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Algorithmic Transparency and Immersive Retail: Investigating the Joint Effects of Explainable AI and Augmented Reality on Consumer Trust and Purchase Decisions

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Abstract

The convergence of artificial intelligence (AI) and augmented reality (AR) is reshaping digital retail, yet how algorithmic transparency, explainable AI, and AR-based immersion jointly shape consumer responses remains theoretically underdeveloped. Drawing on the Stimulus–Organism–Response (S–O–R) model, this study examines the influence of cognitive stimuli (algorithmic transparency and explainable AI) and experiential cues (AR immersion) on trust, perceived usefulness, immersion, purchase decisions, and continued usage intention. Using survey data from 420 online shoppers in the West Bank, Palestine, and analyzed via structural equation modeling, the findings indicate that cognitive evaluations—particularly perceived usefulness and trust—exert stronger effects on purchase decisions than immersion. Specifically, algorithmic transparency enhances trust, while explainable AI strengthens perceived usefulness; AR immersion contributes to engagement, but its behavioral effects remain comparatively weaker. The results suggest that experiential engagement serves as a complementary enhancer, operating most effectively when supported by transparent and useful AI systems. The study extends AI–AR commerce literature by proposing a multi-stage S–O–R framework and demonstrating the conditional role of immersion in emerging digital markets.

Keywords: algorithmic transparency; explainable AI (XAI); augmented reality (AR); immersive retail; consumer trust; purchase decisions; human–computer interaction; E-commerce; S–O–R framework

1. Introduction

The integration of artificial intelligence (AI) and augmented reality (AR) technologies has accelerated the evolution of digital retail environments, transforming how consumers search for products, evaluate alternatives, and make purchase decisions [1–4]. AI-driven recommendation systems enhance personalization by analyzing behavioral and contextual consumer data, whereas AR technologies enrich online shopping through immersive visualization and interactive product experiences [5–8]. Together, these technologies increasingly shape both cognitive evaluations and experiential engagement within contemporary e-commerce platforms [2,9].

Existing literature has extensively examined AI personalization and AR-enabled shopping experiences independently. Prior studies demonstrate that AI recommendation systems improve perceived relevance, convenience, and decision efficiency [5,10], while AR interfaces enhance sensory engagement, spatial presence, and experiential value [6–8].



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More recent work has also begun exploring the integration of AI and AR within digital commerce environments [9,11]. However, limited research has examined how specific AI governance mechanisms, particularly algorithmic transparency and explainable AI, interact with AR-based immersion to jointly shape consumer psychological and behavioral responses within a unified theoretical framework.

This gap is theoretically important because algorithmic transparency and explainable AI may influence consumers through distinct cognitive mechanisms. Transparency reduces uncertainty by serving as a credibility cue that signals accountability, openness, and procedural fairness, thus directly fostering trust [12,13]. In contrast, explainable AI enables cognitive elaboration by helping consumers understand the logic and rationale behind recommendations, thereby enhancing perceived usefulness and decision support [14]. At the same time, AR-based immersive experiences stimulate psychological engagement through both cognitive absorption and affective involvement [7,15]. Understanding how these different technological cues jointly influence consumer behavior remains insufficiently developed in current digital commerce research.

The present study addresses this issue within the context of the West Bank, Palestine, an emerging digital retail environment characterized by increasing dependence on international e-commerce platforms alongside relatively limited digital infrastructure and elevated uncertainty in online transactions. In such contexts, trust formation, transparency perceptions, and technology usefulness may play particularly important roles in shaping consumer adoption of AI-enabled retail technologies. Examining these relationships in an underrepresented emerging-market context therefore extends current understanding beyond highly digitized economies that dominate existing literature.

Grounded in the Stimulus–Organism–Response (S–O–R) framework, this study conceptualizes algorithmic transparency, explainable AI, and AR immersion as complementary technological stimuli that influence internal psychological states, including trust, perceived usefulness, and immersion, which subsequently shape purchase decisions and continued usage intention. By integrating cognitive and experiential technological mechanisms within a unified framework, the study contributes to the growing literature on AI–AR-enabled commerce and consumer behavior in emerging digital markets.

2. Theoretical Background and Hypothesis Development

2.1. Theoretical Background

2.1.1. Stimulus–Organism–Response (S–O–R) Framework

The Stimulus–Organism–Response (S–O–R) framework provides a well-established theoretical foundation for explaining how external environmental cues shape individuals' internal psychological states and subsequent behavioral responses. Rooted in environmental psychology, the framework proposes that external stimuli influence cognitive and affective evaluations within the individual (the organism), which subsequently drive observable behavioral outcomes [16,17]. In digital commerce research, the S–O–R model has been widely employed to explain how online environments, technological interfaces, and interactive platform characteristics affect consumer perceptions, emotions, and decision-making processes [2,3].

Compared with technology-centered adoption theories such as the Technology Acceptance Model (TAM) or UTAUT, the S–O–R framework is particularly suitable for AI–AR integrated commerce because it simultaneously captures both cognitive evaluations and experiential reactions. While TAM primarily emphasizes utilitarian beliefs such as perceived usefulness and ease of use [18,19], immersive commerce environments involve broader psychological mechanisms, including trust formation, sensory engagement, attentional absorption, and interactive immersion. The S–O–R framework therefore offers a more

comprehensive structure for examining how intelligent retail technologies jointly shape consumer cognition, experience, and behavior.

In AI-enabled retail ecosystems, technological stimuli extend beyond static website attributes and increasingly involve adaptive and interactive system characteristics. AI recommendation systems dynamically personalize content based on consumer behavior, whereas AR interfaces create interactive product visualization experiences that simulate physical shopping environments [6,11]. These technologies operate as distinct but complementary environmental stimuli capable of influencing both rational evaluations and experiential engagement during online shopping interactions [3,20].

In the present study, algorithmic transparency and explainable AI serve as cognitive stimuli, while AR-based immersion functions as an experiential stimulus. The specific mechanisms through which each stimulus operates are elaborated in the dedicated sections that follow (Sections 2.1.3 and 2.1.4).

The organism component of the framework reflects consumers' internal psychological processing of these technological stimuli. In digitally immersive commerce environments, these internal states encompass both cognitive and experiential dimensions. Perceived usefulness represents a cognitive evaluation concerning the extent to which technological systems improve shopping efficiency and decision quality [18,19,21]. Trust reflects consumers' confidence in the reliability, integrity, and dependability of AI-enabled systems under conditions of uncertainty and limited physical interaction [22,23]. Immersion, meanwhile, is conceptualized as a multidimensional psychological state involving attentional focus, sensory involvement, and experiential engagement within AR-supported shopping environments [7,15]. Rather than representing a purely affective response, immersion incorporates both cognitive absorption and experiential interaction.

The response component captures consumers' resulting behavioral outcomes. In e-commerce contexts, these outcomes commonly include purchase decisions and continued usage intention [9,12]. Consumers who perceive AI-enabled platforms as trustworthy, useful, and experientially engaging are more likely to complete purchases and sustain long-term interaction with the platform. Accordingly, the present study positions purchase decision and continued usage intention as the primary behavioral responses emerging from consumers' internal evaluations of AI and AR-enabled retail environments.

Overall, the S–O–R framework provides an integrative theoretical lens through which the combined effects of algorithmic transparency, explainable AI, and AR-based immersion can be examined within intelligent commerce ecosystems. By organizing these technological cues as environmental stimuli that shape cognitive and experiential organismic states, the framework enables a structured explanation of how AI–AR integration influences consumer behavioral responses in contemporary digital retail settings.

The proposed research framework is presented in Figure 1.

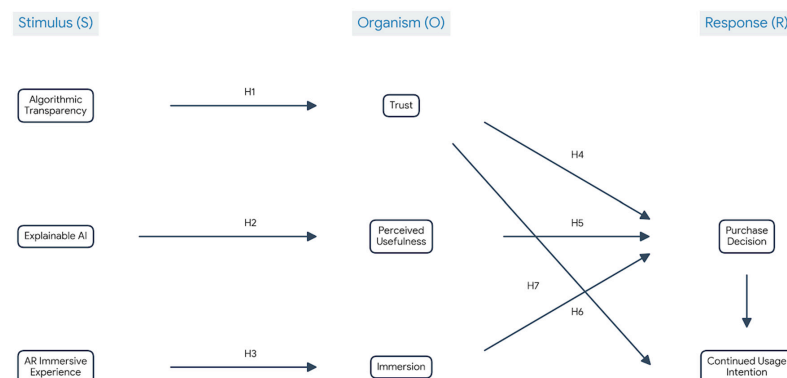


Figure 1. Conceptual research model and hypothesized relationships.

2.1.2. Trust Transfer Theory in AI-Enabled Commerce

Trust represents a central mechanism underlying consumer decision-making in digitally mediated retail environments characterized by technological complexity, information asymmetry, and limited interpersonal interaction. In electronic commerce settings, consumers frequently rely on prior beliefs regarding the credibility and reliability of digital platforms when evaluating newly encountered technological features. Trust Transfer Theory [24] explains this process by suggesting that trust developed toward a familiar entity may extend to related but less familiar components operating within the same environment. Within AI-enabled commerce, this perspective helps explain how confidence in a retail platform may shape users' evaluations of embedded algorithmic systems and automated recommendation mechanisms.

In AI-driven retail ecosystems, consumers typically cannot directly observe how recommendation algorithms generate outputs or personalize content. Consequently, evaluations of AI systems often depend on heuristic judgments regarding the broader platform environment. Prior research indicates that when consumers perceive an e-commerce platform as reliable and technologically competent, they are more likely to accept algorithmically generated recommendations and automated decision support mechanisms. Trust therefore operates as a transferable cognitive evaluation that reduces perceived uncertainty associated with opaque technological processes.

Algorithmic transparency can reinforce this trust transfer by making AI processes more interpretable and thus signaling credibility, while explainable AI primarily enhances understanding rather than directly building trust.

