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# Augmented Reality in Retail:

## Technical and Emotional Factors After Experience - E-Commerce Consumption Decision

Joston Gary
https://orcid.org/0009-0002-1874-2056
*Department of Economics, Management, and Industrial Engineering and Tourism, University of Aveiro, Portugal & Division of Business Administration, Department of Management and Engineering, Linköping University, Sweden & Faculty of Business, City University of Macau, Macau*

Zhou Xixing
https://orcid.org/0009-0003-7165-2508
*Institute of Social Sciences, University of Minho, Portugal*

Yuk Ming Tang
https://orcid.org/0000-0001-8215-4190
*Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong*

Gu Yang
https://orcid.org/0009-0003-2596-0163
*Business Research Unit, ISCTE, University Institute of Lisbon, Portugal & Department of Organization, Strategy, and Entrepreneurship, Maastricht University, The Netherlands*

António Carrizo Moreira
https://orcid.org/0000-0002-6613-8796
*Department of Social Sciences and Management, Universidade Aberta, Portugal & Research Center for Business Sciences, University of Beira Interior, Portugal & Research Center in Business and Economics, Autonomous University of Lisbon, Portugal*
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## ABSTRACT

Retail practice shows that augmented-reality shopping applications with similar technical quality can elicit widely different consumer reactions. This study proposes a dual-pathway Stimulus–Organism–Response model: a technical pathway linking augmented realism, information richness, and personalization to interaction satisfaction, and an emotion-priming pathway where anticipated emotions shape immersion, telepresence, and pleasure without technical appraisal. Both converge at inspiration, the sole System-2 construct converting experience into behavior. Data from quasi-experimental participants were analyzed using PLS-SEM, SHAP-interpreted gradient boosting, and K-Means robustness checks. Information richness showed the strongest technical effect, while anticipated emotions most strongly affected immediate experiences. Inspiration predicted purchase and cross-buying intentions. Machine-learning diagnostics supported the framework and revealed non-linear thresholds in key pathways, clarifying inconsistent AR outcomes and positioning inspiration as the cognitive bridge to purchase.

## KEYWORDS

Augmented Reality, Anticipated Emotions, Inspiration, Nonlinear Exploration, Clustering Algorithm

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## INTRODUCTION

Augmented reality (AR) has emerged as a transformative force in retail, enabling consumers to visualize products in their personal environments through mobile devices (Chakraborty et al., 2025; Chakraborty, Polisetty, et al., 2024; S. Kim et al., 2022). Leading retailers, including IKEA, Sephora, and Nike, have deployed AR applications that allow virtual product trials, generating significant consumer engagement and sales growth (Chakraborty & Zhang, 2025; Söderström et al., 2024). The technology's commercial impact is substantial, with AR commerce revenue projected to exceed \$35 billion by 2026 (Caboni et al., 2024). Yet despite this widespread adoption, retailers frequently encounter a puzzling phenomenon: AR applications with nearly identical technical capabilities often produce markedly different consumer responses and business outcomes—especially in high-adoption markets, like China, where rapid mobile AR integration on platforms, such as Taobao and JD.com, amplifies these variances.

While this study empirically tests the dual-pathway framework within China's high-engagement e-commerce ecosystem, the underlying psychological architecture—modeling parallel technical and affective processing routes—is proposed as a foundational theory for immersive technology experiences. However, the specific cultural manifestations and relative strength of each pathway are likely to vary across contexts. Therefore, we position this model as a testable framework for future cross-cultural research, rather than a universally validated theory.

This inconsistency points to a theoretical short-sightedness in our understanding of AR consumer behavior in contexts like China. The dominant paradigm, the stimulus–organism–response (SOR) framework, provides an essential but incomplete picture. Academic research has predominantly relied on traditional SOR frameworks that model AR effects through single processing pathways (Erensoy et al., 2024). These models assume sequential stimulus-to-response flows but overlook parallel cognitive systems highlighted in dual-process theories (Evans, 2008; Kahneman, 2011). These theories suggest that automatic (system 1) and deliberative (system 2) processes operate concurrently in immersive contexts. In these traditional models, AR characteristics, such as realism and interactivity, sequentially influence cognitive and affective states, which then drive behavioral intentions. While useful, that approach oversimplifies what counts as a "stimulus" and compresses the processes of organisms that often run in parallel rather than in a single sequence. Without addressing both aspects, technically similar applications can appear the same on paper yet diverge in practice.

The first source of short-sightedness concerns the stimulus oversimplification. Studies often aggregate distinct AR features into broad "AR quality" measures, even though evidence shows that these features work through different psychological mechanisms. For instance, augmented realism (AR) primarily engages spatial presence systems, while information richness reduces uncertainty, and personalization (PSN) activates self-congruence processes. Treating these distinct features as a single bundle obscures mechanism-specific effects that are critical for design and prediction (Aslam & Davis, 2024; Caboni et al., 2024; Erensoy et al., 2024; Hoffmann & Mai, 2022; Sharma et al., 2023). An often overlooked stimulus is carried by the user rather than the app: anticipated emotions (ANP) formed before interaction. Ignoring this emotional input narrows the stimulus set to technical features alone and leaves systematic variance unexplained.

The second source relates to organism compression. The single-pathway SOR approach fails to account for parallel processing systems that characterize human cognition. Human processing in AR is not strictly sequential. Consumers can appraise technical qualities and register affective signals at the same time. Dual-process research supports such parallelism (Kahneman, 2011), yet AR studies frequently impose a single, linear route from features to states to intentions. Compressing parallel routes into one chain can mask why some AR experiences convert without strong arousal, while others with high fidelity still underperform.

Third, within this structure, ANP do more than precede feelings during use; they can also function as an independent pathway that bypasses technical evaluation. Pre-interaction emotional expectations can shape users' downstream experience regardless of technical performance (Chekembayeva et al., 2023; Ho et al., 2023; Joo & Yang, 2023). Contemporary emotion research treats ANP as distinct from concurrent responses and highly relevant for technology-related choices (Nawres et al., 2024; Sharma et al., 2023). Framing them as part of the effective stimulus set clarifies why meaning alignment can move outcomes even when technical appraisals are only moderate.

Fourth, a separate methodological concern reinforces the need for sharper theory. Observed relationships may be inflated by stable individual differences in technology responsiveness rather than representing genuine psychological mechanisms. For example, consumers high in technology readiness or experiential openness may rate many constructs higher, producing spurious covariance that looks like a mechanism when it is not. This can create spurious correlations that masquerade as causal relationships. Without checks that separate person-level tendencies from process-level effects, models risk overstating path strengths.

To overcome these limitations, this study develops and tests a dual-pathway extension of the SOR framework, specifically tailored to the complex, immersive nature of AR consumer experiences. The framework separates two concurrent routes: (1) a technical appraisal route linking AR, information richness, and PSN to experiential states and intentions through interaction satisfaction (ITSN) and related evaluations and (2) an emotion-priming route that begins with ANP as an independent input activating experiential states without requiring prior technical evaluation. A reflective bridge then converts experience into intention.

Both pathways converge at inspiration (IPS), a reflective state that turns immediate experience into an action-ready appraisal of possibility. Drawing on embodied cognition (Barsalou, 2008) and dual-process principles (Kahneman, 2011), we treat pleasure (PL), immersion (IMM), and telepresence as automatic experiential states—system 1—, and we treat IPS—system 2—as a reflective bridge that carries experience into intention.

This investigation advances AR consumer research in four ways that directly address the noted short-sightedness. It explains divergent outcomes among technically similar applications by modeling two concurrent routes rather than a single chain. It identifies IPS as the bridge from experience to intention, which helps account for conversions at moderate arousal. It validates ANP as an independent pathway that can shape responses regardless of technical quality, informing emotional design strategies in AR development. In addition, we use unsupervised profiles with hold-out validation to probe whether person-level differences confound inferences; details appear in methods section and appendix A–E. These contributions build on SOR extensions in digital contexts (Eroglu et al., 2001; Manganari et al., 2009) and dual-process applications in consumer technology (Hofmann et al., 2009), offering a framework that explains AR consumer behavior within the specific context of China's high-engagement e-commerce ecosystem. The model's core proposition of dual-pathway processing presents a compelling agenda for future research to examine its boundary conditions and cultural contingencies in other markets.

The study examines three research questions. First, does a technical appraisal route operate in our setting, moving from AR features to experiential states and then to intention? Second, does a meaning-alignment route that begins with ANP influence intention without requiring high arousal? Third, does IPS act as a common reflective bridge from experience to intention? Our focus is on product-linked outcomes after exposure rather than on system adoption; therefore, acceptance beliefs are handled as controls within the technical route.

The next section examines the limitations of single-path SOR logic and outlines the dual-pathway framework. This is followed by a section that develops the research model and hypotheses. Then, there is a section that describes data collection and measures, followed by a section that reports reliability and validity. After that is a section that presents structural results together with machine-learning diagnostics, which is followed by a section that details predictive relevance, mediation, and endogeneity tests. The subsequent sections discuss findings within the dual-pathway perspective and outline the limitations and future work. The final section gives the conclusion.

# LITERATURE REVIEW

## SOR Framework in AR Consumer Research

The appeal of SOR theory for understanding AR consumer behavior seems almost inevitable. When Mehrabian and Russell (1974) first conceived their framework, they could hardly have imagined virtual objects seamlessly integrated into physical shopping environments, yet their logic proves remarkably prescient (Hoffmann & Mai, 2022; Jayaswal & Parida, 2023). AR experiences fundamentally alter the stimulus environment in ways that traditional retail research has struggled to conceptualize (Erensoy et al., 2024; Söderström et al., 2024).

What makes AR particularly fascinating from a theoretical standpoint is its capacity to simultaneously activate multiple psychological systems. Unlike conventional digital interfaces that primarily engage cognitive evaluation processes, AR experiences trigger what we might call "embodied stimulus processing"—consumers do not just think about products, they experience them spatially and temporally in ways that blur the boundaries between physical and virtual consumption (Bampouni et al., 2024; Choubey et al., 2025; Leveau & Camus, 2023).

Current SOR applications in AR research have revealed a theoretical short-sightedness. Most studies have treated the organism as a single, linear conduit from AR stimuli to outcomes (Ambika et al., 2023), which does not reflect how cognition works in immersive settings (Iranmanesh et al., 2024). Consumers often process technical qualities and affective cues at the same time, not one after the other. When the organism is compressed into one route, models will miss cases where moderate arousal still converts or where high fidelity underperforms.

Evidence has indicated that AR interactions activate both deliberative and automatic processing systems simultaneously (Clithero et al., 2024; Gronchi et al., 2024). Therefore, we treat these streams as parallel in theory, while acknowledging that we do not directly measure processing modes. A shopper using AR does not first complete a technical evaluation and then experience emotions; both unfold together, which single-path models cannot capture (Whang et al., 2021).

Perhaps more problematic has been oversimplifying the stimuli. Work in AR often collapses distinct technological features into broad constructs, such as "AR quality" or "AR usefulness" (Chakraborty & Rana, 2025; Irshad et al., 2025; Rauschnabel et al., 2022), even though visual realism, information richness, and PSN operate through different mechanisms (Nawres et al., 2024; C. Sun et al., 2022). In addition to these system-provided features, consumers bring emotional primers—anticipated feelings formed before interaction—that also function as stimuli. Treating both the capability features and the emotional primers as the stimulus set helps explain divergent outcomes. Digital commerce platform outcomes are shaped not only by interface quality and consumer psychology but also by how the platform organizes product information, reviews, and promotional pushes across markets. Artificial intelligence (AI)-based seller analytics, timing of targeted online advertising, and consumer use of online reviews have shown that platforms can steer choice even when the task and the interface remain constant, and this effect is visible in both single-country settings and cross-border e-commerce (Batta et al., 2023; Gurbanova & Wang, 2023; Y. Li et al., 2023; L. Pham et al., 2023; Zhou et al., 2023). Online home-service applications, live-commerce switching, and matching between e-commerce channels and advertising appeals further have shown that these information layers must be aligned with local user expectations if platforms want to convert traffic into transactions (Chauhan et al., 2023; Cui et al., 2024; Q. Zhao et al., 2023). Online service experience, impulse buying, and the integration of technology and marketing in emerging economies all point in the same direction: E-commerce performance depends on how well the information layer is managed, not just on the quality of the front-end tool (Jayawardena et al., 2024; Mutambik et al., 2024). By drawing on this line of work, the present study has treated AR stimuli as one layer in a broader information-management setting, where platform-managed cues and user-carried emotional primers work together to produce intention.

These limitations are not merely academic; they represent barriers to understanding how AR influences consumer behavior and, consequently, to developing effective AR marketing strategies. The solution requires a level of theoretical sophistication that current SOR applications lack (Jayaswal & Parida, 2023). By distinguishing between technical appraisal (deliberative and system 2-dominant) and emotional priming (automatic and system 1-dominant), the dual-pathway model addresses inconsistencies in previous AR-SOR studies, such as those by Irshad et al. (2025) and Rauschnabel et al. (2022), which treated features as undifferentiated stimuli. This model is also aligned with emerging evidence of parallel processing in immersive technology (Clithero et al., 2024; Gronchi et al., 2024). This extension positions the framework as a bridge between SOR's environmental focus and dual-process' cognitive architecture, enhancing applicability to AR's blended physical-virtual demands.

AR consumer experiences operate through dual processing pathways that reflect the fundamental cognitive architecture of human information processing (Brocas & Carrillo, 2014; Gronchi & Perini, 2024). The first pathway involves a deliberative evaluation of AR technical features, progressing through satisfaction assessments to experiential states. The second pathway operates through affective priming mechanisms, in which ANP directly influence experiential processing, independent of technical feature evaluation.

This dual-pathway framework addresses several theoretical gaps simultaneously. It recognizes that consumers bring emotional expectations to AR experiences that influence outcomes regardless of technical quality (Castro-Alonso et al., 2024). It acknowledges that different AR features may operate through distinct cognitive mechanisms. It also provides a foundation for understanding how AR experiences generate lasting psychological effects through post-interaction processing.

Understanding when and why each pathway dominates consumer processing offers practical insights for AR design and marketing strategy. Some consumers may be primarily influenced by technical excellence, while others respond more strongly to emotional priming. Therefore, effective AR marketing requires understanding this psychological heterogeneity (Barta et al., 2025).

## Dual-Pathway Extension of SOR Framework in AR Consumer Experience

This framework aligns with, but extends beyond, technology-acceptance accounts. Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) can explain whether consumers intend to use a system by modeling pre-usage beliefs, such as usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003). However, these models focus on system adoption rather than post-experience, product-specific outcomes, like purchase intentions (PI), in AR retail—a distinction highlighted in recent critiques of TAM's limited applicability to immersive, hedonic contexts, such as those discussed by Childers et al. (2001) and Novak et al. (2000). The present focus is different: It assesses post-experience, product-linked outcomes after exposure to AR. Within the model, acceptance beliefs are incorporated into the technical route as antecedents or controls, while a parallel meaning-alignment route begins with emotional primers and also shapes experience. This positioning clarifies the novelty of the approach without discarding established acceptance theory and addresses SOR's single-path limitations in AR by integrating dual-process coordination (Kahneman, 2011; Strack & Deutsch, 2004), where technical and emotional inputs converge via IPS rather than linear mediation.

The gaps above call for a more precise account of AR consumer behavior that still builds on SOR (Barrett et al., 2024; Gahler et al., 2023; Minton et al., 2017; Xu et al., 2024). The solution is not to abandon SOR but to separate two concurrent routes that converge on behavior: (1) a technical appraisal route from AR capability features to experience and (2) a meaning-alignment route that begins with emotional primers and also feeds experience (Chartrand et al., 2008; Forgas, 1995; Kahneman, 2011). Acceptance frameworks (Davis, 1989; Venkatesh et al., 2003) remain relevant for beliefs in the technical route, while the emotional route extends the space beyond adoption outcomes.

This dual-pathway framework conceptualizes these routes as distinct in their primary psychological origin—one is rooted in the deliberative evaluation of system-provided features (technical appraisal) and the other in the user's preexisting affective expectations (emotional priming). However, in the lived experience of the user, these pathways are not hermetically sealed. Certain AR stimuli, such as PSN, can possess a dual character: They function as technically evaluable features (e.g., the accuracy of fit recommendations) while simultaneously acting as powerful emotional primers (e.g., evoking a feeling of being uniquely understood by the system).

The framework's value lies not in asserting the pathways' complete independence in every instance but in specifying their dominant mechanisms. The technical route is primarily driven by cognitive assessments of functionality and performance, while the emotional route is primarily driven by affective expectations that color the experience. A feature, like PSN, can activate both pathways, but the underlying psychological process and its subsequent influence on the user's state are theoretically separable. For instance, a poorly executed PSN algorithm (low technical performance) might still generate positive feelings if the user had high ANP, and vice-versa (Alimamy & Gnoth, 2022; Forgas, 1995). This model allows for the disentanglement and measurement of these distinct psychological contributions, which are often conflated in single-pathway models.

Consider what actually happens when consumers interact with AR shopping applications (Gahler et al., 2023; Hu et al., 2022; J. Li et al., 2020). They do not first evaluate technical features in isolation, then form emotions about those features, and finally decide whether to purchase (Davis, 1989; Hunter et al., 2022; Taufique et al., 2024). Instead, they bring preexisting emotional expectations to the experience while simultaneously processing technical characteristics, with both streams of information influencing their ultimate response (Forgas, 1995; Hao et al., 2024; Minton et al., 2017). This concurrent processing reflects what neuroscience has long established about human cognition: Humans are fundamentally dual-processing organisms (Chartrand et al., 2008; Kahneman, 2011; Lerner & Keltner, 2000).

AR technologies present consumers with concrete, evaluable attributes that trigger systematic processing (Davis, 1989; Taufique et al., 2024; Venkatesh et al., 2003). When consumers encounter AR, information richness, and PSN features, they engage in what technology acceptance research has consistently documented: a deliberative assessment of functional utility (Hu et al., 2023; Mensah & Khan, 2024; Xue et al., 2024). This pathway operates through ITSN as a crucial mediating mechanism, especially when information is complex (Barrett et al., 2024; Gahler et al., 2023; Hunter et al., 2022).

The logic presented here builds directly on decades of research in technology acceptance (Davis, 1989; Mensah & Khan, 2024; Venkatesh et al., 2003). Users evaluate digital technologies based on their perceived usefulness and ease of use, leading to satisfaction when technologies deliver on their functional promises (Hu et al., 2023; Taufique et al., 2024; Xue et al., 2024). In AR contexts, this translates to consumers asking fundamental questions: Does this virtual try-on accurately represent how the product will look? Does the AR interface provide rich, useful information? Do the PSN features actually match my preferences?

When AR technologies deliver positive answers to these questions, consumers experience ITSN —a sense that the technology has successfully facilitated their shopping goals (Barrett et al., 2024; Davis, 1989; Taufique et al., 2024). This satisfaction then channels into deeper cognitive states, including telepresence and IPS, as consumers recognize that the AR experience has provided reliable, useful information for their purchase decisions (Gahler et al., 2023; Hunter et al., 2022; J. Li et al., 2020).

The second pathway operates through affective priming (Forgas, 1995; Kousi et al., 2023; Lerner & Keltner, 2000). Before any technical assessment, consumers bring emotional expectations to the encounter (Chartrand et al., 2008; Hao et al., 2024; Minton et al., 2017). These ANP act as primers that shape immediate experience during AR use, and they can do so even when technical performance is only moderate.

