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École Doctorale SÉSAM

Réponses des consommateurs aux technologies émergentes dans le commerce en ligne : Application au chatbot d'IA générative et à la réalité augmentée

Thèse en vue de l'obtention du titre du Docteur en Sciences Économiques

Lina Anggraini

4th of December, 2025

Sous la direction de Prof. Dr. Nathalie Demoulin

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Customer Responses to Emerging Technologies in Online Retail: Evidence from Generative AI Chatbot and Augmented Reality

Thesis submitted in partial fulfillment of the requirements for the degree of Doctor in Economic Sciences

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4th of December, 2025

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Résumé Général

Le commerce en ligne évolue rapidement à mesure que les détaillants adoptent des technologies telles que les chatbots d'IA générative et la réalité augmentée (RA) pour améliorer l'expérience client et rester compétitifs. Malgré des investissements importants, deux défis persistent : l'engagement des clients envers ces technologies demeure inégal et leur adoption est freinée par des résistances liées à diverses préoccupations. Cette dissertation examine comment les détaillants peuvent renforcer l'engagement, réduire la résistance et accroître l'adoption à travers trois études complémentaires portant sur les chatbots d'IA générative et la RA.

Le premier article analyse la manière dont les chatbots d'IA générative transforment l'engagement des clients. Alors que les détaillants cherchent à offrir des interactions plus personnalisées et plus humaines, les chatbots traditionnels peinent souvent à susciter un engagement significatif. L'IA générative représente une avancée majeure, mais son impact réel sur l'engagement et le rôle du type de produit restent encore mal compris. En mobilisant la Social Response Theory et quatre expériences basées sur des scénarios, l'étude montre que les chatbots d'IA générative renforcent le contrôle perçu, ce qui accroît l'engagement, en particulier pour les choix de produits complexes. Au-delà de leur sophistication technologique, ces chatbots réduisent l'incertitude et améliorent le traitement de l'information. L'étude contribue à la recherche sur l'engagement technologique et offre des recommandations sur l'utilisation de l'IA pour créer de la valeur à long terme.

Le deuxième article examine les barrières qui alimentent la résistance des consommateurs à la RA dans le commerce en ligne. Bien que la RA offre des expériences immersives et présente un intérêt stratégique pour les détaillants, son adoption par les clients demeure limitée. Cet écart entre les investissements importants des détaillants et le faible usage par les consommateurs souligne la

nécessité de comprendre les obstacles à l'adoption. S'appuyant sur l'Innovation Resistance Theory et une approche mixte (entretiens et enquête), l'étude identifie des barrières perçues liées à l'authenticité, à la confidentialité, à la sécurité et à l'obsolescence, ainsi que des préoccupations éthiques et des tensions identitaires. En révélant de nouvelles barrières psychologiques, individuelles et liées au risque, cette étude étend l'IRT et montre que l'adoption ne peut être obtenue par le seul perfectionnement technique. Les détaillants doivent intégrer la RA d'une manière qui réponde à ces préoccupations et s'harmonise avec l'expérience globale d'achat.

Le troisième article explore les raisons qui motivent l'adoption de la RA en identifiant les valeurs qui sous-tendent ce comportement. Bien que la RA soit largement utilisée pour enrichir l'expérience d'achat, les niveaux d'adoption restent modestes et la recherche s'est principalement centrée sur ses caractéristiques technologiques, notamment via le TAM. Pour combler ces lacunes, cette étude mobilise la Theory of Consumption Values et adopte une approche mixte. Les résultats montrent que les valeurs de consommation influencent l'adoption indirectement à travers l'expérience client, particulièrement dans les contextes de forte implication. Cette perspective conçoit l'adoption comme un processus fondé sur les valeurs et sensible au contexte. L'étude suggère que les détaillants devraient concevoir des solutions de RA qui offrent non seulement des visualisations précises, mais qui répondent également à des besoins expérientiels plus larges, tels que le partage social, l'expression de soi via la personnalisation, et des décisions d'achat plus éclairées et durables.

Dans l'ensemble, cette dissertation contribue à la recherche sur le commerce de détail et l'adoption technologique en montrant que les technologies émergentes atténuent certains points de friction tout en introduisant de nouvelles tensions qui influencent les réponses des consommateurs. Elle soutient que la réussite de la mise en œuvre de ces technologies dépend de leur capacité à

créer une valeur authentique dépassant la simple utilité fonctionnelle. L'avenir du commerce en ligne reposera sur une intégration des technologies perçue comme intentionnelle et porteuse de sens, afin que leur adoption soit vécue comme une amélioration plutôt qu'une contrainte dans l'expérience d'achat

Mots-clés : *commerce en ligne, chatbots d'IA générative, réalité augmentée (RA), engagement client, résistance des consommateurs, valeurs de consommation, expérience client, adoption technologique.*

General Abstract

Online retail is rapidly evolving as retailers adopt technologies such as generative AI chatbots and augmented reality (AR) to enhance customer experience and remain competitive. Despite substantial investment, two challenges persist: customer engagement with these technologies is uneven, and adoption is slowed by resistance linked to diverse concerns. This dissertation addresses these issues by examining how retailers can foster engagement, reduce resistance, and increase adoption through three complementary studies on generative AI chatbots and AR.

The first paper investigates how generative AI chatbots reshape customer engagement. While retailers aim to create more personalized and human-like interactions, traditional chatbots often fail to generate meaningful involvement. Generative AI represents a major advancement, yet its actual impact on engagement and the role of product type remain unclear. Drawing on Social Response Theory and four scenario-based experiments, the study shows that generative AI chatbots enhance perceived control, which strengthens engagement, particularly for complex product choices. Beyond technological sophistication, generative AI reduces uncertainty and improves information processing. The study contributes to technology-enabled engagement research and offers guidance on using AI to deliver long-term value.

The second paper examines barriers driving customer resistance to AR in online retail. Although AR offers immersive try-on experiences and strategic benefits, customer adoption remains limited. This gap between high retailer investment and low usage underscores the need to understand what prevents adoption. Guided by Innovation Resistance Theory and using interviews and a survey, the study identifies perceived barriers related to authenticity, privacy, security, and obsolescence, as well as ethical concerns and tensions with personal identity. By revealing new psychological, individual, and risk-related barriers, the study extends IRT and shows that adoption cannot be

achieved through technical refinement alone. Retailers must integrate AR in ways that address these concerns and align with the broader shopping experience.

The third paper explores why customers adopt AR by identifying the values that drive this behavior. While AR is widely used to enrich online shopping, adoption levels remain modest, and existing research has focused mainly on technological attributes through frameworks such as TAM. To address this gap, this study draws on the Theory of Consumption Values and uses a mixed-method approach. Findings show that consumption values influence adoption indirectly through customer experience, especially in high-involvement contexts. This perspective positions adoption as a value-based and context-sensitive process. The study suggests that retailers should design AR solutions that not only provide accurate visualizations but also support social sharing, self-expression through personalization, and informed, sustainable decisions.

Overall, this dissertation contributes to retail and technology adoption research by showing that emerging technologies both alleviate and create new tensions in the customer journey. It argues that successful implementation depends on creating meaningful value that goes beyond functional utility. The future of online retail will rely on integrating technologies in ways that feel purposeful to customers, ensuring that adoption enhances rather than burdens the shopping experience.

Keywords: *Online retail, generative AI chatbots, augmented reality (AR), customer engagement, customer resistance, consumption values, customer experience, technology adoption.*

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CHAPTER 1: INTRODUCTION

1.1 Customer-interfacing retail technologies

Customer-facing retail technologies have become central to the digital transformation of commerce, reshaping how customers interact with retailers across all stages of the shopping journey. A broad array of technologies has been integrated into online retail, in the pre-purchase stage, recommendation systems and conversational agents help customers articulate their preferences and navigate product assortments (Grewal et al., 2020). Search engagement technologies such as AR further support product visualization and virtual trial, reducing uncertainty and facilitating evaluation (Javeed et al., 2024; Tom Dieck and Han, 2022). At the purchase stage, mobile wallets, automated checkout, and AI-enabled payment systems streamline transactions and enhance convenience (Grewal et al., 2023). In the post-purchase stage, relationship technologies including loyalty apps, customer relationship management platforms, and mobile engagement tools strengthen trust and foster repeat patronage (Quinones et al., 2023). Collectively, these technologies generate informational, experiential, and relational value across the online shopping journey (Roggeveen and Sethuraman, 2020).

Roggeveen & Sethuraman (2020) provide a framework that situates these technologies within the stages of the customer journey, which include pre-purchase, purchase, and post-purchase, and identifies their functional roles as needs management, search engagement, transaction, and relationship building. Their review highlights that these technologies are not just peripheral addition but integral components of the shopping process that shape customer decisions and relationships with retailers. Within this framework, AI chatbots and AR are strategic enablers that influence customer decision processes and retailer competitiveness in digital environments in the pre-purchase stage (Roggeveen & Sethuraman, 2020).

The customer response to these technologies is uneven, as their impact varies across implementations and usage situations (Roggeveen and Sethuraman, 2020). Verhoef et al. (2021) argue that digital transformation fundamentally reshapes customer experience and emphasize the need to examine how technologies alter perceptions of value, trust, and engagement. Empirical studies support that chatbots and recommendation agents replicate aspects of in-store sales assistance, which strengthens relational value (Grewal et al., 2020, 2023), while AR increases confidence in purchase decisions by enabling immersive product evaluation (Javeed et al., 2024; Tom Dieck & Han, 2022).

However, risks and resistance remain, Quinones et al. (2023) show that systems designed to personalize the shopping journey, such as recommendation engines or targeted offers, can enhance relevance but also trigger privacy concerns because of their reliance on customer data. Javeed et al. (2024) note that unrealistic AR experiences may create skepticism, and Grewal et al. (2023) find that poorly designed chatbot interactions risk frustration. Retailers continue to face challenges in effectively integrating these technologies into their online channels, often resulting in fragmented unrealized value creation (Grewal et al., 2021; Roggeveen et al., 2023). Understanding how to better embed customer-interfacing technologies into retail strategy is therefore essential for both academic research and managerial practice. Doing so can enhance customer engagement, sustain competitiveness, and reduce the risk of lost profitability associated with weak technology adoption (Grewal et al., 2020; Roggeveen et al., 2023).

Therefore, adopting these technologies has become a strategic priority for retailers seeking to strengthen customer engagement and maintain competitiveness in increasingly digital markets. Yet many firms continue to face difficulties in aligning these innovations with customer expectations, leading to uneven adoption and limited return on technological investments (Roggeveen et al., 2023). Understanding how to integrate customer-facing technologies effectively is therefore crucial for both academic research and managerial practice, as it can improve shopping experience, and prevent profit losses caused by mismatches between technological investments and customer adoption (Grewal et al., 2020; Roggeveen et al., 2023). Overall, this dissertation addresses this issue through three complementary papers that examine key aspects of customer–technology interaction in online retail; how generative AI chatbots enhance engagement, why customers resist adopting AR, and which consumption values drive AR adoption. Collectively, these papers offer insights into how retailers can strategically implement technologies that elicit positive customer responses and foster greater acceptance of digital innovations.

1.2 The pre-purchase stage in technology-enabled retail

The pre-purchase stage is an important phase of the customer journey because it is where customers recognize needs, collect information, and evaluate alternatives. Roggeveen & Sethuraman (2020) argue that this stage plays a decisive role in the overall customer journey, influencing both evaluation and decision-making. It sets the foundation for purchase and post-purchase outcomes, and it is where customers rely heavily on technologies to reduce uncertainty and build trust. If retailers do not provide effective support during pre-purchase interactions, customers are more likely to disengage or abandon their decision process, which limits conversion and weakens long-term relationships (Roggeveen & Sethuraman, 2020).

Technologies are especially important in this stage because they help customers navigate complex product choices and address information asymmetries. Needs management tools such as recommendation systems and conversational agents guide customers toward relevant options and lower search costs, which enhances confidence in decision making (Grewal et al., 2020;

Roggeveen & Sethuraman, 2020). Search engagement technologies such as AR enables customers to visualize and interact with products, reducing perceived risk and facilitating evaluation, particularly for products that are difficult to judge before purchase (Javeed et al., 2024; Tom Dieck & Han, 2022). These tools support customers in processing information more effectively, which makes them more willing to advance in the decision journey.

From a broader perspective, the pre-purchase stage is also critical for digital transformation strategies of the retailers. Customer experience lies at the core of digital transformation and understanding how technologies affect customer perceptions of value and engagement is essential for retailers (Verhoef et al., 2021). When implemented effectively, customer-facing technologies can increase both efficiency and experience, offering retailers opportunities to differentiate themselves early on the journey. This suggests that the pre-purchase stage is not only about supporting functional needs but also about shaping the relational and experiential aspects of shopping that determine purchase likelihood and long-term loyalty (Grewal et al., 2023).

1.2.1 Position in Roggeveen's framework

As illustrated in Figure 1, Roggeveen & Sethuraman (2020) conceptualize retail technologies as embedded across the customer journey and structured around technology nodes that perform distinct functions. In the pre-purchase stage, two nodes are central: *needs management technologies* and *search engagement technologies.* Needs management refers to tools that help customers articulate and refine their needs, while search engagement refers to tools that help them explore and evaluate alternatives. This framework highlights that technologies in the pre-purchase stage are not only instrumental for efficiency but also influence trust, engagement, and perceived value. By situating technologies within customer journey stages and nodes, Roggeveen et al.

(2020) encourage a broader perspective that views technologies not as isolated tools but as integral to how customers progress toward purchase.

1.2.2 Technology nodes: needs management and search engagement

Needs management technologies aim to simplify the decision-making process by reducing the cognitive effort required to navigate extensive product assortments and by replicating elements of human sales assistance in digital environments. These technologies are designed to support customers in articulating their needs and narrowing down choices that align with their preferences and purchase goals. Generative AI chatbots, in particular, can function both as recommendation systems and personalization engines, assisting customers in identifying relevant product options, lowering search costs, and enhancing decision confidence. By providing interactive and adaptive guidance, such technologies emulate the conversational and advisory roles of in-store sales associates.(Alexander & Kent, 2022a; Grewal et al., 2020). Their contribution extends beyond efficiency, as effective personalization can foster a sense of being understood, which strengthens relational engagement. Nevertheless, these technologies may also introduce risk, such as concerns about the extent of data use in personalization. (Grewal et al., 2023).

Moreover, search engagement technologies play a crucial role in shaping customers' online shopping experiences by reducing uncertainty and enhancing product evaluation. These technologies provide richer product information and create immersive experiences that enable customers to better understand and assess products before purchase. AR serves as a prominent example, as it allows customers to visualize products within their own environments and interact with them virtually, thereby bridging the gap between digital and physical shopping. However, these technologies are not without risks. Unrealistic visualizations, technical limitations, or poor usability may undermine perceived authenticity, frustrate customers, and foster skepticism toward both the technology and the retailer implementing it (Hoffmann & Mai, 2022; Javeed et al., 2024; Xu et al., 2024).