Within immersive retail environments, augmented reality technologies provide consumers with interactive product experiences that may reinforce confidence in the technological competence of the platform. However, in the present study, immersion is conceptualized as a distinct experiential organismic state reflecting psychological absorption and focused involvement during technology-mediated shopping experiences rather than as a direct antecedent of trust. This distinction helps maintain conceptual separation between cognitive evaluations of technological reliability and experiential responses to immersive interaction.

Accordingly, Trust Transfer Theory [25] is incorporated in this study as a complementary interpretive lens that supports the trust formation process embedded within the broader S-O-R framework rather than as an independently tested causal framework. Specifically, the theory helps explain why transparency-related technological cues may strengthen trust toward AI-enabled retail systems, which subsequently influence consumer purchase decisions and continued platform usage. By integrating trust transfer reasoning with the S-O-R perspective, the proposed framework captures how cognitive evaluations of technological credibility operate alongside experiential immersion in shaping consumer responses within AI-AR commerce environments.

2.1.3. Algorithmic Transparency and Explainable AI

The increasing use of artificial intelligence in digital commerce has transformed how consumers receive, evaluate, and act upon product-related information. AI-driven recommendation systems now serve as important decision-support mechanisms by filtering extensive product data and generating personalized suggestions aligned with users' preferences and behavioral patterns. Despite their functional advantages, many AI systems operate through computational processes that remain difficult for consumers to observe or interpret directly. This opacity, commonly described as the "black-box" nature of algorithmic decision-making, may create uncertainty regarding the fairness, reliability, and credibility of automated recommendations. Consequently, algorithmic transparency has

emerged as an important design principle for reducing information asymmetry in AI-enabled commerce environments.

Algorithmic transparency refers to the degree to which consumers can access meaningful information regarding how algorithmic outputs are generated, including the logic, data usage, and procedural basis underlying recommendation processes. In online retail settings, transparency may be conveyed through recommendation disclosures, preference-adjustment options, or indicators explaining why certain products are prioritized. Such signals help consumers evaluate whether AI systems operate in a predictable and reliable manner. Prior research suggests that transparent algorithmic communication reduces perceived uncertainty and strengthens perceptions of procedural fairness, thereby supporting trust formation toward digital platforms and embedded AI technologies. Within technology-mediated retail environments, transparency therefore functions primarily as a trust-building mechanism that signals accountability and system reliability.

Explainable artificial intelligence (XAI), while conceptually related to transparency, serves a more specific interpretive function. XAI focuses on enabling AI systems to generate human-understandable explanations that clarify how particular recommendations or decisions are produced. In retail applications, explanation mechanisms may include statements such as “recommended based on your previous purchases” or “suggested because similar users preferred this item.” Unlike general transparency signals that communicate openness, explainability facilitates consumers’ cognitive understanding of how recommendation outputs relate to their preferences and shopping goals. This interpretability can enhance users’ perceptions that AI-supported recommendations are useful, informative, and relevant to decision-making tasks. Existing research indicates that explainable interfaces improve perceived comprehension, user control, and acceptance of AI-enabled services.

From an S–O–R perspective, algorithmic transparency and explainable AI operate as distinct informational stimuli that activate different cognitive evaluations within digital retail environments. Transparency primarily reduces uncertainty and supports trust formation by signaling system integrity and accountability, whereas explainability enhances perceived usefulness by improving consumers’ understanding of recommendation relevance and functional value. Although both constructs reduce uncertainty, they do so through distinct pathways: transparency reduces uncertainty by signaling accountability and procedural fairness (thereby building trust), whereas explainability reduces uncertainty by improving comprehension of the logic behind recommendations (thereby enhancing perceived usefulness). This distinction is theoretically important because the two mechanisms influence different aspects of consumer evaluation despite both originating from AI-enabled informational cues. In this study, transparency is therefore linked primarily to trust-related evaluations, while explainable AI is associated more directly with perceptions of informational usefulness and decision support.

The role of these informational stimuli becomes more salient in retail environments where AI technologies are integrated with immersive applications such as augmented reality. In such settings, consumers encounter both algorithmic recommendations and interactive product visualizations within a unified digital experience. Transparency cues help users interpret the credibility of AI-generated suggestions, while explainable recommendation features improve understanding of why particular products are presented. Simultaneously, immersive AR interactions provide experiential confirmation by allowing consumers to evaluate products in visually enriched and interactive contexts. Through this combination of informational and experiential cues, consumers form psychological evaluations regarding the reliability and usefulness of AI-enabled retail systems.

This study further draws on Trust Transfer Theory [25] to explain how transparency-related cues facilitate confidence in embedded AI technologies. When consumers perceive

the broader digital platform as reliable and transparent, that confidence may extend to the recommendation algorithms operating within the same environment. Transparency mechanisms therefore support the transfer of trust from the platform level to less visible AI decision systems, reducing perceived uncertainty associated with automated recommendations. Within the proposed framework, algorithmic transparency and explainable AI are conceptualized as complementary informational stimuli that shape consumers' trust and perceived usefulness, which subsequently influence purchase-related decision-making in AI-enabled commerce environments.

2.1.4. Augmented Reality and Immersive Retail Experience

Augmented reality (AR) has emerged as a significant technological interface in contemporary digital retail by enabling consumers to interact with products through interactive and contextually enriched visualizations. Unlike conventional online shopping environments that primarily depend on static images and textual descriptions, AR overlays virtual product representations onto users' physical surroundings, allowing consumers to examine products through real-time spatial interaction and three-dimensional visualization [6,20]. These functionalities enhance consumers' ability to evaluate product attributes such as size, fit, appearance, and contextual compatibility before purchase. Prior research indicates that such interactive visualization capabilities reduce perceived product uncertainty and improve decision confidence by partially replicating elements of in-store product evaluation within online environments [8,26–29]. Consequently, AR technologies are increasingly adopted in e-commerce platforms to support richer product evaluation and more informed consumer decision-making.

Beyond improving product visualization, AR environments influence how consumers cognitively and affectively engage with digital retail interfaces. In technology-mediated consumption contexts, immersion refers to a multidimensional psychological state characterized by focused attention, mental absorption, perceived realism, and emotional engagement within a mediated environment [6,15]. Importantly, immersion should not be viewed solely as an affective reaction; rather, it encompasses both cognitive processes (e.g., attentional concentration and experiential processing) and affective responses (e.g., enjoyment and engagement). AR-enabled retail interfaces facilitate immersion through technological features such as interactivity, spatial augmentation, virtual try-on functions, and real-time manipulation of digital objects. These features encourage consumers to transition from passive information processing toward more active and experiential forms of product evaluation. Empirical evidence suggests that immersive AR environments enhance perceived realism, experiential engagement, and evaluative confidence, thereby strengthening consumers' assessments of product suitability and shopping quality [7,15].

Although AR system experience and immersion are conceptually associated within immersive commerce environments, they represent theoretically distinct constructs in the S–O–R framework. AR system experience reflects the technological and environmental characteristics of the stimulus, including realism, interactivity, and spatial augmentation capabilities of the platform. In contrast, immersion represents the consumer's internal psychological state characterized by attentional absorption, cognitive involvement, and experiential engagement during interaction with AR functionalities. Consistent with S–O–R logic, external technological stimuli are expected to precede and shape organismic experiential responses rather than constitute the same construct.

AR-based immersion also helps address the “product experience gap” commonly associated with online retail environments, where purchase decisions are often made using limited sensory information [6,20]. By enabling consumers to simulate product usage and visualize products within personally relevant contexts, AR supports experiential learning

and mental imagery formation during the shopping process. For instance, virtual fitting technologies allow users to assess apparel appearance on digital representations, while AR furniture applications enable consumers to evaluate spatial compatibility within their own living environments [7,11]. These experiential interactions complement informational cues provided by product descriptions and AI-generated recommendations, thereby improving consumers' ability to assess product relevance and utility. Accordingly, AR contributes not only to hedonic engagement but also to more informed and diagnostically rich decision-making processes.

Within the Stimulus–Organism–Response (S–O–R) framework, AR technological features can be conceptualized as environmental stimuli that activate internal psychological responses during digital shopping experiences [16,17]. Specifically, characteristics such as vividness, interactivity, and simulated realism function as external stimuli that shape consumers' organismic states, particularly immersion. This conceptualization is theoretically important because it distinguishes the technological environment itself from the consumer's subsequent psychological reaction to that environment. When AR interfaces are perceived as realistic, interactive, and experientially engaging, consumers are more likely to experience heightened cognitive absorption and emotional involvement with the shopping process [6,30]. These organismic responses subsequently influence downstream behavioral outcomes, including product evaluation, purchase decisions, and continued engagement with the retail platform.

The role of AR immersion becomes particularly salient in AI-enabled retail ecosystems where immersive visualization technologies operate alongside AI-driven recommendation systems. In such environments, AR serves as an experiential interface through which consumers can interact with algorithmically generated recommendations in more concrete and contextually meaningful ways [9,11]. While AI systems provide personalized informational guidance, AR enables consumers to experientially validate those recommendations through simulated product interaction. Thus, within the proposed research model, AR technological features function as experiential stimuli that foster immersion as an organismic state, which subsequently shapes consumer responses toward AI-supported retail decision-making environments.

2.1.5. AI–AR Integrated Commerce Environment

The increasing convergence of artificial intelligence (AI) and augmented reality (AR) is reshaping digital retail into technologically integrated commerce environments that combine algorithmic intelligence with immersive consumer interaction. Earlier research generally examined these technologies separately, with AI studies emphasizing recommendation systems, predictive analytics, and personalization mechanisms, while AR research focused on immersive visualization and experiential product interaction [6,7]. More recent electronic commerce research, however, suggests that consumers increasingly encounter AI and AR simultaneously within unified retail ecosystems, where algorithmic recommendations are embedded directly into interactive and immersive shopping interfaces [2,9]. Consequently, understanding how these technologies jointly shape consumer cognition and behavior has emerged as an important issue in contemporary digital commerce research.