This emotional priming effect reflects well-established psychological principles that separate hedonic and utilitarian drivers (Hu et al., 2023; Kousi et al., 2023; Lerner & Keltner, 2000). When consumers anticipate an engaging and exciting AR experience, these expectations create attentional and interpretive filters that shape how they process the actual AR content (Chartrand et al., 2008; Forgas, 1995; Minton et al., 2017). A consumer expecting AR to be fun and immersive will interpret ambiguous stimuli more positively, attend more readily to engaging elements, and experience higher levels of PL and IMM regardless of objective technical quality (Barrett et al., 2024; Hao et al., 2024; Kousi et al., 2023).

Crucially, this emotional pathway can operate independently of technical feature evaluation (Forgas, 1995; Kahneman, 2011; Lerner & Keltner, 2000). A consumer might experience high PL and IMM from AR shopping, even when the technical features are mediocre, simply because their emotional expectations have been primed for a positive experience (Hao et al., 2024; Kousi et al., 2023; Minton et al., 2017). Conversely, negative emotional expectations can dampen positive responses even to technically superior AR implementations (Chartrand et al., 2008; Forgas, 1995; Lerner & Keltner, 2000).

The theoretical foundation for this dual-pathway approach lies in dual-process theories of cognition (Chartrand et al., 2008; Kahneman, 2011; Minton et al., 2017). Human information processing operates through two distinct but interconnected systems: (1) an automatic, experiential system (system 1) that generates rapid responses and (2) a controlled, analytical system (system 2) that engages in deliberative processing (Forgas, 1995; Kahneman, 2011; Lerner & Keltner, 2000).

In AR consumer experiences, PL, IMM, and telepresence represent system 1 processing—immediate, automatic experiential states that occur without conscious deliberation (Chartrand et al., 2008; Forgas, 1995; Kousi et al., 2023). These states arise from both technical quality and emotional priming, where ANP directly influence felt experiences (Barrett et al., 2024; Hao et al., 2024; Minton et al., 2017). Telepresence, in this context, primarily manifests as an automatic sense of spatial presence, transporting users without requiring deliberate cognitive effort (Gahler et al., 2023; Hu et al., 2023; J. Li et al., 2020).

IPS, by contrast, represents system 2 processing—controlled cognitive analysis that emerges from deeper reflection on the AR experience (Davis, 1989; Hunter et al., 2022; Kahneman, 2011). Consumers form IPS when they consciously reflect on how the AR experience has opened new possibilities for consumption, synthesizing both their immediate experiential states and their evaluation of technical functionality (Barrett et al., 2024; Gahler et al., 2023; Taufique et al., 2024).

The dual pathways do not simply operate in parallel; they unfold across time in theoretically meaningful ways (Gahler et al., 2023; J. Li et al., 2020; Minton et al., 2017). Technical evaluation and emotional processing occur during AR interaction, but their effects extend beyond the immediate experience through the formation of IPS (Barrett et al., 2024; Hao et al., 2024; Kousi et al., 2023).

IPS represents the crucial convergence point where both pathways meet (Barrett et al., 2024; Gahler et al., 2023; J. Li et al., 2020). Immediate affective states (PL, IMM) feed forward into IPS as consumers reflect on the positive feelings generated by the AR experience (Forgas, 1995; Kousi et al., 2023; Lerner & Keltner, 2000). Simultaneously, ITSN influences IPS through a cognitive route, as consumers recognize that the AR technology successfully supported their shopping goals (Davis, 1989; Taufique et al., 2024; Venkatesh et al., 2003).

This temporal sequencing explains why AR experiences often generate behavioral intentions that persist long after the initial interaction (Gahler et al., 2023; J. Li et al., 2020; Minton et al., 2017). Unlike simple exposure to traditional marketing stimuli, AR experiences create lasting IPS that continues to influence purchase decisions through extended post-experience processing (Barrett et al., 2024; Chartrand et al., 2008; Kahneman, 2011).

The practical implications are clear, demanding that strategies account for both utilitarian and hedonic motivations (Hu et al., 2023; Kousi et al., 2023; Taufique et al., 2024). Effective AR marketing must succeed on both pathways: delivering technical excellence to satisfy utilitarian evaluation while managing emotional expectations to prime positive affective responses (Forgas, 1995; Minton et al., 2017; Venkatesh et al., 2003). Understanding this dual-pathway architecture provides the theoretical foundation for comprehending why AR consumer behavior exhibits the complexity that single-pathway models cannot capture (Kahneman, 2011; Mensah & Khan, 2024; Xue et al., 2024).

### Theoretical Foundation and Temporal Logic of AR Consumer Processing

The dual-pathway framework proposed above raises fundamental questions about how specific AR characteristics trigger distinct psychological mechanisms and how these mechanisms unfold over time. Rather than simply cataloguing constructs, it is necessary to understand why certain technological features activate particular cognitive pathways and how the temporal sequence of consumer processing creates lasting behavioral effects. This deeper theoretical analysis reveals the psychological architecture underlying AR consumer experiences, which recent empirical research has begun to validate through sophisticated methodological approaches (Caboni et al., 2024; Söderström et al., 2024).

The three AR characteristics in the technical pathway—AR, information richness, and PSN—operate through fundamentally different perceptual and cognitive mechanisms yet converge to influence ITSN through a process of diagnostic information processing.

AR functions through ecological perception principles originally articulated by Gibson (1979). When virtual objects achieve high perceptual fidelity, they trigger the same spatial presence mechanisms that govern real-world object recognition and environmental navigation. This effect extends beyond visual quality to what Dennis and Kinney (1998) described as "cue multiplicity"—the simultaneous activation of multiple sensory channels that generate authentic spatial understanding. Recent digital experience research has confirmed that perceptual authenticity becomes a crucial quality signal that consumers use to evaluate technological competence (Söderström et al., 2024). Contemporary AR marketing studies demonstrate that AR operates through cue-utilization mechanisms, in which visual and interactive cues inform judgments about product quality and brand reliability (Kumar et al., 2024).

Information richness operates through different mechanisms rooted in uncertainty reduction. Drawing from the accessibility–diagnosticity framework, AR's capacity to provide multiple visual cues, contextual information, and interactive feedback reduces what behavioral economists term "choice ambiguity" (Maity et al., 2018). When consumers can rotate virtual products, zoom in on details, and access contextual information overlays, they gain diagnostic confidence comparable to the information-processing advantages of examining physical products. This diagnostic function explains why information richness effects are strongest for complex or high-involvement products where uncertainty costs are highest. Recent research has indicated that susceptibility to information overload varies considerably, with some consumers benefiting from rich AR information, while others experience decision paralysis (Hunter et al., 2022). The holistic framework for AR usage modes suggests that information richness serves different functions across distinct consumer usage patterns—from basic information seeking to complex experiential exploration (Caboni et al., 2024).

PSN represents a psychologically complex mechanism, operating through self-congruence principles (Sirgy, 2018) that extend far beyond simple preference matching. When AR systems adapt to individual user characteristics—a process often supported by big data analytics (Theodorakopoulos & Theodoropoulou, 2024)—, they activate "self-verification processes," which is the fundamental human need to have one's self-concept confirmed and validated. The psychological power of PSN lies less in utilitarian convenience than in its ability to signal that the technology understands the user, thereby fostering trust and engagement. Recent studies have revealed that AR PSN enables value co-creation, allowing consumers to shape their shopping experiences in alignment with their ideal self-concept (Alimamy & Gnoth, 2022). This self-congruence mechanism is particularly powerful when consumers pursue their "ideal self," as AR PSN supports experimentation with identity expression in low-risk virtual environments (Zogaj et al., 2024).

These three AR characteristics converge through ITSN, a construct that requires careful theoretical positioning. ITSN is not simply a hedonic response but a cognitive reconciliation between technological expectations and experienced performance—a process extensively documented in expectancy–disconfirmation research (Schiebler et al., 2025; Marikyan et al., 2020; Alamäki et al., 2021). In digital contexts, ITSN operates through both instrumental and identity-confirming pathways, with technological competence serving as both a functional enabler and a psychological validator (C. Tam et al., 2020).

ITSN is theoretically notable for its dual character: It represents both a technical evaluation (e.g., whether the AR system provided useful information) and a psychological validation (e.g., whether the experience confirmed a sense of technological competence). Evidence suggests that technically superior AR systems can lead to lower satisfaction when they undermine perceived control or competence. Studies of AR retail applications have demonstrated that interactivity, IPS, and perceived usefulness work synergistically to enhance engagement through flow states, in which the technical and psychological dimensions of satisfaction become inseparable (Arghashi & Yuksel, 2022).

The experiential states—PL, IMM, and telepresence—operate through rapid, automatic processing consistent with system 1 cognition in dual-process theory. Their theoretical interest lies in their susceptibility to both technical quality and emotional priming effects. Advances in immersive technology research have indicated that these states arise through distinct yet interconnected psychological pathways that can be influenced by specific AR design choices (Pfeifer et al., 2023).

PL in AR contexts represents an affective response to both the aesthetic and functional success of technology. Unlike simple hedonic responses to attractive stimuli, AR PL often emerges from "competence satisfaction"—the positive affect associated with successfully mastering novel technological capabilities. This effect helps explain why AR PL can intensify with repeated use rather than diminishing through habituation. Research on cue utilization and habituation reveals that PL responses vary between first-time and habitual users, with enjoyment becoming increasingly important for sustained engagement (Söderström et al., 2024).

IMM and telepresence, while both automatic responses, are driven by different psychological mechanisms. IMM reflects attentional absorption—the narrowing of consciousness when AR content successfully captures cognitive resources. Telepresence involves spatial presence—the sensation of "being there" created when AR integrates virtual and physical environmental cues, which can influence post-PI (Chakraborty, Mehta, et al., 2024; Saleem et al., 2024). Studies in virtual retail environments have demonstrated that telepresence can be systematically enhanced through specific design features, resulting in stronger engagement and PI (Muhammad Sohail Jafar et al., 2024). Moreover, research using the SOR framework has found that IMM and telepresence both mediate the relationship between technological stimuli and behavioral responses (Erensoy et al., 2024).

IPS constitutes the most theoretically complex construct in the framework because it bridges automatic experiential states and deliberative cognitive processing. Unlike immediate experiential states, IPS requires "reflective cognitive integration" (Khatri, 2018; Lawrie, 2024)—a process in which consumers consciously synthesize AR experiences into actionable insights about consumption possibilities. Evidence from AR retail contexts has shown that IPS arises from the interplay between interactivity and perceived usefulness, mediated by flow experiences that link automatic and controlled processing (Arghashi & Yuksel, 2022).

The temporal dimension is central: IPS typically emerges after the AR interaction, during post-experience reflection on products, preferences, and consumption possibilities. This delay helps explain why IPS often predicts behavior more strongly than immediate experiential states—it represents the crystallization of the AR experience into stable cognitive attitudes that shape future behavior.

IPS's dual inputs—from satisfaction and experiential states—reflect its integrative nature. Consumers combine deliberative assessments of AR technical performance with automatic experiential responses, creating "affectively informed cognition." This integration explains why AR experiences often generate stronger IPS than non-AR experiences: They deliver both rich diagnostic information and engaging experiential processing that feed into post-experience reflection.

The temporal logic embedded in the framework has important implications for empirical testing. Although the constructs represent theoretically ordered psychological processes, the framework is examined using cross-sectional data that capture post-experience retrospective assessments.

Cross-sectional measurement is defensible when temporal ordering is embedded in construct definitions rather than requiring longitudinal observation. The model specifies that IPS arises through post-experience reflection on satisfaction and experiential states—a process completed before survey measurement. Similarly, ITSN is defined as cognitive reconciliation that occurs during or immediately after an AR interaction, while experiential states are the immediate responses to AR stimuli. Methodological research on temporal inference has confirmed that theoretically ordered mediation can be tested in cross-sectional designs when the temporal sequence is psychologically meaningful rather than purely chronological (Yang et al., 2024). The SOR framework provides a robust theoretical basis for analyzing these temporal dynamics, as recent systematic reviews have demonstrated across diverse domains of consumer behavior (Kıymalıoğlu et al., 2024). Mediation is interpreted as consistent with the theoretical ordering embedded in these constructs rather than as direct evidence of temporal causation.

## HYPOTHESIS AND RESEARCH MODEL

### AR Stimuli and ITSN

AR enhances consumers' confidence in virtual product evaluations by accurately mirroring physical product attributes. Realistic AR stimuli reduce cognitive processing barriers, facilitating fluent understanding and improving the ease with which consumers interpret virtual representations (Hilken et al., 2017; Javornik, 2016, Yim et al., 2017). This heightened "perceived augmentation" allows consumers to make better judgments, thereby increasing their satisfaction with the interaction (Sarkis et al., 2025; Uhm et al., 2022). Therefore, we hypothesize:

**H1.** AR deepens consumers' evaluative certainty, positively influencing their ITSN with AR shopping experiences.

Information vividness and richness (IVR) provide detailed product representations through multiple sensory channels, significantly reducing ambiguity and enhancing diagnostic capabilities (Ngo et al., 2025; Yim et al., 2017). This detailed, interactive information allows consumers to evaluate products more thoroughly and confidently, boosting ITSN during AR experiences (Coyle & Thorson, 2001; Uhm et al., 2022; Yim et al., 2017). Hence, we hypothesize:

**H2.** IVR clarify product understanding, positively influencing consumers' ITSN with AR shopping experiences.

PSN tailors AR product presentations to consumers' individual preferences and contexts, increasing perceived relevance and congruence with personal expectations (Lambillotte et al., 2022; H.-H. Lee & Chang, 2011). Customized AR content enhances consumer perceptions of product fit and personal resonance by making the experience more playful and useful, driving higher levels of ITSN (J. H. Song & Zinkhan, 2008; K.Y. Tam & Ho, 2006). Thus, we hypothesize:

**H3.** PSN heightens perceived relevance, positively influencing consumers' ITSN with AR shopping experiences.

### ITSN and Consumer Affective Responses

ITSN arising from successful AR product evaluations fosters immersive experiences by promoting continuous and effortless engagement with virtual environments (Slater, 2018; Yim et al., 2017). Higher satisfaction signals effective and fluent interaction, which, in turn, allows for deeper attentional absorption into the AR experience (Naveen et al., 2025; Reber et al., 2004; Sicilia et al., 2005). Accordingly, we hypothesize:

**H4.** ITSN promotes experiential focus, positively influencing consumer IMM in AR environments.

Moreover, satisfied consumers perceive AR environments as more authentic and believable, enhancing the sensation of telepresence (Chong et al., 2018; K. M. Lee, 2004). ITSN strengthens the cognitive alignment between virtual experiences and physical reality, as effective interaction is a core component of how presence is established (Baños et al., 2000; J. H. Song & Zinkhan, 2008). Therefore, we hypothesize:

**H5.** ITSN strengthens spatial authenticity, positively enhancing ARIT.

Additionally, ITSN enhances the hedonic quality of AR experiences by ensuring seamless and enjoyable interactions, subsequently increasing consumer PL (Babin et al., 1994; Ngo et al., 2025). Satisfied consumers experience heightened emotional PL due to the processing fluency that comes from effortless and rewarding interactions with virtual products (Reber et al., 2004; Yim et al., 2017). Thus, we hypothesize:

**H6.** ITSN enhances hedonic tone, positively amplifying consumer PL during AR use.

## ANP and Consumer Affective Responses

ANP represent future-oriented affective states that enhance consumers' immediate engagement with AR environments. These anticipatory emotions, as explained by the affect infusion model, color judgment and perception, making consumers more receptive to engaging experiences (Damasio, 2018; Forgas, 1995). A consumer anticipating a fun or useful interaction is primed to experience it as such, leading to deeper engagement (Ha & Jang, 2010; Krishna, 2012). Thus, we hypothesize:

**H7.** ANP energize affective engagement, with (a) higher anticipation increasing IMM, (b) heightening ARIT, and (c) amplifying PL during AR use.

## Consumer Affective Responses and Cognitive IPS

IMM involves deep experiential engagement with AR environments, promoting reflective cognitive processes that result in IPS (Böttger et al., 2017; Visch et al., 2010). Immersed consumers are more likely to experience the profound insights and motivational states that characterize IPS, which arises from meaningful and engaging interactions (Thrash & Elliot, 2003; Yang et al., 2024). Therefore, we hypothesize:

**H8.** IMM stimulates reflective insight, positively influencing consumer IPS.

Similarly, ARIT enhances consumers' cognitive elaboration by creating a vivid perception of virtual products as real entities, thereby fostering IPS (Böttger et al., 2017; K. M. Lee, 2004). The feeling of "being there" makes the experience more potent and memorable, facilitating deeper reflection on product benefits and promoting inspirational cognitive responses (Baños et al., 2000; Thrash & Elliot, 2003). Hence, we hypothesize:

**H9.** ARIT enriches cognitive elaboration, positively influencing consumer IPS.

Moreover, PL arising from AR interactions strengthens motivational states and energizes cognitive elaboration, enhancing the formation of IPS (Babin et al., 1994; Böttger et al., 2017). Pleasurable experiences, which are often a component of hedonic value, intensify cognitive openness and creative processing, further fostering the positive state of IPS (Reber et al., 2004; Yang et al., 2024). Thus, we hypothesize:

**H10.** PL boosts motivational openness, positively influencing consumer IPS.

## IPS and Consumer Behavioral Intentions

Consumer IPS, resulting from meaningful AR interactions, directly shapes future-oriented behaviors by enhancing consumers' purchase and cross-buying intentions (CBI) (Böttger et al., 2017; Yang et al., 2024). Inspired consumers envision clearer and more desirable future product experiences, which provides the motivational thrust to transition from idea to action, thus increasing their willingness to purchase and explore complementary products (Sarkis et al., 2025; Thrash & Elliot, 2003). Accordingly, we hypothesize:

**H11.** IPS accelerates behavioral commitment, with (a) stronger IPS increasing PI and (b) elevating cross-buying intention.

Based on research hypotheses, the conceptual model is shown in Figure 1.

**Figure 1. Conceptual Model**

## RESEARCH METHOD

### Measures, Sample, and Data Collection

The constructs used in the study were measured using established scales, as shown in Table 1 (Cotarelo et al., 2021; Rodríguez-Torrico et al., 2020). A 7-point Likert scale ranging from different aspects provided clear and precise response options for respondents (Asún et al., 2015). Data collection was conducted through an online survey (using the Credamo platform) and adopted purposive sampling (nonprobability sampling), using AR stimuli as activation cues, partially funded by a small grant from the authors, targeting residents of Mainland China. The study has a sample size of 779 participants, which meets the guidelines for partial least squares structural equation modeling (PLS-SEM), recommending a minimum sample size of 10 to 15 times the number of indicators for the most complex structures (Chin, 1998). Analysis was conducted on 779 participants from Mainland China who had experience with AR shopping. Participants were offered a cash reward of 72 Chinese yuan (approximately 10 United States dollars).