1.2.3 Technology types: generative AI chatbots and AR

This dissertation focuses specifically on generative AI chatbots and AR as representative technologies within the pre-purchase stage. Generative AI chatbots exemplify needs management technologies because they extend beyond rule-based interactions to provide adaptive, conversational support. By engaging in human-like dialogue, they help customers clarify needs, explore options, and receive tailored advice, which increases engagement and reduces uncertainty in decision-making (Bhattarai, 2023; Jiang et al., 2022). AR exemplifies search engagement technologies by allowing customers to virtually try products, assess fit, and contextualize them in their own environments. Studies show that AR not only improves product evaluation but also enhances experiential value by creating interactive and immersive shopping experiences (Chen & Lin, 2022; Vaidyanathan & Henningsson, 2023). Therefore, these technologies were selected because they represent distinct yet complementary mechanisms; AI chatbots address informational and relational challenges, while AR addresses experiential and perceptual challenges. Examining them together provides a richer understanding of how the central technologies in pre-purchase stage enhance engagement, trigger resistance, and influence adoption dynamics in digital retail (Chen et al., 2022; Javeed et al., 2024; Rejeb et al., 2023)

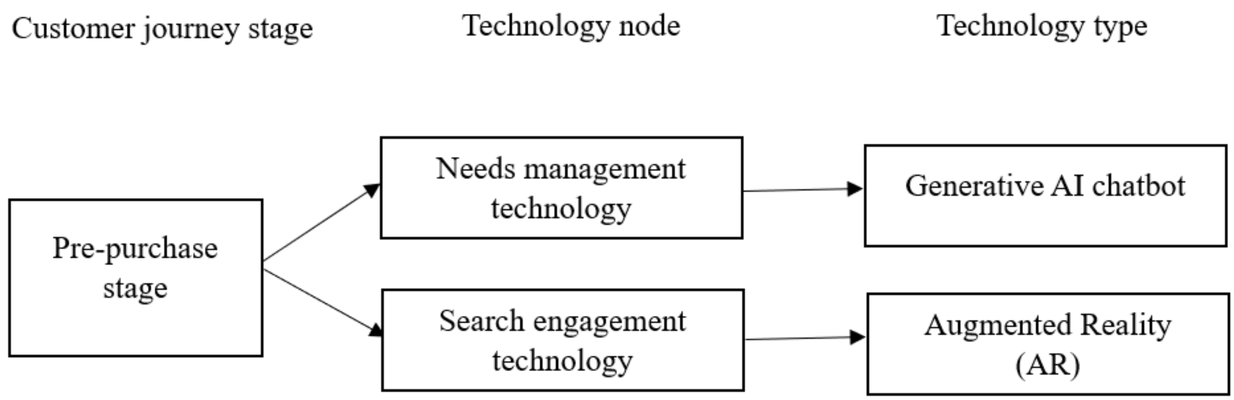

Figure 1. Positioning of generative AI Chatbots and AR within the pre-purchase stage of the customer journey (adapted from Roggeveen and Sethurama, 2020)

1.3 Research objectives and questions

Across three papers, this dissertation aims to provide both theoretical and practical insights for advancing customer behavior research in online retail environments (Brodie et al., 2011; Gahler et al., 2023; Heidenreich & Handrich, 2015).

Paper 1: Generative AI chatbots and customer engagement with the retailer: does product type matter?

Authors: *Anggraini Lina, Demoulin Nathalie, and De Kerviler Gwarlann.*

Status: *Revise and resubmit in Journal of Business Research*

The main objective of paper 1 in this study is to investigate the role of generative AI chatbots in driving customer engagement and to identify the underlying psychological mechanisms and contextual factors influencing their effectiveness. Although pre-defined chatbots or traditional conversational agents are increasingly adopted in online retail, limited empirical evidence exists on how advanced generative AI chatbots influence customer engagement and how factors such as product type and choice complexity shape their effectiveness (Pappas et al., 2023; Whang et al., 2021; Wien & Peluso, 2021). This leads to the following research questions:

RQ1.1 To what extent does interaction with a generative AI chatbot influence customer engagement in online retail settings?

RQ1.2 How does perceived control mediate the relationship between generative AI chatbot interaction and customer engagement in online retail?

RQ1.3 How does product type (search versus experience goods) influence the relationship between generative AI chatbot interaction and customer engagement in online retail?

RQ1.4 To what extent does choice overload influence the impact of generative AI chatbots on customer engagement, and how does this relationship differ between search and experience goods?

Paper 2: Resistance to AR adoption in online retail

Authors: *Anggraini Lina, Demoulin Nathalie, and Cocco Helen.*

Status: *Submitted to Journal of Business Research*

The main purpose of paper 2 is to identify the barriers that hinder AR adoption in online retail and to investigate how these barriers influence customer resistance and subsequent behavioral intentions. Existing research on technology resistance has primarily focused on domains such as digital banking, mobile applications, and the Internet of Things (Joachim et al., 2018; T. Laukkanen, 2007; Mani & Chouk, 2018). However, resistance toward AR in online retail remains underexplored, particularly in settings where the technology's immersive and interactive nature may give rise to distinctive functional, psychological, and individual barriers (Jayaswal & Parida, 2023b; Uhlendorf & Uhrich, 2024). This motivates the following research questions:

RQ2.1 What are the barriers that hinder customers from adopting AR in online retail?
RQ2.2 To what extent does perceived intrusiveness mediate the relationship between the identified barriers to AR adoption intention in online retail?

RQ2.3 What is the influence of perceived intrusiveness on the relationships between barriers to AR adoption, customer resistance, and intention to use AR in online retail?

Paper 3 - Investigating the effects of AR on customer experience and adoption intention in online retail

Authors: *Anggraini Lina, Cocco Helen and Demoulin Nathalie*

Status: *Submitted to Electronic Commerce Research*

The aim of paper 3 is to analyze how multiple value dimensions shape AR adoption through customer experience pathways. While previous research on AR adoption has primarily focused on technological characteristics influencing technology acceptance, limited attention has been paid to the broader value-based mechanisms that drive customer adoption, highlighting the need to explore alternative theoretical perspectives (Jayaswal and Parida, 2023). In particular, understanding the different types of value that customers seek from AR-enabled online retail platforms is critical for explaining adoption behavior. This paper addresses this gap by offering a comprehensive understanding of how multiple consumption values shape AR adoption through customer experience in online retail contexts (Flavián et al., 2019; Gahler et al., 2023). This leads to the following research questions:

RQ3.1 What are the consumption values that lead customers to adopt AR in online retail?

RQ3.2 To what extent does customer experience mediate the relationship between consumption values and AR adoption intention in online retail?

RQ3.3 What is the influence of product involvement on the relationships between consumption values, customer experience, and intention to use AR in online retail?

1.4 Customer responses toward technology in online retail

Customer response to technology in online retail captures how customers react to and interact with advanced digital tools that now mediate product search, evaluation, and purchase. Whereas early e-commerce relied on static interfaces and basic search, contemporary online retail adopts interactive technologies such as generative AI chatbots and AR. These two are especially relevant because chatbots provide informational support through conversational guidance, while AR enables experiential product visualization. Together they capture how online retail technologies replicate key aspects of in-store shopping while also creating novel digital experiences (Grewal et al., 2020; Roggeveen & Sethuraman, 2020). These technologies do more than transmit information; they shape customer responses by influencing how products are perceived, how decisions are made, and how retailers are evaluated (Inman & Nikolova, 2017; Riegger et al., 2021). Consequently, customer response to technology has become a decisive factor in online retail effectiveness, affecting not only purchase behavior but also post-purchase attitudes and longer-term engagement with the retailer (Jiang et al., 2022).

Within this evolving landscape, two technologies have emerged as particularly influential in redefining the nature of customer–technology interaction; generative AI chatbots and AR. Generative AI chatbots engage customers through adaptive, conversational exchanges that can tailor product recommendations, clarify purchase options, and reduce the cognitive burden of decision-making (Christou et al., 2024). Their capacity to respond flexibly to unstructured queries and replicate elements of human service interaction marks a departure from earlier rule-based chatbots. However, their effectiveness is context-dependent, and research suggests that the nature of the product category, such as search goods versus experience goods can determine whether such tools enhance engagement or fail to meet expectations (Jiménez & Mendoza, 2013; Lim et al., 2015).

Moreover, AR offers a different form of interaction by integrating digital product representations into the customer's physical environment, enabling virtual try-ons and visualization (Sekri et al., 2024). AR can enrich product evaluation by providing sensory and spatial cues that reduce uncertainty, particularly for visually dependent categories such as fashion, cosmetics, and furniture. Yet despite these advantages, adoption remains limited, with studies pointing to persistent functional, psychological, and individual barriers (Jayaswal & Parida, 2023b; Uhlendorf & Uhrich, 2024). These barriers underscore that the value of technology-mediated interaction is not inherent to the technology itself but is contingent on how well it aligns with customer needs and contexts.

Beyond adoption barriers, AR's effectiveness in online retail depends on the quality of the customer experience it delivers. Customer experience captures the cognitive, affective, symbolic, and relational responses that arise during interactions with a retailer's technology (Flavián et al., 2019; Gahler et al., 2023). In the context of AR, these experiences are shaped by how well the technology communicates product information, supports identity expression, and facilitates meaningful engagement throughout the shopping journey (Ambika et al., 2023; Hilken, Chylinski, et al., 2022; Hilken et al., 2017). A rich and positive AR experience may enhance adoption intentions, while poorly designed experiences may lead to disengagement, even when the technology is technically functional (Bonetti et al., 2019).

Overall, this dissertation examines customer responses to technology in online retail, with particular attention to engagement, resistance, and adoption. It explores how generative AI chatbots and AR shape customer behavior, highlighting the psychological mechanisms, barriers, and value-driven experiences that underpin technology use. Rather than assuming that technological novelty ensures success, the dissertation shows that customer responses to emerging technologies depend on their ability to align with their needs, values, and situational contexts.

1.5 Generative AI chatbot and customer engagement

Generative artificial intelligence (AI) chatbots represent a new stage in conversational technologies, offering retailers adaptive and context-sensitive interactions that go beyond the limitations of rule-based systems. Unlike earlier chatbots that relied on scripted responses, generative AI models can process open-ended queries, generate detailed explanations, and simulate aspects of natural conversation (Christou et al., 2024). In online retail, where the absence of physical sales staff can create uncertainty and overwhelm, these capabilities position generative AI chatbots as tools for delivering personalized guidance, responsive dialogue, and richer online shopping experiences (Davenport et al., 2021; Grewal & Roggeveen, 2020).

Customer engagement is widely recognized as a multidimensional construct involving cognitive, emotional, and behavioral engagement with the retailer (Brodie et al., 2011; Hollebeek et al., 2014). Chatbots offer one setting in which such engagement can be strengthened through interactivity, personalization, and decision support (Jiang et al., 2022). Generative AI is particularly promising because its adaptive responses may enhance perceived control and relevance, which are known to sustain deeper engagement in digital environments (Hu & Wise, 2021; Sun et al., 2024).

However, engagement outcomes are unlikely to be consistent across contexts. Prior work shows that factors such as product type and choice complexity shape how customers respond to interactive technologies (Chernev et al., 2015; Jiménez & Mendoza, 2013). Search goods can typically be evaluated through objective attributes, reducing the need for conversational assistance, while experience goods are harder to assess before purchase and may therefore benefit more from tailored chatbot interactions (Girard & Dion, 2010). These distinctions highlight the importance of examining not only what generative AI chatbots can do but also when they are most likely to enhance customer engagement in online retail (Puntoni et al., 2021a; Whang et al., 2022). By positioning generative AI chatbots as more than technical add-ons, this dissertation frames them as interactional tools whose impact depends on their ability to address decision challenges and strengthen meaningful forms of customer engagement in online shopping.

1.6 Customer resistance in adopting AR

In online retail, AR is promoted as a way to enrich online shopping by enabling customers to visualize products in their own environment, simulate try-on experiences, and reduce uncertainty when purchasing without physical inspection. Despite these promised benefits, customer adoption remains limited, with only around 13% of online shoppers having used it (The Interline, 2024; Wurmser, 2022). This gap highlights that curiosity or initial trials do not necessarily translate into sustained use, and that understanding resistance is as important as identifying adoption drivers. While much of the literature on AR has emphasized its potential to increase decision confidence and enjoyment, the reality of low adoption rates suggests that many customers remain hesitant to incorporate AR into their shopping routines (Barta et al., 2025; Berman & Pollack, 2021).

Innovation Resistance Theory (IRT) provides a foundation for explaining this phenomenon, arguing that resistance occurs when an innovation is perceived as incompatible with customers' needs, routines, or values (Ram & Sheth, 1989). Earlier applications of IRT in mobile banking, self-service technologies, and IoT (Laukkanen et al., 2007; Mani & Chouk, 2018) show that resistance may arise not only from functional limitations but also from deeper psychological or value-based conflicts. Rather than being a simple reaction to usability issues, resistance reflects deeper negotiations over how digital tools reshape the boundaries of personal data, the credibility of product evaluations, and the social meaning of shopping in online environments (Hoffman et al., 2022; Pfaff & Spann, 2023).

Therefore, this perspective positions resistance as more than just obstacles to be resolved through better usability. Instead, it represents a structural customer response that reflects broader concerns about authenticity, ethical considerations, and the alignment of technology with personal identity. This emphasizes the need for extending resistance theory to account for immersive and data-intensive technologies like AR (Ram & Sheth, 1989; Riegger et al., 2021).

1.7 Consumption values, customer experience, and AR adoption

Adoption of AR in online retail cannot be explained solely by technological sophistication. While features such as interactivity, immersion, and usability enhance perceptions of AR (Huang & Chung, 2024; Lin et al., 2025; McLean & Wilson, 2019), they do not clarify why customers ultimately decide to adopt or reject it. Ultimately, the critical question is whether AR generates value that connects with customers and whether such value translates into experiential outcomes that drive their behavioral responses (Schultz & Kumar, 2024; Wang et al., 2023a).

The TCV (Sheth et al., 1991) provides a useful framework for examining these drivers of adoption. Functional, social, emotional, epistemic, and conditional values capture both utilitarian benefits, such as convenience and accuracy, and hedonic or symbolic benefits, such as enjoyment, curiosity, self-expression, and sustainability. In an AR shopping context, customers may value the ability to reduce cognitive effort, personalize choices, or preview products sustainably. These values represent the motivations that can initiate adoption, but they require a mechanism to connect them to actual behavioral outcomes (Schultz & Kumar, 2024).

Customer experience is increasingly recognized as the mechanism that connects consumption values to behavioral outcomes. Values on their own describe what customers find important, but they acquire behavioral relevance only when expressed through experiential domains such as cognitive, affective, relational, and symbolic responses. This perspective positions customer experience as the pathway through which value perceptions inform adoption decisions in digital commerce, including the use of AR. By highlighting this process, we shift attention from isolated value preferences or system attributes to the broader experiential conditions that determine whether technologies are meaningfully integrated into customer shopping journey (Becker & Jaakkola, 2020; Gahler et al., 2023).

Existing research has often overlooked this linkage between values, experiences, and adoption. Many studies have treated AR adoption as a direct response to system characteristics. These fragmented approaches describe customer perceptions but leave unresolved the question of how underlying value perceptions are converted into adoption through customer experience (Baytar et al., 2020; Fan et al., 2020; Wang et al., 2022).

1.8 Research contributions

In this dissertation, each chapter contributes to literature and practice in distinct ways. Although advanced technologies such as generative AI chatbots and AR are frequently promoted as transformative tools in online retail, much of the literature has concentrated on describing system features or measuring adoption outcomes, without examining the underlying processes that shape customer responses. As online retail continues to expand and traditional retailers struggle to create meaningful digital experiences (Grewal & Roggeveen, 2020), developing a more critical understanding of customer responses toward technology has become essential. The overall contribution of this dissertation is to show that customer responses in online retail; whether expressed as engagement, resistance, or adoption are not uniform, but contingent on whether technologies enhance control, address barriers, and create value in ways that resonate with customers across different shopping contexts (Hoyer et al., 2020).

In the first paper, the focus is on how generative AI chatbots influence customer engagement in online retail. While earlier research has mainly studied rule-based systems with outcomes such as purchase intention, satisfaction, or loyalty (Cheng & Jiang, 2021; Chung et al., 2020; Lee & Li, 2023; Rese et al., 2020), little is known about how generative AI chatbots, with their adaptive and conversational abilities, shape engagement. This chapter shows that their contribution lies not in mimicking human conversation, as much of the anthropomorphism literature suggests (Sheehan et al., 2020; Sun et al., 2024), but in enhancing perceptions of control and decision quality when choices are complex. It further clarifies perceived control as the psychological mechanism linking chatbot use to engagement and demonstrates that effects vary with product type and assortment complexity (Chernev et al., 2015; Girard & Dion, 2010; Turri & Watson, 2023). For retailers, the findings suggest that generative AI chatbots should not be seen as a universal solution but deployed strategically. They add most value when customers face uncertainty, such as with experience goods or choice overload, while AR enhances engagement for experience goods, clear and detailed product information is often more effective for search goods (Arce-Urriza et al., 2025).

Chapter 3 contribution lies in the way how addressing why customers resist adopting AR, despite its promise of immersive product evaluation. Prior resistance research has largely examined conventional technologies such as digital banking or IoT (Laukkanen et al., 2007; Mani & Chouk, 2017, 2018), leaving immersive, data-intensive tools like AR underexplored. Moreover, AR studies have emphasized adoption drivers rather than barriers (Jayaswal & Parida, 2023b). This chapter shows that resistance is not reducible to usability issues but reflects structural concerns around privacy, inauthenticity, and ethics, such as fears of overconsumption and reduced social interaction (Chylinski et al., 2020a; Mainardes et al., 2023; Wang et al., 2024). It also refines psychological and individual barriers, introducing perceived inauthenticity, expanding traditional barriers to include reliance on sales assistance and preference for exploratory shopping, and reconceptualizing image barriers as rooted in retailer reputation rather than technological skepticism (de Bellis & Venkataramani Johar, 2020; Mani & Chouk, 2018). For retailers, the findings highlight that AR adoption will remain fragile unless these concerns are addressed directly. This requires transparent data practices, realistic product previews, and ethical design choices that align with customer values and protect trust (Riegger et al., 2021).