Within integrated retail environments, AI and AR perform theoretically distinct yet complementary functions. AI-driven systems primarily operate as informational and analytical mechanisms that reduce consumers' search costs and decision complexity through personalized recommendations derived from behavioral and transactional data [1,31]. Through personalization, prediction, and adaptive learning, AI systems influence consumers' cognitive evaluations of relevance, efficiency, and decision support. By contrast, AR technologies function primarily as experiential interfaces that enable consumers to

interact with products through immersive visualization, spatial simulation, and virtual manipulation [6,20]. These immersive capabilities enrich sensory engagement and help consumers evaluate product fit, appearance, and contextual compatibility prior to purchase. Rather than operating independently, AI and AR jointly create a digitally mediated shopping environment in which analytical intelligence and experiential interaction reinforce one another [9,11].

Importantly, the integration of AI and AR transforms algorithmic recommendations from abstract informational outputs into experiential consumption encounters. AI-generated suggestions often remain cognitively evaluated at the informational level unless consumers can meaningfully contextualize the recommended products within realistic usage environments. AR interfaces address this limitation by allowing consumers to visualize and interact with recommended products in simulated real-world contexts, thereby reducing uncertainty associated with online purchasing [6,29]. This experiential validation process strengthens consumers' confidence in recommendation relevance and enhances the perceived usefulness of AI-supported retail systems. In this sense, AR does not merely complement AI technologically; it operationalizes and reinforces the experiential credibility of algorithmic recommendations.

The integration of AI and AR also enables adaptive feedback mechanisms that continuously refine personalization processes. Immersive AR interactions generate rich behavioral and contextual data, including interaction duration, object manipulation patterns, and spatial engagement behaviors [7]. When integrated into AI-driven analytics systems, these data allow recommendation algorithms to update predictive models dynamically and provide increasingly context-sensitive suggestions. Such reciprocal interaction between consumer behavior and algorithmic adaptation transforms the retail platform into an evolving intelligent environment characterized by continuous learning and personalization. Nevertheless, prior studies indicate that the effectiveness of such integrated systems may vary according to factors such as technological familiarity, digital trust, privacy concerns, and product category characteristics [22,31]. Acknowledging these contextual contingencies is important for avoiding deterministic assumptions regarding technological effectiveness.

Accordingly, the integrated AI-AR commerce environment should not be viewed merely as a technological configuration, but rather as a psychologically embedded retail ecosystem in which informational credibility and experiential engagement jointly shape consumer decision-making processes. This integrated perspective extends existing electronic commerce research by explaining how technologically distinct mechanisms collectively influence consumer cognition, emotional engagement, and behavioral intention within digitally mediated retail environments.

2.2. Hypothesis Development

Algorithmic transparency has emerged as a critical governance mechanism in AI-enabled commerce environments, particularly as consumers increasingly rely on algorithmically generated recommendations and automated decision systems. In digital retail contexts, algorithmic transparency refers to the extent to which consumers can understand how AI systems collect data, process information, and generate recommendations or decisions [12,27]. Transparency reduces informational asymmetry by making system procedures more visible and interpretable, thereby mitigating uncertainty surrounding automated decision processes. Prior research demonstrates that opaque algorithmic systems often evoke skepticism, perceived risk, and concerns regarding procedural fairness, all of which undermine user confidence in AI-mediated interactions [13,14].

Importantly, transparency primarily influences consumers through a trust-building mechanism rather than through functional utility alone. When consumers perceive that an

AI system openly communicates how recommendations are generated and how personal data are utilized, they are more likely to interpret the system as accountable, reliable, and procedurally fair [13,27]. This process aligns with trust transfer logic, whereby confidence established in the transparency of algorithmic mechanisms extends to broader evaluations of the retail platform itself [25]. In technologically mediated commerce environments characterized by limited human interaction, such trust becomes essential for reducing perceived vulnerability and encouraging reliance on AI-generated recommendations [22,32]. Accordingly, algorithmic transparency functions as an informational stimulus that strengthens consumers' trust toward AI-enabled retail systems.

H1. *Algorithmic transparency positively influences consumer trust.*

Closely related to transparency, explainable artificial intelligence (XAI) represents another mechanism designed to enhance users' understanding of algorithmic outputs. However, unlike transparency, which primarily addresses system credibility and procedural openness, explainability affects consumers through cognitive utility and interpretability mechanisms. As conceptualized in Section 2.1.3, explainable AI provides human-understandable justifications for its recommendations, allowing consumers to evaluate the rationale behind AI outputs [14,28].

From a Technology Acceptance Model (TAM) perspective, such explanations enhance perceived usefulness because they improve consumers' ability to evaluate recommendation relevance, reduce cognitive effort, and support more informed decision making [19]. Explanatory cues therefore increase perceptions that the AI system effectively assists shopping-related tasks and improves decision quality. Prior studies indicate that consumers are more likely to perceive AI systems as useful when recommendations are accompanied by meaningful and comprehensible explanations [3,14]. Thus, while transparency primarily supports trust formation through uncertainty reduction, explainability enhances perceived usefulness through improved interpretability and decision support capabilities.

H2. *Explainable AI positively influences perceived usefulness.*

Augmented reality technologies introduce an experiential layer into digital commerce by enabling consumers to interact with products through vivid visualization, spatial simulation, and real-time manipulation. Unlike conventional online shopping interfaces that rely primarily on static images and textual descriptions, AR environments provide interactive product experiences that more closely approximate physical shopping encounters [6,29]. Features such as virtual try-on systems, three-dimensional product inspection, and contextual product placement increase consumers' sensory engagement with digital content and enhance perceptions of realism and presence.

In line with its treatment in Section 2.1.4, immersion is understood as a multidimensional state involving cognitive absorption and affective engagement [6,15]. AR environments characterized by high interactivity and vividness intensify consumers' attentional concentration and experiential involvement, thereby facilitating stronger immersion experiences. Prior research in immersive retail contexts demonstrates that interactive AR interfaces significantly enhance users' sense of spatial presence, engagement, and experiential absorption [7,15]. Accordingly, AR experiential quality functions as an environmental stimulus that strengthens consumers' immersion within AI-enabled retail environments.

H3. *AR experiential quality positively influences consumer immersion.*

Trust has consistently been recognized as a central determinant of consumer behavior in electronic commerce, particularly under conditions characterized by technological complexity and information asymmetry. In AI-enabled retail environments, consumers frequently rely on algorithmic systems to filter products, personalize recommendations, and support purchase decisions. Under such circumstances, trust reduces perceived uncertainty and increases consumers' willingness to depend on AI-generated outputs [22,32]. When consumers trust the technological infrastructure underlying a digital platform, they are more likely to perceive recommendations as credible and dependable guides for purchase decisions. Prior studies consistently demonstrate that higher levels of trust increase transactional confidence and purchasing behavior in online environments [18,22].

H4. *Consumer trust positively influences purchase decisions.*

Perceived usefulness similarly represents a central cognitive mechanism underlying technology-enabled consumer behavior. Perceived usefulness refers to the extent to which consumers believe that a technological system enhances decision effectiveness and shopping efficiency [19]. In AI-enabled commerce environments, intelligent recommendation systems reduce information overload by filtering irrelevant alternatives and presenting personalized suggestions aligned with users' preferences [4]. When consumers perceive that AI-supported systems facilitate more efficient and effective shopping decisions, they are more likely to rely on the platform during purchase evaluation processes. Existing e-commerce research consistently identifies perceived usefulness as a significant predictor of behavioral intention and purchasing behavior [5,18].

H5. *Perceived usefulness positively influences purchase decisions.*

Beyond cognitive evaluations, immersive psychological engagement also shapes consumer responses within technologically enriched retail environments. Immersion reflects a state of deep mental involvement in which consumers allocate substantial attentional and emotional resources to the mediated environment [6,15]. Higher immersion enhances perceptions of product realism, personal relevance, and experiential engagement, thereby increasing consumers' behavioral involvement with the shopping process. Prior studies indicate that immersive retail experiences encourage prolonged interaction, stronger product engagement, and greater purchase intention [15,29]. Consequently, consumers experiencing stronger immersion are more likely to translate experiential engagement into actual purchase decisions.

H6. *Consumer immersion positively influences purchase decisions.*

While trust strongly influences immediate purchase behavior, its effects often extend beyond individual transactions to shape long-term platform engagement. Continued usage intention refers to consumers' willingness to repeatedly use a technological system over time [24]. In AI-enabled commerce, trust reduces uncertainty associated with future interactions and strengthens consumers' confidence in relying on automated recommendation systems during subsequent shopping activities [3]. Trust therefore reinforces psychological commitment to the platform and promotes sustained technology usage behaviors. Prior digital commerce research consistently identifies trust as a key predictor of platform continuance and user loyalty [22,32].

H7. *Consumer trust positively influences continued usage intention.*

3. Data and Methods

3.1. Sampling and Data Collection

To empirically examine the proposed research model, this study employed a quantitative cross-sectional survey design. Data were collected through a structured online questionnaire targeting consumers with prior experience using AI-enabled e-commerce platforms incorporating augmented reality (AR) shopping functionalities. The survey was distributed through social media communities, university networks, and online consumer groups across the West Bank, Palestine. The study aimed to capture consumers' evaluations of algorithmic transparency, explainable AI capabilities, and AR-enabled shopping experiences, and to investigate how these technological stimuli shape psychological states and behavioral outcomes within AI-mediated retail environments. Measurement scales were informed by prior technology adoption research [33].

Two screening questions were included at the beginning of the questionnaire to ensure respondents possessed relevant technological experience. The first asked whether participants had previously purchased products through online shopping platforms such as Amazon, Shein, AliExpress, or similar e-commerce applications commonly used in Palestine. The second asked whether respondents had interacted with AI-driven recommendation systems or AR-based visualization features, including virtual try-on and interactive product preview tools. Only respondents answering "yes" to both questions were allowed to proceed to the main questionnaire.