**Table 1. Reliability of the Constructs**

| Construct | Items | Factor Loading | α/CR/AVE | Mean | Std |
|---|---|---|---|---|---|
| Augmented realism (AR) (Baños et al., 2000) | AR1 | 0.800 | 0.885/0.887/0.636 | 4.77 | 1.004 |
| | AR2 | 0.836 | | | |
| | AR3 | 0.795 | | | |
| | AR5 | 0.741 | | | |
| | AR6 | 0.797 | | | |
| Interaction satisfaction (ITSN) (Yim et al., 2017; Yoo et al., 2010; L. Zhao & Lu, 2012) | ITSN1 | 0.766 | 0.874/0.876/0.614 | 5.03 | 0.971 |
| | ITSN 2 | 0.810 | | | |
| | ITSN 3 | 0.819 | | | |
| | ITSN 4 | 0.803 | | | |
| | ITSN 5 | 0.746 | | | |
| | ITSN 6 | 0.755 | | | |
| Information vividness and richness (IVR) (Babin & Burns, 1998; D. Kim & Ko, 2019; Yim et al., 2017) | IVR1 | 0.790 | 0.868/0.868/0.654 | 5.30 | 0.951 |
| | IVR2 | 0.807 | | | |
| | IVR3 | 0.818 | | | |
| | IVR4 | 0.821 | | | |
| | IVR5 | 0.803 | | | |
| Personalization (PSN) (J. Park, 2014) | PSN1 | 0.841 | 0.793/0.799/0.707 | 5.18 | 1.07 |
| | PSN2 | 0.838 | | | |
| | PSN3 | 0.845 | | | |
| Immersion (IMM) (Y. Sun et al., 2019) | IMM1 | 0.821 | 0.793/0.795/0.707 | 5.12 | 1.089 |
| | IMM2 | 0.846 | | | |
| | IMM3 | 0.863 | | | |

*continued on following page*

**Table 1. Continued**

| Construct | Items | Factor Loading | α/CR/AVE | Mean | Std |
|---|---|---|---|---|---|
| AR-induced telepresence (ARIT) (J. Kim et al., 2021) | ARIT1 | 0.877 | 0.819/0.823/0.734 | 4.78 | 1.221 |
| | ARIT2 | 0.848 | | | |
| | ARIT3 | 0.847 | | | |
| Pleasure (PL) (J. Kim & Lennon, 2013; Mehrabian & Russell, 1978; Wei et al., 2023) | PL1 | 0.872 | 0.833/0.833/0.749 | 5.28 | 1.04 |
| | PL2 | 0.853 | | | |
| | PL3 | 0.874 | | | |
| Inspiration (IPS) (Böttger et al., 2017; Thrash & Elliot, 2003; Zanger et al., 2022) | IPS1 | 0.754 | 0.849/0.851/0.624 | 5.22 | 0.974 |
| | IPS2 | 0.766 | | | |
| | IPS3 | 0.808 | | | |
| | IPS4 | 0.832 | | | |
| | IPS5 | 0.793 | | | |
| Anticipated emotions (ANP) (Baumgartner et al., 2008; Chekembayeva et al., 2023) | ANP1 | 0.786 | 0.884/0.886/0.632 | 5.40 | 0.945 |
| | ANP2 | 0.820 | | | |
| | ANP3 | 0.828 | | | |
| | ANP4 | 0.763 | | | |
| | ANP5 | 0.801 | | | |
| | ANP6 | 0.796 | | | |
| Purchase intention (PI) (Zanger et al., 2022) | PI1 | 0.804 | 0.888/0.889/0.691 | 5.36 | 1.022 |
| | PI2 | 0.840 | | | |
| | PI3 | 0.834 | | | |
| | PI4 | 0.836 | | | |
| | PI5 | 0.846 | | | |
| Cross-buying intention (CBI) (Mukerjee, 2020; Wu et al., 2022) | CBI1 | 0.803 | 0.881/0.881/0.678 | 5.19 | 1.034 |
| | CBI2 | 0.804 | | | |
| | CBI3 | 0.838 | | | |
| | CBI4 | 0.839 | | | |
| | CBI5 | 0.836 | | | |

*Note*. CR = composite reliability; AVE = average variance extracted; AR = augmented realism; ITSN = interaction satisfaction; IVR = information vividness and richness; PSN = personalization; IMM = immersion; ARIT = = augmented reality-induced telepresence; PL = pleasure; IPS = inspiration; ANP = anticipated emotions; PI = purchase intention; CBI = cross-buying intention.

The survey was designed and refined based on feedback from senior marketing scholars in Portugal, Hong Kong, and Macau. The questionnaire was pretested with 100 AR users from an e-commerce platform to ensure its validity and reliability. The final survey was conducted from May to August 2024. To ensure the credibility of the research, we implemented a rigorous data collection process. Respondents were required to answer questions based on their previous AR shopping experiences. Two screening questions were included to identify invalid responses. These screening questions were similar in wording to two actual survey items but had opposite meanings. If a respondent provided the same answers to both the screening and actual questions, their response was deemed invalid. Only individuals who reported prior AR shopping experience were invited to participate in the formal survey. In the initial phase, 520 potential respondents were prescreened based on their experience with AR shopping and the platforms they used. After careful screening, we retained 243 high-quality, valid responses. In addition, 1,154 questionnaires were distributed during the second phase. Following the same rigorous screening criteria, 536 additional valid responses were obtained. Combining both phases, the final sample size totaled 779 respondents. The data collection period spanned from May to August 2024. The effective recovery rate was 46.54%, which exceeds the recommended 25% (Ramshaw, 2023). The sample excluded pretest participants. Notably, this dataset was very balanced, with no missing or incomplete answers, as the online format prevented incomplete submissions.

This study employed a hybrid analytical strategy, integrating PLS-SEM with advanced machine learning techniques (extreme gradient boosting-Shapley additive explanations [XGBoost-SHAP] and k-nearest neighbor [KNN] + k-means), using Python (Version 3.12.9) for its optimization capabilities (such as iterative weighting via libraries, like Convex Python - CVXPY or scikit-optimize). This combination is theoretically grounded in the dual-process nature of AR experiences, which involve both intuitive, affective responses (system 1) and deliberate, cognitive evaluations (system 2) (Forgas, 1995; Kahneman, 2011; Lerner & Keltner, 2000). While PLS-SEM is first used to validate the foundational hypotheses and layered mediation of the proposed SOR-based path model (Mehrabian & Russell, 1974), its linear assumptions are insufficient to capture the full complexity of immersive psychological processes. Therefore, XGBoost-SHAP is applied to identify critical nonlinear thresholds and feature interactions—such as S-shaped IMM effects that may signal a transition between cognitive systems—, which are often obscured in standard models. Subsequently, KNN + k-means clustering quantifies consumer heterogeneity to test the robustness of these pathways across distinct segments, such as defined by technology readiness, ensuring the identified mechanisms are not artifacts of aggregation. Thus, this multimethod approach is not merely technical but is essential for a nuanced, theory-driven dissection of AR's psychological architecture.

Results from these analytical tools are reported selectively to prioritize theoretical insights over exhaustive outputs, illuminating AR's psychological architecture while maintaining focus on the central narrative. The experimental stimuli are detailed in appendix E.

### Trigger Effect Check

The model requires isolating ANP as an exogenous influence distinct from experiential states during AR interaction. We conducted a pretest to validate our emotional priming manipulation using established protocols in consumer emotion research (Bagozzi et al., 1999; M. T. Pham, 2004). Forty-three participants ($M_{age}$ = 24.3 years, 58% female) completed baseline measures of ANP. After engaging with our text scenario (appendix D) and a one-minute imagination period, participants completed the same measures. A repeated-measures analysis of variance revealed a large and significant increase in anticipated positive emotions from baseline ($M = 3.45$, $SD = 0.97$) to post-manipulation ($M = 5.77$, $SD = 0.83$), $F$ (1, 42) = 115.32, $p < 0.001$, partial $\eta^2 = 0.73$. This effect size (Cohen's $f = 1.66$) substantially exceeds benchmarks for large effects, confirming that our manipulation successfully elevated positive emotional expectations prior to any AR exposure.

## MODEL ANALYSIS AND RESULTS

### Descriptive Statistics

Respondents were selected based on their prior experience using e-commerce platforms across multiple channels (physical stores, websites, and mobile applications), ensuring that each participant had engaged in at least three purchase transactions within the past year. The sample comprised 30.80% male and 67.30% female participants, with a small proportion (1.90%) opting not to disclose their gender. The age distribution showed that most participants were between 21 and 25 years

(62.50%), followed by those under 20 years (16.70%), and participants aged 26–30 years (16.70%). In terms of e-commerce platform usage, 43.20% of the respondents made purchases 3–5 times within the past month, while 31.40% made purchases more than six times during the same period. More than 65.70% of users have a positive attitude toward AR shopping, and 68.10% and 66.2% of users believe that the primary use of AR technology is for online shopping and consumer entertainment, respectively.

## Common Method Bias (CMB)

Common method bias (CMB) may pose a threat to the validity of the research if all data were collected from a single source. For that, the variance inflation factor (VIF) test was used to demonstrate that CMB has been adequately addressed. Since no VIF values greater than 3.30 were detected in the PLS output (see Table 2), this provides evidence that the data do not suffer from severe CMB (Kock, 2015). Additionally, none of the latent constructs had correlations with other constructs exceeding 0.9 (Bagozzi et al., 1991), confirming that CMB is within acceptable limits.

**Table 2. $R^2$, Variance Inflation Factor (VIF), and $Q^2$**

| Variable | $R^2$ | $Q^2$ | VIF |
|---|---|---|---|
| AR | \ | 0.000 | 2.064 |
| ANP | \ | 0.000 | 1.511 |
| IVR | \ | 0.000 | 2.140 |
| PSN | \ | 0.000 | 1.756 |
| ARIT | 0.451 | 0.326 | 2.107 |
| CBI | 0.477 | 0.320 | 1.000 |
| IMM | 0.503 | 0.352 | 2.423 |
| IPS | 0.586 | 0.358 | 1.000 |
| IS | 0.656 | 0.398 | 1.756 |
| PI | 0.481 | 0.328 | 1.000 |
| PL | 0.588 | 0.436 | 2.420 |

*Note*. All variance inflation factor (VIF) values are below 3.3, indicating no severe multicollinearity; AR = augmented realism; ANP = anticipated emotions; IVR = information vividness and richness; PSN = personalization; ARIT = augmented reality-induced telepresence; CBI = cross-buying intention; IMM = immersion; IPS = inspiration; ITSN = interaction satisfaction; PI = purchase intention; PL = pleasure.

## Measurement Model Assessment

Firstly, the factor loadings of the scale items exceeded the recommended threshold of 0.70 (Hair et al., 2011), Cronbach's alpha values surpassed the suggested minimum of 0.70 (Nunnally, 1978), and the composite reliability also exceeded the minimum value of 0.70 (Nunnally, 1978). Through the analysis of the average variance extracted, the convergent validity of the reflective constructs was confirmed, with all values exceeding 0.50 (Bagozzi & Yi, 1988).

$R^2$ measures the proportion of variance in the dependent variable explained by the structural model, with higher values indicating stronger explanatory power. According to Table 2, the $R^2$ values for ITSN (65.6%), IPS (58.6%), PL (58.8%), IMM (50.3%), PI (48.1%), CBI (47.7%), and ARIT (45.1%) demonstrate moderate to strong explanatory power. Notably, ITSN, IPS, and PL show particularly high $R^2$ values, indicating that the model accounts for a substantial proportion of variance in these constructs. $Q^2$ assesses the model's predictive relevance through a blindfolding procedure, where values greater than 0 indicate predictive capability. Based on the $Q^2$ values, PL (43.6%) and ITSN (39.8%) exhibit strong predictive relevance, while IPS (35.8%), IMM (35.2%), PI (32.8%), ARIT

(32.6%), and CBI (32.0%) show moderate to strong predictive accuracy. Although the $Q^2$ values for the exogenous variables AR, ANP, IVR, and PSN are zero—as expected for independent predictors that are not predicted themselves—, they remain important sources of variance within the structural framework.

The discriminant validity of each construct was verified by analyzing the heterotrait-monotrait ratio. The results, as shown in Table 3, indicate that all variables had values below 0.85 (Kline, 2011).

**Table 3. Discriminant Validity Heterotrait-Monotrait Ratio**

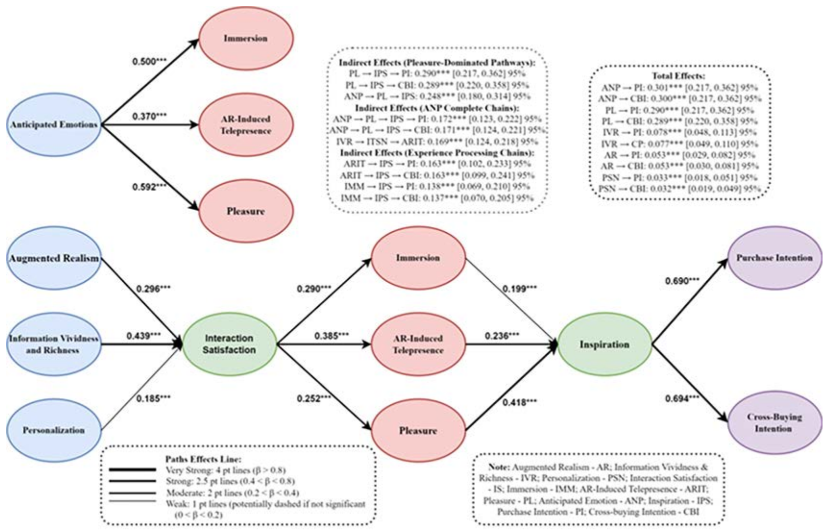
| | AR | ITSN | IVR | PSN | IMM | ARIT | PL | IPS | ANP | PI | CBI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AR | 1 | | | | | | | | | | |
| ITSN | 0.706 | 1 | | | | | | | | | |
| IVR | 0.672 | 0.751 | 1 | | | | | | | | |
| PSN | 0.598 | 0.627 | 0.609 | 1 | | | | | | | |
| IMM | 0.614 | 0.581 | 0.624 | 0.595 | 1 | | | | | | |
| ARIT | 0.667 | 0.592 | 0.585 | 0.575 | 0.666 | 1 | | | | | |
| PL | 0.579 | 0.597 | 0.639 | 0.590 | 0.723 | 0.670 | 1 | | | | |
| IPS | 0.537 | 0.575 | 0.615 | 0.560 | 0.654 | 0.642 | 0.714 | 1 | | | |
| ANP | 0.513 | 0.580 | 0.598 | 0.531 | 0.665 | 0.587 | 0.737 | 0.722 | 1 | | |
| PI | 0.541 | 0.577 | 0.600 | 0.537 | 0.653 | 0.596 | 0.681 | 0.688 | 0.773 | 1 | |
| CBI | 0.555 | 0.532 | 0.565 | 0.512 | 0.596 | 0.625 | 0.648 | 0.688 | 0.692 | 0.750 | 1 |

*Note*. Values less than 0.85 indicate adequate discriminant validity. AR = augmented realism; ITSN = interaction satisfaction; IVR = information vividness and richness; PSN = personalization; IMM = immersion; ARIT = augmented reality-induced telepresence; PL = pleasure; IPS = inspiration; ANP = anticipated emotions; PI = purchase intention; CBI = cross-buying intention.

## Model Assessment

Prior to evaluating the structural paths, collinearity diagnostics were conducted to ensure the robustness of the estimation. All VIF values were below the conservative threshold of 3.3, indicating the absence of multicollinearity concerns (Kock, 2015). To test the proposed hypotheses, a bootstrapping procedure with 5,000 resamples was employed. The structural model results, as presented in Figure 2, Table 4, and the overall effect model in Figure 2, reveal consistent and statistically significant relationships across the proposed paths.

**Figure 2. Path Effects**




*Note. AR = augmented reality; IVR = information vividness and richness; PSN = personalization; IMM = immersion; ITSN = interaction satisfaction; ARIT = augmented reality-induced telepresence; PL = pleasure; ANP = anticipated emotions; IPS = inspiration; PI = purchase intention; CBI = cross-buying intention.*

**Table 4. Summary of Hypothesis Test Results**

| Hypothesis | β | Std | *T*-Statistics | *P* | 5% Confidence Intervals | | Results |
|---|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound | |
| H1: AR →ITSN | 0.296*** | 0.039 | 7.637 | < 0.001 | 0.220 | 0.371 | Supported |
| H2: IVR →ITSN | 0.439*** | 0.041 | 10.792 | < 0.001 | 0.357 | 0.518 | Supported |
| H3: PSN →ITSN | 0.185*** | 0.038 | 4.934 | < 0.001 | 0.112 | 0.258 | Supported |
| H4: ITSN → IMM | 0.290*** | 0.038 | 7.626 | < 0.001 | 0.217 | 0.366 | Supported |
| H5: ITSN → ARIT | 0.385*** | 0.043 | 8.926 | < 0.001 | 0.299 | 0.470 | Supported |
| H6: ITSN → PL | 0.252*** | 0.033 | 7.671 | < 0.001 | 0.187 | 0.315 | Supported |
| H7a: ANP → IMM | 0.500*** | 0.038 | 13.149 | < 0.001 | 0.422 | 0.571 | Supported |
| H7b: ANP → ARIT | 0.370*** | 0.043 | 8.552 | < 0.001 | 0.283 | 0.454 | Supported |
| H7c: ANP → PL | 0.592*** | 0.033 | 18.029 | < 0.001 | 0.526 | 0.657 | Supported |
| H8: IMM → IPS | 0.199*** | 0.050 | 3.961 | < 0.001 | 0.102 | 0.297 | Supported |
| H9: ARIT → IPS | 0.236*** | 0.050 | 4.719 | < 0.001 | 0.145 | 0.338 | Supported |
| H10: PL → IPS | 0.418*** | 0.049 | 8.506 | < 0.001 | 0.319 | 0.511 | Supported |
| H11a: IPS → PI | 0.694*** | 0.025 | 28.205 | < 0.001 | 0.644 | 0.741 | Supported |
| H11b: IPS → CBI | 0.690*** | 0.027 | 25.992 | < 0.001 | 0.637 | 0.741 | Supported |

*Note*. **p* < 0.05, ***p* < 0.01, ****p* < 0.001; n/a = no significant or mediation. AR = augmented realism; ITSN = interaction satisfaction; IVR = information vividness and richness; PSN = personalization; IMM = immersion; ARIT = augmented reality-induced telepresence; PL = pleasure; ANP = anticipated emotions; IPS = inspiration; PI = purchase intention; CBI = cross-buying intention.

All three stimulus variables exhibited significant positive effects on ITSN. Specifically, AR (AR → ITSN: $\beta = 0.296$, $p < 0.001$), IVR (IVR → ITSN: $\beta = 0.439$, $p < 0.001$), and PSN (PSN → ITSN: $\beta = 0.185$, $p < 0.001$) each significantly enhanced consumers' ITSN with AR experiences, confirming H1–H3.

ITSN significantly predicted all three affective responses: immersion (ITSN → IMM: $\beta = 0.290$, $p < 0.001$), ARIT (ITSN → ARIT: $\beta = 0.385$, $p < 0.001$), and PL (ITSN → PL: $\beta = 0.252$, $p < 0.001$), supporting H4–H6.

ANP had a strong positive effect on IMM (ANP → IMM: $\beta = 0.500$, $p < 0.001$), ARIT (ANP → ARIT: $\beta = 0.370$, $p < 0.001$), and PL (ANP → PL: $\beta = 0.592$, $p < 0.001$), confirming H7a–H7c. Each of the three affective value constructs positively influenced ITSN: IMM (IMM → IPS: $\beta = 0.199$, $p < 0.001$), ARIT (ARIT → IPS: $\beta = 0.236$, $p < 0.001$), and PL (PL → IPS: $\beta = 0.418$, $p < 0.001$), supporting H8–H10.

IPS significantly predicted both PI (IPS → PI: $\beta = 0.694$, $p < 0.001$) and CBI (IPS → CBI: $\beta = 0.690$, $p < 0.001$), thereby validating H11a and H11b.

The model demonstrates strong explanatory power across the stimulus, value, and role dimensions, with all proposed hypotheses supported and statistical significance maintained at the 0.001 level. Indirect effect estimations and total effects further corroborate the robustness of the hypothesized value transformation chains, particularly those initiated by ANP and ITSN (see Figure 2, right-side insets).