Chapter 4 reframes AR adoption through the lens of consumption values and customer experience. Prior AR research has largely emphasized technological characteristics or isolated experiential constructs that drive customer engagement with AR (Huang & Chung, 2024; Lin et al., 2025; McLean & Wilson, 2019). However, this focus leaves open the question of how underlying value perceptions are converted into adoption, since identifying technological characteristics alone does not explain why such features matter for customer behavior. This chapter identifies AR specific sub-dimension of consumption values such as cognitive offloading, personalization, self-expression, and sustainability, and shows that these values shape adoption only when expressed through customer experience; cognitive, affective, relational, and symbolic dimensions (Alexander & Kent, 2022a; Gahler et al., 2023). It further demonstrates that product involvement moderates these pathways. In high involvement contexts such as appliances, customers emphasize accuracy and reliability, while in low involvement contexts such as fashion accessories, symbolic and experiential benefits are more persuasive. For retailers, the findings emphasize the importance of tailoring AR to product involvement. High stakes purchases require precise and reliable decision support, whereas everyday shopping benefits from playful, personalized, and socially engaging features that enhance enjoyment (Celsi & Olson, 1988; Ha & Lennon, 2010; Walten & Wiedmann, 2023).

1.9 Research design and approach

This dissertation adopts a multi-paper format, combining quantitative and mixed-methods designs to provide a comprehensive understanding of customer–technology interactions in online retail. The first paper in chapter 2 applies a quantitative experimental design to examine the causal effects of generative AI chatbot interaction on customer engagement. An experiment was chosen for its ability to control extraneous variables and isolate the effects of perceived control, product type, and choice overload on engagement outcomes, consistent with established recommendations for testing causal relationships in marketing and technology adoption research (Jiang et al., 2022; Lim et al., 2015; Weathers et al., 2007).

The second paper in chapter 3 employs a mixed-methods sequential exploratory design (Clark, 2019), beginning with qualitative interviews to inductively identify barriers to augmented reality (AR) adoption in online retail. The insights from this phase inform the development of a survey instrument, which is then used to quantitatively examine how these barriers influence customer resistance and intention to adopt AR. This approach enables theory building in an underexplored area before validating relationships in a larger sample.

The third paper in chapter 4 employs a mixed-methods exploratory approach, beginning with interviews to contextualize the values that customers associate with AR in online retail. The qualitative findings inform the operationalization of value dimensions, which are then tested through a survey to assess their impact on adoption intention via customer experience, as well as the moderating effect of product involvement. This combination allows for the refinement of theoretical frameworks to capture context-specific value drivers prior to empirical testing (Venkatesh et al., 2012).

Collectively, this multi-method approach research ensures that findings are both theoretically robust and practically relevant to the evolving landscape of immersive online retail technology.

1.10 Dissertation structure

This dissertation is organized into six chapters, each contributing to an integrated understanding of customer adoption and resistance toward immersive technologies in online retail.

Chapter 1 presents literature reviews on customer-interfacing retail technologies, generative AI chatbots, AR, and customer experience in online retail. This chapter provides an overview of prior research and positions the three empirical studies within the broader literature. The chapter also provides the structure of the dissertation.

Chapter 2 presents the first empirical study, a quantitative experiment examining the effects of generative AI chatbot interaction on customer engagement. The study investigates the mediating role of perceived control and the moderating effects of product type and choice overload.

Chapter 3 presents the second empirical study, a mixed-method investigation into customer resistance to AR adoption in online retail. The qualitative phase identifies barriers that hinder customers from adopting AR, while the quantitative phase tests their effects on customer resistance and adoption intention.

Chapter 4 presents the third empirical study, also using a mixed-method design, which applies the Theory of Consumption Values (TCV) to AR adoption. It examines how functional, social, emotional, epistemic, and conditional values influence adoption intention through multidimensional customer experience and tests the moderating effect of product involvement.

Chapter 5 synthesizes the conclusions and contributions of the three studies, critically reflects on their limitations, and proposes directions for future research.

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CHAPTER 2: GENERATIVE AI AND CUSTOMER ENGAGEMENT WITH THE RETAILER: DOES PRODUCT TYPE MATTER?

Generative AI and customer engagement with the retailer: Does product type matter?

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Status: *Revise and resubmit in Journal of Business Research*

2.1 Abstract

Generative artificial intelligence (AI) is reshaping the retail sector, ushering in an era in which personalization and automation redefine customer experience. This study contributes to knowledge by exploring the emerging role of generative AI chatbots, their impact on customer engagement, and the psychological mechanism of perceived control, demonstrating how generative AI chatbots can alleviate decision-making challenges. Using four scenario-based experiments, our research shows that generative AI chatbots boost customer engagement by increasing cognitive and behavioral control. Notably, this mediated effect is moderated by product type, with a stronger impact on experience goods due to their evaluation complexity. By contrast, clear product descriptions are often more effective in search goods with small assortments. The results suggest that companies selling experience goods should prioritize chatbots, while those focused on search goods may benefit more from structured product information. This ensures that chatbot investments are aligned with customer needs.

Keywords: *generative AI chatbot (ChatGPT), search goods, experience goods, customer engagement, online retailer, perceived control*

2.2 Introduction

Generative artificial intelligence (AI) is rapidly transforming the landscape of online retail, as retailers are increasingly deploying AI-powered chatbots, such as ChatGPT, to enhance customer interactions, deliver personalized recommendations, and support decision-making throughout the customer journey (Kumar et al., 2024; Pappas et al., 2023). This technological shift is not only incremental but also represents a fundamental change in how firms engage with customers in digital environments. Recent industry reports have forecast that 80% of businesses will adopt generative AI tools by 2025, with more than half of all AI models tailored to industry-specific needs by 2027 (Gartner, 2024). E-commerce platforms such as Mercari and Shopify are already integrating ChatGPT-based assistants into their customer service operations (Practical Commerce, 2023).

Despite these advancements, scholars and practitioners face some critical questions, for instance, there remains uncertainty about how generative AI chatbots shape customer engagement in online retail, as well as the mechanisms that drive customer responses to these more flexible and "human-like" AI agents. Furthermore, it is not well understood how product type and assortment choice complexity affect their effectiveness. While traditional chatbots with pre-defined rules have been studied extensively (Table 1), with research highlighting factors such as purchase intention Kim et al., 2023; Lo Presti et al., 2021; Sivaramakrishnan et al., 2007), customer satisfaction (e.g., Chen et al., 2021; Chung et al., 2020), brand loyalty (Lee & Li, 2023), and customer acceptance (Rese et al., 2020; Y. Zhu et al., 2022), other works have also considered anthropomorphism (Araujo, 2018a; Go & Sundar, 2019a), perceived competence (Jiménez-Barreto et al., 2023), and messaging strategies (Sun et al., 2024).

The introduction of generative AI chatbots represents a significant leap in conversational ability and user experience. However, it remains unclear whether and how these advanced systems enhance customer engagement or how retailers can leverage them to improve the overall shopping experience. More importantly, customer engagement with online retailers is widely recognized as critical for shaping customer behavior (Brodie et al., 2011; Thakur, 2018) and influencing purchases and long-term loyalty (Demangeot & Broderick, 2016; Islam & Rahman, 2016). However, how advanced AI systems affect this engagement and the psychological mechanisms involved remain unclear.

We suggest that one such mechanism is perceived control, which plays a central role in shaping customer responses to digital technologies. Although prior research has suggested that interaction with smart technologies can enhance engagement (Fan et al., 2020), the relationship between perceived control and generative AI chatbot use has not been sufficiently examined. This is particularly relevant in complex purchase scenarios, such as those involving choice overload, in which customers face an overwhelming large number of options. In addition, we argue that the effectiveness of generative AI chatbots may vary by product type, especially when comparing search goods (with easily assessed attributes) and experience goods (which require trial or use to evaluate) (Guo & Li, 2022; Turri & Watson, 2023).

This study addresses these research gaps by examining how generative AI chatbots influence customer engagement in online retail. Specifically, it investigates (1) the mediating role of perceived control, (2) the moderating effects of product type (search vs. experience goods), and (3) the effect of assortment complexity, particularly in scenarios involving choice overload. In doing so, the study offers new insights into how generative AI systems can support customer decision-making in increasingly complex online environments.

By focusing on generative AI chatbots capable of delivering contextually rich, adaptive, and personalized interactions, this research responds to recent calls to go beyond static chatbot features toward a deeper understanding of customer–AI dynamics (Christou et al., 2024; Paul et al., 2023; Sadhotra & Gupta, 2023). It contributes to the literature by (1) exploring the emerging role of generative AI chatbots in driving customer engagement, (2) clarifying the psychological mechanisms—specifically, perceived control—through which this occurs, and (3) examining how product characteristics and choice overload shape these interactions. The findings offer actionable insights for researchers and practitioners seeking to deploy generative AI effectively in online retail environments.

Insert Table 1 here

2.3 Literature review and hypothesis development

2.3.1 AI chatbots in online retailing

AI chatbots are advanced computer programs powered by AI technologies designed for text-based interactions and automated assistance (Cheng & Jiang, 2022; Han & Kim, 2020; Kadasah, 2023). These chatbots continuously enhance their language comprehension and response generation by analyzing extensive datasets, which leads to more accurate and personalized interactions (Chen et al., 2022). Their strength lies in processing and generating text-based content, making them particularly effective in written communication (Van den Broeck et al., 2019a). Chatbots are widely adopted across industries. In customer service, they offer instant support and handle frequently asked questions (Cheng & Jiang, 2022). In online retail, chatbots act as sales assistants by providing product recommendations, order tracking, and personalized shopping experiences. They also gather and analyze customer behavior data, which offer valuable insights into preferences and buying patterns (Chung et al., 2020).

This paper examines the most advanced version of the generative AI chatbot, commonly known as ChatGPT, recognized for its ability to generate original, contextually relevant responses without relying solely on pre-defined rules (Kumar et al., 2024; Paul et al., 2023), thus creating unique interactions with customers that can trigger different reactions from those triggered by non-generative AI chatbots. ChatGPT is pre-trained on vast datasets to generate human-like responses in real time, thus ensuring fluency and coherence (Dwivedi et al., 2023). Furthermore, it can mimic human conversational patterns and adapt their language styles to match the user's tone and context. Generative AI chatbots can reduce negative reactions and support a more positive customer experience (Korzynski et al., 2023), as they can handle complex, open-ended conversations and adapt to different contexts.

ChatGPT can also personalize responses, thus making it useful for marketing, customer service, and business automation. Whereas traditional chatbots require manual updates and structured inputs, ChatGPT continuously improves through fine tuning and external integration, offering a more flexible and intelligent solution for businesses and challenges. We challenge the common belief that greater reliance on technology always leads to improved decision-making outcomes (Klaus & Zaichkowsky, 2022;Kalla & Smith, 2023).

2.3.2 Social response theory (SRT)

Introduced by Nass and Moon (2000), SRT posits that individuals tend to treat computers and other media as social actors, applying human social rules and communication norms, even when fully aware that these systems are artificial. Although SRT was initially developed in the context of simple computer interfaces, subsequent research has demonstrated its relevance in a wide range of digital agents, including generative AI chatbots (Gnewuch et al., 2022; Gupta et al., 2024; Kumar et al., 2025). Users often attribute intent, responsiveness, and social presence to these technologies, engaging with them as if they are interacting with human partners (Nass & Moon, 2000; Nass et al., 1994).

Recent empirical studies have confirmed that generative AI chatbots are capable of evoking meaningful social responses from customers, especially in online shopping contexts. Kumar et al. (2025) show that generative AI chatbots can enhance customer engagement and experience and support decision-making during the purchase journey. Gnewuch et al. (2022) highlight that elements such as response quality and interaction style contribute to users' perceptions of social presence and can influence trust and satisfaction. Gupta et al. (2024) identify that the adoption and effectiveness of generative AI chatbots in retail are closely linked to their ability to facilitate fluid, interactive, and responsive communication, which customers readily interpret as socially engaging.

In online retail, the dynamics explained by SRT become especially salient in complex or uncertain purchase situations, such as when evaluating experience products whose key attributes, such as quality and fit, are difficult to assess before purchasing. In these scenarios, generative AI chatbots can support customers by providing contextualized information, clarifying doubts, and enabling interactive product exploration (Kumar et al., 2025). Through natural language interactions that reflect human-like communication patterns, generative AI chatbots foster social presence, make the shopping process feel more engaging and trustworthy, and encourage customers to rely on their support (Gnewuch et al., 2022).

By mirroring conversational norms, such as turn taking, responsiveness, and empathy, generative AI chatbots can facilitate cognitive engagement (by offering relevant information and recommendations), affective engagement (by providing supportive, context-aware interactions), and behavioral engagement (by encouraging exploration and interaction) (Pentina et al., 2023). Especially in high-uncertainty purchase situations, such as those involving experience products, this socially responsive interaction can reduce ambiguity, increase trust, and ultimately foster greater engagement with the technology and the retailer (Araujo, 2018; Skjuve et al., 2022).

In summary, SRT provides a robust framework for understanding how and why customers interact with generative AI chatbots as social partners in online retail environments. SRT is particularly relevant for situations in which product evaluation is complex, highlighting the importance of social presence, communication quality, and responsive support in driving customer engagement and intention to use generative AI chatbots.

2.3.3 Customer engagement with online retailers

Customer engagement has gained prominence in relationship marketing, in which it is recognized as a multidimensional construct encompassing cognitive, emotional, and behavioral involvement with a company (Brodie et al., 2011; Vivek et al., 2012). Brodie et al. (2011) identify customer engagement as a key driver of customer loyalty and advocacy. Customer engagement consists of three interconnected dimensions—cognitive processing, affection, and activation—which together illustrate the dynamic interplay of engagement's cognitive, affective, and behavioral aspects (Hollebeek et al., 2014).

The cognitive processing dimension reflects the extent of retail-related thought processing and customer involvement in understanding the retailer. The emotional dimension, or affection, captures the positive emotional connection a customer has with a retailer, which influences their loyalty and future engagement. The behavioral dimension, or activation, indicates the energy, effort, and time a customer devotes to a retailer, with higher activation suggesting stronger engagement and positive outcomes, such as increased loyalty.

In the context of online retail, customer engagement involves the cognitive, emotional, and behavioral aspects of the customer–retailer relationship, which are influenced by the retail environment and customer service interactions. Extending Hollebeek et al.'s (2014) concept, we define customer engagement with an online retailer as the level of cognitive, emotional, and behavioral involvement. It affects customer loyalty and future interactions and reflects the interactive nature of engagement.

2.3.4 AI chatbots and customer engagement

Chatbots are designed to simulate conversational sales assistants and enhance customer engagement by influencing cognitive, emotional, and behavioral dimensions (Hari et al., 2022; Hollebeek et al., 2014; Lo Presti et al., 2021; Nass and Moon, 2000). This study draws on SRT to explain how generative AI chatbot assistants, such as ChatGPT, can contribute to customer engagement. SRT suggests that individuals naturally apply social behaviors when interacting with technology, even when they are aware that it is non-human (Nass & Moon, 2000). When AI systems exhibit human-like attributes and respond promptly, they foster a sense of trust and emotional connection with users (Dutta & Mishra, 2025). Generative AI chatbots, powered by advanced language models, facilitate interactive conversations, provide personalized recommendations, and demonstrate responsiveness. By incorporating verbal and behavioral cues that simulate human interactions, these generative AI assistants create a perceived social presence, thus making users feel acknowledged and valued. This sense of attentiveness and responsiveness enhances customer engagement (Honora et al., 2024; Paul et al., 2023).