To further assess respondents' familiarity with AI- and AR-enabled retail technologies, participants were additionally asked to report the frequency with which they use such technologies during online shopping activities. As shown in Table 1, 21.0% reported almost daily usage, 36.4% used such features several times per week, 30.5% reported occasional usage, and 12.1% indicated very limited usage. This distribution suggests that the majority of respondents possessed recurring exposure to AI-supported and AR-enabled shopping environments, thereby supporting the suitability of the sample for evaluating the proposed constructs. Nevertheless, the relatively smaller proportion of low-frequency users suggests that consumer familiarity with immersive retail technologies remains heterogeneous, which should be considered when interpreting the findings.

A stratified convenience sampling approach was employed to reach active digital consumers within the West Bank. Because no comprehensive sampling frame exists for users of AI- and AR-enabled e-commerce technologies in Palestine, probability-based sampling was not feasible. Accordingly, the questionnaire was disseminated through targeted online communities and university mailing lists where digital shopping activity is common. Although this approach limits statistical generalizability, it is considered appropriate for theory-driven empirical investigations involving emerging technology adoption behaviors in underexamined digital commerce contexts.

Several procedural and statistical remedies were implemented to reduce the potential influence of common method bias (CMB). Procedurally, questionnaire items were randomly ordered to reduce response pattern effects, participation was anonymous, and respondents were informed that the study was conducted exclusively for academic purposes. Reverse-coded items were also incorporated into selected measurement scales to encourage attentive responses. Statistically, Harman's single-factor test was conducted following data collection. The first unrotated factor accounted for less than 50% of the total variance, suggesting that common method bias was unlikely to pose a substantial threat to the validity of the findings [34]. In addition, full collinearity variance inflation factor (VIF) values remained below recommended threshold levels, providing further evidence that common method bias was not a major concern [35].

Table 1. Descriptive statistics of sample characteristics.

Category	Sub-Category	Frequency	Percentage (%)	Cumulative %
Gender	Female	234	55.7%	55.7%
	Male	186	44.3%	100.0%
Age	18–25	177	42.1%	42.1%
	26–35	146	34.8%	76.9%
	36–45	63	15.0%	91.9%
	Above 45	34	8.1%	100.0%
Education Level	Bachelor's degree	170	40.5%	40.5%
	Master's degree	124	29.5%	70.0%
	Diploma	78	18.6%	88.6%
	High school or below	48	11.4%	100.0%
Shopping Frequency	Almost daily	88	21.0%	21.0%
	Several times/week	153	36.4%	57.4%
	Occasionally	128	30.5%	87.9%
	Very rarely	51	12.1%	100.0%
Total		420	100%	

Note: “Very rarely” refers to participants who have used AI recommendation or AR visualization features at least once but less than once per month, indicating minimal but non-zero experience with such technologies.

To assess potential non-response bias, early and late respondents were compared using independent-samples *t*-tests across key demographic and construct variables. No statistically significant differences were observed between the two groups, indicating that non-response bias was unlikely to materially affect the results.

During the data collection period, 470 questionnaires were initially distributed. After excluding incomplete responses, patterned responses, and questionnaires with excessively short completion times, 420 valid responses remained for analysis, representing an effective response rate of 89.36%. The final sample size exceeds commonly recommended thresholds for structural equation modeling and is considered adequate for estimating the proposed model and testing the hypothesized relationships [36–38].

Table 1 presents the demographic characteristics of the respondents. Female participants represented 55.7% of the sample, while 44.3% were male. The sample was relatively young, with 42.1% aged between 18 and 25 years and 34.8% between 26 and 35 years. Most respondents possessed university-level education, including bachelor's degrees (40.5%) and master's degrees (29.5%). Overall, the demographic composition reflects a digitally engaged consumer segment with substantial exposure to online retail technologies.

The demographic distribution indicates that the sample largely consisted of active and relatively young digital consumers who regularly engage with e-commerce platforms. Moreover, although respondents varied in their frequency of online shopping activities, all participants possessed at least minimal prior exposure to AI-driven recommendation systems or AR visualization features, consistent with the screening criteria employed in this study. This profile was considered appropriate for examining consumer responses toward AI-enabled retail technologies in the Palestinian digital commerce context.

3.2. Measures

To operationalize the proposed conceptual model within AI–AR integrated e-commerce environments, this study adopted a multi-construct measurement approach

grounded in the Stimulus–Organism–Response (S–O–R) framework [16]. Consistent with prior research on AI-enabled retail technologies and immersive digital commerce [9,11], eight latent constructs were specified to capture technological stimuli, consumers’ internal psychological states, and subsequent behavioral responses. All measurement items were adapted from previously validated scales and refined to reflect the specific context of AI-driven recommendation systems and AR-based shopping experiences in the West Bank, Palestine. Minor wording modifications were introduced to ensure contextual clarity while preserving the conceptual meaning of the original scales. All constructs were measured using a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

The stimulus dimension represents external technological cues that shape consumers’ perceptions and experiences within AI-enabled retail environments. Algorithmic transparency was measured using three items adapted from prior studies on transparency and AI disclosure [13,27]. These items assess the extent to which consumers perceive the recommendation system as open, understandable, and observable in its decision-making processes. Explainable AI (XAI) was operationalized using a three-item scale adapted from Shin [14] and Ribeiro et al. [28], capturing users’ perceptions regarding the clarity and usefulness of AI-generated explanations accompanying product recommendations. AR system experience was measured using three items adapted from prior augmented reality retail studies [6–8], focusing on realism, sensory engagement, and perceived presence during virtual shopping interactions.

The organism dimension reflects consumers’ internal psychological states activated by technological stimuli. In line with the S–O–R framework, this study conceptualized these states as comprising both cognitive evaluations and experiential engagement processes [16]. Trust was measured through three items adapted from prior research on online trust and AI-enabled commerce [18,22,32], reflecting perceptions of platform reliability, integrity, and confidence in AI-generated recommendations. Perceived usefulness was assessed using three items derived from Davis’s Technology Acceptance Model (TAM) framework and subsequent digital commerce research [2,21], capturing the extent to which consumers perceive that integrated AI and AR functionalities improve shopping efficiency and decision quality. Immersion was conceptualized as a multidimensional psychological state involving both cognitive absorption and affective engagement within the AR shopping environment. Accordingly, three items adapted from AR experience literature [6,7] were used to measure users’ attentional focus, engagement, and sense of psychological involvement during AR-assisted shopping interactions.

The response dimension captures consumers’ behavioral intentions resulting from these internal psychological states. Purchase decision was measured using three items adapted from prior AI-enabled commerce studies [9,24], reflecting users’ likelihood of purchasing products after interacting with AI recommendation and AR visualization features. Continued usage intention was measured with three items assessing consumers’ intentions to continue using the platform for future online shopping activities [9,24]. Together, these constructs represent the behavioral response component of the S–O–R framework by linking technological stimuli and psychological states to observable consumption intentions.

Table 2 presents the full set of measurement items, while detailed reliability and validity results are reported in subsequent sections. The complete questionnaire is provided in Appendix A.

Table 2. Questionnaire Content.

Variable	Item	Measurement Statement
Algorithmic Transparency (AT)	AT1	The platform clearly discloses how its recommendation system operates.
	AT2	I can see the factors that influence the recommendations I receive.
	AT3	The decision-making process of the system is transparent and observable.
Explainable AI (EAI)	EAI1	The platform provides clear explanations for why specific products are recommended to me.
	EAI2	The explanations provided by the system are easy to understand.
	EAI3	The system's explanations help me evaluate whether the recommendations are appropriate.
AR system experience (AR)	AR1	The AR features create a realistic shopping environment similar to physical stores.
	AR2	I feel as if I am physically interacting with products when using AR features.
	AR3	The AR experience enhances my sense of presence within the shopping environment.
Trust (TR)	TR1	I trust that the platform handles my personal information securely.
	TR2	I believe the platform provides reliable and honest information.
	TR3	I trust the recommendations provided by the system.
Perceived Usefulness (PU)	PU1	Using this platform improves my efficiency in finding suitable products.
	PU2	The AI and AR features enhance the quality of my purchase decisions.
	PU3	Overall, the platform is useful for achieving my shopping goals.
Immersion (IM)	IM1	I feel deeply engaged when interacting with AR features on the platform.
	IM2	I lose awareness of my surroundings while using AR shopping features.
	IM3	The AR experience fully captures my attention during the shopping process.
Purchase Decision (PD)	PD1	I am more likely to purchase products after interacting with this platform.
	PD2	The platform increases my confidence in making purchase decisions.
	PD3	I often decide to buy products based on the platform's features and recommendations.
Continued Usage Intention (CUI)	CUI1	I intend to continue using this platform in the future.
	CUI2	I will regularly use this platform for online shopping.
	CUI3	I will frequently use this platform when making purchase decisions.

4. Results

4.1. Common Method Bias and Robustness Assessment

Given that the study employed a cross-sectional, self-reported survey design, several procedural and statistical remedies were implemented to reduce the potential influence of common method variance (CMV) [34,35].

First, Harman's single-factor test was conducted through an unrotated exploratory factor analysis including all measurement items. The results indicated that the first unrotated factor accounted for 26.84% of the total variance, which does not represent a dominant proportion of the covariance structure. Consistent with prior SEM research, this finding suggests that CMV is unlikely to substantially distort the observed relationships among the study constructs rather than conclusively eliminating the possibility of method bias [34].

Second, procedural remedies recommended by Podsakoff et al. [34] were incorporated during questionnaire design and data collection. Specifically, respondent anonymity and confidentiality were emphasized to reduce evaluation apprehension and socially desirable responding. Questionnaire items were also randomized to minimize pattern answering and respondents' implicit attempts to infer theoretical relationships among constructs. In addition, reverse-coded items were included where conceptually appropriate to reduce acquiescence bias.