## Mediation Effect Analysis

To test the indirect effects in our dual-pathway framework, we conducted a formal mediation analysis following the guidelines of X. Zhao et al. (2010). The analysis examined how AR stimuli influence consumer responses through a series of layered psychological mechanisms within the SOR structure. Results confirmed systematic support for both proposed pathways (Table 5). The technical pathway illustrates how AR characteristics (AR, IVR, and PSN) impact behavioral intentions through ITSN, experiential states, and IPS. The mediation chain AR → ITSN → PL → IPS → PI yielded a significant indirect effect ($\beta = 0.089$, $p < 0.01$), indicating that technical quality perceptions translate into PI through satisfaction-enabled experiential processing.

**Table 5. Summary of Mediation Analysis Test Results**

| Indicators | Path | β | Std | *T*-Statistics | *P* | 5% Confidence Intervals | | Results |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound | |
| Total indirect effect | ANP → IPS | 0.434*** | 0.049 | 8.833 | < 0.001 | 0.338 | 0.530 | Supported |
| | AR → ARIT | 0.114*** | 0.020 | 5.700 | < 0.001 | 0.075 | 0.153 | Supported |
| | AR → IMM | 0.086*** | 0.016 | 5.375 | < 0.001 | 0.055 | 0.117 | Supported |
| | AR → PL | 0.075*** | 0.014 | 5.357 | < 0.001 | 0.048 | 0.102 | Supported |
| | ARIT → CBI | 0.163*** | 0.037 | 4.405 | < 0.001 | 0.090 | 0.236 | Supported |
| | ARIT → PI | 0.163*** | 0.034 | 4.794 | < 0.001 | 0.096 | 0.230 | Supported |

*continued on following page*

**Table 5. Continued**

| Indicators | Path | β | Std | *T*-Statistics | *P* | 5% Confidence Intervals | | Results |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound | |
| | IMM → CBI | 0.137*** | 0.035 | 3.914 | < 0.001 | 0.068 | 0.206 | Supported |
| | IMM → PI | 0.138*** | 0.036 | 3.833 | < 0.001 | 0.067 | 0.209 | Supported |
| | IVR → ARIT | 0.169*** | 0.024 | 7.042 | < 0.001 | 0.122 | 0.216 | Supported |
| | IVR → IMM | 0.127*** | 0.021 | 6.048 | < 0.001 | 0.086 | 0.168 | Supported |
| | IVR → PL | 0.111*** | 0.018 | 6.167 | < 0.001 | 0.076 | 0.146 | Supported |
| | ITSN → IPS | 0.254*** | 0.031 | 8.280 | < 0.001 | 0.194 | 0.314 | Supported |
| | PL → CBI | 0.289*** | 0.035 | 8.257 | < 0.001 | 0.220 | 0.358 | Supported |
| | PL → PI | 0.290*** | 0.038 | 7.632 | < 0.001 | 0.216 | 0.364 | Supported |
| | PSN → ARIT | 0.071*** | 0.017 | 4.176 | < 0.001 | 0.038 | 0.104 | Supported |
| | PSN → IMM | 0.054*** | 0.013 | 4.154 | < 0.001 | 0.029 | 0.079 | Supported |
| | PSN → PL | 0.047*** | 0.011 | 4.273 | < 0.001 | 0.025 | 0.069 | Supported |
| Specific indirect effect | IMM → IPS → CBI | 0.137*** | 0.035 | 3.975 | < 0.001 | 0.068 | 0.206 | Supported |
| | AR → ITSN → PL | 0.075*** | 0.014 | 5.286 | < 0.001 | 0.048 | 0.102 | Supported |
| | ARIT → IPS → PI | 0.163*** | 0.034 | 4.801 | < 0.001 | 0.096 | 0.230 | Supported |
| | IMM → IPS → PI | 0.138*** | 0.036 | 3.832 | < 0.001 | 0.067 | 0.209 | Supported |
| | ANP → ARIT → IPS | 0.087*** | 0.023 | 3.836 | < 0.001 | 0.042 | 0.132 | Supported |
| | ANP → IMM → IPS | 0.099*** | 0.027 | 3.667 | < 0.001 | 0.046 | 0.152 | Supported |
| | PL → IPS → CBI | 0.289*** | 0.035 | 8.139 | < 0.001 | 0.220 | 0.358 | Supported |
| | PL → IPS → PI | 0.290*** | 0.038 | 7.723 | < 0.001 | 0.216 | 0.364 | Supported |
| | ANP → PL → IPS | 0.248*** | 0.034 | 7.270 | < 0.001 | 0.181 | 0.315 | Supported |
| | ARIT → IPS → CBI | 0.163*** | 0.037 | 4.436 | < 0.001 | 0.090 | 0.236 | Supported |

*continued on following page*

**Table 5. Continued**

| Indicators | Path | β | Std | *T*-Statistics | *P* | 5% Confidence Intervals | | Results |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound | |
| | ITSN→ ARIT → IPS | 0.091*** | 0.019 | 4.830 | < 0.001 | 0.054 | 0.128 | Supported |
| | ITSN→ IMM → IPS | 0.058*** | 0.016 | 3.515 | < 0.001 | 0.027 | 0.089 | Supported |
| | PSN → ITSN→ ARIT | 0.071*** | 0.017 | 4.283 | < 0.001 | 0.038 | 0.104 | Supported |
| | PSN → ITSN→ IMM | 0.054*** | 0.013 | 4.186 | < 0.001 | 0.029 | 0.079 | Supported |
| | PSN → ITSN→ PL | 0.047*** | 0.011 | 4.196 | < 0.001 | 0.025 | 0.069 | Supported |
| | IVR → ITSN→ ARIT | 0.169*** | 0.024 | 7.056 | < 0.001 | 0.122 | 0.216 | Supported |
| | IVR → ITSN→ IMM | 0.127*** | 0.021 | 6.010 | < 0.001 | 0.086 | 0.168 | Supported |
| | IVR → ITSN→ PL | 0.111*** | 0.018 | 6.049 | < 0.001 | 0.076 | 0.146 | Supported |
| | ITSN→ PL → IPS | 0.105*** | 0.018 | 5.847 | < 0.001 | 0.070 | 0.140 | Supported |
| | AR → ITSN→ ARIT | 0.114*** | 0.020 | 5.581 | < 0.001 | 0.075 | 0.153 | Supported |
| | AR → ITSN→ IMM | 0.086*** | 0.016 | 5.224 | < 0.001 | 0.055 | 0.117 | Supported |

*Note*. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; n/a = no significant or mediation. ANP = anticipated emotions; ITSN = interaction satisfaction; AR = augmented realism; ARIT = augmented reality-induced telepresence; IMM = immersion; PL = pleasure; CBI = cross-buying intention; PI = purchase intention; IVR = information vividness and richness; IPS = inspiration; PSN = personalization.

The emotional pathway shows that ANP directly activate experiential states without prior technological evaluation. ANP strongly predicted PL (β = 0.592, $p < 0.001$), IMM (β = 0.500, $p < 0.001$), and telepresence (β = 0.370, $p < 0.001$). These experiential states then mediate the relationship between ANP and IPS, which drives behavioral outcomes. Experiential states (PL, IMM, telepresence) serve as central mediators between both stimulus types and IPS. Their consistent mediation role across tested chains confirms that these states channel both technical assessments and emotional expectations toward reflective cognitive processing. ITSN subsequently mediates the relationship between experiential states and both PI (β = 0.421, $p < 0.001$) and CBI (β = 0.338, $p < 0.001$). Furthermore, the dual-process perspective embedded in the model was empirically confirmed: Automatic affective states (system 1), such as PL and IMM, channel into more reflective cognitive judgments (system 2), culminating in behavioral outcomes.

The mediation patterns reveal distinct temporal characteristics. Technical pathway effects showed longer chains with smaller individual coefficients but substantial cumulative influence, consistent with deliberative processing. Emotional pathway effects demonstrated shorter chains with larger individual coefficients, reflecting immediate affective priming. Both pathways converged through shared experiential mechanisms, supporting the integrative nature of AR consumer processing.

## Nonlinear Relationship

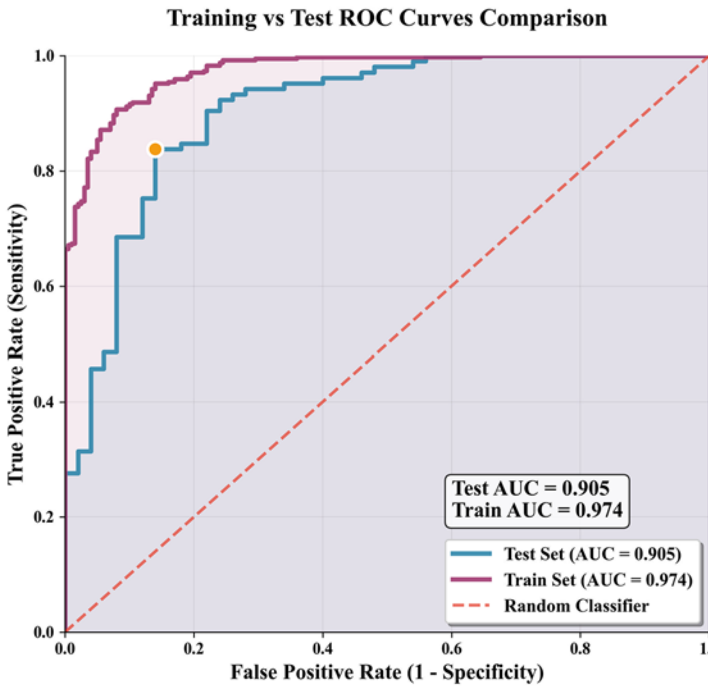
This study leveraged XGBoost, a gradient-boosting decision tree algorithm, in conjunction with SHAP, to explore and visualize potential nonlinearities and threshold effects that traditional linear approaches, such as PLS-SEM, may overlook. Specifically, we focused on IPS as the intermediate cognitive processing state, predicted by stimulus (technical features) and experience states (system 1: automatic experiences), in alignment with the proposed conceptual framework. The model demonstrated strong predictive performance for IPS (Table 6 and Figure 3), achieving an accuracy of 0.871 and an area under the curve (AUC) of 0.905 on the test set, indicating robust classification capabilities without significant overfitting (train AUC = 0.974).

**Table 6. Performance Results (Extreme Gradient Boosting-Shapley Additive Explanations [XGBoost-SHAP])**

<table>
<tr><th>Metric</th><th colspan="2">Class 0 (Negative)</th><th colspan="2">Class 1 (Positive)</th><th>Result</th></tr>
<tr><td>Precision</td><td colspan="2">0.830</td><td colspan="2">0.890</td><td>All supported</td></tr>
<tr><td>Recall</td><td colspan="2">0.760</td><td colspan="2">0.924</td><td>All supported</td></tr>
<tr><td>F1-score</td><td colspan="2">0.792</td><td colspan="2">0.907</td><td>All supported</td></tr>
<tr><td>Support</td><td colspan="2">50</td><td colspan="2">105</td><td>155</td></tr>
<tr><td>Accuracy</td><td colspan="4">0.871</td><td>Higher</td></tr>
<tr><td>AUC-ROC</td><td colspan="4">0.905</td><td>Higher</td></tr>
<tr><td colspan="6">Class Imbalance</td></tr>
<tr><td rowspan="2">Macro average<br>(no consideration)</td><td>Precision</td><td colspan="2">Recall</td><td>F1-score</td><td>Support</td></tr>
<tr><td>0.858</td><td colspan="2">0.842</td><td>0.849</td><td>155</td></tr>
<tr><td rowspan="2">Weighted average<br>(consideration)</td><td>Precision</td><td colspan="2">Recall</td><td>F1-score</td><td>155</td></tr>
<tr><td>0.869</td><td colspan="2">0.871</td><td>0.869</td><td>155</td></tr>
<tr><td colspan="6">XGBoost Feature Importance</td></tr>
<tr><td>Number</td><td colspan="4">Variables</td><td>Value</td></tr>
<tr><td>0</td><td colspan="4">Anticipated emotions (ANP)</td><td>0.870</td></tr>
<tr><td>1</td><td colspan="4">Pleasure (PL)</td><td>0.610</td></tr>
<tr><td>2</td><td colspan="4">Immersion (IMM)</td><td>0.430</td></tr>
<tr><td>3</td><td colspan="4">AR-induced telepresence (ARIT)</td><td>0.320</td></tr>
<tr><td>4</td><td colspan="4">Personalization (PSN)</td><td>0.180</td></tr>
<tr><td>5</td><td colspan="4">Augmented realism (AR)</td><td>0.160</td></tr>
<tr><td>6</td><td colspan="4">Interaction satisfaction (ITSN)</td><td>0.160</td></tr>
<tr><td>7</td><td colspan="4">Information vividness and richness (IVR)</td><td>0.120</td></tr>
</table>

*Note*. AUC = area under the curve; ROC = receiver operating characteristic; ANP = anticipated emotions; PL = pleasure; AR = augmented reality; ARIT = augmented reality-induced telepresence; PSN = personalization; ITSN = interaction satisfaction; IVR = information vividness and richness; IMM = immersion.

**Figure 3. Receiver Operating Characteristic (ROC) Curves Comparison**




*Note. ROC = receiver operating characteristic; AUC = area under the curve.*

We trained an XGBoost model with the eight stimulus–experience predictors as input and the dichotomized IPS score as output. The trees produce the log-odds of being in the "high-IPS" class, which is transformed into a probability through the logistic link as (1):

$$\Pr\left\{ IPS = 1 \mid x \right\} = \sigma(F(x)) = \frac{1}{1 + e^{-F(x)}}$$

. (1)

The partial-dependence function for a single predictor is defined as (2) (Friedman, 2001):

$$\mathrm{PD}_s\left(x_s\right) = \frac{1}{n}\sum_{i=1}^{n} F!\left(x_s, x_{C,i}\right)$$

, (2)

where $x_{C,i}$ denotes the observed values of all other predictors for the $i$-th respondent. Plotting (1) against the observed range of $x_s$ produces the curves in Figure 3, thereby giving the shape of the marginal effect while averaging out the remaining covariates.

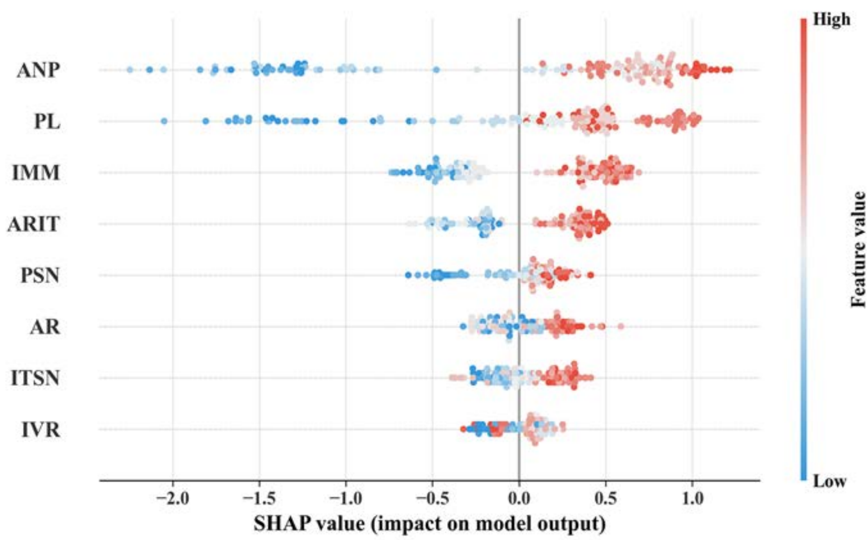
The SHAP value for predictor $j$ (Lundberg & Lee, 2017) decomposes the individual prediction into additive contributions:

$$F(x) = \phi_0 + \sum_{j=1}^{p} \phi_j, \phi_j = \sum_{S \subseteq \mathcal{F} \setminus \{j\}} \frac{|S|!(p - |S| - 1)!}{p!} \left[ f_{S \cup \{j\}}(x) - f_S(x) \right]$$

, (3)

with $\mathcal{F}$ being the full feature set of size $p$. Then, (2) guarantees a fair attribution of the model output to each input variable, which is why the bars in Figure 4 sum exactly to the model log-odds.

**Figure 4. Shapley Additive Explanations (SHAP) Value**




*Note. ANP = anticipated emotions; PL = pleasure; IMM = immersion; ARIT = augmented reality-induced telepresence; PSN = personalization; AR = augmented reality; ITSN = interaction satisfaction; IVR = information vividness and richness; SHAP = Shapley additive explanations.*

Model performance is summarized in Table 6. A test AUC of 0.905 confirms that a single intermediate construct (IPS) already explains a large share of the variance in subsequent behavior, while the gap to the training AUC (0.974) remains acceptable.

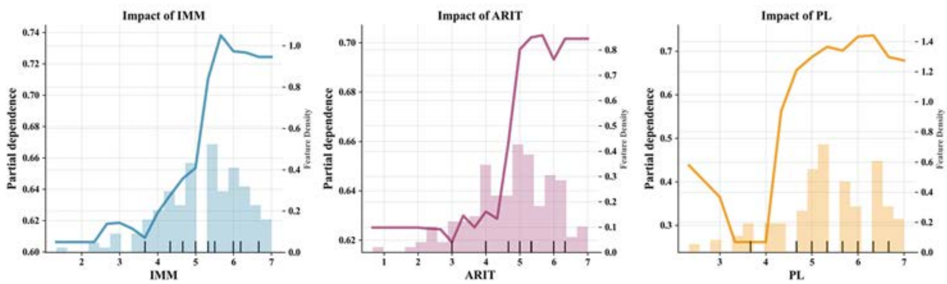
The SHAP summary plot indicates that ANP, PL, and IMM were the dominant contributors, with ARIT following closely. The direction of impact is monotone: Blue points (low scores) pull the log-odds to the left, while red points (high scores) push it to the right.

In (2), three distinct functional forms are revealed. PL is best described by an inverted-U, IMM by an S-shaped threshold function, and telepresence by a nearly step-like jump. These shapes signal that the transition from automatic experience to reflective ITSN is not a linear accumulation but, rather, occurs only after qualitative state changes, an interpretation that mirrors dual-process theory.

We deliberately restricted the machine-learning pass to IPS because the conceptual model specifies IPS as the sole direct antecedent of behavior (H11a/b). Including PI and CBI in the same equation would introduce direct paths that are not postulated by the theory, thereby conflating mediation with nonlinear main effects. If one wishes to explore nonlinearities beyond IPS, we propose a hierarchical two-stage design. In stage 1, the fitted probability $\widehat{Pr}\{\text{IPS} = 1 \mid x\}$ computed from (2); in stage 2, this predicted value enters a second XGBoost model that takes PI or CBI as the dependent variable. The procedure retains the original path structure while still allowing SHAP and partial-dependence diagnostics for the outcome variables. This study retains additional explorations in the supplementary materials.

SHAP analysis identified ANP, PL, and IMM as critical drivers of IPS. ARIT also demonstrated notable influence. Technical variables, while influential, exhibited comparatively modest importance. The SHAP summary plot (Figures 4 and 5) further elucidates the directionality of these effects, confirming that higher levels of key predictors positively influence the likelihood of experiencing ITSN.