Generative AI chatbots enhance cognitive engagement by delivering personalized recommendations and relevant content, promptly addressing customer inquiries, and leaving a lasting positive impression (Lin & Wu, 2023). In terms of affective engagement, AI chatbots evoke positive emotional responses through engaging and dynamic interactions. Chatbots that utilize conversational and expressive communication styles strengthen emotional connections between customers and online retailers, leading to increased affective engagement (Li & Shin, 2023; Schuetzler et al., 2020; Sundar et al., 2016a). Behavioral engagement is also influenced by generative AI chatbots through their ability to streamline shopping experiences and encourage active participation. These chatbots facilitate seamless product discovery and guide users through purchasing decisions. In addition, features such as automated reminders, order tracking, and exclusive promotions encourage customers to continue engaging with the retailer beyond the initial interaction. By promoting a sense of ongoing interaction and responsiveness, AI chatbots motivate users to browse products, make purchases, and even share recommendations with others, reinforcing deeper behavioral engagement (Kull et al., 2021; Tsai et al., 2021). Based on these considerations, we propose our first hypothesis:

H1: Generative AI chatbots increase customer engagement (affective, cognitive, and behavioral).

2.3.5 The role of control

In today's competitive marketplace, strong customer engagement is crucial for business success. A key factor influencing customer engagement is perceived control, which empowers customers to navigate the complexities of the online landscape. Perceived control significantly affects online customers' decisions and actions (Koufaris et al., 2001). Averill (1973) suggests that individuals who feel in control of their environment and behavior are more confident and engaged with their surroundings. Perceived control has two main components, namely cognitive and behavioral, both of which influence shopping experiences. Perceived cognitive control refers to individuals' belief in their ability to manage cognitive processes, such as decision-making and attention. High perceived cognitive control is associated with confidence in one's mental abilities, whereas low perceived cognitive control leads to doubts in these areas (Mackie et al., 2013; Mushtaq et al., 2011; Posner et al., 2004). Behavioral control, as explained by Ajzen's (1991) theory of planned behavior, refers to individuals' belief in their ability to perform specific actions (Trafimow et al., 2002). When customers feel that they have cognitive and behavioral control, they are more likely to engage positively with an online retailer. Interactions with a retailer through message exchanges enhance customers' perceptions of communication and control (Liu & Shrum, 2002; Song & Zinkhan, 2008). Therefore, in this research, cognitive control and behavioral control are proposed as mediators in the relationship between generative AI chatbots and customer responses.

2.3.6 Perceived control and customer engagement

Averill (1973) defines cognitive control as the process of imposing meaning and reducing uncertainty. The interactive nature of AI chatbots, which provide relevant information, enhances customers' cognitive control by making information more accessible and predictable (Cheng & Jiang, 2022; Hagberg et al., 2016). According to SRT, individuals respond to machines as social actors, applying human-like cognitive and emotional processing to seek clear information during interactions (Nass & Moon, 2000). AI chatbots leverage these mechanisms by offering personalized, real-time responses and helping customers navigate product details and purchase options, thereby reinforcing cognitive control (Burger, 1989; Mushtaq et al., 2011). By simulating real-life sales interactions, AI chatbots not only satisfy customers' need for clarity but also encourage them to apply familiar social and cognitive norms to the interaction (SRT). This increased cognitive control leads to greater engagement with online retailers (Lin & Wu, 2023; Whang et al., 2021).

Moreover, behavioral control, another key aspect of perceived control, refers to individuals' perceptions of how easy or difficult it is to perform a particular behavior (Ajzen, 1991). High perceived behavioral control is closely associated with self-efficacy, in which individuals who feel capable of carrying out a task are more likely to engage in it (Bandura, 1986; Compeau & Higgins, 1995). From an SRT perspective, AI chatbots enhance behavioral control by actively assisting users in executing actions, such as modifying selections or navigating checkout processes. Unlike cognitive control, behavioral control concerns task facilitation and ensures that users can act effortlessly on their decisions. Customers who perceive chatbots as competent and socially responsive agents feel more confident in managing the shopping process, thus strengthening their sense of behavioral control over their actions. AI chatbots can lower barriers to action by reducing uncertainty in decision execution and helping customers feel more in control throughout their shopping journey (Hoyer et al., 2020; Soares et al., 2022). By removing technical obstacles and guiding users seamlessly through each step, chatbots increase confidence in completing purchases and encourage sustained engagement with the retailer. Therefore, we propose our second hypothesis:

H2: The effect of generative AI chatbots on customer engagement (affective, cognitive, and behavioral) is mediated by perceived control (cognitive and behavioral).

2.3.7 Product type: Search versus experience goods

Products can be categorized based on how easily their attributes can be evaluated before or after a purchase (Klein, 1998; Nelson, 1974). Search goods, which have clearly defined and measurable attributes (e.g., price, quality, and size), allow customers to make informed decisions before purchasing. By contrast, experience goods, which require post-purchase evaluation (e.g., performance and satisfaction), pose greater challenges for pre-purchase assessment (Girard & Dion, 2010). As the difficulty of obtaining reliable information increases, so does the level of perceived risk, particularly for experience goods (Chaudhuri, 1998).

For search goods, customers typically possess a high degree of cognitive and behavioral control, as the decision-making process is relatively straightforward, and objective product attributes can be evaluated with minimal information (Bei et al., 2004). The ease with which customers can independently assess product characteristics reduces their reliance on external advice, making the assistance of chatbots less essential in these contexts. By contrast, experience goods require customers to rely more heavily on subjective judgments and external information, prompting a more extensive information search and greater dependence on outside guidance (Jiménez & Mendoza, 2013). Because experience goods are often associated with higher perceived risk and greater complexity, customers are motivated to seek additional support and reassurance to mitigate uncertainty and facilitate their decisions (Lim et al., 2015).

Conversely, the evaluation of experience goods relies more heavily on subjective assessments and external input, as their quality and attributes cannot be easily assessed prior to purchase

(Jiménez & Mendoza, 2013). The greater perceived risk and complexity associated with experience goods prompt customers to seek additional support and reassurance to guide their decisions (Lim et al., 2015). In these circumstances, generative AI chatbots can play a pivotal role by offering detailed, real-time, and personalized assistance. This support enhances customers' cognitive and behavioral control, enabling them to make more informed and confident choices when considering experience goods (Whang et al., 2022).

Therefore, the influence of generative AI chatbots, such as ChatGPT, on cognitive and behavioral control depends on the product type. For search goods, cognitive control and behavioral control are already established because of the clarity of product attributes and higher self-efficacy (Ajzen, 1991; Averill, 1973), making chatbot assistance less impactful. Conversely, for experience goods, which involve greater uncertainty and perceived risk (Girard & Dion, 2010), chatbots play a more significant role in strengthening cognitive and behavioral control by reducing ambiguity and providing structured guidance. Accordingly, we propose our third hypothesis:

H3: The type of product (search vs. experience) moderates the mediations of cognitive and behavioral control in the effect of generative AI chatbots on customer engagement (affective, cognitive, and behavioral), such that the effect is stronger for experience goods than for search goods.

2.3.8 Choice overload

Choice overload, which is driven by the number of available options, increases decision-making complexity, often reducing confidence or leading to indecision (Guo & Li, 2022; Reutskaja et al., 2022). Research has explored various strategies to mitigate these effects, including the use of technological filters, such as online recommendation agents (Kim et al., 2023; Turri & Watson, 2023). This study examines how the availability of product options influences the conditional effect of product type (search and experience goods), depending on whether the choices are limited or excessive. When faced with an overwhelming number of options, customers experience heightened uncertainty, which can hinder decision-making and lower confidence. To counteract this, individuals actively seek assistance that simplifies choices and provides clarity, thus reducing the cognitive burden associated with complex decisions (Kim et al., 2023).

Generative AI chatbots, such as ChatGPT, play a particularly valuable role with regard to experience goods, in which uncertainty is naturally higher due to the difficulty of pre-purchase evaluation. Their ability to provide personalized guidance, filter options, and highlight key differentiating factors makes them instrumental in complex decision contexts. By contrast, customers buying search goods, whose attributes can be objectively assessed before purchase, typically have lower uncertainty and higher self-efficacy (Ajzen, 1991; Averill, 1973). For search goods, detailed product information is often sufficient for decision-making, making chatbot assistance less impactful. However, for experience goods in which information asymmetry and perceived risk are higher (Girard & Dion, 2010), chatbots serve as uncertainty-reducing agents by structuring information and guiding decision-making, thereby enhancing customers' cognitive and behavioral control.

However, we argue that a large number of search goods options can create a purchasing scenario for a search good that is now perceived as equally complex as buying an experience good. To explore how generative AI chatbots function at different levels of decision complexity, we consider choice overload, a situation in which an excess of options increases decision-making difficulty and cognitive strain (Chernev & Hamilton, 2009; Mittal, 2016). We predict that a choice overload with regard to search goods can amplify uncertainty, making chatbot assistance valuable by reducing information overload and streamlining options (Chen, Qiu, et al., 2022; Ruan & Mezei, 2022). By offering tailored recommendations and simplifying complex decisions, chatbots help customers regain a sense of control and reinforce their engagement with the retailer. Thus, we anticipate that in the case of choice overload when buying search goods, customer engagement with the retailer will increase as much as when they buy experience goods, and generative AI chatbots will increase customer engagement with the retailer for both search and experience products:

H4: Choice overload in search goods strengthens the effect of generative AI chatbots on customer engagement, whereas a limited number of choices weakens this effect. This relationship is consistently strong for small and large assortments of experience goods.

Insert Figure 1 here

2.4 Methodology and results

Study 1: Direct effect of chatbots on customer engagement

Method

Study 1 aimed to assess the effect of generative AI chatbots on affective, cognitive, and behavioral customer engagement with the retailer using ChatGPT for AI-generated recommendations. We recruited 120 US participants on Prolific for a between-subjects experiment with one factor (generative AI chatbot: generative bot vs. no bot). The final sample was N = 117 (47% women; M_{age} = 41 years). Three participants were excluded from the final sample: two for failing the attention check and one for completing the survey in substantially less time than the minimum expected completion time, indicating potential speeding. The participants imagined shopping for perfume to be worn at a family member's formal wedding anniversary and choosing between two options on an online retailer's site. In the chatbot condition, they had to imagine that they were engaging in a dialog with a chatbot offering product recommendations, while in the non-chatbot condition, they had to imagine that they were browsing the site and reading product information. This method has been validated in previous studies, reinforcing the robustness of our approach (Agnihotri & Bhattacharya, 2024; Beattie et al., 2020; Lo Presti et al., 2021b; Song et al., 2023). The stimuli of the study are presented in Appendix A. The participants rated their cognitive, affective, and behavioral engagement (Hollebeek et al., 2014). The constructs, items utilized, and Cronbach's alpha values are reported in Table 2.

Insert Table 2 here

Results and discussion

After reading the scenario, the participants assessed cognitive engagement (three items; $\alpha = 0.90$), affective engagement (four items; $\alpha = 0.94$), and behavioral engagement (three items; $\alpha = 0.93$) (Hollebeek et al., 2014). The manipulation for generative AI chatbots was successful: a t-test confirmed that the participants who received chatbot recommendations reported significantly higher agreement on "I have received a recommendation from a chatbot" (MBot = 6.42, MNoBot = 1.47, [1, 115] = 774.469, $p < 0.001$). We verified the effect of chatbots on engagement (cognitive, affective, and behavioral). A one-way analysis of variance was conducted to compare customer engagement when generative AI chatbots were present and not present. The results indicate that generative AI chatbots have a significant positive effect on cognitive engagement (MBot = 5.62, MNoBot = 4.41, [1, 115] = 27.20, $p < 0.001$), affective engagement (MBot = 5.65, MNoBot = 4.48, [1, 115] = 25.11, $p < 0.001$), and behavioral engagement (MBot = 5.56, MNoBot = 4.06, [1, 115] = 32.29, $p < 0.001$).

Thus, H1 is supported (see Table 3A for a summary of the direct effect results).

Insert Figure 2 here

Insert Table 3A here

Study 2: Mediating role of perceived control

Method

Study 2 aimed to investigate how perceived cognitive and behavioral control mediate the relationship between chatbots and customer engagement. Utilizing ChatGPT's generative capabilities, AI-generated recommendations were crafted for the participants. We recruited US participants on Prolific for a between-subjects experiment (generative bot vs. no bot), N = 246 (51.2% women; M_{age} = 39.5 years). The participants were asked to envision shopping online for office pants under a formal business dress code. Both conditions (generative bot vs. no bot) were manipulated as in Study 1, with similar measures used to assess cognitive, affective, and behavioral engagement (Hollebeek et al., 2014). We used established measures for cognitive control and behavioral control (Compeau & Higgins, 1995; McMillan & Hwang, 2002). The details of the scales and Cronbach's alpha values for each variable are reported in Table 2.

Results and discussion

The manipulation for generative AI chatbots was successful. A t-test confirmed that the participants who received chatbot recommendations reported significantly higher agreement on "I have received a recommendation from a chatbot" (M_{Bot} = 6.41, M_{NoBot} = 1.94, [1, 244] = 1453.851, $p < 0.001$). We also confirmed the believability (MBelieveBot = 6.03, p < 0.001) and realism (MReal = 5.98, p < 0.001) of the scenario. To test H2, we performed a mediation analysis using the Hayes PROCESS macro (Model 4) with bootstrapping (5,000 bootstrap samples) and 95% bias-corrected confidence intervals (CIs), with generative AI chatbots (dummy-coded: 1 = Bot, 0 = No Bot) as the independent variable; cognitive engagement, affective engagement, and behavioral engagement as the dependent variables; and cognitive control and behavioral control as the mediators.

The chatbot significantly increased cognitive control ($b = 4.060$, $SE = 0.087$, $t = 46.451$, $p < .001$, 95% CI = 3.889–4.233) and behavioral control ($b = 3.871$, $SE = 0.094$, $t = 40.993$, $p < .001$, 95% CI = 3.685–4.057). Both mediators significantly predicted cognitive engagement, with effects for cognitive control ($b = 0.322$, $SE = 0.108$, $t = 2.965$, $p = .003$, 95% CI = 0.108–0.536) and behavioral control ($b = 0.379$, $SE = 0.100$, $t = 3.775$, $p < .001$, 95% CI = 0.181–0.577). The direct effect was nonsignificant ($b = 0.834$, $SE = 0.285$, $t = 3.255$, $p = .113$, 95% CI = −0.363–1.485), indicating mediation. The indirect effect through cognitive control was significant (index = 1.307, 95% CI = 0.041–2.602), as was the indirect effect through behavioral control (index = 1.468, 95% CI = 0.066–2.583). The total indirect effect was strong (index = 2.775, 95% CI = 1.843–3.165), demonstrating that generative AI enhances cognitive engagement primarily by increasing perceived control.

The chatbot significantly increased cognitive control ($b = 4.060$, 95% CI = 3.889–4.233) and behavioral control ($b = 3.871$, 95% CI = 3.685–4.057). Both mediators predicted affective engagement, with cognitive control showing a significant effect ($b = 0.382$, $SE = 0.086$, $t = 4.450$, $p < .001$, 95% CI = 0.213–0.552) and behavioral control also significant ($b = 0.352$, $SE = 0.080$, $t = 4.431$, $p < .001$, 95% CI = 0.196–0.509). The direct effect of the chatbot was nonsignificant ($b = 0.715$, $SE = 0.256$, $t = 3.344$, $p = .202$, 95% CI = −0.269–1.158), indicating full mediation. The indirect effect via cognitive control was significant (index = 1.553, 95% CI = 0.521–2.372), as was the indirect effect via behavioral control (index = 1.364, 95% CI = 0.552–2.215). The total indirect effect was substantial (index = 2.917, 95% CI = 2.180–3.249), showing that perceived control is the key mechanism driving affective engagement.

The chatbot significantly increased cognitive control (b = 4.060, 95% CI = 3.889–4.233) and behavioral control (b = 3.871, 95% CI = 3.685–4.057). Both mediators predicted behavioral engagement, with cognitive control showing a positive effect (b = 0.298, SE = 0.085, t = 3.516, $p < .001$, 95% CI = 0.131–0.465) and behavioral control showing an even stronger effect (b = 0.544, SE = 0.078, t = 6.933, $p < .001$, 95% CI = 0.389–0.698). The direct effect was nonsignificant (b = 0.459, SE = 0.222, t = 2.678, p = .311, 95% CI = −0.131–1.007), demonstrating full mediation. The indirect effect via cognitive control was significant (index = 1.209, 95% CI = 0.089–2.222), and the indirect effect via behavioral control was larger and significant (index = 2.104, 95% CI = 1.055–3.190). The total indirect effect was strong (index = 3.313, 95% CI = 2.718–3.638), indicating that behavioral engagement is primarily driven by increased perceived control. Thus, H2 is supported (see Table 3B for a summary of the mediation effect results).