Third, to strengthen methodological rigor, a non-response bias assessment was conducted by comparing early and late respondents across key demographic characteristics and principal construct means. The analysis revealed no statistically significant differences between the two groups, suggesting that non-response bias is unlikely to materially affect the results.

Collectively, these procedural and statistical assessments provide reasonable evidence that common method-related distortions are unlikely to substantially compromise the robustness of the subsequent SEM analysis.

4.2. Validity Analysis

To evaluate the adequacy of the measurement model, confirmatory factor analysis (CFA) was conducted using AMOS 28 based on covariance-based structural equation modeling (CB-SEM) procedures. The assessment focused on overall model fit, construct reliability, convergent validity, and discriminant validity prior to testing the structural relationships proposed within the S–O–R framework.

As reported in Table 3, the measurement model demonstrated satisfactory fit with the observed data across multiple goodness-of-fit indices ($\chi^2/df = 1.527$; GFI = 0.948; AGFI = 0.929; CFI = 0.982; TLI = 0.978; RMSEA = 0.036). All indices exceeded the commonly recommended threshold values suggested by Hu and Bentler [39] and Kline [38], indicating that the latent construct structure adequately represented the covariance matrix of the observed indicators. Given that the subsequent structural model retained the same latent configuration with limited additional constraints, only marginal differences in fit statistics were expected between the measurement and structural models.

Table 3. CFA Model Fit Indices.

Index Category	Name of Index	Acceptance Level	Index Value	Model Fit
Absolute Fit	CMIN/df	<3.0	1.527	Yes
	GFI	>0.90	0.948	Yes
	RMSEA	<0.08	0.036	Yes
Incremental Fit	AGFI	>0.90	0.929	Yes
	CFI	>0.90	0.982	Yes
	TLI	>0.90	0.978	Yes

Convergent validity was subsequently assessed using standardized factor loadings, composite reliability (CR), and average variance extracted (AVE), following the recommendations of Fornell and Larcker [36]. As shown in Table 4, all standardized factor loadings were statistically significant ($p < 0.001$) and exceeded the recommended threshold of 0.70, supporting indicator reliability. In addition, CR values ranged from 0.892 to 0.936, surpassing the recommended minimum value of 0.70, while AVE values ranged from 0.673 to 0.785, exceeding the recommended threshold of 0.50 [36,39]. Collectively, these findings support satisfactory internal consistency and convergent validity across all latent constructs.

Table 4. Reliability and Convergent Validity of the Measurement Model.

Construct	Measurement Item	Std. Loading	AVE	CR
Algorithmic Transparency (AT)	AT1	0.861	0.693	0.901
	AT2	0.834		
	AT3	0.742		
Explainable AI (EAI)	EAI1	0.873	0.722	0.912
	EAI2	0.845		
	EAI3	0.756		
AR system experience (AR)	AR1	0.889	0.755	0.924
	AR2	0.861		
	AR3	0.768		
Trust (TR)	TR1	0.871	0.704	0.905
	TR2	0.842		
	TR3	0.781		
Perceived Usefulness (PU)	PU1	0.865	0.689	0.896
	PU2	0.821		
	PU3	0.759		
Immersion (IM)	IM1	0.882	0.738	0.918
	IM2	0.847		
	IM3	0.773		
Purchase Decision (PD)	PD1	0.861	0.673	0.892
	PD2	0.824		
	PD3	0.748		
Continued Usage Intention (CUI)	CUI1	0.888	0.785	0.936
	CUI2	0.842		
	CUI3	0.782		

Note: CR = Composite Reliability; AVE = Average Variance Extracted. All factor loadings are significant at the $p < 0.001$ level. Descriptive statistics for all measurement items are reported in Appendix B. Beyond statistical adequacy, the measurement properties also support the conceptual distinction between the cognitive and affective dimensions embedded within the proposed framework. Specifically, constructs such as perceived usefulness and trust capture evaluative cognitive assessments associated with technology acceptance and risk reduction, whereas immersion reflects a broader experiential state involving attentional engagement and psychological absorption during AR interaction. Although moderate correlations were observed among several constructs, particularly between AR system experience and immersion, the magnitudes remained below critical thresholds, suggesting conceptual relatedness without empirical redundancy.

Discriminant validity was further examined using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT), reflecting recent recommendations for more rigorous construct validation in SEM research. As reported in Table 5, the square root of the AVE for each construct exceeded its corresponding inter-construct correlations, satisfying the Fornell–Larcker criterion [40]. These findings indicate that each construct explains more variance in its own indicators than in other latent variables within the model.

Table 5. Discriminant Validity (Fornell–Larcker Criterion).

Constructs	AT	EAI	AR	TR	PU	IM	PD	CUI
AT	(0.833)							
EAI	0.421	(0.850)						
AR	0.398	0.436	(0.869)					
TR	0.512	0.548	0.467	(0.839)				
PU	0.476	0.521	0.489	0.563	(0.830)			
IM	0.392	0.447	0.615	0.458	0.482	(0.859)		
PD	0.441	0.498	0.532	0.587	0.564	0.521	(0.820)	
CUI	0.417	0.462	0.508	0.573	0.546	0.498	0.622	(0.886)

Note: Values on the diagonal represent the square root of the average variance extracted ($\sqrt{\text{AVE}}$), while off-diagonal values indicate inter-construct correlations.

To provide a more conservative assessment of discriminant validity, HTMT ratios were additionally evaluated following Henseler et al. [41]. Although HTMT was initially introduced within variance-based SEM literature, recent SEM research has increasingly adopted the criterion as a general diagnostic for construct distinctiveness across SEM approaches. As shown in Table 6, all HTMT values remained below the conservative threshold of 0.85, supporting adequate discriminant validity and indicating that the latent constructs capture empirically distinguishable conceptual domains.

Table 6. Heterotrait–Monotrait Ratio (HTMT).

Constructs	AT	EAI	AR	TR	PU	IM	PD	CUI
AT	—							
EAI	0.487	—						
AR	0.463	0.502	—					
TR	0.612	0.638	0.544	—				
PU	0.571	0.603	0.566	0.671	—			
IM	0.455	0.518	0.722	0.529	0.548	—		
PD	0.529	0.581	0.617	0.702	0.688	0.603	—	
CUI	0.504	0.552	0.589	0.691	0.672	0.577	0.741	—

Note: HTMT values below the 0.85 threshold are generally considered to indicate adequate discriminant validity [29].

In addition, variance inflation factor (VIF) values were examined during the structural analysis stage to assess potential multicollinearity concerns among predictor constructs. All VIF values remained below the recommended threshold of 3.3, suggesting that collinearity did not materially threaten parameter estimation or interpretability.

4.3. Structural Model Assessment, Mechanism Analysis, and Mediation Testing

After establishing the adequacy of the measurement model, the structural model was estimated using covariance-based structural equation modeling (CB-SEM) to examine the hypothesized relationships among the latent constructs. The structural model demonstrated satisfactory overall fit to the observed data. As reported in Table 7, the fit indices exceeded the recommended threshold values ($\chi^2/\text{df} = 1.527$; CFI = 0.982; TLI = 0.978; RMSEA = 0.036), indicating acceptable correspondence between the proposed theoretical structure and the empirical covariance matrix [36,39].

Table 7. Structural Model Fit Indices.

Index	Acceptance Level	Value
CMIN/df	<3.0	1.527
CFI	>0.90	0.982
TLI	>0.90	0.978
RMSEA	<0.08	0.036

The structural model fit indices were nearly identical to those of the measurement model because the structural specification introduced limited additional constraints beyond the validated latent measurement structure. Such similarity may occur in CB-SEM when the theoretical model closely aligns with the covariance structure of the latent constructs and does not substantially reduce model flexibility [36].

The standardized structural path coefficients are presented in Table 8. The results indicate that all hypothesized relationships are positive and statistically significant at $p < 0.001$. Specifically, algorithmic transparency significantly influences trust ($\beta = 0.46$), supporting the argument that transparent algorithmic processes reduce uncertainty and strengthen consumer confidence in AI-enabled retail systems. Explainable AI positively affects perceived usefulness ($\beta = 0.49$), suggesting that interpretability and understandable system outputs enhance consumers' evaluations of system utility and decision support functionality. In addition, AR system experience significantly affects immersion ($\beta = 0.44$), indicating that interactive and vivid AR environments increase consumers' psychological involvement during online shopping interactions. In this study, AR system experience refers to consumers' perceptions of the technological characteristics of the AR environment (e.g., interactivity and vividness), whereas immersion reflects the resulting psychological state of cognitive and affective involvement.

Table 8. Structural Path Coefficients and Hypothesis Testing.

Hypothesis	Path	β	S.E.	C.R.	p -Value	Result
H1	AT $\rightarrow$ TR	0.46	0.052	8.85	***	Supported
H2	EAI $\rightarrow$ PU	0.49	0.048	10.21	***	Supported
H3	AR $\rightarrow$ IM	0.44	0.055	8.02	***	Supported
H4	TR $\rightarrow$ PD	0.34	0.049	6.94	***	Supported
H5	PU $\rightarrow$ PD	0.41	0.047	8.72	***	Supported
H6	IM $\rightarrow$ PD	0.23	0.051	4.51	***	Supported
H7	TR $\rightarrow$ CUI	0.52	0.046	11.30	***	Supported

Note: *** $p < 0.001$.

At the organism–response level, trust ($\beta = 0.34$), perceived usefulness ($\beta = 0.41$), and immersion ($\beta = 0.23$) all exert significant positive effects on purchase decision. Among these predictors, perceived usefulness demonstrates the largest standardized effect size, suggesting that functional evaluations of technological value may play a comparatively stronger role in shaping purchase decisions within AI-enabled retail environments. However, the significant effect of immersion also indicates that experiential engagement contributes meaningfully to consumer behavioral responses. Furthermore, trust significantly influences continued usage intention ($\beta = 0.52$), emphasizing the importance of trust formation in sustaining long-term interaction with AI-supported commerce platforms.

