability (Cronbach's alpha > 0.70 for all constructs), and identify potential ambiguities. Following pilot testing, two items were revised for clarity.

4.4 Data Collection Procedure

Primary data collection was conducted over a period of three months (January–March 2024) using a combination of online survey (Google Forms) and assisted face-to-face interviews in

metropolitan cities (Delhi-NCR, Mumbai, Bengaluru, and Hyderabad). Informed consent was obtained from all respondents. To ensure data quality, attention check questions were embedded in the survey, resulting in the exclusion of 28 incomplete or invalid responses from an initial collection of 440 responses. The final dataset of 412 responses was used for analysis.

4.5 Analytical Framework

Data analysis proceeded in two phases. Phase 1 involved descriptive statistical analysis of the demographic profile and a Common Method Variance (CMV) check using Harman's Single Factor Test and Variance Inflation Factor (VIF) analysis. Phase 2 involved Confirmatory Factor Analysis (CFA) to assess measurement model fit, reliability, and validity, followed by Structural Equation Modeling (SEM) using AMOS 24.0 with Maximum Likelihood Estimation to test the hypothesized relationships. Moderation analysis (H4) was conducted using the product-indicator approach. Group invariance tests were conducted to examine demographic differences (H5).

5. DEMOGRAPHIC PROFILE OF THE RESPONDENTS

Table 1 presents the demographic profile of the 412 respondents. The sample is broadly representative of India's online shopping population in terms of age, gender, education, and digital engagement levels.

Table 1: Demographic Profile of Respondents. (N=412)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	224	54.4
	Female	179	43.4
	Non-Binary / Prefer not to say	9	2.2
Age Group	18–24 years	132	32.0
	25–34 years	158	38.3
	35–44 years	87	21.1
	45–50 years	35	8.5
Education	Undergraduate (Bachelor's)	198	48.1
	Postgraduate (Master's)	167	40.5
	Doctoral / Professional	47	11.4

Demographic Variable	Category	Frequency (n)	Percentage (%)
Monthly Income	Below ₹25,000	98	23.8
	₹25,001 – ₹50,000	134	32.5
	₹50,001 – ₹1,00,000	121	29.4
	Above ₹1,00,000	59	14.3
Online Shopping Frequency	Daily	68	16.5
	Weekly	143	34.7
	Monthly	158	38.3
	Rarely	43	10.4
AR Platform Used	Amazon (Virtual Try-On)	189	45.9
	IKEA Place App	143	34.7
	Myntra Style Studio	87	21.1
	Lenskart 3D Try-On	98	23.8
	Nykaa Virtual Makeup	76	18.4
AR Experience (Months)	Less than 3 months	87	21.1
	3–12 months	198	48.1
	More than 12 months	127	30.8

The demographic data reveals that the sample is skewed towards younger consumers (18–34 years: 70.3%), consistent with the demographic profile of AR technology early adopters in India. Approximately 54% of respondents were male, reflecting the slight male dominance in active online shopping among Indian consumers. A significant majority (88.6%) held at least a Bachelor's degree, indicating that the sample is educationally well-qualified and digitally literate. The most commonly used AR platform was Amazon's Virtual Try-On (45.9%), followed by IKEA Place (34.7%). Nearly 80% of respondents had been using AR features for 3 months or more, ensuring substantive experiential basis for their perceptions.

6. DATA ANALYSIS & MODEL DEVELOPMENT

6.1 Common Method Variance (CMV) Assessment

Since all data were collected from a single source using self-report measures, Common Method Variance (CMV) was assessed using Harman's Single Factor Test. The unrotated

principal component analysis extracted a total of 11 factors, with the first factor accounting for 23.7% of the total variance (well below the threshold of 50%), indicating that CMV is not a significant concern in this dataset. Additionally, VIF values for all constructs ranged from 1.23 to 2.87, falling well below the conventional threshold of 10, confirming the absence of multicollinearity.

6.2 Confirmatory Factor Analysis (CFA) and Measurement Model

Confirmatory Factor Analysis was conducted to assess the reliability and validity of the measurement model. Overall model fit indices indicate good model fit: $\chi^2/df = 2.14$ (acceptable threshold < 3.0), CFI = 0.961, TLI = 0.954, RMSEA = 0.047 (90% CI: 0.038–0.056), SRMR = 0.053. All fit indices exceed recommended thresholds (Hair et al., 2019), confirming adequate model fit.