Insert Figure 3 here

Insert Table 3B here

Study 3: Moderating role of product type

Pretest for Studies 3 and 4: Product type

To ensure the validity of the manipulation for product type (search vs. experience goods), we pretested whether products on a list were categorized as search or experience goods using a procedure similar to that used by Weathers et al. (2007). A total of 128 participants (53.7% women, M_{age} = 39) assessed experience and search qualities (see Table 2 for the measurement). The respondents in the search product condition perceived the search attributes to be higher for recipe books and multivitamins ($M_{BooksSearch}$ = 5.07, $M_{BooksExperience}$ = 2.18, two-tailed $p < 0.001$); ($M_{MultivitaminsSearch}$ = 5.11, $M_{MultivitaminsExperience}$ = 3.52, two-tailed $p < 0.001$), while the respondents in the experience product condition perceived the experience attributes to be higher for pants and blazers ($M_{PantsSearch}$ = 3.81, $M_{PantsExperience}$ = 5.92, two-tailed p < 0.001); ($M_{BlazersSearch}$ = 3.21, $M_{BlazersExperience}$ = 6.1, two-tailed p < 0.001).

Method

Study 3 examined how product type (search or experience) moderates the mediation effect of perceived control. We used ChatGPT to create AI-generated recommendations, explicitly highlighting ChatGPT's role in producing these recommendations. A total of 245 US participants (53% women; M_{age} = 37 years) on Prolific took part in a between-subjects 2 (generative bot vs. no bot) × 2 (search vs. experience product) experiment.

In the search condition, the participants imagined shopping for a recipe book to prepare desserts for a wedding anniversary reception. In the experience condition, they focused on selecting office pants suitable for a business formal dress code. The chatbot and no-chatbot conditions were manipulated as in Studies 1 and 2. The participants then answered questions using measures similar to those in previous studies, assessing cognitive, affective, and behavioral engagement, as well as cognitive and behavioral control (Higgins & Scholer, 2009; McMillan & Hwang, 2002). The details of the scales and the Cronbach's alpha values for each variable are reported in Table 2.

Results and discussion

The manipulation for generative AI chatbots was successful. A t-test confirmed that the participants who received chatbot recommendations reported significantly higher agreement on "I have received a recommendation from a chatbot" (M_{Bot} = 6.52, M_{NoBot} = 1.65, [1, 423] = 4241.527, p < 0.001). We confirmed the believability (MBelieveBot = 6.32, p < 0.001) and realism (MReal =

6.12, $p < 0.001$) of the scenario. These results indicate that the participants found the scenario to be believable and realistic.

We evaluated the participants' perceptions of search and experience goods using an established scale (Weathers et al., 2007). Using a similar measure as in Study 2, we verified that the respondents in the search product condition perceived the search attributes to be higher ($M_{BooksSearch} = 6.67$, $M_{BooksExperience} = 2.18$, two-tailed $p < 0.001$), while those in the experience product condition perceived the experience attributes to be higher ($M_{PantsSearch} = 2.09$, $M_{PantsExperience} = 6.26$, two-tailed $p < 0.001$).

To test H3, we performed a moderated mediation analysis using Hayes' PROCESS macro (Model 7) with bootstrapping (5,000 bootstrap samples) and 95% bias-corrected CIs, with generative AI chatbots (dummy-coded: 1 = bot, 0 = no bot) as the independent variable; cognitive engagement, affective engagement, and behavioral engagement as the dependent variables; cognitive control and behavioral control as the mediators; and product type (dummy-coded: 0 = search, 1 = experience) as the moderator.

We observed significant conditional indirect effects of generative AI chatbots on cognitive, affective, and behavioral engagement through cognitive control, with product type serving as the moderator. For cognitive engagement, these effects were evident for search goods, with a negative effect of −2.421 (95% CI = −3.265 to −1.634), and experience goods, with a positive effect of 2.391 (95% CI = 1.601–3.244). Similarly, for affective engagement, we found a negative effect for search goods of −1.461 (95% CI = −2.066 to −0.848) and a positive effect for experience goods of 1.443 (95% CI = 0.835–2.067). For behavioral engagement, we observed a negative effect for search goods of −0.638 (95% CI = −1.174 to −0.121) and a positive effect for experience goods of 0.630 (95% CI = 0.118–1.161). Therefore, the overall moderated mediation model through cognitive control was supported for cognitive engagement (index = 4.812, 95% CI = 3.250–6.497), affective engagement (index = 2.904, 95% CI = 1.685–4.108), and behavioral engagement (index = 1.268, 95% CI = 0.240–2.343).

We noted significant conditional indirect effects on cognitive, affective, and behavioral engagement through behavioral control, with product type as the moderator. For cognitive engagement, the effects were evident for both search goods, with a negative effect of −2.212 (95% CI = −2.012 to −0.372), and experience goods, with a positive effect of 1.178 (95% CI = 1.952–3.361). Similarly, for affective engagement, we found a negative effect for search goods of −2.092 (95% CI = −2.714 to −1.465) and a positive effect for experience goods of 2.032 (95% CI = 1.436–2.640). For behavioral engagement, we observed a negative effect for search goods of −3.050 (95% CI = −3.565 to −2.513) and a positive effect for experience goods of 2.963 (95% CI = 2.445–3.456). Therefore, the overall moderated mediation model through behavioral control was supported for cognitive engagement (index = 2.390, 95% CI = 0.739–3.962), affective engagement (index = 4.124, 95% CI = 2.894–5.344), and behavioral engagement (index = 6.012, 95% CI = 4.964–7.003). Thus, H3 is supported (see Table 3C for a summary of the results of the moderation effect of product type (search goods: recipe books vs. experience goods: pants)).

Insert Figure 4 here

Insert Table 3C here

Study 4: Conditional moderated mediation by the number of choices

Method

Study 4 examined whether choice overload during the purchase of *search goods* would change the usual pattern in which engagement tends to be lower when a chatbot is present and higher when it is absent. We wanted to explore whether the presence of a chatbot would help increase engagement with the retailer by making decision-making easier when customers are faced with a large number of options for search goods. When customers experience choice overload, even with search goods, they may value chatbot support because it helps them manage the abundance of options and regain a sense of control. For experience goods, in which uncertainty and risk are naturally higher, chatbots may be even more valuable because they can provide real-time, personalized information that bridges information gaps and reduces ambiguity (Bei et al., 2004; Whang et al., 2022). These considerations led us to design Study 4 to investigate whether introducing choice overload in the context of search goods would make chatbot support more important for fostering customer engagement.

A total of 493 (50.4% women; M_{age} = 33 years) US participants on Prolific took part in a 2 (generative AI chatbot: generative bot vs. no bot) × 2 (product type: search goods (multivitamins) vs. experience goods (blazers)) × 2 (assortment size: small (3 options) vs. large (10 options)) between-subjects experiment. The decision to use assortment size (small (3 options) vs. large (10 options)) was based on a prior study by Haynes (2009).

The chatbot and no-chatbot conditions were manipulated, as in previous studies. For search goods, the participants envisioned shopping for dependable multivitamins to meet their nutritional needs. For experience goods, the participants imagined shopping for a blazer for an upcoming conference in Norway. The participants faced different assortment sizes for each product type: small (3 options) and large (10 options). These option quantities were selected following the experiment conducted by Haynes (2009). After reading the scenario, the participants responded to questions with measures similar to those used in previous studies for cognitive, affective, and behavioral engagement (Hollebeek et al., 2014) and cognitive and behavioral control (Compeau

& Higgins, 1995; McMillan & Hwang, 2002). The details of the scales and Cronbach's alpha values for each variable are reported in Table 2.

Results and discussion

The manipulation for generative AI chatbots was successful, as the participants who received chatbot recommendations reported significantly higher agreement on "I have received a recommendation from a chatbot" (M_{Bot} = 6.73, M_{NoBot} = 1.54, [1, 491] = 4607.407, $p < 0.001$). As in Study 3, we evaluated the participants' perceptions of search and experience goods by using the scale developed by Weathers et al. (2007). The respondents in the search goods condition better perceived the search attributes ($M_{MultivitaminSearch}$ = 6.41, $M_{MultivitaminExperience}$ = 1.81; $p < 0.001$), while those in the experience goods condition better perceived the experience attributes ($M_{BlazerSearch}$ = 1.74, $M_{BlazerExperience}$ = 6.54, $p < 0.001$). We confirmed the believability (MBelieveBot = 6.11, p < 0.001) and realism of the scenario (MReal = 6.02, p < 0.001), as in prior studies.

To test H4, we performed a conditional moderated mediation analysis using Hayes' PROCESS macro (Model 11) with bootstrapping (5,000 bootstrap samples) and 95% bias-corrected CIs, with the presence of a generative AI chatbot (dummy-coded: 0 = no bot; bot = 1) as the independent variable; cognitive engagement, affective engagement, and behavioral engagement as the dependent variables; cognitive control and behavioral control as the mediators; product type (dummy-coded: search = 0; experience = 1) as the moderator; and assortment size (small vs. large) as the conditional moderating variable.

The generative chatbot affected perceived cognitive control and behavioral control as a function of product type and assortment size. For search goods, the chatbot had a significant effect on cognitive control when the assortment was small (b = −4.210, p < .001, 95% CI [−4.545, −3.874]) and when the assortment was large ($b = 3.398$, $p < .001$, 95% CI [3.061, 3.735]). For experience goods, the chatbot also had significant effects on cognitive control under both small assortments ($b = 4.643$, $p < .001$, 95% CI [4.304, 4.983]) and large assortments ($b = 4.392$, $p < .001$, 95% CI [4.052, 4.731]).

A similar pattern was observed for behavioral control. For search goods, the chatbot significantly affected behavioral control under small assortments ($b = -4.434$, $p < .001$, 95% CI [−4.814, −4.054]) and large assortments ($b = 3.664$, $p < .001$, 95% CI [3.283, 4.045]). For experience goods, the chatbot had significant effects on behavioral control under both small assortments ($b = 4.419$, $p < .001$, 95% CI [4.034, 4.803]) and large assortments ($b = 4.324$, $p < .001$, 95% CI [3.939, 4.708]).

These effects translated into conditional indirect effects on customer engagement. Through cognitive control, the chatbot had significant indirect effects on cognitive engagement for search goods under small assortments ($b = -2.632$, 95% CI [−3.294, −1.948]) and large assortments ($b = 2.124$, 95% CI [1.457, 2.851]). For experience goods, the indirect effects through cognitive control on cognitive engagement were significant under both small assortments ($b = 2.903$, 95% CI [2.149, 3.600]) and large assortments ($b = 2.746$, 95% CI [1.979, 3.498]). The same pattern was observed for affective and behavioral engagement. For search goods, indirect effects through cognitive control were significant under small assortments (affective: $b = -2.253$, 95% CI [−3.127, −1.391]; behavioral: $b = -2.243$, 95% CI [−3.100, −1.331]) and large assortments (affective: $b = 1.819$, 95% CI [1.056, 2.678]; behavioral: $b = 1.810$, 95% CI [1.032, 2.646]). For experience goods, all indirect effects through cognitive control were significant under both assortment sizes.

Indirect effects through behavioral control showed a comparable pattern. For search goods, the chatbot had significant indirect effects on cognitive engagement under small assortments (b =

−1.211, 95% CI [−1.893, −0.572]) and large assortments (b = 1.001, 95% CI [0.488, 1.532]). For experience goods, the indirect effects through behavioral control on cognitive engagement were significant under both small assortments (b = 1.207, 95% CI [0.581, 1.842]) and large assortments (b = 1.181, 95% CI [0.568, 1.772]). Similar indirect effects were observed for affective and behavioral engagement across conditions.

Finally, the presence of conditional moderated mediation was confirmed by the indices of moderated mediation. Through cognitive control, the moderated mediation was significant for cognitive engagement (index = −4.914, 95% CI [−6.270, −3.555]), affective engagement (index = −4.207, 95% CI [−5.907, −2.557]), and behavioral engagement (index = −4.187, 95% CI [−5.874, −2.481]). Through behavioral control, the moderated mediation was also significant for cognitive engagement (index = −2.238, 95% CI [−3.478, −1.077]), affective engagement (index = −2.244, 95% CI [−3.867, −0.642]), and behavioral engagement (index = −1.910, 95% CI [−3.577, −0.358]). The conditional moderated mediation effect was verified (Figure 5). For experience goods, the generative bot had a positive effect on engagement regardless of assortment size. However, for search goods, the generative bot decreased engagement when the assortment size was small but increased engagement when the assortment size was large. Thus, H4 is validated.

2.5 Discussion

In the first study, we found strong evidence that generative AI chatbots significantly enhance cognitive, affective, and behavioral engagement. A key factor is the dynamic, two-way conversation they can offer, as opposed to static messages or predetermined answers (Hill et al., 2015; Klein, 1998). Chatbots interact by asking questions, providing suggestions, and responding interactively and can therefore capture customer attention (Behera et al., 2024). This dynamic interaction can lead to positive cognitive evaluations (Puntoni et al., 2021), strengthen emotional connections with the retailer (Beattie et al., 2020; Schuetzler et al., 2020; Van Noort et al., 2012), and promote longer interactions and adherence to retailer recommendations (Tsai et al., 2021).

The second study demonstrated that cognitive and behavioral control significantly mediate the relationship between generative AI chatbots and customer engagement. Cognitive control, defined as the process of reducing uncertainty (Averill, 1973), is enhanced by chatbots, which can improve cognitive information processing and make situations more understandable and predictable (Kim et al., 2019; Lew et al., 2018; Lin & Wu, 2023). This increased cognitive control aids customers in making informed decisions, thus boosting engagement with online retailers. In addition, behavioral control, which is related to self-efficacy and autonomy, is positively affected by chatbots, leading to greater engagement with the retailer (Bhattarai, 2023; Esmark et al., 2016; Zheng et al., 2018).

In the third study, we found that the type of product (search goods vs. experience goods) moderated the mediation effect of perceived control between chatbot presence and customer engagement. The effects of generative AI chatbots on engagement through cognitive and behavioral control were stronger for experience than for search goods. Experience goods, which are characterized by higher perceived informational complexity and risk, require more extensive search and trial (Girard & Dion, 2010), leading customers to rely more on generative AI chatbots for online purchases. This results in increased customer engagement (Hoyer et al., 2020). By contrast, for search goods, in which attributes are easily evaluated before purchase, customers experience lower uncertainty and higher self-efficacy (Ajzen, 1991; Averill, 1973). Here, the assistance of generative AI chatbots has a weaker effect on cognitive and behavioral control, leading to lower customer engagement (McLean et al., 2021).

In the fourth study, we explored whether the number of product options (limited vs. overloaded) conditionally moderates the previously identified pattern. We tested a choice overload scenario in which the participants were presented with 10 options for experience goods and three options for search goods (Haynes, 2009). When customers faced a large assortment of search goods, the presence of a generative AI chatbot significantly enhanced customer engagement. For experience goods, the chatbot consistently increased engagement regardless of the number of choices available. This suggests that generative AI chatbots can mitigate the effects of information overload (Chen, Qiu, et al., 2022; Ruan & Mezei, 2022), thereby improving decision-making support and increasing customer engagement (Chernev & Hamilton, 2009; Mittal, 2016; S. Park & Kang, 2022).

In conclusion, our research provides valuable insights into the intricate interplay between generative AI chatbots, product type, choice overload, and customer engagement, highlighting the nuanced effects of these chatbots in diverse shopping scenarios.

2.6 Theoretical contributions

This research makes several key theoretical contributions. First, this study is among the first to critically examine the role of generative AI chatbots, such as ChatGPT, in shaping customer engagement in online retail, an area that remains underexplored due to the novelty of this technology and the context-dependent nature of its effectiveness. While ChatGPT has started to be adopted in business, research on its effects is still in its early stages, particularly in understanding how its effectiveness varies based on factors such as product type (search vs. experience goods) and choice overload. Existing studies have primarily focused on the anthropomorphism aspects of chatbots (Sheehan et al., 2020; Sun et al., 2024; Van Esch et al., 2019) and general chatbot acceptance and user satisfaction (Chen, Le, et al., 2021; Han & Kim, 2020; Luo et al., 2019; Rese et al., 2020; Sundar et al., 2016), without fully addressing whether advanced versions, such as ChatGPT, can enhance decision-making differently across product categories. For instance, while ChatGPT's ability to provide detailed descriptions and interactive recommendations may be particularly useful for experience goods, its role in reducing choice overload is effective across both search and experience products, helping customers navigate vast product assortments more efficiently. Given that these factors are critical in shaping customer engagement and purchase decisions, this study provides timely insights into the nuanced impact of ChatGPT on online retail, highlighting the opportunities and potential challenges for retailers integrating AI-driven customer assistance (Huh et al., 2023; Kim, Kim, et al., 2023; Rathore, 2023).