The structural model did not include a direct path from purchase decision (PD) to continued usage intention (CUI). Therefore, no sequential mediation through PD was formally estimated in the final structural model.

To evaluate the explanatory power of the model, the coefficients of determination (R^2) were examined for all endogenous constructs. As shown in Table 9, the model explains 58% of the variance in purchase decision and 42% of the variance in continued usage intention, indicating acceptable explanatory capability for the primary behavioral outcomes. In contrast, lower R^2 values were observed for trust (0.21), perceived usefulness (0.24), and immersion (0.19). These findings suggest that although the proposed technological stimuli significantly influence consumers' internal evaluations, a considerable proportion of variance remains unexplained. Additional factors, such as technological familiarity, platform reputation, product type, perceived risk, and digital literacy, may further contribute to the formation of trust, usefulness perceptions, and immersive engagement in AI–AR commerce environments.

Table 9. Coefficient of determination (R^2) for endogenous constructs.

Construct	R^2	Interpretation
TR	0.21	Moderate
PU	0.24	Moderate
IM	0.19	Weak–Moderate
PD	0.58	Substantial
CUI	0.42	Moderate–High

Because the S–O–R framework assumes that environmental stimuli influence behavioral responses through internal psychological states, additional mediation analysis was conducted to evaluate the indirect transmission mechanisms linking technological stimuli and consumer responses.

To examine the indirect effects underlying the proposed relationships, mediation analysis was conducted using bootstrapping with 5000 resamples. As reported in Table 10, all estimated indirect effects were statistically significant because the associated 95% confidence intervals excluded zero. Specifically, algorithmic transparency indirectly influenced purchase decision through trust ($\beta = 0.142$), while explainable AI indirectly affected purchase decision through perceived usefulness ($\beta = 0.181$). Similarly, AR experience exerted an indirect influence on purchase decision through immersion ($\beta = 0.094$). These findings support the proposed S–O–R mechanism in which technological stimuli shape behavioral responses through internal psychological evaluations.

Table 10. Indirect Effects and Specific Mediation Testing.

Path	Indirect Effect (β)	Boot SE	95% CI (LL–UL)	Result
AT → TR → PD	0.142	0.031	[0.089, 0.210]	Supported
EAI → PU → PD	0.181	0.033	[0.124, 0.248]	Supported
AR → IM → PD	0.094	0.027	[0.051, 0.153]	Supported

Note: Bootstrapping based on 5000 resamples; CI = confidence interval. Mediation is supported when zero is not included within the confidence interval.

Importantly, the mediation results indicate indirect-only mediation rather than full mediation because the study did not estimate competing direct paths from the technological stimulus variables (AT, EAI, and AR) to purchase decision. Therefore, the findings should

be interpreted as evidence supporting theoretically mediated relationships rather than definitive proof of full mediation effects [42].

From a theoretical perspective, the findings provide empirical support for the applicability of the S–O–R framework in explaining consumer responses to AI–AR-enabled retail technologies. The results indicate that technological stimuli influence behavioral outcomes through differentiated psychological mechanisms, including trust formation, usefulness evaluation, and immersive engagement. While perceived usefulness exhibited the strongest association with purchase decision among the organism variables, the findings should not be interpreted as diminishing the relevance of experiential processes. Rather, they suggest that utilitarian and experiential evaluations jointly contribute to consumer decision-making in digitally augmented commerce environments.

The findings contribute to the emerging literature on AI-enabled retail technologies by demonstrating how algorithmic transparency, explainability, and AR experience operate through distinct psychological pathways. In particular, transparency appears more closely associated with uncertainty reduction and trust formation, whereas explainability contributes primarily to consumers' assessments of functional utility and decision support quality.

Finally, although the model demonstrates satisfactory explanatory capability for purchase behavior and continuance intention, the relatively lower R^2 values for trust, perceived usefulness, and immersion indicate the potential relevance of additional contextual and individual-level variables. Future research may therefore examine moderating effects associated with product category, consumer technological readiness, digital literacy, and cultural context. Figure 2 presents the final structural model with standardized path coefficients and explained variance (R^2).

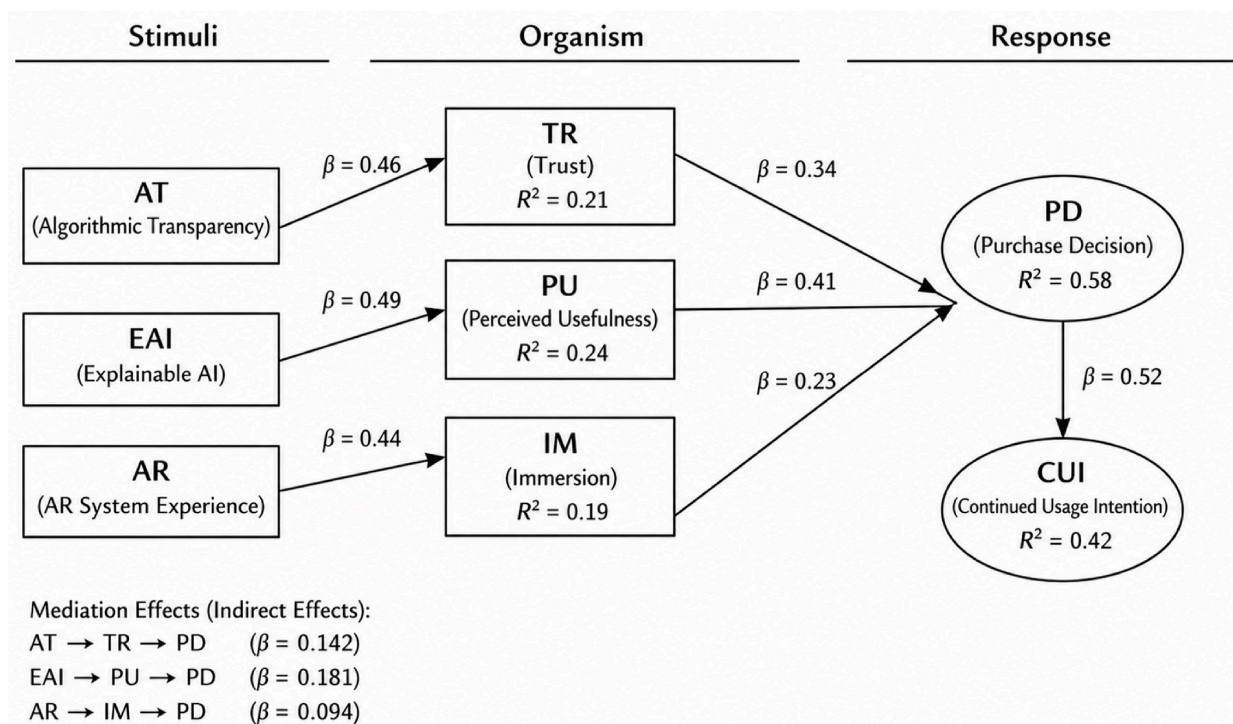


Figure 2. Final structural model with standardized path coefficients and explained variance (R^2). Only hypothesized and empirically tested paths are displayed. All structural relationships are significant at $p < 0.001$.

5. Discussion

Drawing on the Stimulus–Organism–Response framework, the present study offers a comparative, mechanism-driven account of how AI and AR technologies jointly influence

consumer behavior in digital retail settings. Unlike prior work that often treats AI and AR effects as complementary or roughly equal in strength, the current findings reveal a structurally asymmetric causal architecture in which cognitive mechanisms consistently outweigh experiential pathways [9,16].

More specifically, algorithmic transparency ($\beta = 0.46$) and explainable AI ($\beta = 0.49$) primarily activate trust and perceived usefulness, respectively [13,14,28], whereas AR system experience ($\beta = 0.44$) predominantly drives immersion [6–8]. Although this differentiation aligns with earlier conceptualizations of AI as a cognitive stimulus and AR as an experiential enhancer [16,24], the present results go further by demonstrating that these organismic states do not contribute equally to behavioral outcomes. In doing so, they extend recent S-O-R reviews that acknowledge multiple organismic pathways but do not clearly establish their relative dominance [3].

A central contribution of the study lies in resolving an ongoing debate within immersive commerce literature. Prior research frequently positions immersion as a primary driver of consumer behavior, suggesting that heightened sensory engagement leads directly to stronger purchase intentions [15,17]. The current findings challenge that assumption: perceived usefulness ($\beta = 0.41$) and trust ($\beta = 0.34$) exert significantly stronger effects on purchase decisions than immersion ($\beta = 0.23$). Thus, contrary to immersion-centric narratives, experiential engagement alone is insufficient to generate behavioral outcomes. Instead, consumers rely more heavily on functional evaluation and decision support value—a pattern consistent with technology acceptance research [18,32] but at odds with immersion dominant models.

This contradiction carries theoretical weight. Studies such as [6] and [8] emphasize the transformative role of AR in enhancing engagement and purchase intention, yet the present results suggest that such effects are conditional rather than universal. Immersion appears to function as a secondary enhancer whose influence becomes behaviorally relevant only after cognitive validation has been established [9,11]. The finding thus extends immersive experience theory by introducing a hierarchical structure in which experiential value depends on prior cognitive appraisal rather than acting as an independent driver.

Mediation analysis reinforces this comparative picture. Cognitive mediation pathways are consistently stronger than affective ones. For instance, the indirect effect of explainable AI through perceived usefulness ($\beta = 0.181$) surpasses the experiential pathway ($AR \rightarrow IM \rightarrow PD$, $\beta = 0.094$). This pattern supports recent arguments that AI-driven systems influence consumer behavior primarily through internal evaluative processes rather than direct emotional stimulation [2,43], while also refining those perspectives by empirically ranking the relative strength of competing mechanisms.

At the same time, these findings partly diverge from trust-centric literature, which often positions trust as the dominant mediator in AI-enabled environments [22,32]. Trust remains a significant predictor, especially for continued usage intention ($\beta = 0.52$), yet the present study demonstrates that perceived usefulness consistently exerts stronger direct and indirect effects on purchase behavior [14,24]. In transactional contexts, consumers appear to prioritize performance-based evaluation over relational assurance, thereby refining trust transfer theory [25] by positioning trust as a complementary rather than dominant pathway in purchase decision formation.