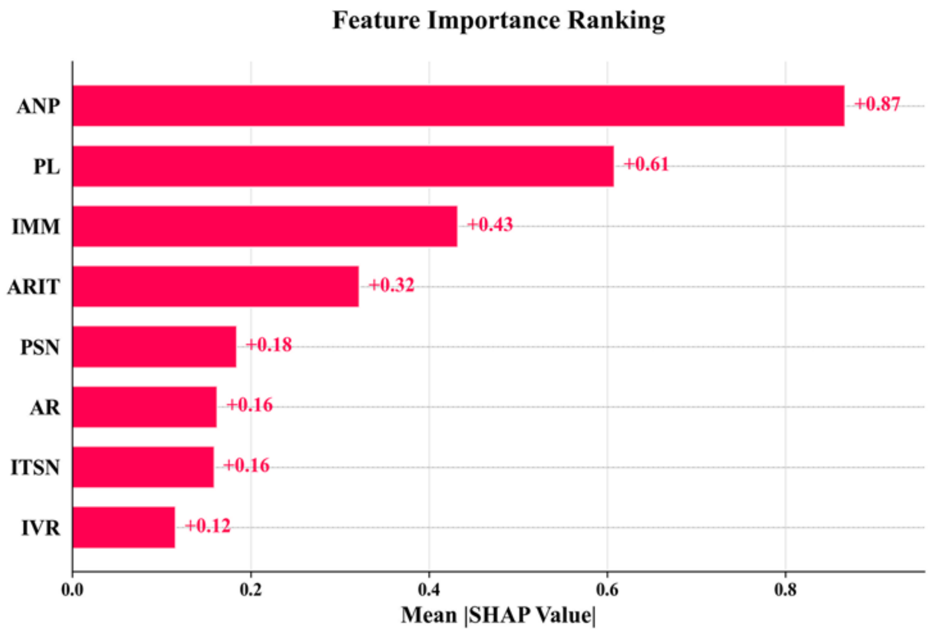
**Figure 5. Feature Importance Ranking**




*Note. ANP = anticipated emotions; PL = pleasure; IMM = immersion; ARIT = augmented reality-induced telepresence; PSN = personalization; AR = augmented reality; ITSN = interaction satisfaction; IVR = information vividness and richness; SHAP = Shapley additive explanations.*

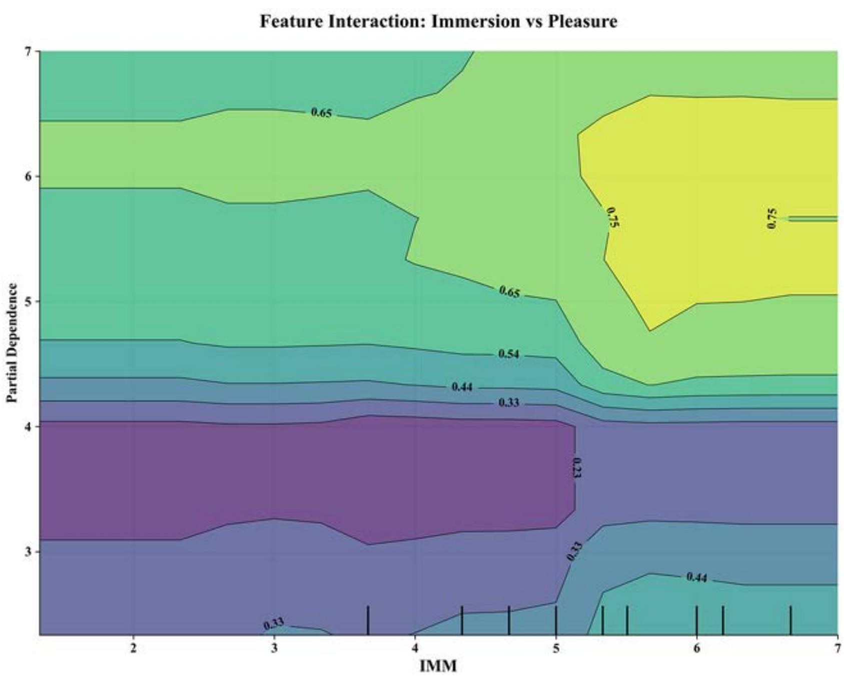
The partial dependence plots (Figure 6) provide deeper insights into the underlying relationships. IMM reveals an S-shaped threshold pattern, with notable increases in ITSN becoming apparent only after IMM reaches a critical level around 5 on a 7-point scale. ARIT shows a clear step-function, significantly boosting ITSN after surpassing approximately 4.5. PL displays an inverted U-shaped curve, suggesting a plateau at moderate levels followed by substantial gains in ITSN, eventually reaching saturation near a score of 6. Interaction analysis (Figure 7) further highlights a synergistic effect between IMM and PL, indicating that high levels of both factors significantly elevate ITSN beyond what either factor could achieve individually. This finding underscores a cooperative, multiplicative interaction consistent with dual-process theoretical expectations.

**Figure 6. Threshold Effect on Inspiration (IPS)**




*Note. IMM = immersion; ARIT = augmented reality-induced telepresence; PL = pleasure.*

**Figure 7. Feature Interaction Effect**




*Note. IMM = immersion.*

We purposefully constrained the machine learning analysis to the intermediate state IPS due to theoretical considerations outlined in our dual-process model. IPS acts as a cognitive bridge between immediate experiences (system 1) and deliberate behavioral outcomes (system 2). By isolating this intermediate construct, the analysis identifies thresholds and nonlinear effects in the initial processing stage without conflating subsequent decision-making processes. Including PI and CBI directly within a single-step analysis would obscure mediation effects, detracting from theoretical clarity.

Should a comprehensive nonlinear exploration of PI or CBI be warranted, a theoretically aligned sequential approach is recommended. In this approach, an initial XGBoost model predicts IPS from stimulus and experience variables, capturing IPS predictions. Subsequently, these predicted IPS values can be integrated into a second XGBoost model that predicts PI or CBI. Incorporating IPS alongside select experience states (IMM, PL) would enable testing of residual direct effects, verifying mediation strength, and further exploring potential nonlinear or threshold effects on behavioral outcomes. This two-stage analytic strategy respects established theoretical pathways, clarifying mediation relationships while maintaining flexibility to identify complex nonlinearities.

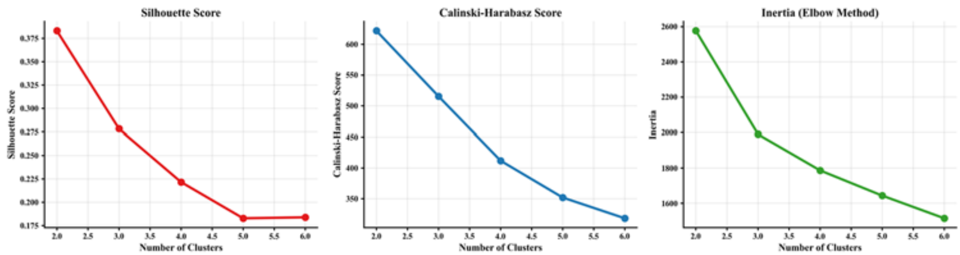
## ROBUSTNESS ANALYSIS

Following Hult et al. (2018), we assessed potential endogeneity using Park and Gupta's (2012) Gaussian copula approach. First, Kolmogorov-Smirnov tests confirmed nonnormal distribution of the latent variable scores (Sarstedt & Mooi, 2019). The Gaussian copula results (appendix B1) showed no significant endogeneity ($p > 0.05$) for the model constructs. Assessment of nonlinear effects using quadratic terms (appendix B2) found no significant unobserved nonlinear effects ($p > 0.05$). These analyses support the robustness of the structural model results.

In addition, our PLS-SEM analysis confirmed the hypothesized SOR pathways, and XGBoost-SHAP revealed nonlinear relationships. A critical methodological concern remained regarding the potential confounding effects of individual differences on our dual-processing framework. Specifically, correlations between experiential variables (system 1 processing) and cognitive outcomes (system 2 processing) may be artificially inflated by systematic individual differences in responsiveness rather than representing genuine psychological mechanisms. This concern is particularly salient in technology adoption research, where individual traits, such as "technology readiness" or "experiential openness," could create spurious correlations across all measured constructs. To address this fundamental threat to causal inference, we implemented a two-stage robustness validation framework combining k-means clustering for individual difference control with KNN classification for cluster stability validation (Fordellone & Vichi, 2020). This approach enables us to test whether our theoretical relationships survive when individual heterogeneity is statistically controlled, thereby distinguishing genuine psychological processes from statistical artifacts arising from unmeasured individual differences.

The selection of the optimal number of clusters followed a rigorous validation protocol using multiple clustering quality metrics. As illustrated in Figure 8, the three complementary indices converged on a two-cluster solution as the optimal solution. The silhouette score reached its maximum at $k = 2$ (0.383), indicating superior within-cluster cohesion and between-cluster separation compared to alternative cluster numbers. The Calinski-Harabasz score sharply declined after $k = 2$, suggesting that additional clusters would not capture meaningful psychological heterogeneity. The inertia plot revealed a clear elbow at $k = 2$, confirming that this solution optimally balances model parsimony with explanatory power.

**Figure 8. The Number of Clusters**

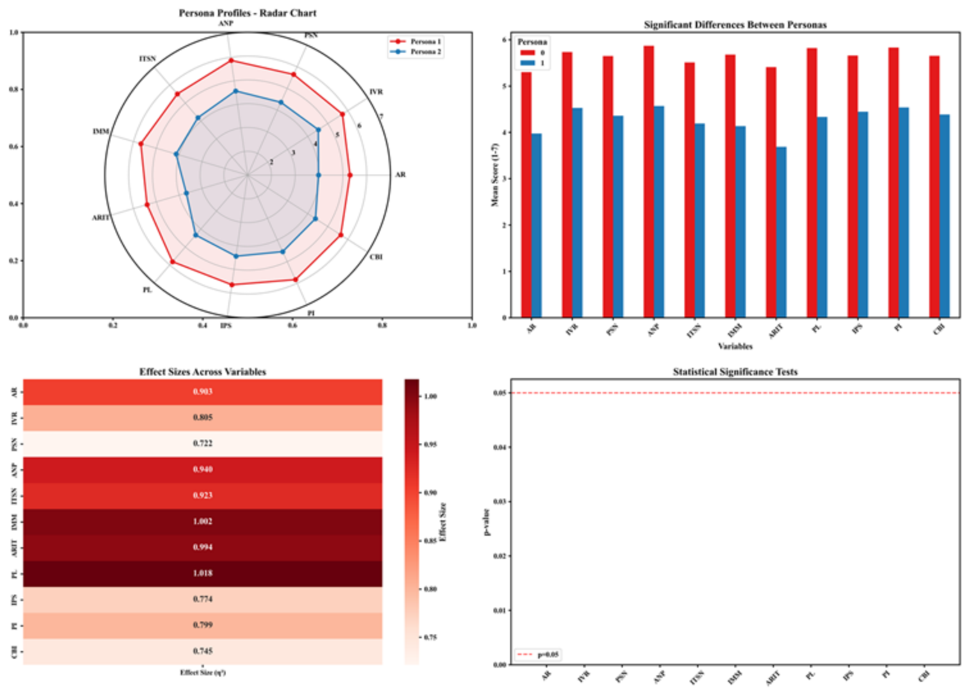



This convergent evidence across multiple validation criteria provides strong statistical justification for the two-cluster solution, while avoiding the arbitrary selection of cluster numbers that might bias subsequent analyses. The silhouette score of 0.383 exceeds the threshold for acceptable cluster quality (>0.25) and approaches the good cluster quality range (>0.50), indicating that our identified personas represent meaningful psychological groupings rather than random data partitions.

Clustering analysis utilized six theory-driven variables representing individual differences in experiential responsiveness: IMM (*M* = 5.12, SD = 1.09), ARIT (*M* = 4.78, *SD* = 1.22), PL (*M* = 5.28, *SD* = 1.04), ITSN (*M* = 5.03, *SD* = 0.97), technical feature responsiveness (AR, *M* = 4.82, *SD* = 0.98), and ANP (*M* = 5.40, *SD* = 0.95). These variables were selected because they capture the experiential and early cognitive responses most susceptible to individual difference confounding while excluding final behavioral outcomes to avoid tautological clustering.

The radar chart analysis presented in Figure 9 reveals distinct psychological profiles for each persona. Persona 1 (*n* = 494, 63.7%) exhibited consistently elevated responsiveness across all constructs, with particularly high scores for ANP (*M* = 5.87), PI (*M* = 5.83), and PL (*M* = 5.82). This group exhibited a pattern of high experiential engagement and strong behavioral intentions, indicating a “AR enthusiast” profile characterized by heightened receptivity to AR experiences. Persona 2 (*n* = 281, 36.3%) exhibited more moderate response patterns, with ANP (*M* = 4.57), PI (*M* = 4.54), and interactive augmented reality features (*M* = 4.53) representing the highest-scoring constructs. This “selective adopter” profile indicated more cautious, but still positive, engagement with AR technology.

**Figure 9. The Radar Chart Analysis**




*Note. ANP = anticipated emotions; AR = augmented reality; IVR = information vividness and richness; PSN = personalization; ITSN = interaction satisfaction; IMM = immersion; ARIT = augmented reality-induced telepresence; PL = pleasure; IPS = inspiration; PI = purchase intention; CBI = cross-buying intention.*

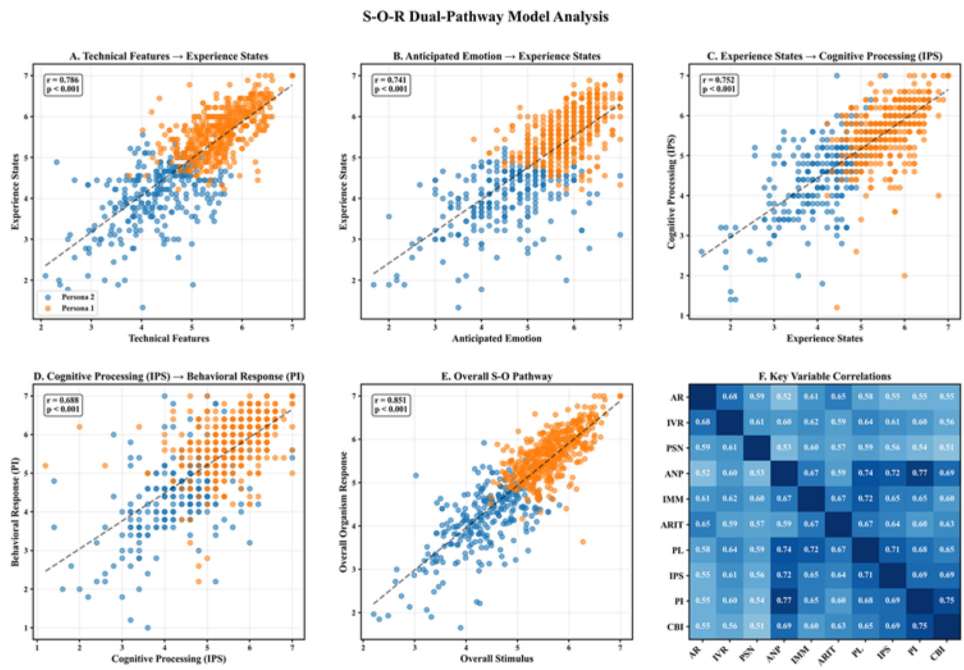
The effect size analysis confirms substantial between-person differences across all measured constructs. PL ($\eta^2 = 1.018$), IMM ($\eta^2 = 1.002$), and ARIT ($\eta^2 = 0.994$) showed the largest effect sizes, indicating that these experiential variables most strongly differentiate between the two user types. All measured variables demonstrated statistically significant differences ($p < 0.001$), confirming that the persona distinction captures systematic individual differences rather than random variation.

A critical concern in clustering-based robustness testing is whether identified clusters represent stable psychological types or merely sampling artifacts. To address this concern, we implemented a formal reproducibility validation protocol using the KNN classification method. The dataset was randomly split into training ($n = 581$, 75%) and hold-out ($n = 194$, 25%) sets. K-means clustering was performed on the training data to identify the two-cluster structure, and a KNN classifier was trained to learn the mapping from psychological variables to cluster assignments.

The reproducibility results provided exceptional evidence for cluster stability. The hold-out accuracy reached 96.39%, indicating that cluster assignments could be predicted with near-perfect accuracy in new data. More importantly, the adjusted Rand index (ARI) of 0.8594 demonstrated excellent agreement between predicted and actual cluster structures, well above the threshold for substantial agreement (ARI > 0.6). These results confirm that our identified personas represent reliable underlying psychological structures rather than random sampling variations, thereby validating the use of these clusters for confounding control analysis.

The SOR dual-pathway analysis presented in Figure 10 provides compelling visual evidence for both the strength of our theoretical relationships and the systematic differences between personas. Each pathway in our model demonstrated clear linear relationships with strong correlation coefficients: technical features to experience states ($r = 0.786$), ANP to experience states ($r = 0.741$), experience states to cognitive processing ($r = 0.752$), cognitive processing to behavioral response ($r = 0.688$), and the overall stimuli–organism (S–O) pathway ($r = 0.851$). The color-coding by persona revealed that, while both groups follow similar relationship patterns, persona 1 (orange points) consistently clusters in the higher ranges of both predictor and outcome variables, while persona 2 (blue points) occupies the lower-to-moderate ranges.

**Figure 10. Theoretical Pathway Visualization**

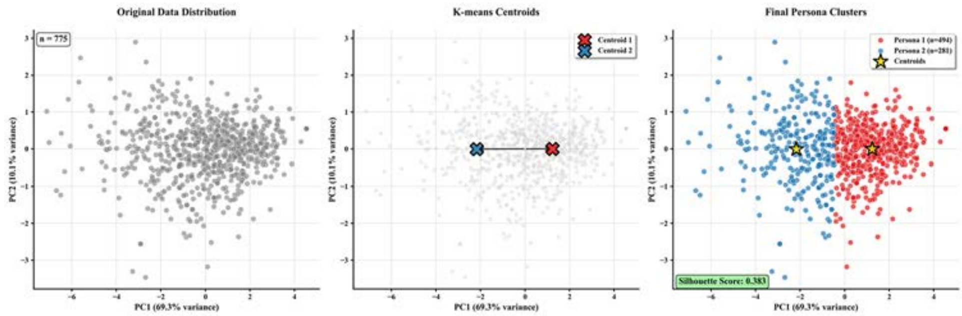



*Note. S–O–R = stimulus–organism–response; IPS = inspiration; PI = purchase intention; AR = augmented reality; IVR = information vividness and richness; PSN = personalization; ANP = anticipated emotions; IMM = immersion; ARIT = augmented reality-induced telepresence; PL = pleasure; CBI = cross-buying intention.*

This visualization pattern is crucial for interpreting our confounding analysis because it demonstrates that the strong overall correlations partially reflect the systematic differences between high- and low-responder groups. The clear separation between persona clusters across all pathway plots suggests that individual differences contribute substantially to the magnitude of observed relationships, supporting the need for within-persona robustness testing.

The k-means clustering process visualization in Figure 11 provides transparent documentation of our analytical approach and cluster quality assessment. The original data distribution illustrates the natural variation in our six-dimensional psychological space, reduced to two dimensions via Principal Component Analysis (PCA), which explains 79.4% of the total variance (PC1 = 69.3%, PC2 = 10.1%). The centroid positioning reveals optimal separation between the two cluster centers, with the final persona assignments demonstrating clear spatial separation and minimal overlap between groups.