Second, our study further explores the psychological mechanism of perceived control and demonstrates how it influences customers' online shopping experiences. While previous literature has highlighted the benefits of interactive technologies in marketing (Cuevas et al., 2021; Hu & Wise, 2021; Zimmermann et al., 2023), mechanisms from the customer perspective are often neglected (Hu, 2023; Roy & Mukherjee, 2023). Our study addresses this gap by exploring how perceived control mediates the positive effects of these technologies in response to Hu's (2023) call to investigate the role of perceived control in online retail interactions. We reveal how perceived control links technology to customer engagement and show that it plays a critical role in eliciting positive responses and enhancing the effectiveness of marketing efforts that leverage technology (Hu & Wise, 2021). Generative AI chatbots enhance customer control, thereby making interactions more personalized and meaningful (Hu, 2023; Tsai et al., 2021). This empowerment promotes stronger connections with retailers and drives engagement and loyalty. By understanding the role of perceived control, we gain insights into how customer interest and engagement in interactive marketing are shaped (Ariffin et al., 2021; Lavoye et al., 2023).

Third, our study integrates the effects of product type and choice overload and shows how generative AI chatbots can alleviate decision-making challenges. We challenge the common belief that greater reliance on technology always leads to improved decision-making outcomes (Klaus & Zaichkowsky, 2022). Our findings suggest that the effectiveness of generative AI chatbots, such as ChatGPT, depends on product type. Previous research has suggested that customers are less likely to prefer AI for evaluating experience products (Xie et al., 2022; Y. Zhu et al., 2022), but our study shows that advanced generative AI chatbots, with their improved customization and interactive capabilities, can effectively manage choice overload and guide customers through product options. This results in a more engaging and satisfying shopping experience (Paul et al., 2023; Suganya & Pranesh, 2023). In addition, our study addresses the effect of choice overload on engagement. We find that generative AI chatbots enhance engagement with large assortments of search goods and maintain high engagement for experience goods regardless of assortment size, highlighting the contingent roles of product type and choice complexity in moderating chatbot effects.

In summary, the effects of generative AI chatbots are highly context dependent. The mere presence of chatbots does not automatically guarantee better customer interactions or decision-making. Our findings challenge the assumption that more technology inherently leads to improved outcomes and offer a nuanced understanding of the value and effectiveness of chatbots in enhancing customer engagement.

2.7 Managerial implications

From a practical standpoint, this study offers guidance for companies on the selective and effective implementation of generative AI chatbots by indicating when they are most beneficial to customers. Our findings have important implications for online retailers aiming to enhance customer service and the overall online shopping experience. First, with the rapid growth of online shopping, retailers must provide a positive and engaging online experience to remain competitive. Second, as chatbots become increasingly common, retailers are investing heavily in developing effective systems. Third, well-designed chatbots can improve customer satisfaction, reduce customer service workloads, and potentially increase sales (Aarthi et al., 2020; Hoyer et al., 2020; Rese et al., 2020; Soares et al., 2022). Retailers should consider the nature of their products and the level of customer assistance required to make informed decisions about chatbot investments.

Investing in generative AI chatbots, such as ChatGPT, requires significant resources for development, maintenance, and ongoing evaluation. For retailers primarily offering search goods, extensive chatbot assistance may be less necessary. In these cases, focusing on clear online product descriptions and key information could be more effective, as chatbot investments could be inefficient due to high costs (Kaushal & Yadav, 2023). Conversely, for experience goods, which involve more complex and uncertain decision-making, investing in generative AI chatbots can be advantageous. These chatbots can provide valuable assistance by helping customers navigate complex choices and making the purchasing process more manageable (Bei et al., 2004; Chaudhuri, 1998).

Companies should assess their product types and customer assistance needs before investing in chatbots. If customers feel confident in making informed decisions independently, they may view AI interventions as unnecessary. However, if customers face complex decisions, chatbots can offer significant support that enhances their ability to make informed choices and improve their overall experience. Understanding these needs ensures that AI investments align with customer expectations, leading to a better customer experience. Thus, it is crucial for retailers to consider the expected return on investment when deciding whether to implement ChatGPT or other generative AI solutions. Assessing factors such as cost savings, efficiency improvements, customer engagement, and potential revenue growth helps ensure that the technology delivers tangible business value (Arman & Lamiyar, 2023).

Retailers should view ChatGPT as a complementary tool rather than a replacement for human customer service. While it can efficiently handle a broad range of customer inquiries, certain situations still require personalized assistance from human representatives. To enhance customer experience, businesses should maintain a strategic balance between AI-driven chatbots and human support, ensuring that customers can seamlessly access the level of assistance they need (Kumar et al., 2024).

2.8 Limitations and further research

This study has several limitations that provide opportunities for future research. First, although our experimental approach offers valuable initial insights, future studies could use real online retailer websites and actual generative AI chatbots to provide more realistic, externally valid contexts. Field studies in naturalistic settings would allow for a more comprehensive exploration of customer engagement with generative AI chatbots.

Second, while our model captures key dimensions of engagement, future research could extend this work by incorporating cognitive absorption to determine whether deeper cognitive involvement with generative AI chatbots influences overall engagement with the retailer. Future studies could also expand the scope to include advanced technologies, such as augmented or virtual reality, to assess their effectiveness in different product types and their effects on customer engagement.

Third, several important risks associated with generative AI chatbots should be considered. There is a risk of inaccurate or unvalidated information, as ChatGPT and similar chatbots may generate content that is not always reliable or verified, potentially leading to misinformation or errors in customer-facing settings (Sigala et al., 2024). This risk may undermine customer trust and harm retailer reputation if not properly managed (Paul et al., 2023). In addition, generative AI chatbots may perpetuate or even amplify the biases present in their training data, resulting in biased, unfair, or inappropriate outputs (Christou et al., 2024; Følstad et al., 2021). These concerns raise important ethical questions and may have implications for customer perceptions and legal compliance.

Furthermore, an overreliance on generative AI chatbots in customer service could erode meaningful human interaction, making the customer experience less personal and potentially reducing trust in both the technology and the retailer (Shankar, 2024). From a brand and operational perspective, insufficient oversight of generative AI chatbots can lead to the production of off-brand, irrelevant, or even harmful content, potentially working against the retailer's intended interests (Christou et al., 2024).

Despite these limitations, this study underscores the importance of considering product type when implementing generative AI chatbots to enhance customers' cognitive, affective, and behavioral engagement. By doing so, online retailers can make more informed and cost-effective decisions regarding the adoption of generative AI chatbots.

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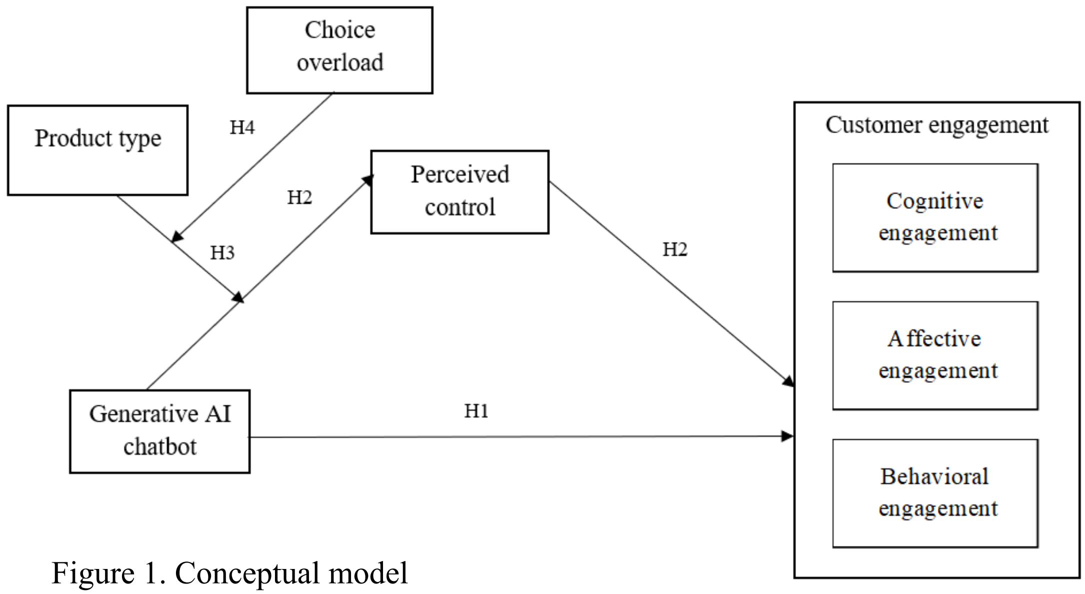


Figure 1. Conceptual model

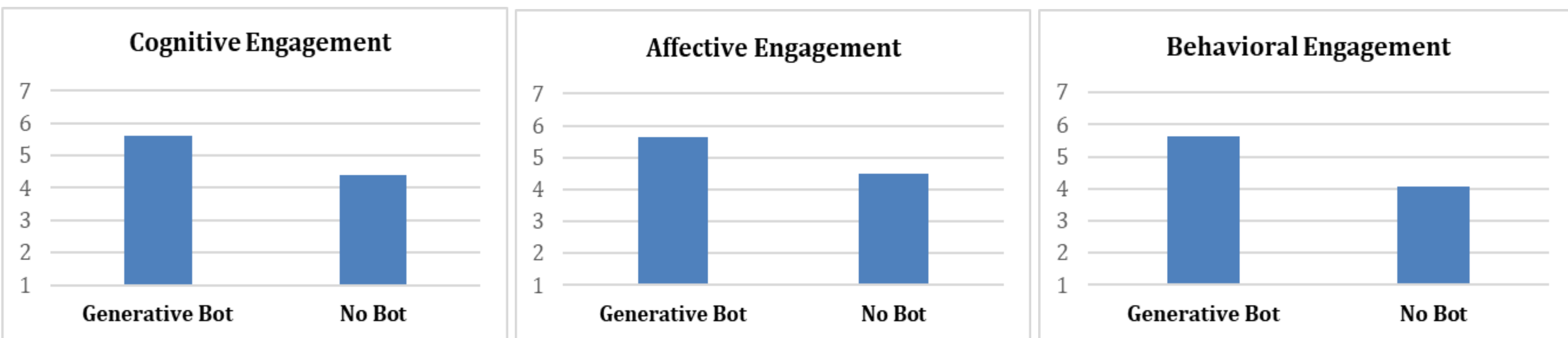
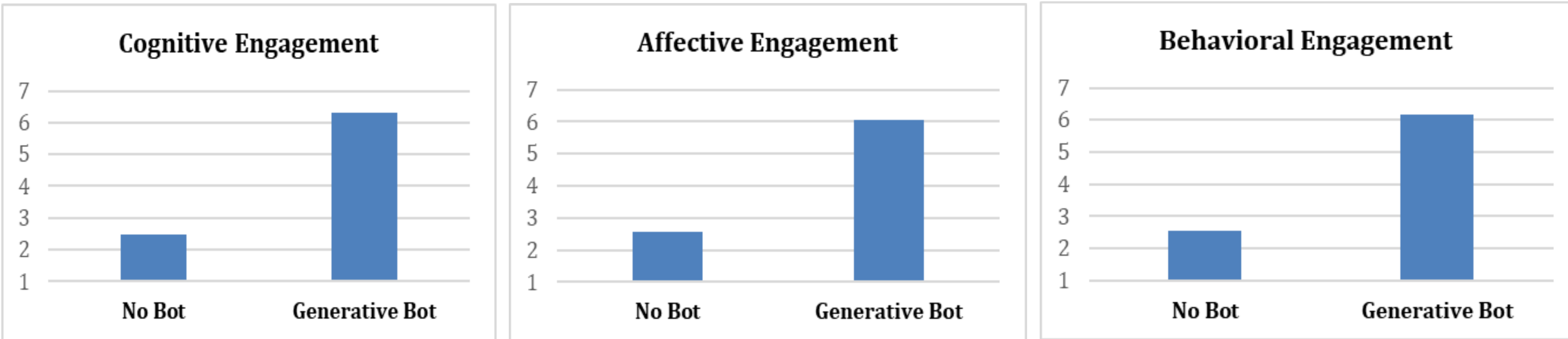
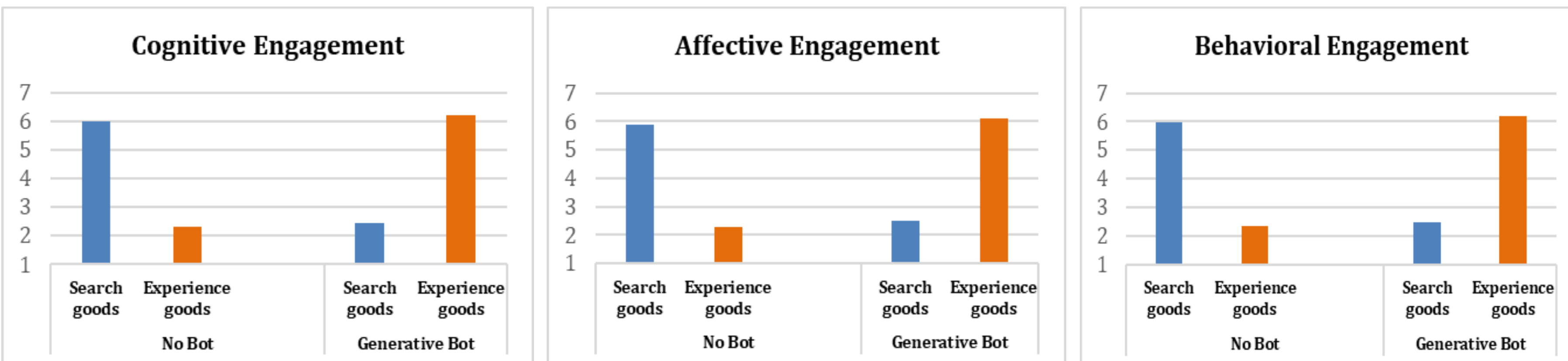


Figure 2. Effects of a generative AI chatbot (generative bot vs. no bot) on customer engagement



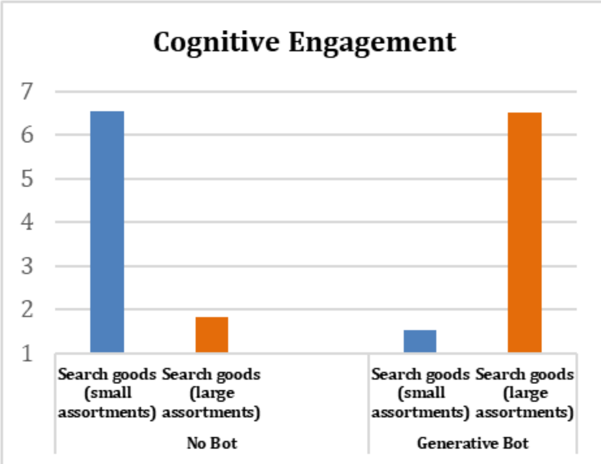
(a) Cognitive engagement (b) Affective engagement (c) Behavioral engagement

Figure 3. Effects of a generative AI chatbot (generative bot vs. no bot) × (pants) on customer engagement