Another comparative insight emerges from the sequential mediation structure linking trust and perceived usefulness to continued usage intention through purchase decision. While prior research acknowledges the importance of trust for long-term engagement [3,13], it often treats behavioral intention as a direct outcome. The current findings reveal a multi-stage behavioral formation process in which purchase decision acts as a critical intermediary. This extends existing models by demonstrating that consumer loyalty is

behaviorally constructed rather than immediately formed, adding temporal depth to the S–O–R framework.

From a contextual perspective, the findings also provide boundary condition insights largely absent from prior AI–AR research. In emerging digital markets such as the West Bank, where technological uncertainty and institutional trust may be comparatively low, the dominance of cognitive mechanisms suggests that consumers rely more heavily on clarity, transparency, and functional value. This contrasts with findings from more mature markets, where experiential engagement may play a stronger role [22]. Hence, the study highlights that the relative importance of cognitive versus experiential pathways is context dependent rather than universally fixed.

Overall, this study advances the S–O–R framework beyond simple validation toward comparative theoretical refinement. It demonstrates that AI–AR-enabled consumer behavior is governed by a cognitively dominant, hierarchically structured, multi-stage causal system in which: (i) cognitive evaluation precedes experiential engagement, (ii) perceived usefulness outweighs trust in transactional decisions, and (iii) immersion operates as a conditional enhancer rather than a primary driver. This integrated perspective reconciles conflicting findings in the prior literature and establishes a clear theoretical position, thereby elevating the explanatory power of S–O–R in intelligent and immersive retail environments.

5.1. Theoretical Implications

The present study contributes to the emerging literature on AI-enabled commerce by extending the application of the S–O–R framework within integrated AI–AR retail environments. While prior studies have frequently examined AI-driven personalization, algorithmic transparency, explainable AI, or augmented reality independently, limited research has investigated their simultaneous operation within a unified behavioral framework. By incorporating algorithmic transparency, explainable AI, and AR system experience into a single S–O–R model, the study provides a more integrated explanation of how multiple technological stimuli jointly shape consumer responses in digitally augmented retail settings [2,3]. Unlike prior work that examined these technologies in isolation, this study demonstrates how cognitive and experiential stimuli operate through distinct, empirically ranked pathways within a unified model.

A central theoretical contribution lies in demonstrating that cognitive evaluations, particularly perceived usefulness, represent an important mechanism linking AI-related technological stimuli to purchase behavior. The relatively stronger effect of perceived usefulness on purchase decision, compared with immersion, suggests that consumers in AI-enabled commerce environments may place substantial emphasis on functional utility and decision-support value when evaluating advanced retail technologies. Nevertheless, the significant influence of immersion indicates that experiential engagement also contributes meaningfully to consumer behavioral responses. Rather than establishing a strict hierarchy between cognition and experience, the findings suggest that utilitarian and experiential processes operate concurrently within digitally mediated shopping environments.

The study further contributes to the literature on algorithmic transparency and explainable AI by demonstrating that these constructs influence consumer behavior through differentiated psychological mechanisms. Specifically, algorithmic transparency appears to strengthen trust by reducing uncertainty and enhancing perceptions of system credibility, whereas explainable AI primarily enhances perceived usefulness by improving consumers' understanding of system outputs and decision-support capabilities. This distinction provides additional conceptual precision regarding how transparency-related technological attributes operate within AI-enabled commerce systems [12–14].

In addition, the findings reinforce the applicability of the S–O–R framework for explaining consumer responses to technologically enhanced retail environments. Within the proposed model, technological stimuli function as external environmental cues, whereas trust, perceived usefulness, and immersion represent internal psychological states that shape subsequent behavioral responses. The results also demonstrate how TAM-related cognitive evaluations, particularly perceived usefulness, can be theoretically integrated within the broader S–O–R structure to explain consumer decision-making in AI-supported commerce contexts.

Another contribution concerns the role of AR system experience in shaping immersion. By conceptualizing AR system experience as consumers' evaluations of technological characteristics such as interactivity and vividness, the study distinguishes the external technological stimulus from the resulting psychological state of immersion. This clarification contributes to immersive commerce research by separating technological design features from consumers' internal cognitive and affective engagement processes [6,15,20].

Finally, the study contributes contextual evidence from an emerging digital commerce environment characterized by evolving consumer trust structures and varying levels of technological familiarity. The findings therefore provide additional insight into how AI- and AR-enabled retail technologies operate within developing digital market contexts, where issues related to trust formation, system understanding, and technology acceptance may become particularly salient.

5.2. Practical Implications

The findings offer actionable implications for e-commerce practitioners, especially those integrating AI and AR technologies into digital retail environments. First, the strong effect of algorithmic transparency on trust ($\beta = 0.46$) and the subsequent impact of trust on both purchase decision ($\beta = 0.34$) and continued usage intention ($\beta = 0.52$) indicate that transparency should be treated as a strategic design priority rather than a technical add-on. Firms should actively disclose how recommendation systems operate, provide clear explanations of data usage, and incorporate user-facing transparency cues (e.g., "why this product is recommended"). Such practices enhance perceived fairness and credibility, which are critical for sustaining long-term user engagement [13,14].

Second, the dominant role of perceived usefulness in driving purchase decisions ($\beta = 0.41$) and its stronger mediation effects relative to trust highlight the necessity of prioritizing functional value in AI system design. Retailers should focus on improving recommendation accuracy, relevance, and decision support capabilities rather than relying solely on advanced technological features. AI systems must demonstrably reduce search effort, improve decision quality, and deliver personalized value to users, aligning with prior research that emphasizes perceived usefulness as the most critical determinant of technology adoption and consumer decision making in digital commerce [18,19].

Third, while AR system experience significantly enhances immersion ($\beta = 0.44$), its relatively weaker effect on purchase decision ($\beta = 0.23$) and indirect influence ($\beta = 0.094$) suggest that experiential technologies alone are insufficient to drive conversion outcomes. AR functionalities should therefore be strategically integrated with AI-driven features to create a balanced experience combining engagement with utility. For instance, AR try-on tools should be complemented with intelligent recommendations, product comparisons, and contextual explanations to ensure that immersive experiences translate into actual purchasing behavior [9,11,18].

Fourth, the mediation results reveal that consumer behavior is shaped through multi-stage cognitive and affective processes rather than direct technological influence. Platform designers should adopt a holistic experience architecture that simultaneously addresses

trust formation, cognitive evaluation, and experiential engagement. In practice, this involves synchronizing transparency mechanisms (to build trust), explainability features (to enhance usefulness), and immersive interfaces (to increase engagement) within a unified system design. Such integration is critical for maximizing the overall effectiveness of AI–AR ecosystems in influencing consumer decisions [16,22].

Finally, the substantial explanatory power of the model for purchase decision ($R^2 = 0.58$) and continued usage intention ($R^2 = 0.42$) underscores the strategic importance of investing in AI–AR integration as a driver of competitive advantage. Retailers operating in emerging markets, such as the West Bank context examined here, can particularly benefit from these technologies by enhancing user trust, reducing uncertainty, and improving decision efficiency. Digital transformation strategies should therefore not only focus on technology adoption but also on optimizing the psychological mechanisms through which these technologies influence consumer behavior.

Overall, the successful deployment of AI and AR in e-commerce requires a balanced, user-centric approach that integrates transparency, usefulness, and immersive experience into a coherent strategic framework [9,11,19].

5.3. Limitations and Future Research

Despite its theoretical and empirical contributions, the present study is subject to several limitations that also provide meaningful directions for future research.

First, the study was conducted within a single-country context (West Bank–Palestine), which may limit the generalizability of the findings across different cultural, economic, and technological environments. Consumer responses to algorithmic transparency, explainable AI, and AR-related experiences are likely influenced by contextual factors such as digital infrastructure, technological familiarity, and institutional trust. Future cross-cultural and multi-country investigations are therefore necessary to determine whether the observed relationships remain stable across markets characterized by varying levels of digital maturity and AI adoption.

Second, the cross-sectional design restricts the ability to capture the dynamic evolution of consumer perceptions and behavioral responses over time. Constructs such as trust, perceived usefulness, immersion, and continued usage intention may develop progressively through repeated interactions with AI-enabled retail systems. Accordingly, longitudinal research designs would provide stronger insight into causal ordering, temporal stability, and the persistence of consumer engagement within AI–AR commerce environments.

Third, although the model demonstrated acceptable explanatory capability for the primary behavioral outcomes, particularly purchase decision ($R^2 = 0.58$), the explanatory power for trust, perceived usefulness, and immersion remained comparatively moderate. This suggests that substantial variance in these organism variables may be influenced by additional psychological, technological, and contextual factors not incorporated within the present framework. Future studies should therefore consider integrating constructs such as technology readiness, perceived risk, privacy concerns, platform reputation, product involvement, and digital literacy, and perceived intrusiveness [44] to achieve a more comprehensive understanding of consumer behavior in AI-enabled commerce settings.

Fourth, the present study examined primarily direct and mediated linear relationships within the S–O–R framework without incorporating moderating mechanisms or contextual boundary conditions. The effectiveness of AI transparency, explainability, and AR system experience may vary according to user expertise, product category, cultural orientation, or platform design characteristics. Future research employing moderation analysis and conditional process modeling could provide more nuanced insight into when and for whom AI–AR technologies exert stronger behavioral effects.

Fifth, while AR system experience was modeled as a unified technological stimulus, the study did not separately evaluate specific experiential dimensions such as vividness, interactivity, or telepresence. Distinguishing these subdimensions may provide greater conceptual precision regarding how technological characteristics generate psychological immersion and behavioral engagement. Future research should therefore decompose AR-related experiences into more differentiated constructs to refine theoretical understanding of experiential mechanisms within digital retail environments.