**Figure 11. Clustering Process**

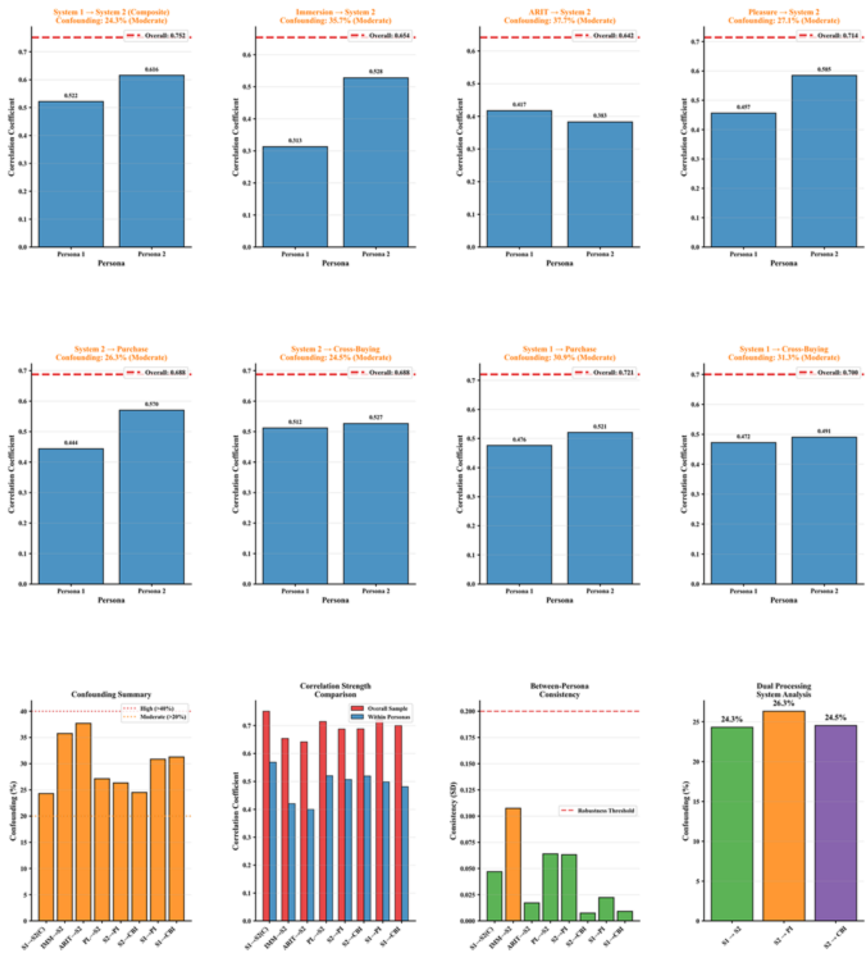



*Note. PC = Principal component.*

With stable clusters established, we conducted systematic robustness testing of our key theoretical pathways within each persona. The central hypothesis was that if our observed correlations reflected genuine psychological processes rather than individual difference artifacts, they should remain significant within homogeneous persona groups. Conversely, substantial attenuation of relationships within clusters would indicate confounding by unmeasured individual traits.

Figure 12 presents the comprehensive confounding analysis across all tested pathways. The analysis focused on the critical system 1 → system 2 pathway that represents the core dual processing concern. The overall correlation between the system 1 composite (combining IMM, ARIT, and PL) and system 2 (IPS) was $r = 0.752$ across the full sample. However, when examined within personas, this relationship showed meaningful but not dramatic attenuation: persona 1 as $r = 0.522$ and persona 2 as $r = 0.616$, yielding an average within-persona correlation of $r = 0.569$. This represents a 24.3% reduction in correlation strength, which we classify as moderate confounding severity.

**Figure 12. Comprehensive Confounding Analysis**



*Note. ARIT = augmented reality-induced telepresence; S1 = system 1; S2 = system 2; IMM = immersion; PL = pleasure; CBI = cross-buying intention; PI = purchase intention.*

Individual system 1 components revealed somewhat higher levels of confounding. The IMM → IPS pathway showed 35.7% confounding (overall $r = 0.654$ versus within-persona average $r = 0.420$), while ARIT → IPS demonstrated 37.7% confounding (overall $r = 0.642$ versus within-persona average $r = 0.400$). Notably, PL → IPS showed lower confounding at 27.1% (overall $r = 0.714$ versus within-persona average $r = 0.521$), suggesting that hedonic responses may be less susceptible to individual difference artifacts than spatial or immersive experiences.

Beyond the primary dual processing concern, we examined the robustness of downstream pathways from system 2 to behavioral outcomes. Surprisingly, these relationships showed confounding levels comparable to the system 1 → system 2 pathway rather than the expected reduction. The IPS → PI pathway exhibited 26.3% confounding (overall $r = 0.688$ versus within-persona average $r = 0.507$), while IPS → CBI showed 24.5% confounding (overall $r = 0.688$ versus within-persona average $r = 0.519$).

The confounding summary visualization in Figure 12 reveals a consistent pattern across all tested pathways, with confounding levels ranging from 24.3% to 37.7% but averaging around

30%. This distributed confounding pattern suggests that individual differences operate more broadly across our theoretical model than initially anticipated. Rather than concentrated confounding at the experiential-cognitive interface, we observed systematic response style differences affecting all pathway relationships approximately equally.

The correlation strength comparison demonstrates that, while overall sample correlations (red bars) consistently exceed within-persona correlations (blue bars), the relationships remain substantial and significant within controlled subgroups. The between-persona consistency analysis shows remarkably low variability (*SD* ranging from 0.007 to 0.107), indicating that, while effect sizes vary between personas, the directionality and significance of relationships remain stable across different user types.

Robustness analysis yields several critical insights for causal interpretation of AR experience effects. First, the moderate confounding levels (24%–38%) indicate that individual differences do inflate correlations but do not invalidate our theoretical claims. The substantial within-persona correlations ($r = 0.40$–$0.62$) demonstrate that genuine psychological relationships persist even after controlling for systematic individual differences, supporting the causal validity of our SOR framework.

Second, the distributed nature of confounding across all pathways suggests that our original concern about dual processing-specific confounding was overly narrow. The dual processing system analysis shown in Figure 12 reveals that system 1 → system 2 confounding (24.3%) is actually lower than system 2 → purchase (26.3%) and comparable to system 2 → cross-buying (24.5%). This pattern indicates general response style differences where some individuals consistently rate all psychological constructs higher than others, rather than pathway-specific confounding mechanisms.

Third, the excellent cluster stability validation (ARI = 0.86, hold-out accuracy = 96.4%) provides confidence that our confounding control method captures meaningful psychological heterogeneity rather than arbitrary statistical groupings. The high reproducibility demonstrates that these individual differences represent stable traits that would likely emerge in independent samples, supporting the generalizability of our robustness findings.

Key indicators are shown in appendix C1 to C3.

## DISCUSSION

In light of current work on information management in e-commerce, these findings can be read beyond the Chinese AR setting. Platforms that sell across countries need to coordinate several information layers simultaneously: the AR or rich-media layer that delivers realism and product data, the review and recommendation layer that guides attention, and the promotion or live-commerce layer that creates a short-term lift. E-commerce platforms actually adjust these layers differently across markets, which helps explain why technically similar AR features lead to uneven engagement and conversion (Batta et al., 2023; Gurbanova & Wang, 2023; Y. Li et al., 2023; L. Pham et al., 2023; Zhou et al., 2023). The findings show that when the affective route is strong, good timing of reviews, social signals, or live content can compensate for moderate AR capability. When the cognitive route is dominant, platforms must provide richer AR information and higher realism to trigger the same level of intention.

This study empirically validates a dual-pathway framework that resolves critical theoretical shortcomings in understanding AR consumer behavior. Our findings demonstrate that AR experiences operate through dual parallel processing pathways that convert technological stimuli into behavioral responses. The technical evaluation pathway operates through ITSN as consumers assess AR capabilities (AR $\beta = 0.296$, information richness $\beta = 0.439$, PSN $\beta = 0.185$). This aligns with but critically extends technology acceptance research (Davis, 1989; Venkatesh et al., 2003) by positioning ITSN as a post-experience competence validator rather than a pre-usage belief. In contrast, the emotional priming pathway activates experiential states through ANP (PL $\beta = 0.592$, IMM $\beta = 0.500$, telepresence $\beta = 0.370$), confirming our thesis that emotional inputs carried by the user function as independent stimuli, a factor often overlooked in prior AR-SOR models (Aslam & Davis, 2024; Sharma et al., 2023). Both pathways converge through IPS, which emerges as the psychological bridge driving PI (β = 0.694) and cross-buying behavior (β = 0.690). This architecture extends SOR by modeling parallel organism routes rather than a single chain and differs from acceptance models by focusing on post-experience, product-linked outcomes rather than adoption. It resolves the puzzle of why technically similar AR applications produce divergent consumer responses and clarifies how automatic experience (system 1) and reflective assessment (system 2) coordinate during and after exposure.

The predictive power of ITSN ($R^2$ = 65.6%) combined with its mediation of all technical feature effects establishes it as different from traditional technology acceptance constructs. In TAM/UTAUT, usefulness and ease of use capture pre-usage beliefs; here, ITSN functions downstream during use as a competence-validation conduit, not a proxy for ease or utility. As such, it also refines SOR by specifying the organism link through which capability features shape experience. A fuller treatment appears in the theoretical implication section. Rather than reflecting ease of use or functional utility, ITSN in AR contexts represents what the research conceptualizes as "embodied technical confidence"—a state where technological competence becomes integrated with the user's sense of environmental mastery.

This technical confidence mechanism operates through three evaluation processes. Information richness and vividness (β = 0.439) create what the study terms "diagnostic certainty," where visual and interactive cues reduce cognitive uncertainty by providing the informational depth consumers require for product assessment. This aligns with accessibility–diagnosticity frameworks while extending them into immersive environments where information processing becomes spatially and temporally distributed. AR (β = 0.296) activates "perceptual authenticity validation," where the visual and interactive fidelity of virtual objects triggers ecological perception mechanisms that assess environmental reliability. PSN (β = 0.185) facilitates "adaptive competence recognition," where the system's responsiveness to individual preferences signals technological sophistication while confirming the user's sense of environmental control.

The convergence of these three technical mechanisms through ITSN reveals that AR success depends not on any single technical feature but on the psychological integration of multiple competence signals into a unified sense of technological mastery. The indirect effects flowing from ITSN to IPS (ITSN → PL → IPS, β = 0.105; ITSN → ARIT → IPS, β = 0.091; ITSN → IMM → IPS, β = 0.058) demonstrate that technical competence validation creates psychological effects that extend beyond the immediate interaction, establishing the foundation for reflective cognitive processing and behavioral commitment.

A pivotal finding is the role of ANP as an autonomous psychological pathway that operates independently of technical quality assessment. The direct effects of ANP on all three experiential states (PL β = 0.592, IMM β = 0.500, telepresence β = 0.370) reveal what the research conceptualizes as "expectational embodiment"—where future-oriented emotional states create psychological readiness that shapes current experience regardless of technological performance. This provides empirical support for recent conceptual work emphasizing the role of pre-interaction affective states (Chekembayeva et al., 2023; Joo & Yang, 2023) and challenges the assumption in many SOR models that emotions are merely outcomes of stimulus evaluation.

This expectational embodiment operates through what the study terms "affective cognitive priming," where anticipated positive emotions create attentional and interpretive filters that enhance receptivity to AR stimuli. Unlike traditional emotion research, which focuses on concurrent emotional responses, the findings demonstrate that pre-experience emotional expectations function as autonomous psychological drivers that can sustain positive engagement even when technical features underperform. The mediation pathway from ANP through PL to IPS (ANP → PL → IPS, β = 0.248) reveals that emotional priming effects persist through extended cognitive processing, influencing behavioral decisions by integrating into reflective assessment.

The implications extend beyond AR to challenge assumptions about technology adoption models. Traditional models assume that emotional responses emerge from technical evaluation, yet the findings demonstrate that emotional expectations can drive positive experiences independently of technological quality. This places adoption beliefs and post-experience processes on distinct timelines: Anticipatory effect can set the processing context before use, while technical appraisal operates during use. The finding that ANP predict telepresence ($\beta = 0.370$)—traditionally considered a cognitive spatial presence construct—demonstrates how emotional priming can override perceptual processing limitations, creating a sense of spatial presence through psychological rather than technological mechanisms.

ITSN functions emerges not merely as an outcome but as the central cognitive architecture where automatic experiential processing meets deliberate cognitive assessment, revealing what the study conceptualizes as "motivational cognitive integration" in the study. Unlike attitude formation, IPS in AR contexts represents a psychological synthesis where immediate experiential states (system 1 processing) inform forward-looking cognitive elaboration (system 2 processing), generating behavioral readiness. The predictive power of IPS for both PI ($\beta = 0.694$) and cross-buying behavior ($\beta = 0.690$) positions it as the most behavioral predictor in the model, exceeding the influence of any individual experiential state.

This motivational cognitive integration operates through what the research terms "experiential insight crystallization," where consumers transform immediate AR experiences into psychological insights about product possibilities and personal preferences. The indirect effects flowing from all experiential states to behavioral intentions through IPS (IMM → IPS → PI $\beta = 0.138$; PL → IPS → PI $\beta = 0.290$; telepresence → IPS → PI $\beta = 0.163$) demonstrate that IPS serves as the psychological bridge that converts technological experiences into behavioral commitments.

The temporal dimension proves central: IPS emerges not during AR interaction but through post-experience cognitive processing, where consumers reflect on what the AR experience revealed about products, their preferences, and consumption possibilities. This temporal delay explains why IPS predicts behavior more than immediate experiential states—it represents the psychological crystallization of AR experiences into cognitive attitudes that guide future behavior. The finding that IPS mediates CBI as it does direct PI reveals what the study terms "inspirational category transfer," where positive AR experiences with one product generate broader consumption confidence through enhanced psychological readiness for related product exploration.

The dual-pathway framework provides evidence for how automatic and controlled cognitive systems coordinate in immersive technology contexts, revealing what the research conceptualizes as "dual-process technological engagement." The three experiential states—IMM, telepresence, and PL—represent system 1 processing, which involves automatic, immediate responses that occur without conscious deliberation. Their activation by both technical features (through ITSN) and emotional priming (through ANP) demonstrates how AR stimuli can trigger multiple automatic processing systems without interference or conflict. System-level labels are used functionally; we do not claim direct measurement of processing modes.

System 2 processing emerges through IPS, which requires what the study terms "controlled experiential integration"—deliberate cognitive effort to synthesize automatic responses into actionable insights. The finding that all three experiential states predict IPS with coefficients (IMM $\beta = 0.199$, telepresence $\beta = 0.236$, PL $\beta = 0.418$) reveals that automatic responses and reflective assessment in AR contexts operate not in sequence but in a coordinated feedback loop where automatic responses inform controlled processing. This offers a more nuanced application of dual-process theory (Evans, 2008; Kahneman, 2011) to consumer technology, moving beyond the notion of competing systems to illustrate their synergistic cooperation in immersive environments.

This coordination reveals insight about human-technology interaction: Immersive technologies succeed not by overwhelming either automatic or controlled processing but by creating what the study terms "cognitive processing synergy", where system 1 responses provide material for system 2 elaboration. The temporal extension of this coordination—where IPS continues to develop through post-experience reflection—demonstrates that AR experiences create cognitive-emotional integration that persists beyond the initial technological encounter. This challenges traditional technology acceptance models, which assume that psychological processing concludes with immediate usage, revealing instead that technology engagement involves extended cognitive integration processes.

Theoretical frameworks often cross cultures only when their core mechanisms are stated at an appropriate level of generality. The model maintains this level at the functional, rather than the label, level: automatic experience states during AR use and a reflective bridge that converts those states into intention. These functions are expected to exist broadly, but the inputs that activate them can be culturally patterned. In markets where social identity and relational harmony are salient, emotional primers may include expectations about social fit and family standing in addition to excitement, potentially strengthening the meaning-alignment route even when technical appraisal is moderate. On the technical route, the same AR capability (for example, PSN) can carry different meanings—signaling self-expression in individualist contexts versus signaling status alignment or trend conformity in more collectivist contexts. The findings support the architecture of two concurrent routes, though future cross-cultural research is needed to verify how the strengths of specific paths may shift across different contexts.

The findings reveal psychological differentiation among AR technical features that extends beyond additive effects. Information richness emerges as the technical predictor ($\beta = 0.439$), operating through what the study terms "cognitive uncertainty reduction," where visual and interactive information reduces decision-making ambiguity. AR ($\beta = 0.296$) functions through "perceptual credibility validation," where visual fidelity triggers ecological perception mechanisms that assess environmental authenticity. PSN ($\beta = 0.185$) activates "adaptive relevance recognition," where system responsiveness to individual preferences signals technological sophistication while confirming user agency.

The three experiential states demonstrate coordination in their response to both technical features and emotional priming. PL shows an emotional pathway coefficient ($\beta = 0.592$) and an effect on IPS ($\beta = 0.418$), positioning it as the study terms the "hedonic integration hub," where positive affect catalyzes cognitive engagement. IMM ($\beta = 0.500$ from ANP, $\beta = 0.199$ to IPS) operates as the "attentional absorption gateway," where focused engagement facilitates cognitive processing. Telepresence ($\beta = 0.370$ from ANP, $\beta = 0.236$ to IPS) functions as the "spatial presence amplifier," where environmental integration enhances the psychological reality of virtual product interactions.

The mediation patterns reveal that these experiential states operate not as independent responses but as coordinated psychological systems that transform AR stimuli into behavioral readiness. Their predictive relationships across both pathways demonstrate what the research terms "experiential state coherence," where multiple psychological responses work together to create unified engagement rather than competing for cognitive resources.

The XGBoost-SHAP analysis reveals nonlinearities in AR psychological processing that traditional linear models cannot capture, demonstrating what the study conceptualizes as "threshold-dependent psychological engagement." The S-shaped relationship between IMM and IPS reveals a psychological threshold around 5.0 on the 7-point scale, below which IMM contributes to IPS, but above which it generates motivational cognitive processing. This suggests that AR experiences must achieve attentional absorption before they can trigger the controlled cognitive processing that drives behavioral intentions.

The step-function relationship between telepresence and IPS (threshold $\approx$ approximately 4.5) demonstrates the research term "spatial presence activation," where a level of environmental integration must be achieved before telepresence contributes to motivation. The inverted-U relationship for PL reveals "hedonic optimization dynamics," where moderate PL levels provide IPS, but PL may overwhelm cognitive processing capacity. These threshold effects suggest that AR design requires calibrated psychological engagement rather than maximizing any single experiential dimension.

The KNN + k-means individual difference analysis reveals the existence of two consumer personas that demonstrate confounding effects. The confounding levels (24%–38% across pathways) confirm that, while individual differences influence response magnitudes, psychological relationships persist within homogeneous consumer groups. The “AR enthusiasts” (63.7%) and “selective adopters” (36.3%) represent psychological types with reproducibility (ARI = 0.86, hold-out accuracy = 96.4%), indicating that AR consumer heterogeneity follows predictable patterns rather than random variation.

The distributed nature of confounding across all pathways, rather than concentrated at the system 1-system 2 interface, reveals that individual differences operate through responsiveness patterns rather than pathway-specific mechanisms. This supports the robustness of the dual-pathway framework while acknowledging that some consumers rate all psychological constructs higher than others, reflecting individual traits in technology engagement rather than measurement artifacts.

## THEORETICAL IMPLICATION

The research extends marketing theory in four ways by introducing and validating a dual-pathway SOR framework that explains the complex psychological mechanisms underlying AR consumer engagement. These theoretical contributions establish new frameworks for understanding technology-mediated consumer behavior while addressing gaps in existing literature on SOR mechanisms and dual-process cognition in digital environments.