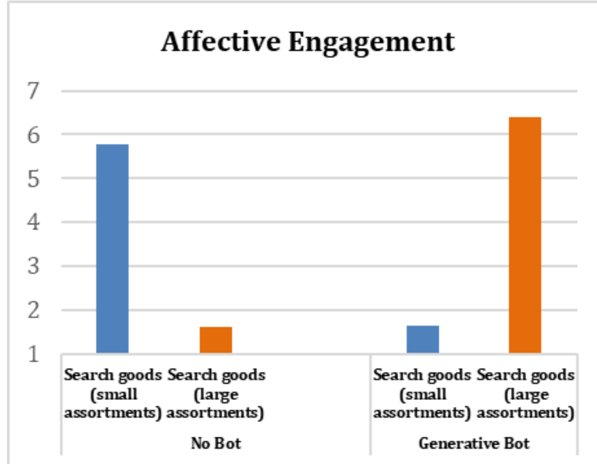


(a) Cognitive engagement (b) Affective engagement (c) Behavioral engagement

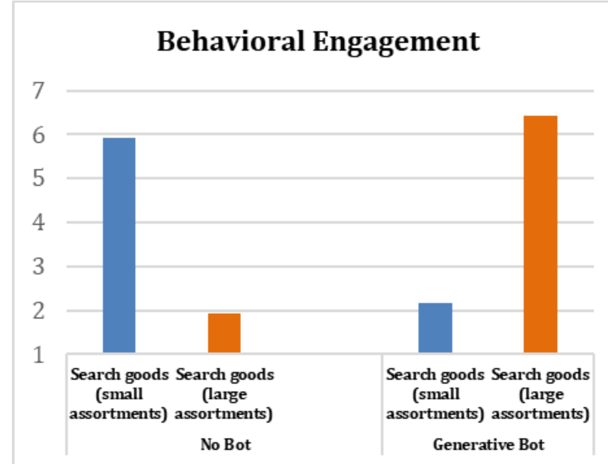
Figure 4. Interaction of a generative AI chatbot (generative bot vs. no bot) × product type (search goods vs. experience goods) in customer engagement



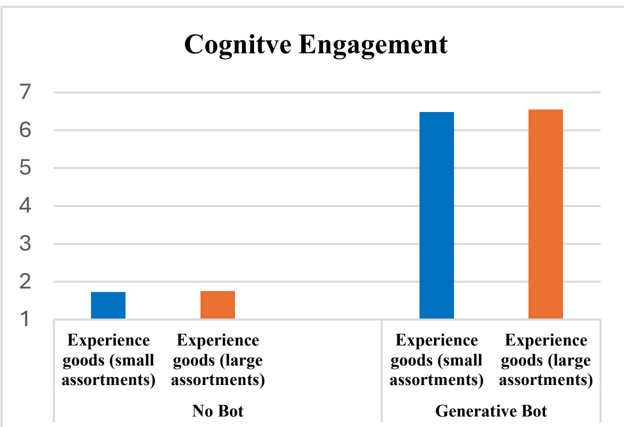
(a.1) Cognitive engagement



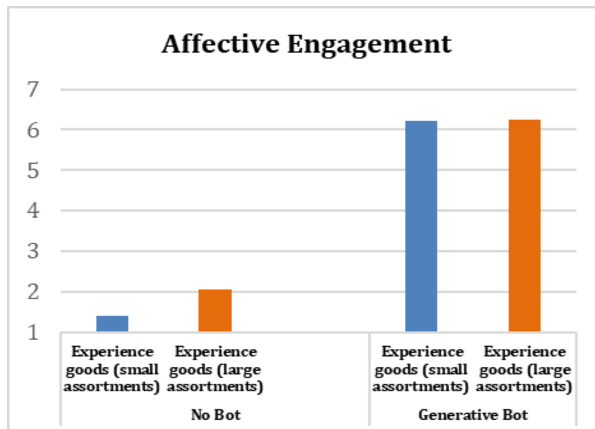
(b.1) Affective engagement



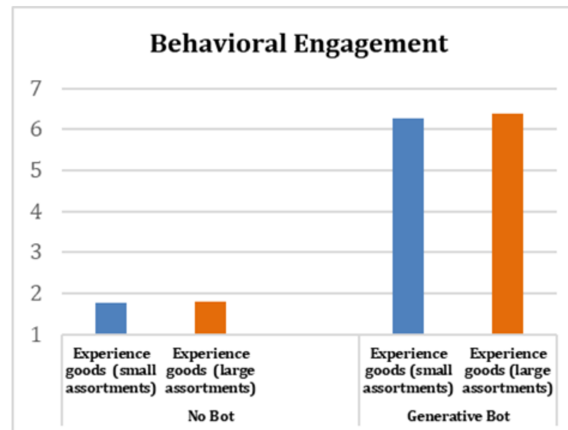
(c.1) Behavioral engagement



(a.2) Cognitive engagement



(b.2) Affective engagement



(c.2) Behavioral engagement

Figure 5. Interaction of a generative AI chatbot (generative bot vs. no bot) × product type (search goods vs. experience goods) × assortment size (small assortments vs. large assortments) in customer engagement.

Table 1. Key characteristics of the empirical literature on chatbots and the present study

Study	Primary research objective	Conditional mechanism		Type of chatbot used	Dependent variable
		Moderator	Mediator		
Nan et al. (2006)	Influence of an anthropomorphic information agent (AIA) on the attitude toward a website	N/A	Perceived credibility Positive emotional response	Pre-defined non-AI chatbot	Attitude toward websites
Sivaramakrishnan et al. (2007)	Influence of an AIA on purchase intention	Static information quantity	N/A	Pre-defined non-AI chatbot	Purchase intention
Hill et al. (2015)	Comparison between chatbots and humans	N/A	N/A	Pre-defined non-AI chatbot	Communication duration
Sundar et al. (2016)	Influence of a digital assistant on the attitude toward a website	N/A	Contingency User engagement	Pre-defined AI chatbot	Attitude toward websites
Mou & Xu (2017)	User responses when interacting with an AI assistant	N/A	N/A	Pre-defined AI chatbot	User responses
Araujo (2018)	Anthropomorphism of disembodied conversational agents	N/A	N/A	Pre-defined non-AI bot	Perceived anthropomorphism
Go & Sundar (2019)	Anthropomorphism of chatbots	N/A	Social presence Homophily Social contingency Dialog	Pre-defined AI chatbot	Perceived anthropomorphism
Luo et al. (2019)	Influence of an AI chatbot on the purchase rate	N/A	Perceived knowledge of the chatbot Perceived empathy of the disclosed chatbot	Pre-defined AI chatbot	Purchase rate
Van den Broeck et al. (2019)	Influence of a chatbot on patronage intention	Perceived message relevance	Message acceptance	Pre-defined AI chatbot	Perceived intrusiveness and patronage intention
Beattie et al. (2020)	Attractiveness of an AI chatbot's message	N/A	N/A	Pre-defined AI chatbot	Message attractiveness
Chung et al. (2020)	Satisfaction with chatbots	N/A	Accuracy Credibility Communication competence	Pre-defined AI chatbot	Satisfaction
Han & Kim (2020)	Customer acceptance of using chatbots	Gender	N/A	Pre-defined AI chatbot	Intention to use chatbot Intention to use chatbots and purchase intention
Rese et al. (2020)	Chatbot acceptance	N/A	N/A	Pre-defined AI chatbot	Acceptance of chatbots
Chen et al. (2021)	Influence of AI chatbots on customer satisfaction	Personality	N/A	Pre-defined AI chatbot	Satisfaction
Lo Presti et al. (2021)	Influence of chatbots on purchase intention	Brand familiarity	N/A	Pre-defined AI chatbot	Purchase intention
Ahn et al. (2022)	Persuasion effect of AI chatbot recommendations on customers	Product type (hedonic vs. utilitarian)	Competence of AI chatbots Warmth of AI chatbots	Pre-defined AI chatbot	Persuasion effect of AI chatbots
Lou et al. (2022)	Competence of service entities that affect customer patronage intentions	Sympathy	Competence and warmth of the service entity	Pre-defined AI chatbot	Patronage intention
Xie et al. (2022)	Influence of AI recommenders on purchase behavior	Product type (search goods vs. experience goods)	N/A	Pre-defined AI chatbot	Purchase behavior

Zhu et al. (2022)	Consumer acceptance of AI chatbots	Product type (search goods vs. experience goods)	Perceived effectiveness	Pre-defined AI chatbot	Consumer acceptance
Cheng & Jiang (2022)	How AI-powered chatbot marketing efforts influence customer–brand communication and relationships (CBR)	N/A	CBR	Pre-defined AI chatbot	Customer response
Gao et al. (2023)	How AI stimuli influence customer engagement and value co-creation	Customer ability readiness	Customer engagement	AI service robot	Value co-creation
Kim et al. (2023)	Influence of AI chatbots on purchase intention	Regulatory focus (promotion vs. prevention)	Risk–benefit perception	Pre-defined AI chatbot	Purchase intention
Jiménez-Barreto et al (2023)	Customer willingness to use chatbots	Shared competence between chatbots and consumers	Perceived competence	Pre-defined AI chatbot	Willingness to use the chatbot
Lee & Li (2023)	How chatbot affordances can foster customer–chatbot identification, leading to brand loyalty	N/A	Customer–chatbot identification	Pre-defined AI chatbot	Brand loyalty
Li & Wang (2023)	Influence of the language style of chatbots on customer intention to use them	Brand affiliation	Parasocial interaction	Pre-defined AI chatbot	Continuance usage intention
Song et al. (2023)	Influence of AI chatbot politeness on post-recovery satisfaction	Time pressure	Self-face concern (acknowledging others as having a favorable image)	Pre-defined AI chatbot	Post-recovery satisfaction
Agnihotri & Bhattacharya (2024)	Chatbots' effectiveness in driving consumers to forgive the firm for service failure	N/A	N/A	Pre-defined AI chatbot	Perceived ability Perceived benevolence Perceived integrity Consumer forgiveness
Sun et al. (2024)	How anthropomorphism, interactivity, and narrativity in chatbot ads influence consumer attitudes and ad persuasiveness	Message interactivity	Social presence	Pre-defined AI chatbot	Chatbot ad persuasiveness
This study	**Effect of using a generative AI chatbot (the latest chatbot development) on customer engagement (cognitive, affective, and behavioral) with an online retailer**	**Product type (search goods vs. experience goods)** **Choice overload (small vs. large assortment)**	**Perceived control (cognitive vs. behavioral)**	**Generative pre-trained transformer chatbot (ChatGPT/generative AI chatbot)**	**Customer engagement with an online retailer**

Table 2. Cronbach's alpha values of each study

Construct	Items	Cronbach's alpha			
		Study 1	Study 2	Study 3	Study 4
Customer engagement (Hollebeek et al., 2014)	**Cognitive engagement**	α = 0.900	α = 0.990	α = 0.990	α = 0.980
	Visiting the online retailer "Inspiration" got me thinking about it.				
	I thought about the online retailer "Inspiration" a lot when I was visiting it.				
	Visiting the online retailer "Inspiration" stimulated my interest to learn more about it.				
	Affective engagement	α = 0.940	α = 0.990	α = 0.980	α = 0.990
	I felt very positive when I visited the online retailer "Inspiration."				
	Visiting the online retailer "Inspiration" made me happy.				
	I felt good when I visited the online retailer "Inspiration."				
	Behavioral engagement	α = 0.930	α = 0.970	α = 0.970	α = 0.980
	I would spend a lot of time shopping at "Inspiration" compared with others.				
	Whenever I'm shopping for products, I would shop at "Inspiration."				
	"Inspiration" is one of the online retailers I visit when I shop.				
Perceived control (Compeau & Higgins, 1995; McMillan & Hwang, 2002)	**Behavioral control**	Not applicable	α = 0.980	α = 0.980	α = 0.980
	This shopping experience allowed me to save time and effort in choosing the product.				
	Through this shopping experience, I felt that I could conveniently experience any product that I want to try.				
	Cognitive control	Not applicable	α = 0.970	α = 0.970	α = 0.960
	The overall shopping experience was easy to understand.				
	The shopping experience was easy to grasp at a glance.				
	The overall shopping experience was easy to predict.				
Search product (Weathers et al., 2007)	**Search product**	Not applicable	Not applicable	α = 0.807	α = 0.940
	I can adequately evaluate (mention the product) using only the information provided by the retailer or manufacturer about the product's attributes and features				
	I can evaluate the qualities of (mention the product) simply by reading information about the product				
Experience product (Weathers et al., 2007)	**Experience product**	Not applicable	Not applicable	α = 0.771	α = 0.827
	It's important for me to see (mention the product) to evaluate how well it will perform				
	It's important for me to touch (mention the product) to evaluate how well it will perform				
	It's important for me to check (mention the product) directly to evaluate how well it will perform				

Table 3A. Summary of the direct effect results

Direct effect	Coefficient	Standard error (SE)	t-value	p-value
Generative AI chatbots --> Cognitive engagement	1.216	0.249	4.889	< 0.001
Generative AI chatbots --> Affective engagement	1.172	0.245	4.784	< 0.001
Generative AI chatbots --> Behavioral engagement	1.502	0.29	5.178	< 0.001

Table 3B. Summary of the mediation effect results

Mediation analysis (DV: Cognitive engagement)	Coefficient	Standard Error (SE)	p-value	95% CI (LLCI, ULCI)
Total indirect effect	2.775	0.335	-	(1.843, 3.165)
Indirect effect via cognitive control	1.307	0.652	-	(0.041, 2.602)
Indirect effect via behavioral control	1.468	0.64	-	(0.066, 2.583)
Mediation analysis (DV: Affective engagement)				
Total indirect effect	2.917	0.272	-	(2.180, 3.250)
Indirect effect via cognitive control	1.553	0.472	-	(0.521, 2.372)
Indirect effect via behavioral control	1.364	0.425	-	(0.552, 2.215)
Mediation analysis (DV: Behavioral engagement)				
Total indirect effect	3.314	0.209	-	(2.782, 3.638)
Indirect effect via cognitive control	1.209	0.548	-	(0.089, 2.221)
Indirect effect via behavioral control	2.104	0.546	-	(1.055, 3.190)

Table 3C. Summary of the moderation effect of product type (search goods: recipe books vs. experience goods: pants) results

Moderation by product type (search vs. experience goods) for DV: Cognitive engagement	Coefficient	Standard error (SE)	95% Confidence interval (LLCI, ULCI)
Total indirect effect	2.775	0.335	(1.843, 3.165)
Indirect effect via cognitive control (search product)	-2.421	0.420	(-3.266, -1.634)
Indirect effect via cognitive control (experience product)	2.391	0.423	(1.601, 3.244)
Indirect effect via behavioral control (search product)	-1.212	0.421	(-2.012, -0.372)
Indirect effect via behavioral control (experience product)	1.178	0.408	(0.361, 1.952)
Index of moderated mediation (cognitive control)	4.812	0.839	(3.250, 6.497)
Index of moderated mediation (behavioral control)	2.390	0.828	(0.739, 3.962)
Moderation by product type (search vs. experience goods) for DV: Affective engagement			
Total indirect effect	2.775	0.335	(1.843, 3.165)
Indirect effect via cognitive control (search product)	-1.461	0.310	(-2.066, -0.848)
Indirect effect via cognitive control (experience product)	1.443	0.310	(0.835, 2.067)
Indirect effect via behavioral control (search product)	-2.092	0.315	(-2.714, -1.465)
Indirect effect via behavioral control (experience product)	2.032	0.305	(1.436, 2.640)
Index of moderated mediation (cognitive control)	2.904	0.618	(1.685, 4.108)
Index of moderated mediation (behavioral control)	4.124	0.616	(2.894, 5.344)

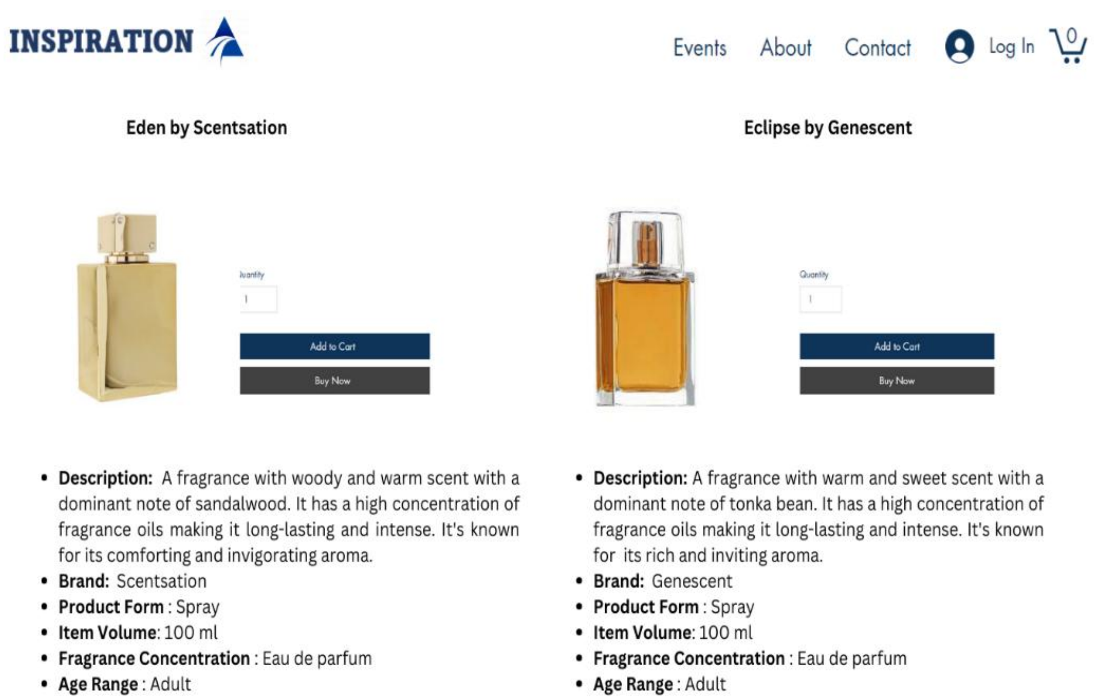
Moderation by product type (search vs. experience goods) for DV: Behavioral engagement			
Total indirect effect	2.775	0.335	(1.843, 3.165)
Indirect effect via cognitive control (search product)	-0.638	0.266	(-1.174, -0.121)
Indirect effect via cognitive control (experience product)	0.630	0.264	(0.118, 1.161)
Indirect effect via behavioral control (search product)	-3.049	0.268	(-3.565, -2.513)
Indirect effect via behavioral control (experience product)	2.963	0.255	(2.445, 3.460)
Index of moderated mediation (cognitive control)	1.269	0.529	(0.240, 2.343)
Index of moderated mediation (behavioral control)	6.012	0.513	(4.964, 7.003)