Finally, future studies may benefit from adopting experimental and mixed-method approaches to complement SEM-based findings. Experimental designs would allow researchers to manipulate transparency, explainability, and AR-related features under controlled conditions, thereby strengthening causal inference. In parallel, qualitative approaches such as interviews, observational studies, or user-experience analysis could provide deeper insight into how consumers cognitively and emotionally interpret AI-driven retail interactions.

Overall, the present study contributes to the emerging literature on integrated AI–AR commerce by identifying differentiated cognitive and experiential pathways within the S–O–R framework. Future research should continue refining these mechanisms through broader contextual settings, longitudinal evidence, additional explanatory variables, and more advanced analytical approaches.

6. Conclusions

This study examined how algorithmic transparency, explainable AI, and AR-enabled immersive experiences jointly influence consumer responses within AI–AR integrated retail environments. Drawing on the S–O–R framework and integrating insights from technology acceptance and trust-based perspectives, the study investigated how cognitive and experiential stimuli shape trust, perceived usefulness, immersion, purchase decisions, and continued usage intention among online consumers in the West Bank, Palestine.

The findings indicate that cognitive evaluation mechanisms—particularly perceived usefulness and trust—play a more substantial role in shaping purchase-related responses than immersive experience alone. While AR-based immersion contributed positively to consumer engagement, the results suggest that immersive features may be most effective when supported by transparent, understandable, and functionally valuable AI systems.

Unlike prior studies that examined AI personalization and AR immersion independently, this study demonstrates that cognitive and experiential stimuli operate with differing explanatory strengths and that immersion serves as a conditional enhancer rather than a primary driver of purchase behavior. This extends existing work by showing that experiential engagement depends on prior cognitive validation.

The study contributes to the literature in several ways. First, it extends S–O–R research by demonstrating that cognitive and experiential stimuli can operate simultaneously but with differing explanatory strengths in AI-enabled commerce settings. Rather than positioning immersion as a substitute for cognitive evaluation, the findings support a complementary interpretation in which experiential engagement reinforces—but does not replace—utilitarian and trust-based assessments. Second, the study contributes to the emerging AI commerce literature by distinguishing the functional role of explainable AI from the uncertainty-reduction role of algorithmic transparency. This distinction provides a more nuanced understanding of how different AI characteristics influence consumer internal states through separate psychological mechanisms. Third, the findings offer contextual insight into consumer behavior in an emerging digital commerce environment, where trust formation and perceived system usefulness may become especially salient under conditions of technological uncertainty and evolving digital infrastructure.

From a managerial perspective, the findings suggest that retailers should avoid relying exclusively on immersive AR functionality as a driver of consumer behavior. Instead, AI-AR platforms should integrate transparent recommendation logic, explainable interfaces, and user-centered design features that enhance both perceived usefulness and trust. Immersive technologies appear to generate stronger commercial value when embedded within systems that consumers perceive as understandable, reliable, and decision-supportive.

The study should also be interpreted in light of several limitations. The use of a cross-sectional design limits causal inference and does not capture how consumer perceptions evolve through repeated interactions with AI-AR systems over time. In addition, the findings are derived from a single-country context characterized by specific technological and market conditions, which may influence patterns of trust formation and technology evaluation. Future research could therefore employ longitudinal and cross-cultural designs, examine moderating variables such as digital literacy or product type, and incorporate additional psychological constructs, including privacy concerns, perceived risk, and technology readiness.

Overall, the study provides empirical evidence that effective AI-AR commerce environments depend not only on immersive technological experiences but also on consumers' cognitive evaluations of transparency, usefulness, and trustworthiness. As intelligent retail technologies continue to evolve, understanding the interaction between experiential engagement and cognitive appraisal will remain essential for advancing both theory and practice in digital commerce research.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Girne American University (protocol code: Fall 20225-2026 and date of approval is 3 March 2025).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Questionnaire Survey

Screening Questions

Only respondents who answered “Yes” to both questions proceeded to the formal survey.

1. Have you ever used online shopping platforms such as Amazon, Shein, AliExpress, or similar e-commerce apps?
☐ yes
☐ no
2. Have you ever used augmented reality (AR) shopping functions (e.g., virtual try-on, 3D product preview, or spatial placement) on such platforms?
☐ yes
☐ no

Thank you for participating in this survey.

The questionnaire is designed to understand your feelings and behavioral tendencies when using artificial intelligence (AI) recommendation systems and augmented reality (AR) shopping features on e-commerce platforms. This survey is conducted anonymously. All data are only used for academic research. We will keep your answers strictly confidential. Please answer according to your real experience.

Demographic Information

3. Gender:
 - ☐ male
 - ☐ female
4. Age:
 - ☐ 18–25
 - ☐ 26–35
 - ☐ 36–45
 - ☐ above 45
5. Education:
 - ☐ high school or below
 - ☐ diploma
 - ☐ Bachelor's degree
 - ☐ Master's degree
6. Frequency of using AI-powered recommendations or AR shopping features:
 - ☐ almost daily (≥ 1 time/day)
 - ☐ several times a week (≥ 4 times/month)
 - ☐ occasionally (1–3 times/month)
 - ☐ very rarely (≤ 1 time/month)

Note: To control common method bias, the items measuring different latent variables are randomly arranged in the questionnaire to avoid the consecutive appearance of items from the same construct. In addition, one reverse-scored item (marked with (R)) is included to encourage careful responses.

Instructions: Please choose the option that best reflects your opinion based on your real experience of using AI-powered recommendations and AR shopping functions on e-commerce platforms.

(1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree)

Item	Statement	Corresponding Latent Variable
1	The platform clearly discloses how its recommendation system operates.	Algorithmic Transparency (AT)
2	The platform provides clear explanations for why specific products are recommended to me.	Explainable AI (EAI)
3	The AR features create a realistic shopping environment similar to physical stores.	AR system experience (AR)
4	I trust that the platform handles my personal information securely.	Trust (TR)
5	Using this platform improves my efficiency in finding suitable products.	Perceived Usefulness (PU)
6	I feel deeply engaged when interacting with AR features on the platform.	Immersion (IM)
7	I am more likely to purchase products after interacting with this platform.	Purchase Decision (PD)
8	I intend to continue using this platform in the future.	Continued Usage Intention (CUI)
9	I can see the factors that influence the recommendations I receive.	Algorithmic Transparency (AT)
10	The explanations provided by the system are easy to understand.	Explainable AI (EAI)
11	I feel as if I am physically interacting with products when using AR features.	AR system experience (AR)

Item	Statement	Corresponding Latent Variable
12	I believe the platform provides reliable and honest information.	Trust (TR)
13	The AI and AR features enhance the quality of my purchase decisions.	Perceived Usefulness (PU)
14	I lose awareness of my surroundings while using AR shopping features.	Immersion (IM)
15	The platform increases my confidence in making purchase decisions.	Purchase Decision (PD)
16	I will regularly use this platform for online shopping.	Continued Usage Intention (CUI)
17	The decision-making process of the system is transparent and observable.	Algorithmic Transparency (AT)
18	The system's explanations help me evaluate whether the recommendations are appropriate.	Explainable AI (EAI)
19	The AR experience enhances my sense of presence within the shopping environment.	AR system experience (AR)
20	I trust the recommendations provided by the system.	Trust (TR)
21	Overall, the platform is useful for achieving my shopping goals.	Perceived Usefulness (PU)
22	The AR experience fully captures my attention during the shopping process.	Immersion (IM)
23	I often decide to buy products based on the platform's features and recommendations.	Purchase Decision (PD)
24	The platform's recommendations seem random and not based on my interests. (R)	Trust (TR)

Note: (R) indicates a reverse-scored item. The order of items has been randomized to reduce common method bias.

Appendix B. Descriptive Statistics of Measurement Items

Latent Variable	Item	Mean (M)	Standard Deviation (SD)	Skewness	Kurtosis
Algorithmic Transparency (AT)	AT1	3.72	0.986	−0.418	−0.352
	AT2	3.68	0.972	−0.392	−0.387
	AT3	3.59	1.013	−0.336	−0.466
Explainable AI (EAI)	EAI1	3.81	0.954	−0.527	−0.181
	EAI2	3.76	0.941	−0.471	−0.263
	EAI3	3.70	0.989	−0.415	−0.322
AR system experience (AR)	AR1	3.94	0.923	−0.638	0.045
	AR2	3.88	0.911	−0.589	−0.088
	AR3	3.85	0.936	−0.552	−0.142
Trust (TR)	TR1	3.44	1.105	−0.295	−0.698
	TR2	3.52	1.084	−0.381	−0.572
	TR3	3.60	1.051	−0.449	−0.456
	TR3R *	2.93	1.187	0.182	−0.732
Perceived Usefulness (PU)	PU1	3.86	0.927	−0.574	−0.107
	PU2	3.79	0.952	−0.516	−0.237
	PU3	3.74	0.968	−0.467	−0.294

Latent Variable	Item	Mean (M)	Standard Deviation (SD)	Skewness	Kurtosis
Immersion (IM)	IM1	3.82	0.944	−0.544	−0.183
	IM2	3.67	1.013	−0.421	−0.392
	IM3	3.77	0.959	−0.494	−0.251
Purchase Decision (PD)	PD1	3.84	0.921	−0.561	−0.115
	PD2	3.78	0.948	−0.509	−0.225
	PD3	3.71	0.983	−0.442	−0.337
Continued Usage Intention (CUI)	CUI1	3.66	1.027	−0.407	−0.417
	CUI2	3.70	1.006	−0.457	−0.330
	CUI3	3.62	1.041	−0.377	−0.481

Note: * TR3R is the reverse-scored item (“The platform’s recommendations seem random and not based on my interests”) included to control common method bias. For this item, higher original scores indicate lower perceived trust; it is reverse-coded before inclusion in the latent construct. Skewness and kurtosis values are within ± 1.0 , supporting the assumption of approximate univariate normality.

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