Table 2: Measurement Model – Reliability and Validity Assessment.

Construct	Items	α (Cronbach)	CR	AVE	MSV
AR Interactivity (ARI)	4	0.887	0.891	0.672	0.312
Visualization Quality (VQ)	3	0.863	0.871	0.693	0.287
Personalization (PERS)	3	0.841	0.852	0.658	0.301
Perceived Usefulness (PU)	4	0.912	0.918	0.736	0.342
Perceived Ease of Use (PEOU)	4	0.894	0.902	0.698	0.289
Information Quality (IQ)	4	0.903	0.907	0.711	0.316
Consumer Trust (CT)	5	0.931	0.934	0.741	0.398
Perceived Risk (PR)	4	0.876	0.883	0.654	0.367
Purchase Intention (PI)	3	0.921	0.927	0.808	0.423

As shown in Table 2, all constructs demonstrate high internal consistency (Cronbach's $\alpha > 0.84$) and composite reliability (CR > 0.85), exceeding the recommended threshold of 0.70 (Hair et al., 2019). Average Variance Extracted (AVE) values ranged from 0.654 to 0.808, all exceeding the 0.50 threshold required for convergent validity. The Maximum Shared Variance (MSV) values were lower than the corresponding AVE values for all constructs, confirming discriminant validity. Standardized factor loadings for all items ranged from 0.72 to 0.91 (all $p < 0.001$), confirming item reliability.

6.3 Structural Model and Hypothesis Testing

The structural model was estimated using Maximum Likelihood Estimation in AMOS 24.0. The overall structural model demonstrated good fit: $\chi^2/df = 2.28$, CFI = 0.957, TLI = 0.951, RMSEA = 0.050 (90% CI: 0.041–0.059), SRMR = 0.056. Table 3 presents the results of hypothesis testing.

Table 3: Structural Model Results – Hypothesis Testing.

Hypothesis	Path	β (Std.)	S.E.	t-value	p-value	Decision
H1a	ARI → PU	0.387	0.048	8.064	***	Supported
H1b	ARI → PEOU	0.412	0.051	8.080	***	Supported
H1c	VQ → IQ	0.453	0.046	9.848	***	Supported
H1d	PERS → PU	0.341	0.052	6.558	***	Supported
H2a	PU → CT	0.298	0.047	6.340	***	Supported
H2b	PEOU → CT	0.267	0.049	5.449	***	Supported
H2c	IQ → CT	0.381	0.044	8.659	***	Supported
H2d*	ARI → CT (Direct)	0.423	0.053	7.981	***	Supported
H3	CT → PI	0.512	0.049	10.449	***	Supported
H4	PR × CT → PI	-0.187	0.038	-4.921	***	Supported
H5a	Age Group differences	–	–	F=4.23	0.006	Supported
H5b	Experience moderates CT→PI	0.143	0.041	3.488	0.001	Supported

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. β = standardized path coefficient; S.E. = standard error. *H2d represents a direct path from AR Interactivity to Consumer Trust, included in the revised model based on modification indices.

6.4 Variance Explained and Effect Sizes

The structural model explains substantial variance in the endogenous constructs: Perceived Usefulness ($R^2 = 0.412$), Perceived Ease of Use ($R^2 = 0.387$), Information Quality ($R^2 = 0.318$), Consumer Trust ($R^2 = 0.589$), and Purchase Intention ($R^2 = 0.674$). The R^2 of 0.674 for Purchase Intention indicates that the model accounts for 67.4% of variance in purchase intention, which is considered substantial in behavioral research (Cohen, 1992). Effect sizes (f^2) ranged from medium to large (0.14–0.49), indicating practical significance of the relationships.

6.5 Mediation Analysis

Bootstrap mediation analysis (5,000 resamples) was conducted to examine indirect effects. Consumer Trust fully mediates the relationship between Information Quality and Purchase Intention (indirect effect = 0.195, 95% CI: [0.143, 0.257]). Consumer Trust partially mediates the relationship between AR Interactivity and Purchase Intention (indirect effect = 0.216, 95% CI: [0.157, 0.283]). These findings underscore the pivotal mediating role of trust in converting AR feature engagement into purchase decisions.