First, the study extends SOR theory into immersive technology contexts by establishing parallel pathway processing as the core mechanism underlying consumer engagement with complex digital interfaces. Traditional SOR applications in marketing assume sequential processing where stimuli flow through singular organism pathways toward behavioral responses (Bagozzi, 1994; Donovan & Rossiter, 1982; Mehrabian & Russell, 1974). Recent applications to digital contexts have maintained this single-pathway assumption, treating technology features as unified stimuli that activate homogeneous cognitive processing (Eroglu et al., 2001; Manganari et al., 2009; Yu et al., 2024). Our framework challenges this oversimplification by demonstrating that immersive technologies simultaneously activate two autonomous processing routes: a technical evaluation pathway flowing through ITSN and an emotional priming pathway initiated by ANP. This “dual-pathway SOR architecture” resolves persistent inconsistencies in technology adoption research where technically similar systems produce divergent consumer responses (Islam et al., 2019; Venkatesh et al., 2003). The framework extends SOR theory beyond traditional retail environments by demonstrating how complex digital stimuli necessitate theoretical models that accommodate parallel rather than sequential psychological processing, thereby addressing issues of more sophisticated organism conceptualization in contemporary consumer research (H. Song et al., 2024; Talwar et al., 2022).

Second, the research advances dual-process theory by providing empirical validation for the coordination of system 1 and system 2 in immersive technology contexts, revealing what the study conceptualizes as “technological dual-process integration.” Although dual-process theories have established that automatic and controlled cognitive systems operate simultaneously in human cognition (Evans, 2008; Kahneman, 2011; Stanovich, 2004), marketing applications have typically treated these systems as competing rather than coordinating mechanisms (Hofmann et al., 2009; Strack & Deutsch, 2004). Our findings provide a clear operationalization: The experiential states (IMM, telepresence, PL) represent system 1 processing, while IPS embodies the reflective synthesis of system 2. The significant paths from all three experiential states to IPS demonstrate a systematic feed-forward mechanism where automatic responses provide the raw material for controlled cognitive elaboration. This extends dual-process theory by illustrating a successful coordination architecture in a high-fidelity technological context, moving beyond the traditional focus on conflict between intuition and reason. The framework extends dual-process theory by demonstrating that effective technology design requires creating synergy between automatic and controlled processing, rather than optimizing either system in isolation. This provides a theoretical foundation for understanding how complex digital interfaces engage human cognitive architecture in ways that traditional dual-process applications have not captured. This linkage continues post-interaction, offering a coordination account for immersive interfaces.

Third, the study establishes IPS as a theoretically distinct construct that operates through motivational cognitive integration, extending beyond traditional attitude-behavior models to capture forward-looking psychological processing. Marketing literature has predominantly focused on immediate attitudinal responses to technology stimuli, treating behavioral intentions as direct outcomes of concurrent cognitive and affective states (Ajzen, 1991; Davis, 1989; Fishbein & Ajzen, 2010). Our findings position IPS as a superior mediator in immersive contexts. Unlike satisfaction, which is a retrospective evaluation, or attitude, which is a general predisposition, IPS is a forward-looking state of motivational arousal (Thrash & Elliot, 2003). The high coefficients from IPS to behavioral intentions ($\beta > 0.69$), exceeding those of all other antecedents, underscore its pivotal role as the decisive catalyst for action. Furthermore, the finding that IPS mediates CBI reveals its capacity to transfer motivational energy beyond the immediate product to related categories. This introduces "inspirational transfer" as a new mechanism for understanding basket-building and category expansion in retail, a phenomenon that traditional attitudinal models poorly explain. ITSN serves as the primary bridge from experience to intention and remains influential after use, which challenges the view that processing ends at system interaction.

## PRACTICAL IMPLICATION

The research provides prioritized, feasible guidance for retailers implementing AR technology by linking dual-pathway processing requirements and nonlinear engagement thresholds that determine consumer response effectiveness, particularly in high-adoption markets. To ensure accessibility, recommendations focus on low-cost, scalable steps that leverage existing tools, drawing on empirical effects, such as $\beta$ values, and prior AR studies for targeted impact.

AR interface designers should prioritize information richness ($\beta = 0.439$) as the primary technical development focus, implementing comprehensive product visualization with multiple detail levels, interactive specification access, and contextual comparison tools in e-commerce platforms. Visual fidelity must emphasize realistic color reproduction and natural object behavior rather than flashy effects that undermine credibility. Similarly, PSN features should begin with rule-based adaptations, such as the size or color filters, to balance technical utility and priming without high AI costs, demonstrating adaptive intelligence through simple progressive learning from user interactions while maintaining user control and agency.

Emotional design elements require equal attention to technical features. Pre-interaction onboarding should build ANP through affordable preview animations, personalized welcome sequences, and progressive feature introduction that measure excitement and confidence. Interface feedback systems should celebrate user exploration achievements and provide positive reinforcement during product evaluation to sustain emotional engagement throughout extended interactions.

The nonlinear threshold effects, revealed through XGBoost-SHAP analysis, calibrate engagement design principles for measurable gains without over-engineering. IMM requires achieving a minimum 5.0-level attentional absorption through short and low-cost guided interaction tutorials and basic gamification elements. Telepresence requires a baseline 4.5-level spatial presence, achieved through realistic environmental lighting and accurate object placement. PL optimization should target sustained engagement rather than peak stimulation to avoid cognitive overload that impairs decision-making processing. These thresholds can be monitored via built-in app analytics for real-time adjustments, ensuring pathways activate efficiently.

Marketing strategy should leverage the emotional pathway independence by implementing pre-experience expectation management campaigns that emphasize AR discovery, empowerment, and PSN benefits rather than purely technical capabilities. Communication should target identified consumer personas: feature-rich, innovation-focused messaging for AR enthusiasts (63.7%) versus simplified, confidence-building approaches for selective adopters (36.3%).

Customer journey strategy must account for IPS's post-experience emergence ($\beta = 0.694$ to PI) by implementing feasible reflection facilitation mechanisms, such as save-for-later features preserving AR configurations, personalized follow-up communications referencing specific interactions, and comparison tools supporting extended cognitive processing. Cross-buying opportunities should leverage inspirational category transfer through related product suggestions immediately following successful AR interactions. For conversion optimization, retailers can track dual pathways via simple satisfaction/emotion surveys, timing follow-ups within 24–48 hours to align with IPS patterns.

Organizational structure requires cross-functional AR teams combining technical developers, consumer psychologists, and marketing strategists to ensure dual or multiple-pathway optimization expertise. Staff training should focus on basic persona awareness to guide experiences, enabling customer-facing employees to direct consumers through appropriate AR interactions and facilitate post-experience reflection conversations that drive IPS and purchase conversion.

Business model integration should position AR as an IPS generation capability rather than simple product visualization tool. This requires metrics systems measuring IPS indicators alongside traditional conversion rates, budget allocation supporting both technical development and emotional design capabilities, and performance evaluation frameworks recognizing the temporal separation between AR interaction and purchase behavior. Industry examples can be used illustratively when mapping capabilities to organizational roles. Retailers or specialists can refer to the business model of the company Kivisense Technology, in China, which integrates AR for e-commerce visualization with user feedback loops to enhance engagement without excessive customization.

Strategic investment priorities should emphasize sustainable competitive advantages through coordinated multiple-pathway excellence rather than technological sophistication alone. This includes developing proprietary emotional design capabilities, building consumer persona profiling systems for automatic experience adaptation, and creating post-experience engagement platforms that facilitate the extended cognitive processing driving behavioral conversion. Organizations achieving coordinated technical competence and emotional priming optimization will establish differentiated market positions in increasingly AR-enabled retail environments.

Implementation should begin with pilot programs testing the effectiveness of psychology across identified consumer personas. Scale should be based on IPS generation and conversion metrics, rather than technical feature adoption, and evolve toward integrated customer experience platforms that leverage AR's unique capacity for creating lasting psychological engagement, extending beyond immediate technological interaction.

## LIMITATIONS AND FUTURE RESEARCH

The cross-sectional design limits causal inference despite theoretically grounded temporal ordering in the dual-pathway framework. While the study establishes that IPS emerges through post-experience reflection, longitudinal designs would strengthen causal claims by capturing the actual temporal unfolding of psychological processes. Future research should implement multiwave panel studies tracking consumers from pre-AR expectations through immediate experience to post-experience reflection and behavioral outcomes.

Experimental designs offer another avenue for establishing causality while controlling individual differences. Researchers should develop controlled laboratory experiments manipulating specific AR features while measuring real-time physiological and psychological responses. The hybrid analytical approach, while innovative, introduces limitations. XGBoost-SHAP provides nonlinear insights but cannot establish causality, whereas KNN + k-means identifies stable personas but may miss dynamic individual differences. Future methodological development should explore dynamic clustering approaches tracking persona stability over time.

The dual-pathway framework requires an examination of the boundary conditions that determine when the technical evaluation and emotional priming pathways operate independently versus interactively. The study establishes parallel processes but does not identify conditions under which pathways interfere or when one pathway dominates processing. Future research should investigate moderating factors, such as product complexity, purchase involvement, and technological expertise, that influence pathway activation patterns.

ITSN emerges as the convergence mechanism, but its boundary conditions remain unexplored. The research demonstrates the mediating role of ITSN but does not examine when ITSN fails to develop despite positive experiences, nor when ITSN occurs without strong AR engagement. Future studies should investigate the threshold conditions necessary for ITSN formation and the factors that enhance or inhibit the transformation of experiential states into motivational cognition.

ITSN functions as the technical pathway gateway, but its relationship to traditional technology acceptance constructs requires clarification. Future research should examine when ITSN diverges from established predictors and identify unique psychological processes underlying competence validation in immersive environments.

The evidence is drawn from a single-country study, which limits external validity across cultural settings, particularly given cultural variations in technology adoption and emotional expression. A logical next step is a multi-country design that holds AR tasks constant while comparing the strength of the meaning-alignment route versus the technical appraisal route. Such research should also test measurement invariance and compositional equivalence before making group comparisons and incorporate context-orientation measures so that cultural differences are modeled rather than assumed.

The retrospective measurement approach may be influenced by memory limitations and post-experience rationalization. Future studies should combine retrospective measures with real-time experience sampling and physiological monitoring to capture authentic psychological responses during AR interaction.

Current findings are based on mobile AR applications, but emerging technologies, such as mixed reality headsets and spatial computing platforms, may operate through different psychological mechanisms. Future research should investigate whether dual-pathway processing is applicable to advanced immersive technologies or necessitates theoretical modification.

Metaverse-based VR experiments offer unprecedented opportunities for controlled manipulation of immersive experiences while maintaining ecological validity. Researchers should develop VR experimental platforms enabling precise environmental control while capturing comprehensive behavioral data. Such platforms could extend beyond retail contexts to examine dual-pathway processing in education, healthcare, and entertainment applications.

AI integration with AR creates new frontiers that require theoretical extensions. AI-powered PSN systems that adapt in real-time to consumer responses may blur pathway boundaries by creating experiences that deliver simultaneous technical competence and emotional relevance. Future research should investigate how the integration of AI affects pathway independence and processing mechanisms.

Cross-product line extension represents another promising direction, leveraging metaverse platforms to examine multipathway processing across diverse product categories while controlling individual and contextual variables.

The intersection of dual processing with emerging theories in consumer psychology presents rich opportunities for theoretical development. Future research should examine how embodied cognition, predictive processing, and enactive perception complement or challenge the dual-pathway framework, potentially leading to more comprehensive models of immersive technology engagement.

These limitations collectively point to an exciting research agenda that extends dual-pathway processing theory while developing sophisticated methodological approaches for understanding consumer behavior in increasingly immersive technological environments.

## CONCLUSION

This study, centered on the Chinese retail market, addressed a critical puzzle in AR retail: why technically similar applications produce vastly different consumer responses. Through an investigation of 779 AR shopping experiences, the research reveals that consumer engagement operates through dual parallel pathways, rather than the single processing routes assumed by traditional models.

The findings establish three core mechanisms driving AR effectiveness. First, ITSN emerges as the technical pathway gateway, with information richness ($\beta = 0.439$), AR ($\beta = 0.296$), and PSN ($\beta = 0.185$) converging to validate technological competence. Second, ANP function as an independent emotional priming pathway, directly activating experiential states, including PL ($\beta = 0.592$), IMM ($\beta = 0.500$), and ARIT ($\beta = 0.370$), regardless of technical performance. Third, IPS serves as the decisive convergence mechanism where both pathways meet, demonstrating the strongest behavioral influence with coefficients of 0.694 for PI and 0.690 for cross-buying behavior.

The methodological innovations provide crucial insights into psychological complexity. XGBoost-SHAP analysis reveals threshold-dependent engagement patterns, where IMM requires achieving a 5.0-level activation, telepresence necessitates a 4.5-level spatial presence, and PL follows inverted-U optimization dynamics. The KNN + k-means approach identifies stable consumer personas (AR enthusiasts, 63.7%; selective adopters, 36.3%) while controlling for individual difference confounding, demonstrating that genuine psychological relationships persist even after accounting for systematic response variation.

These discoveries expand marketing theory by suggesting parallel pathway processing as a potential core mechanism underlying immersive technology engagement in the studied context, validating system 1 and system 2 coordination in digital contexts, and positioning IPS as a distinct motivational cognition construct that converts experiential states into behavioral commitment. The dual-pathway SOR framework resolves persistent inconsistencies in technology adoption research while providing a theoretical foundation for understanding complex digital interfaces.

The practical implications transform the AR implementation strategy by requiring coordinated optimization across technical competence validation and emotional priming rather than pursuing technological sophistication alone. Retailers must implement competence-based design, prioritizing information richness, expectation management, cultivating ANP, and post-experience facilitation supporting IPS development. The nonlinear threshold effects demand engagement calibration, ensuring minimum activation levels across psychological dimensions.

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## COMPETING INTERESTS

The authors of this publication declare that there are no competing interests.

## SUPPLEMENTARY MATERIALS 1

https://drive.google.com/file/d/1lGra_sLl3qsSb4qyncIrcvTI-UCFBII5/view?usp=sharing

## SUPPLEMENTARY MATERIALS 2

https://drive.google.com/file/d/1L4yKFtnf4UETfYrDYbkbsYvITLGZ7Pd4/view?usp=sharing

## CORRESPONDING AUTHOR

Correspondence should be addressed to Joston Gary: lirui@ua.pt

## DATA AVAILABILITY STATEMENT

Data is contained within the article.
**Note:** Joston Gary and Xixing Zhou, co-first authors, contributed equally to this work.

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## APPENDIX A

**Constructs and Their Parameters**

| Constructs | Loading | Item | 7-Point Scale |
|---|---|---|---|
| Augmented realism | AR 1 | How real did the virtual objects seem to you? | 1 = Completely unreal, 7 = Very real |
| | AR 2 | To what extent did the experience seem real to you? | 1 = Not real at all, 7 = Very real |
| | AR 3 | To what extent was the augmented object similar to reality? | 1 = Not similar at all, 7 = Very similar |
| | AR 5 | In your opinion, how was the quality of the images of the website objects? | 1 = Very poor quality, 7 = Excellent quality |
| | AR 6 | To what extent was what you experienced in the augmented world congruent to other experiences in the real world? | 1 = Not congruent at all, 7 = Highly congruent |
| | Interaction satisfaction | ITSN 1 | I felt in control of my overall experience when using the AR application. |
| ITSN 2 | | I could easily navigate through different features in the AR experience. | 1 = Very difficult, 7 = Very easy |
| ITSN 3 | | I had control over which AR content I wanted to view. | 1 = No control at all, 7 = Full control |
| ITSN 4 | | I could adjust the pace of my product exploration in AR as I wished. | 1 = Could not adjust at all, 7 = Fully adjustable |
| ITSN 5 | | The AR application responded quickly to my interactions. | 1 = Very slow response, 7 = Very fast response |
| ITSN 6 | | The AR application allowed me to interact with product information in an engaging manner. | 1 = Not engaging at all, 7 = Highly engaging |
| Information vividness and richness | IVR 1 | I thought the product information provided by AR was vivid and clear. | 1 = Not vivid/clear at all, 7 = Extremely vivid/clear |
| | IVR 2 | The AR experience offered rich and detailed product information. | 1 = Not rich/detailed at all, 7 = Extremely rich/detailed |
| | IVR 3 | The product features presented through AR were well-defined and sharp. | 1 = Not well-defined/sharp at all, 7 = Very well-defined/sharp |
| | IVR 4 | AR provided a clear and detailed view of the product. | 1 = Not clear/detailed at all, 7 = Very clear/detailed |
| | IVR 5 | The AR application offered vivid and comprehensive product information. | 1 = Not vivid / comprehensive at all, 7 = Very vivid/ comprehensive |
| Personalization | PSN 1 | The virtual try on/try out function is to a certain extent personalized. | 1 = Not personalized at all, 7 = Highly personalized |
| | PSN 2 | The virtual try on/try out function can be used in any way I like. | 1 = Cannot be used flexibly at all, 7 = Can be used very flexibly |
| | PSN 3 | The virtual try on/try out function meets my individual needs. | 1 = Does not meet my needs at all, 7 = Fully meets my needs |

*continued on following page*

**Constructs and Their Parameters**

| Constructs | Loading | Item | 7-Point Scale |
|---|---|---|---|
| Immersion | IMM 1 | Your level of involvement in using AR? | 1 = Not deeply engrossed at all, 7 = Completely engrossed |
| | IMM 2 | How attracted are you to AR? | 1 = Not absorbed at all, 7 = Fully absorbed |
| | IMM 3 | My attention was not focused/my attention was focused. | 1 = Not focused at all, 7 = Fully focused |
| AR-induced telepresence | ARIT 1 | I had a sense of the products when I tried on the product using AR. | 1 = No sense of the products, 7 = Strong sense of the products |
| | ARIT 2 | I felt I was trying on the products on the mobile app. | 1 = Did not feel like trying on, 7 = Completely felt like trying on |
| | ARIT 3 | I felt that the products could almost be touched. | 1 = Did not feel touchable at all, 7 = Felt almost touchable |
| Pleasure | PL 1 | I feel happy when using the AR features to explore products. | 1 = Not happy at all, 7 = Very happy |
| | PL 2 | I feel satisfied with the visual experience provided by the AR application. | 1 = Not satisfied at all, 7 = Very satisfied |
| | PL 3 | I find the AR interaction with products pleasurable. | 1 = Not pleasurable at all, 7 = Very pleasurable |
| Inspiration | IPS 1 | Interacting with the AR feature stimulated my imagination about product use. | 1 = Not stimulated at all, 7 = Highly stimulated |
| | IPS 2 | The AR experience gave me new ideas about how to use or style the product. | 1 = No new ideas at all, 7 = Many new ideas |
| | IPS 3 | I unexpectedly discovered new product features or applications through the AR visualization. | 1 = No discoveries at all, 7 = Many discoveries |
| | IPS 4 | The AR experience expanded my understanding of product features and uses. | 1 = No expansion at all, 7 = Great expansion |
| | IPS 5 | I discovered new aspects of the product through the AR experience. | 1 = No discoveries at all, 7 = Many discoveries |
| Anticipated emotion | ANP 1 | Excitement: "I anticipate feeling excited when using the AR feature to explore products." | 1 = No excitement at all, 7 = Very excited |
| | ANP 2 | Satisfaction: "I expect to feel satisfied with the AR shopping experience." | 1 = Not satisfied at all, 7 = Very satisfied |
| | ANP 3 | Curiosity: "I look forward to exploring products with curiosity through AR." | 1 = Not curious at all, 7 = Very curious |
| | ANP 4 | Surprise: "I anticipate being pleasantly surprised by what I discover through AR." | 1 = Not surprised at all, 7 = Very surprised |
| | ANP 5 | Confidence: "I expect to feel more confident in my purchase decisions after using AR." | 1 = No confidence at all, 7 = Very confident |
| | ANP 6 | Engagement: "I anticipate feeling highly engaged while interacting with products in AR." | 1 = Not engaged at all, 7 = Very engaged |
| | ANP 7 | Novelty: "I expect to experience a sense of novelty when using AR for shopping." | 1 = No novelty at all, 7 = Very novel |

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**Constructs and Their Parameters**

| Constructs | Loading | Item | 7-Point Scale |
|---|---|---|---|
| Purchase intention | PI 1 | How likely are you to purchase the product you viewed after using the AR feature? | 1 = Not likely at all, 7 = Very likely |
| | PI 2 | What is the probability that you will buy the product you explored using AR the next time you shop for products in this category? | 1 = Very unlikely, 7 = Very likely |
| | PI 3 | When you next need to purchase a product in this category, how certain are you that you will buy the product you experienced through AR? | 1 = Not certain at all, 7 = Very certain |
| | PI 4 | To what extent has the AR experience increased your intention to buy the product you viewed? | 1 = Not increased at all, 7 = Increased greatly |
| | PI 5 | After using AR to view the product, how much more likely are you to purchase it compared to before using AR? | 1 = Not more likely, 7 = Much more likely |
| Cross-buying intention | CBI 1 | How likely are you to purchase related or complementary products after using AR to view a product? | 1 = Not likely at all, 7 = Very likely |
| | CBI 2 | What is the probability that your AR experience will lead you to buy additional items that complement the product you initially viewed? | 1 = Very unlikely, 7 = Very likely |
| | CBI 3 | How certain are you that your AR experience will increase your interest in purchasing products from categories you did not initially consider? | 1 = Not certain at all, 7 = Very certain |
| | CBI 4 | After using AR for shopping, how likely are you to look for matching or complementary items to create a complete set? | 1 = Not likely at all, 7 = Very likely |
| | CBI 5 | To what extent has the AR shopping experience increased your openness to considering a wider range of products than you originally planned to buy? | 1 = Not increased at all, 7 = Increased greatly |

*Note*. AR = augmented reality; ITSN = interaction satisfaction; IVR = information vividness and richness; PSN = personalization; IMM = immersion; ARIT = augmented reality-induced telepresence; PL = pleasure; IPS = inspiration; ANP = anticipated emotions; PI = purchase intention; CBI = cross-buying intention.