6.6 Moderation Analysis

Moderation analysis using the product-indicator approach confirmed that Perceived Risk significantly moderates the Consumer Trust → Purchase Intention relationship ($\beta = -0.187$, $p < 0.001$). Simple slopes analysis revealed that the positive effect of trust on purchase intention is strong at low risk levels ($\beta = 0.698$, $p < 0.001$) but diminishes substantially at high risk levels ($\beta = 0.312$, $p < 0.01$), confirming H4. This interaction effect explains an additional 2.3% variance in purchase intention ($\Delta R^2 = 0.023$, $p < 0.001$).

6.7 Demographic Group Comparisons

Multi-group SEM analysis revealed significant differences across age groups in AR adoption and trust perceptions. Younger consumers (18–24) exhibited higher AR interactivity perceptions ($M = 3.87$ vs. 3.21, $p < 0.01$) and lower perceived risk ($M = 2.43$ vs. 3.12, $p < 0.001$) compared to older consumers (35–50). Experienced AR users (>12 months) showed significantly higher trust ($M = 4.12$ vs. 3.54, $p < 0.001$) and purchase intention ($M = 4.04$ vs. 3.48, $p < 0.001$), supporting the positive moderating role of prior AR experience.

7. FINDINGS

The analysis yields several significant findings that advance our understanding of consumer behavior in augmented e-commerce environments:

7.1 Core Findings

Finding 1: AR Interactivity as the Primary Trust Driver

AR Interactivity emerged as the strongest direct predictor of Consumer Trust ($\beta = 0.423$, $p < 0.001$), surpassing Information Quality ($\beta = 0.381$), Perceived Usefulness ($\beta = 0.298$), and Perceived Ease of Use ($\beta = 0.267$). This finding indicates that the interactive and immersive nature of AR—characterized by real-time responsiveness, gesture recognition, and multi-dimensional product manipulation—creates a qualitatively richer trust-building experience than informational or usability factors alone. This extends existing TAM-trust frameworks by establishing AR interactivity as a novel and potent trust antecedent.

Finding 2: Information Quality Mediates AR Visualization Impact

Visualization Quality exerts its trust-building effect entirely through Information Quality (indirect effect = 0.307, 95% CI: [0.238, 0.381]), with no significant direct effect on trust (β = 0.089, p = 0.112). This finding suggests that it is not the visual richness of AR per se but the information completeness, accuracy, and representational fidelity facilitated by high visualization quality that builds consumer trust. Practitioners should therefore prioritize information accuracy in AR rendering over aesthetic sophistication.

Finding 3: Consumer Trust as the Central Mediating Mechanism

Consumer Trust fully mediates the relationship between Information Quality and Purchase Intention and partially mediates the AR Interactivity – Purchase Intention relationship. The direct effect of AR Interactivity on Purchase Intention (without trust as mediator) is β = 0.187 ($p < 0.01$), while the mediated effect through trust is β = 0.216, collectively explaining the majority of AR's behavioral influence. This confirms Trust as the central psychological mechanism through which AR features convert engagement into purchase behavior.

Finding 4: Perceived Risk as a Significant Boundary Condition

The moderating effect of Perceived Risk (β = -0.187, $p < 0.001$) reveals that the trust-purchase intention relationship is significantly attenuated in high-risk consumers. At one standard deviation above the mean perceived risk, the trust-purchase intention effect reduces by approximately 36% (from β = 0.698 to β = 0.312). This finding has critical managerial implications: AR platforms must not only build trust but also actively address risk perceptions through privacy assurances, return policies, and accuracy guarantees to fully convert trust into purchases.

Finding 5: Experience-Based Trust Amplification

Prior AR shopping experience positively moderates the trust formation process: experienced users form trust faster and at higher levels than novices for equivalent AR quality perceptions. This suggests a virtuous cycle—positive AR experiences build trust, which encourages further AR engagement, which reinforces trust. The managerial implication is that reducing barriers to first AR trial (via guided tutorials, gamification, and incentivized first use) is likely to yield long-term trust and loyalty dividends.

Finding 6: Demographic Heterogeneity

Significant demographic variations were observed across age groups and income levels. Younger consumers (18–24) demonstrate higher AR adoption propensity and lower risk perceptions, while older consumers (35–50) place greater emphasis on information quality and vendor credibility as trust antecedents. Middle-to-high income consumers exhibit

significantly higher purchase intention at equivalent trust levels, suggesting that AR investment may yield the highest ROI when targeting the 25–44, middle-income segment.

8. MANAGERIAL IMPLICATIONS

8.1 AR Interface Design Imperatives

The finding that AR interactivity is the strongest trust driver implies that e-commerce platforms should invest in maximizing the interactive fidelity of AR features. This includes implementing real-time object tracking, enabling multi-angle product manipulation (rotation, scaling, zoom), and incorporating haptic feedback where device capabilities permit. Features that merely display a static 3D overlay without interactive engagement deliver suboptimal trust benefits. Design teams should adopt iterative user testing protocols that measure trust formation outcomes, not merely usability metrics.

8.2 Information Accuracy as a Non-Negotiable AR Quality Standard

Given that information quality fully mediates the visualization quality–trust relationship, managers should establish strict product representation accuracy standards for AR renderings. This is particularly critical for color fidelity, dimensional accuracy, material texture representation, and size reference scaling. Implementation of AR quality audits—comparing consumer perception of AR-rendered products against actual physical product attributes—should become a standard pre-launch quality assurance process. Inaccurate AR representations that create a 'post-purchase dissonance' can destroy trust rapidly and generate negative reviews.

8.3 Perceived Risk Mitigation Strategies

The moderation finding indicates that trust alone is insufficient to drive purchase intention among high-risk consumers. E-commerce platforms should implement explicit risk reduction mechanisms alongside AR trust-building features. Recommended strategies include: prominent display of return and refund policies within the AR interface, privacy-by-design principles for camera data (local processing, no data retention), real-time customer reviews and ratings linked to AR product views, AR accuracy guarantees (e.g., 'True-to-Life Guarantee'), and secure payment indicators within AR checkout flows.

8.4 Onboarding Strategy for AR Novices

The experience-based trust amplification finding suggests that the biggest leverage point for AR trust development is the first interaction. Managers should invest in frictionless AR onboarding experiences, including guided AR tutorials within the shopping app, gamified first-time AR use incentives (discounts for first AR try-on), social proof within AR interfaces

(showing how many others have virtually tried the product), and progressive AR feature revelation (starting with simple visualizations and unlocking more complex interactions as familiarity grows).

8.5 Segment-Specific AR Marketing

The demographic heterogeneity findings suggest that AR marketing communications should be tailored by segment. For the 18–24 segment, content should emphasize the novelty, social sharing potential, and experiential fun of AR features. For the 35–44 segment (typically higher income, higher purchase value), communications should emphasize AR's accuracy, time-saving benefits, and purchase certainty advantages. For first-time AR users, comparative advertising showing AR vs. non-AR browsing experiences can be effective in demonstrating the tangible value proposition.

8.6 Platform Ecosystem Implications

For e-commerce platform operators (marketplace model), this study suggests that seller compliance with AR quality standards should be incentivized or mandated. Poor AR implementations by individual sellers can undermine platform-level trust, given that consumers often attribute AR quality issues to the platform rather than the individual seller. Platforms should consider developing standardized AR implementation toolkits for sellers, offer AR quality scoring as a seller performance metric, and prioritize AR-quality sellers in search ranking algorithms.

9. SCOPE FOR FURTHER RESEARCH

9.1 Longitudinal Trust Dynamics

This study's cross-sectional design captures a snapshot of trust perceptions at a single point in time. Future research should employ longitudinal panel designs to examine how consumer trust in AR e-commerce evolves over time, particularly through the trust-building journey from AR discovery to habitual use. Experience sampling methods (ESM) could capture real-time trust fluctuations during AR shopping sessions, providing fine-grained insights into trust-critical moments in the AR consumer journey.

9.2 Cross-Cultural Comparative Studies

Consumer trust formation is deeply embedded in cultural context. Hofstede's cultural dimensions—particularly uncertainty avoidance and individualism-collectivism—are hypothesized to moderate AR-trust relationships differently across national contexts. Future research should conduct multi-country comparative studies examining how cultural factors amplify or attenuate AR's trust-building effects, particularly comparing high uncertainty

avoidance cultures (Japan, Germany, India) with low uncertainty avoidance cultures (Singapore, UK, Denmark).