## *Appendix B1*

**Assessment of Endogeneity Test Using the Gaussian Copula Approach**

| Test | Construct Path | Coefficient | *P*-Value |
|---|---|---|---|
| Gaussian copula of model 1 (endogenous variables; AR) | GC (AR) → ANP | 0.260 | 0.202 |
| | GC (AR) → IPS | 0.085 | 0.659 |
| | GC (AR) → PL | 0.007 | 0.967 |
| Gaussian copula of model 2 (endogenous variables; ITSN) | GC (ITSN) → ANP | 0.007 | 0.093 |
| | GC (ITSN) → IPS | 0.298 | 0.961 |
| | GC (ITSN) → PL | 0.011 | 0.047 |

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**Assessment of Endogeneity Test Using the Gaussian Copula Approach**

| Test | Construct Path | Coefficient | *P*-Value |
|---|---|---|---|
| Gaussian copula of model 3 (endogenous variables; IVR) | GC (IVR) → ANP | 0.019 | 0.884 |
| | GC (IVR) → IPS | 0.005 | 0.973 |
| | GC (IVR) → PL | 0.153 | 0.153 |
| Gaussian copula of model 4 (endogenous variables; PSN) | GC (PSN) → ANP | 0.018 | 0.889 |
| | GC (PSN) → IPS | 0.053 | 0.612 |
| | GC (PSN) → PL | 0.183 | 0.056 |
| Gaussian copula of model 5 (endogenous variables; PL) | GC (PL) → ARIT | 0.001 | 0.985 |
| | GC (PL) → IMM | -0.000 | 0.997 |
| | GC (PL) → PI | -0.027 | 0.716 |
| Gaussian copula of model 5 (endogenous variables; IPS) | GC (IPS) → ARIT | 0.154 | 0.176 |
| | GC (IPS) → IMM | 0.067 | 0.543 |
| | GC (IPS) → PI | -0.057 | 0.567 |
| Gaussian copula of model 5 (endogenous variables; ANP) | GC (ANP) → ARIT | -0.043 | 0.708 |
| | GC (ANP) → IMM | -0.016 | 0.846 |
| | GC (ANP) → PI | -0.179 | 0.076 |
| Gaussian copula of model 5 (endogenous variables; IMM) | GC (IMM) → PI | -0.203 | 0.045 |
| Gaussian copula of model 5 (endogenous variables; ARIT) | GC (ARIT) → CBI | -0.011 | 0.870 |
| Gaussian copula of model 5 (endogenous variables; PI) | GC (PI) → CBI | 0.023 | 0.809 |

*Note*. When $p$ is greater than 0.05, interaction satisfaction (ITSN) means there is no endogeneity problem, and vice versa. GC = Gaussian copula; AR = augmented realism; IVR = information vividness and richness; PSN = personalization; IMM = immersion; ARIT = augmented reality-induced telepresence; PL = pleasure; IPS = inspiration; ANP = anticipated emotions; PI = purchase intention; CBI = cross-buying intention.

## *Appendix B2*

**Assessment of Nonlinear Effects**

| Construct Path | Coefficient | *P*-Value | $f^2$ | *T*-Value |
|---|---|---|---|---|
| GC (AR) → ANP | 0.024 | 0.431 | 0.001 | 0.787 |
| GC (AR) → IPS | 0.019 | 0.459 | 0.001 | 0.741 |
| GC (AR) → PL | -0.024 | 0.358 | 0.001 | 0.919 |
| GC (ITSN) → ANP | 0.017 | 0.620 | 0.001 | 0.496 |
| GC (ITSN) → IPS | -0.001 | 0.980 | 0.000 | 0.025 |
| GC (ITSN) → PL | 0.037 | 0.241 | 0.003 | 1.173 |
| GC (IVR) → ANP | -0.010 | 0.780 | 0.000 | 0.280 |
| GC (IVR) → IPS | -0.035 | 0.337 | 0.002 | 0.961 |
| GC (IVR) → PL | 0.000 | 0.993 | 0.000 | 0.009 |
| GC (PSN) → ANP | 0.016 | 0.657 | 0.001 | 0.444 |
| GC (PSN) → IPS | 0.011 | 0.668 | 0.000 | 0.429 |
| GC (PSN) → PL | 0.025 | 0.315 | 0.002 | 1.005 |
| GC (PL) → ARIT | -0.037 | 0.182 | 0.003 | 1.334 |

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**Assessment of Nonlinear Effects**

| Construct Path | Coefficient | *P*-Value | $f^2$ | *T*-Value |
|---|---|---|---|---|
| GC (PL) → IMM | -0.046 | 0.080 | 0.006 | 1.749 |
| GC (PL) → PI | -0.043 | 0.138 | 0.005 | 1.484 |
| GC (IPS) → ARIT | 0.036 | 0.308 | 0.004 | 1.020 |
| GC (IPS) → IMM | 0.041 | 0.163 | 0.006 | 1.396 |
| GC (IPS) → PI | 0.013 | 0.638 | 0.001 | 0.471 |
| GC (ANP) → ARIT | 0.008 | 0.799 | 0.000 | 0.255 |
| GC (ANP) → IMM | 0.009 | 0.753 | 0.000 | 0.315 |
| GC (ANP) → PI | -0.006 | 0.857 | 0.000 | 0.181 |
| GC (IMM) → PI | -0.025 | 0.383 | 0.002 | 0.872 |
| GC (ARIT) → CBI | 0.030 | 0.215 | 0.004 | 1.240 |
| GC (PI) → CBI | -0.014 | 0.529 | 0.001 | 0.630 |

*Note*. When $p$ is greater than 0.05, interaction satisfaction (ITSN) means there is no unobserved nonlinear effects (endogeneity) problem, and vice versa. GC = Gaussian copula; AR = augmented realism; ANP = anticipated emotions; IPS = inspiration; PL = pleasure; IVR = information vividness and richness; PSN = personalization; ARIT = augmented reality-induced telepresence; IMM = immersion; PI = purchase intention; CBI = cross-buying intention.

## Appendix C1

**Clustering Validation Metrics and Persona Characteristics**

| Metric Category | Metric Name | Value / Interpretation |
|---|---|---|
| Clustering quality | Silhouette score | 0.383 (good separation quality) |
| Clustering quality | Calinski-Harabasz index | 625.4 ($k$ = 2, confirms optimal clusters) |
| Clustering quality | Inertia value | 2,580 ($k$ = 2, elbow method support) |
| Clustering quality | PCA explained variance | 79.4% (dimensionality reduction effectiveness) |
| Stability validation | Hold-out accuracy | 96.39% (excellent reproducibility) |
| Stability validation | Adjusted Rand index (ARI) | 0.8594 (high clustering consistency) |
| Stability validation | Train/test split | 581 / 194 (75% / 25%) |
| Persona distribution | Persona 1 (high responders) | 494 (63.7%)—AR enthusiasts |
| Persona distribution | Persona 2 (moderate responders) | 281 (36.3%)—selective adopters |

*Note*. PCA = Principal Component Analysis; ARI = adjusted Rand index; AR = augmented reality.

## Appendix C2

**Dual Processing Robustness Analysis Detailed Results**

| Pathway | Overall Correlation | Persona 1 Correlation | Persona 2 Correlation | Average Within Correlation | Drop | Drop % | Severity | Consistency (*SD*) | Robust |
|---|---|---|---|---|---|---|---|---|---|
| System 1 → system 2 (composite) | 0.752 | 0.522 | 0.616 | 0.569 | 0.183 | 24.3% | Moderate | 0.047 | Yes |
| Immersion → system 2 | 0.654 | 0.313 | 0.528 | 0.420 | 0.234 | 35.7% | Moderate | 0.107 | Yes |

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**Dual Processing Robustness Analysis Detailed Results**

| Pathway | Overall Correlation | Persona 1 Correlation | Persona 2 Correlation | Average Within Correlation | Drop | Drop % | Severity | Consistency (*SD*) | Robust |
|---|---|---|---|---|---|---|---|---|---|
| ARIT → system 2 | 0.642 | 0.417 | 0.383 | 0.400 | 0.242 | 37.7% | Moderate | 0.017 | Yes |
| Pleasure → system 2 | 0.714 | 0.457 | 0.585 | 0.521 | 0.194 | 27.1% | Moderate | 0.064 | Yes |
| System 2 → purchase intention | 0.688 | 0.444 | 0.570 | 0.507 | 0.181 | 26.3% | Moderate | 0.063 | Yes |
| System 2 → cross-buying | 0.688 | 0.512 | 0.527 | 0.519 | 0.169 | 24.5% | Moderate | 0.007 | Yes |
| System 1 → purchase intention | 0.721 | 0.476 | 0.521 | 0.498 | 0.222 | 30.9% | Moderate | 0.022 | Yes |
| System 1 → cross-buying | 0.700 | 0.472 | 0.491 | 0.481 | 0.219 | 31.3% | Moderate | 0.009 | Yes |

*Note*. *SD* = standard deviation; ARIT = augmented reality-induced telepresence.

## *Appendix C3*

**Persona Descriptive Statistics and Effect Size Analysis**

| Variable | Persona 1 Mean ($N$ = 494) | Persona 1 *SD* | Persona 2 Mean ($N$ = 281) | Persona 2 *SD* | Eta² | *F*-Statistic | *P*-Value |
|---|---|---|---|---|---|---|---|
| AR technical features | 5.30 | 0.75 | 3.98 | 0.89 | 0.903 | 1247.3 | <0.001 *** |
| Interactive AR | 5.74 | 0.68 | 4.39 | 0.92 | 0.805 | 892.1 | <0.001 *** |
| Personalization | 5.66 | 0.71 | 4.21 | 0.84 | 0.722 | 678.9 | <0.001 *** |
| Anticipated emotion | 5.87 | 0.52 | 4.57 | 0.78 | 0.940 | 1534.2 | <0.001 *** |
| Interaction satisfaction | 5.51 | 0.61 | 4.12 | 0.85 | 0.923 | 1289.7 | <0.001 *** |
| Immersion | 5.63 | 0.68 | 4.14 | 0.91 | 1.002 | 1687.4 | <0.001 *** |
| AR-induced telepresence | 5.41 | 0.74 | 3.69 | 0.95 | 0.994 | 1623.8 | <0.001 *** |
| Pleasure | 5.82 | 0.59 | 4.27 | 0.88 | 1.018 | 1732.6 | <0.001 *** |
| Inspiration (IPS) | 5.66 | 0.68 | 4.33 | 0.89 | 0.774 | 845.2 | <0.001 *** |
| Purchase intention | 5.83 | 0.61 | 4.54 | 0.87 | 0.799 | 912.7 | <0.001 *** |
| Cross-buying intention | 5.75 | 0.64 | 4.45 | 0.82 | 0.745 | 798.1 | <0.001 *** |

*Note*. *SD* = standard deviation; ARIT = augmented reality-induced telepresence; AR = augmented reality; IPS = inspiration.

## *Appendix D: Augmented Reality (AR) Shopping Experience Expectation Priming Stimulus*

### *A.1: Introduction Statement*

Dear Participant,
Ready to explore the future of shopping?
Augmented reality (AR) will transform how you experience products:

### *A.2: Core AR Features*

- Spatial integration: Virtual products appear seamlessly in your physical environment, accessible at your fingertips.
- Detail visualization: Material textures, precise colors, and functional details become vividly apparent.
- Personalized curation: Discover recommendations and displays tailored to your preferences.
- Interactive engagement: Experience hands-on exploration with intuitive interactions.

### *A.3: Guided Imagination Task*

Imagine:

- rotating items 360° for comprehensive inspection;
- observing microlevel details with clarity;
- controlling the exploration at your own pace; and
- enjoying an experience transcending traditional e-commerce.

### *A.4: Expected Emotional Responses*

This journey may evoke:

- anticipation with curiosity and excitement;
- novelty through refreshing surprise;
- confidence in purchasing decisions; and
- satisfaction from fulfilling engagement.

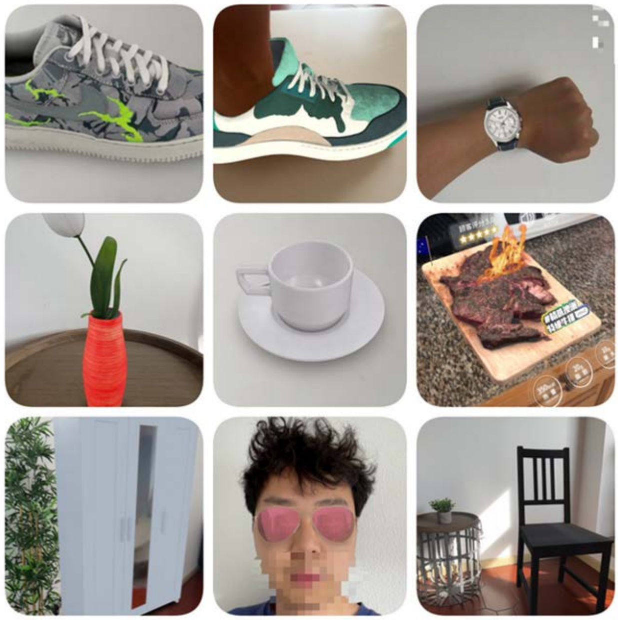
### *A.5: Priming Instruction*

"Please take 60 seconds to immerse yourself in this scenario, focusing on your anticipation for the upcoming AR shopping experience."

Final prompt: Begin your exploration?

*Appendix E: Experimental Stimulus Items (Part of Them)*

**Figure 13.**



*Joston Gary is a PhD candidate in marketing at University of Aveiro, University of Minho (Portugal) and Linköping University (Sweden). He holds an MPhil in business administration (marketing) from the City University of Macau, Macau S.A.R; a BEng in civil engineering from Chongqing Institute of Engineering, China; a BSc in psychology from JSS Academy of Higher Education and Research, India; a BSc in computer science from University of the People, USA. His research applies quantitative methods in marketing, psychology, and artificial intelligence, focusing on structural equation modeling, machine learning, and cross-cultural studies, particularly on music's influence on consumer behavior. He has published in Q1 journals. He has also trained in business analytics, data science, and digital marketing, holding data analysis roles with The Hong Kong Polytechnic University and City University of Macau. He is an ABS journal reviewer.*

*Xixing Zhou is currently pursuing her PhD in cultural studies from the school of social sciences at University of Minho, Portugal. She holds a bachelor's degree in literature from Henan University of Science and Technology, China, and a master's degree in international Chinese education from Soochow University, China. Her research areas include education, second language teaching, cultural studies, intercultural communication, and communication science. Her research focuses on enhancing cultural diversity and intercultural communication competence in the context of globalization.*

*Dr. Yuk Ming Tang is currently the senior lecturer in the department of industrial and systems engineering at The Hong Kong Polytechnic University. He is the lab-in-charge of the Integrated Product Design Laboratory, deputy lab-in-charge of Ng Tat Lun Digital Factory, a key and initiating member of the Joint Research Center for Immersive Learning and Educational Technology, and co-principal investigator of the Non-PAIR Research Centre for Assistive Technology. Additionally, Dr. Tang is the president of the Institute of Industrial and Systems Engineers–Hong Kong and a member of The Hong Kong Institution of Engineers. His achievements have been highly recognized, as evidenced by his receipt of the Faculty Award for Outstanding Achievement in Teaching (Individual), Faculty Merit Award in Teaching (Individual) and Service (Team), Distinguished Educator Award, and Best Researcher Award, among others. Additionally, he has been nominated for the UGC Teaching Award in the General Faculty Members category. Dr. Tang's research interests include artificial intelligence, virtual reality, Internet of Things, digital twin, blockchain, sustainable technology in Industry 4.0, and healthcare applications. In the span of three years, Dr. Tang has published over 80 internationally referred journal articles, 10 book chapters, edited 4 books, and received 2 patents. His publications are mainly published in top-ranked journals, such as Computers & Education (C&E), Expert Systems with Applications (ESWA), Information Sciences, Engineering Applications of Artificial Intelligence, and others. He serves as an editor in several renowned journals, including Internet of Things and Journal of Industrial Information Integration. He was a speaker at the Hospital Authority Convention and was interviewed in the episodes of* 香港故事_創科夢工場:活在元宇宙 *[Hong Kong Story Innovation and Technology Dream Factory: Living in the Metaverse] and* 創科導航 *[Innovation GPS], television programs on local channels RTHK and TVB, respectively.*

*Yang Gu is a PhD candidate in business research unit at ISCTE–University Institute of Lisbon, Portugal, and Maastricht University. He holds a MRes of research in management and innovation from SKEMA business school and Université Côte d'Azur, as well as a bachelor's degree of business administration from City University of Macau. His research interests include organization theory, institutional theory, corporate governance, and organization behavior.*

*Prof. António Carrizo Moreira (email: antonio.moreira@uab.pt) received his bachelor's degree in electrical engineering and a master's degree in management from the University of Porto, Portugal. He holds a PhD from the University of Manchester, England. He received scholarships from two important institutions: Science and Technology Research National Board and Science and Technology Foundation. He is professor at Universidade Aberta [Open University], Portugal.*