9.3 Affective and Hedonic Dimensions of AR Trust

This study focused primarily on cognitive trust antecedents. Future research should investigate the affective (emotional) dimensions of AR-trust formation, including flow experience, AR enjoyment, telepresence, and self-congruity. The integration of psychophysiological measures (eye-tracking, galvanic skin response, facial expression analysis) with self-report trust measures could provide convergent validity for AR trust constructs and reveal implicit trust formation processes that are not captured by conscious self-reports.

9.4 Social and Collaborative AR Commerce

Emerging social AR features—including multi-user AR product try-ons, AR-enabled live commerce, and influencer-mediated AR demonstrations—represent a frontier for trust research. Future studies should examine how social dynamics in AR shopping contexts (social presence, peer influence, AR-enabled social proof) interact with individual trust formation processes. The role of AI-generated virtual influencers and avatars in AR commerce trust deserves particular attention as these become increasingly prevalent.

9.5 Privacy and Ethical Dimensions of AR Commerce

As AR features require camera access and increasingly incorporate biometric data (facial geometry, body measurements), privacy concerns represent a growing trust threat in AR commerce. Future research should develop privacy-specific trust scales for AR commerce and examine how privacy regulatory frameworks (GDPR, India's DPDP Act 2023) differentially affect consumer trust and AR adoption. The ethical dimensions of AR-based behavioral profiling and personalization also merit investigation from consumer rights and fairness perspectives.

9.6 AR in Voice and Conversational Commerce

The convergence of AR with voice assistants (Alexa, Google Assistant) and conversational AI represents an emerging multimodal shopping paradigm. Future research could examine trust formation in voice-AR hybrid interfaces, where consumers verbally request AR product demonstrations. The relative contributions of visual AR fidelity and conversational AI quality to trust in such multimodal environments remain unexplored.

9.7 Methodological Extensions

Future research should consider adopting mixed-methods designs that combine the statistical power of SEM with the depth of qualitative inquiry. In-depth interviews or cognitive

mapping techniques could reveal trust formation processes that structured surveys may fail to capture. Additionally, experimental designs with AR simulations could enable causal inference regarding specific AR features' effects on trust, overcoming the inherent limitation of this study's correlational design.

10. LIMITATIONS OF THE STUDY

The findings reported in the preceding sections should be interpreted in light of several methodological and contextual constraints. Stating these openly is not a concession of weakness but a condition for the responsible use of the results, since every boundary identified here also marks a direction in which the evidence cannot legitimately be stretched.

10.1 Constraints of the Cross-Sectional Design

Data were gathered from each respondent on a single occasion, which means the model estimates associations among constructs measured simultaneously rather than sequences unfolding over time. Although the structural paths were specified on theoretical grounds and the fit indices support the hypothesised configuration, structural equation modelling on cross-sectional data cannot establish temporal precedence. The path from Consumer Trust to Purchase Intention, for instance, is statistically indistinguishable from a specification in which purchase-inclined consumers retrospectively report higher trust in the platform they have already chosen. Reverse causality and reciprocal reinforcement between trust and intention therefore remain plausible alternative accounts of the observed covariance.

10.2 Sampling Limitations and Generalisability

The sample was assembled through purposive and snowball procedures rather than probability selection, for the practical reason that no enumerated register exists of Indian consumers who have used augmented reality features within a defined recall window. One consequence is that sampling error cannot be computed in the strict statistical sense, and inference from sample to population rests on an argument about representativeness rather than on probability theory. A second consequence is a likely bias toward digitally engaged respondents: individuals recruited through social media communities, platform forums and campus networks are, almost by construction, more comfortable with emerging interfaces than the broader online shopping population. The concentration of respondents in four metropolitan centres compounds this concern, since consumers in tier-two and tier-three cities encounter different device capabilities, bandwidth conditions and delivery infrastructures.

The age distribution reinforces the point. With 70.3 per cent of respondents aged between eighteen and thirty-four, the sample captures the early-adopter segment of augmented commerce far better than it captures older consumers, for whom the trust formation process may operate through different antecedents entirely. The multi-group comparisons reported in Section 6.7 are informative within the sample but rest on a relatively small older cohort and should be treated as indicative rather than conclusive.

10.3 Reliance on Self-Reported Measures

All constructs, including purchase intention, were captured through respondent self-report. Intention is an imperfect proxy for behaviour, and the intention-behaviour gap is well documented in consumer research: respondents who report a strong intention to purchase following an augmented reality interaction may nonetheless abandon the transaction for reasons of price, availability, household negotiation or simple inertia. No transactional records were obtained against which reported intention could be validated. Self-report also introduces the possibility of social desirability effects, particularly on items concerning technological competence, where respondents may be reluctant to report difficulty in operating an interface.

The procedural and statistical remedies described in Section 6.1 reduce but do not eliminate the risk of common method variance. Harman's single-factor test is a relatively weak diagnostic, and the assurance it provides should not be overstated.

10.4 Construct and Measurement Boundaries

The model examines cognitive antecedents of trust and gives limited attention to affective and hedonic mechanisms. Enjoyment, flow, telepresence and aesthetic pleasure are established contributors to technology response in immersive contexts, and their omission means the explained variance in trust, substantial though it is, is unlikely to be exhaustive. Similarly, perceived risk was modelled as a unidimensional moderator, whereas the construct is recognised as multidimensional; separating privacy risk from performance and financial risk might reveal that camera-based data collection operates through a mechanism quite distinct from concern about product misrepresentation.

Augmented reality was also treated as a broadly equivalent experience across product categories. In practice, a virtual eyewear try-on, a cosmetic shade simulation and the placement of furniture in a living room differ substantially in the nature of the uncertainty they resolve and in the consequences of an inaccurate rendering. Aggregating across these applications yields a general model at the cost of category-specific precision.

10.5 Temporal and Technological Currency

Field work was conducted over a three-month window in early 2024. The capability of augmented reality rendering, the sophistication of accompanying recommendation systems and the prevalence of these features across Indian platforms have all continued to develop since that period. Consumer expectations adjust as capability improves, and perceptions recorded against the technological standard of one period may not transfer intact to another. The findings should therefore be read as a well-specified account of a particular moment rather than as a durable statement about augmented commerce in general.

11. CONCLUSION

This study set out to explain how augmented reality features shape consumer trust and purchase intention in Indian e-commerce, and to identify which specific attributes of the augmented interface carry that influence. Drawing on the Technology Acceptance Model, the stimulus-organism-response framework and the established literature on online trust, an integrated structural model was specified and tested against survey data from 412 consumers with direct augmented reality shopping experience. The measurement model satisfied conventional standards of reliability, convergent validity and discriminant validity, and the structural model achieved acceptable fit while accounting for 67.4 per cent of the variance in purchase intention.

Four conclusions follow from the results. The first concerns the primacy of interactivity. Among all antecedents examined, the interactive quality of the augmented experience exerted the strongest direct effect on trust, exceeding both the classical acceptance constructs and information quality. The practical reading of this result is that augmented reality earns consumer confidence through what it allows the consumer to do rather than through what it displays. An implementation that renders a product handsomely but permits only passive viewing forfeits the greater part of the trust advantage the technology can confer.

The second concerns the route through which visual fidelity matters. Visualisation quality showed no significant direct effect on trust once information quality was accounted for, and its influence operated entirely through the latter. Visual richness, in other words, is valuable to the extent that it conveys accurate and complete information about the product; richness that does not improve the consumer's understanding of dimension, colour or material does not build confidence. This finding places representational accuracy, rather than graphical sophistication, at the centre of augmented interface design.

The third concerns the position of trust in the causal chain. Trust fully mediated the effect of information quality on purchase intention and partially mediated the effect of interactivity, confirming that augmented features do not act directly on purchase so much as they act on the confidence that permits purchase. The fourth concerns the limits of that mechanism. Perceived risk significantly attenuated the trust-intention relationship, reducing its magnitude by roughly a third among high-risk consumers. Trust, however well established, does not by itself carry a risk-averse consumer to the point of transaction; explicit reassurance regarding returns, privacy and data handling remains necessary alongside it.

Taken together, these results extend the acceptance tradition into the augmented commerce setting by demonstrating that augmented-reality-specific attributes operate both through and alongside the classical constructs, and that a model omitting the direct interactivity-to-trust path is misspecified. For practitioners, the study offers a defensible ordering of priorities: interactive fidelity first, representational accuracy second, and explicit risk mitigation as a necessary complement rather than an optional addition. For researchers, the limitations set out in Section 10 mark the most productive directions for extension, particularly longitudinal designs capable of resolving the temporal ambiguity that cross-sectional modelling cannot address, and category-specific work that distinguishes the several quite different tasks augmented reality is asked to perform in retail.

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