2.10 Appendix A: Stimuli

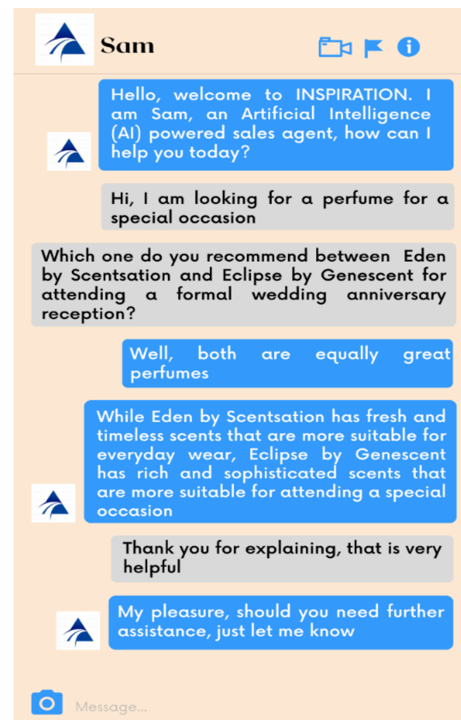
Study 1

For the bot condition, after displaying the retailer's website, the participants were guided through a scenario simulating a conversation with the chatbot. By contrast, for the non-bot condition, only the retailer's website was shown.

Website:



Chatbot conversation:



CHAPTER 3: INVESTIGATING CUSTOMER RESISTANCE TO AUGMENTED REALITY

Investigating customer resistance to augmented reality adoption in online retail

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3.1 Abstract

Augmented reality (AR) has the potential to transform customer engagement in online retail through immersive experiences, with researchers and industry experts highlighting its capacity to bridge the sensory gap in online shopping through real-time product interaction. However, limited customer adoption undermines this potential. To address this contradiction, this study uses a mixed-methods approach to investigate customer resistance to AR adoption. In-depth interviews confirmed and advanced prior research by identifying four new barriers that deepen understanding: concerns about AR encouraging excessive consumption, reduced social interaction, perceived inauthenticity, and customer–technology identification. A subsequent quantitative survey confirmed these findings, highlighting resistance as a key mediator between the barriers identified and AR adoption intentions, with intrusiveness significantly amplifying privacy risk through moderated mediation. This study makes a theoretical contribution by identifying new barriers to AR adoption and presenting a comprehensive framework for understanding resistance mechanisms. It also offers practical strategies to overcome resistance and promote AR adoption in online retail.

Keywords: *Augmented reality (AR)*, *adoption*, *customer resistance*, *barriers*, *immersive experience*, *online shopping*

3.2 Introduction

AR is reshaping online retail by transforming how customers interact with products through immersive experiences. For retailers, AR adoption represents both a technological upgrade and a strategic imperative to remain competitive and to enhance customer satisfaction through immersion, enjoyment, and engagement (Xi et al., 2024). By 2027, around 98% of the world's largest retailers will implement AR (Cubix, 2025). This rapid adoption is driven by the technology's benefits; improved product visualization, reduced return rates, and stronger customer engagement (Reydar, 2025),with the AR market projected to reach $100 billion by 2030 (Hanson, 2024). Nevertheless, only 13% of customers report having used AR (The Interline, 2024; Wurmser, 2022). This highlights the need to address barriers to customers' AR adoption.

Research has examined technology resistance within digital banking (Kuisma et al., 2007; Laukkanen et al., 2007), mobile applications (Joachim et al., 2018), and the Internet of things (IoT) (Mani and Chouk, 2018). To date, however, only one study has considered AR resistance (Uhlendorf and Uhrich, 2024), and this did not consider online retail. While studies have identified adoption barriers including functional barriers, risk, and psychological resistance (Laukkanen, 2016), AR presents distinct challenges due to its immersive and interactive nature. While the literature has emphasized AR shopping adoption drivers, very few studies have discussed the barriers to customer acceptance of AR in e-tailing (Jayaswal & Parida, 2023b). Moreover, the AR literature scantly addresses functional barriers (usage, value, and risk) and has overlooked two crucial psychological barriers: tradition and image barriers (Jayaswal & Parida, 2023b). Thus, this study comprehensively examines AR adoption barriers in online shopping, integrating technological, psychological, and societal factors.

This study augments literature in three key ways. First, it extends innovation-resistance theory (IRT) by identifying new risk, psychological, and individual barriers to AR usage intention during online shopping. While IRT generally frames risk as functional (Mani and Chouk, 2018; Ram and Sheth, 1989), including performance uncertainty and potential technology inefficiencies, earlier models were largely developed using a product-centric lens regarding technology adoption, focusing on whether the innovation worked as intended and how it disrupted established habits. These frameworks are less applicable to AR; beyond being a functional tool, AR is an interactive, immersive, and data-driven technology that raises concerns beyond usability. We find that AR introduces complex risks, as customers question data security, long-term viability, and ethical implications, which actively shape behaviors and social interactions (Riar et al., 2023). These extensions enhance theoretical clarity while offering practical insights for retailers to improve AR transparency, personalization, and ethical considerations to reduce resistance (Kowalczuk et al., 2021; Pantano and Vannucci, 2019).

Second, we identify new risk barriers to AR adoption in online retail, demonstrating that resistance extends beyond usability concerns and warrants reclassification as a distinct category. This challenges prior models' view that resistance is primarily driven by functional and technical limitations, and failure to account for how privacy, security, time, technology obsolescence, and ethical concerns impact customer resistance to AR adoption (Antioco and Kleijnen, 2010; Kleijnen et al., 2009; Mani and Chouk, 2018; Ram and Sheth, 1989). The introduction of ethical risks reveals that customers perceive AR as encouraging impulse-driven consumption and diminishing social interaction, highlighting its potential to disrupt (vs. improve) the shopping experience (Carrington et al., 2021; Wright, 2011). Furthermore, the risk of technology obsolescence raises customer concerns about AR's long-term relevance and compatibility, and customer adoption stability (Acikgoz et al., 2024). Ignoring these risks could provoke customer distrust, regulatory scrutiny, and ethical backlash; thus, retailers and developers must prioritize transparency, data security, and responsible AR implementation to ensure sustainable adoption.

Third, we introduce new barriers and refine existing knowledge regarding psychological and individual barriers (Antioco and Kleijnen, 2010; Mani and Chouk, 2018). The identification of perceived inauthenticity challenges the assumption that AR enhances customer confidence, showing instead that it may create false certainty that erodes trust (Schallehn et al., 2014). The concept of “tradition barriers” is expanded to encompass (a) trust in sales assistance and (b) preference for exploratory shopping. Customers accustomed to in-store guidance may perceive AR as unreliable for decision-making, while others may resist AR because they value human interaction or spontaneously discovering products. These factors highlight the nuanced nature of AR adoption resistance (Lee and Park, 2024; Streicher et al., 2021). Similarly, refining the tradition and image barrier concepts helps correct previous misinterpretations. Image barriers stem not from concerns about the technology itself but from negative perceptions of the retailer (Laukkanen et al., 2008; Laukkanen, 2016; Mani and Chouk, 2017). Lastly, the customer–technology identification barrier underscores that AR is both functional and tied to identity, such that acceptance depends on whether users feel it aligns with their self-perceptions (Pérez, 2009).

Overall, by introducing new barriers, refining existing ones, and expanding the classification of psychological and individual barriers to AR adoption in online retail, we advance theoretical understanding and provide insights for AR strategy design that effectively addresses customer resistance. Moreover, because these barriers arise from AR’s immersive and interactive qualities, the framework can be generalized to other immersive technologies (e.g., virtual reality [VR], mixed reality, the metaverse), thereby extending the relevance of IRT beyond a single technological context (Suh, 2024).

3.3 Literature review

3.3.1 AR in online retailing

AR enhances online retail by offering interactive and immersive product experiences. It integrates physical and virtual interactions, real-time overlays, and precise 3D registration. Unlike VR, which creates a fully digital environment, AR superimposes virtual objects onto the real world. In retail, AR features including virtual try-ons, 3D visualizations, and spatial placement tools help customers make informed purchases (Kowalczuk et al., 2021), thereby reducing uncertainty (Heller et al., 2019; Pérez, 2009; Hsu et al., 2021). Prominent retailers (e.g., Amazon, Alibaba) use AR to enhance product presentation and shopping experiences (Hilken, Chylinski, et al., 2022). AR boosts engagement and personalization, helping brands compete and enhancing conversion rates (Hilken, Heller, et al., 2022; Massa and Ladhari, 2023).

3.3.2 Innovation-resistance theory

IRT is customer resistance that arises when innovations threaten norms, beliefs, or personal comfort. It includes functional and psychological barriers (Ram and Sheth, 1989), which Heidenreich and Kraemer (2015) further classified into active (functional, stemming from innovation characteristics) and passive (psychological, rooted in belief conflicts). Passive resistance also includes image and tradition barriers (Yu and Chantatub, 2016). Appendix A, Table 1, summarizes studies on customer resistance to innovation.

Functional barriers

Functional barriers arise when innovations disrupt established routines, creating incompatibility with existing behaviors (Ram and Sheth, 1989). Since customers favor familiar habits, technologies requiring behavioral change often face adoption hurdles (Kleijnen et al., 2009; Laukkanen et al., 2007; Park and Koh, 2017) surrounding usage, value, and risk (Ram and Sheth, 1989). Usage barriers occur when innovation integrations seem difficult, as seen in Internet banking (Kuisma et al., 2007; Laukkanen et al., 2007), IoT (Mani and Chouk, 2018), and mobile ticketing (Chen et al., 2022).

Ram and Sheth's (1989) usage barrier typology (see Appendix A, Table 1) remains foundational, with many later classifications intersecting it. Complexity and compatibility barriers (Talke and Heidenreich, 2014) reflect cognitive effort and learning burden, resembling usage barriers. Other barriers map onto categories such as value barriers (i.e., insufficient perception of benefits) (Heidenreich and Spieth, 2013), and codependence and trialability barriers, which relate to risk (Heidenreich et al., 2016; Heidenreich and Kraemer, 2016). Visibility, communicability, and amenability (Joachim et al., 2018) further amplify customers' value and risk concerns.

Value barriers arise when innovation benefits seem insufficient compared to alternatives (Chen et al., 2022). They have been noted in online banking (Kuisma et al., 2007; Laukkanen et al., 2008), over-the-top streaming (OTT) service (Agarwal et al., 2023a), and IoT (Mani and Chouk, 2018), where doubts about convenience, security, affordability, or long-term reliability hinder adoption.

Finally, risk barriers entail concerns about potential negative outcomes of using an innovation (Ram and Sheth, 1989). Ram and Sheth classified risk barriers as functional, associated primarily with technological performance issues (see also Heidenreich and Kraemer, 2015; Heidenreich and Spieth, 2013; Iyanna et al., 2022; Kuisma et al., 2007; Laukkanen et al., 2008; Laukkanen et al., 2007; Sham et al., 2023; Uhlendorf and Uhrich, 2024); Heidenreich and Kraemer (2016) extended this by incorporating social perception.

Research has blurred risk classifications; for instance, Talke and Heidenreich (2014) grouped personal, functional, economic, and social risks under psychological barriers, though many extend beyond psychology. Existing typologies thus overlook concerns like privacy, financial uncertainty, ethics, and social consequences. We refine risk barriers as a distinct category, extending beyond functional issues while remaining separate from psychological barriers.

Psychological barriers

Psychological barriers reflect customers' perceptions and attitudes toward new technologies (Ram and Sheth, 1989). They arise from cognitive or affective responses, such as distrust, preference for human assistance, or conflicts with social norms and cultural values (Kleijnen *et al.*, 2009; Ram and Sheth, 1989).

Tradition barriers arise when innovations clash with cultural norms or preferences for personal interaction (e.g., resistance to digital banking due to the absence of staff; Antioco and Kleijnen, 2010; Laukkanen et al., 2007; Ram and Sheth, 1989). Image barriers concern perceptions shaped by brand, industry, or country of origin, where negative associations influence adoption regardless of performance (Aktan and Anjam, 2022; Ram and Sheth, 1989). While often misinterpreted as complexity or usability concerns, image barriers are linked to stereotypes about origin or manufacturer reputation (Laukkanen, 2016; Laukkanen et al., 2007; Ram and Sheth, 1989). Psychological barriers have also been expanded to include technology vulnerability, encompassing technology dependence (Mani and Chouk, 2018; Venkatesh and Davis, 2000).

Classifications often misplace risk-related concerns under psychological barriers (Heidenreich and Kraemer, 2016; Heidenreich and Spieth, 2013; Joachim et al., 2018; Talke and Heidenreich, 2014). Norm barriers largely intersect with tradition (Heidenreich and Spieth, 2013; Talke and Heidenreich, 2014), while social risk and information barriers are better viewed as risk-related (Joachim *et al.*, 2018; Heidenreich and Kraemer, 2016). Economic and functional risks have also been misclassified as psychological despite their financial and reliability foundations (Joachim *et al.*, 2018). These inconsistencies reinforce that psychological barriers should remain defined by psychological factors alone.

Individual barriers

Mani and Chouk (2018) expanded IRT (Ram and Sheth, 1989) by introducing individual barriers regarding IoT adoption; for example, inertia is an individual-specific barrier that reflects resistance to change, driven by satisfaction with existing habits. It is rooted in customers' personal traits, dispositions, or identity-related factors. These factors reflect a technology's fit with one's self-concept or habitual tendencies that remain relatively stable across contexts, influencing resistance independent of situational perceptions. Thus, even when new technologies provide clear benefits, customers favor familiar routines over adoption. This perspective aligns with the status quo bias concept, which describes a preference for current conditions over potentially superior alternatives due to comfort and risk avoidance (Samuelson and Zeckhauser, 1988). Inertia, therefore, reinforces the role of habit in impeding innovation adoption.

3.4 Methodology

Study 1: Preliminary qualitative study to identify AR adoption barriers

In Study 1, semi-structured interviews were conducted with 20 British non-adopters. The qualitative phase identified salient customer barriers; the quantitative phase validated these findings and tested their relationships with resistance and adoption intentions. This sequential design ensured depth and generalizability, yielding a richer account of customer resistance versus using either method alone (Johnson et al., 2007).

Table 1 shows participant details. We define non-adopters as customers who, while aware of AR in online retail, have not used it for shopping. This definition draws on IRT, which emphasizes that resistance emerges after awareness but before adoption (Ram and Sheth, 1989). This framing ensures that the analysis captures meaningful resistance, which is an active decision not to use AR rather than a lack of awareness or ignorance of AR's existence.

The interview transcripts were analyzed using NVivo 14, incorporating thematic analysis (Braun and Clarke, 2006)to systematically identify and interpret patterns across the dataset while capturing participants' perspectives. The data were reviewed several times and coded; AR adoption barriers were grouped by similarity into categories and subcategories, with irrelevant codes discarded. To assess validity, member-checking was conducted, with participants confirming written summaries of emerging categories (Cho and Trent, 2006; Creswell and Miller, 2000) to ensure alignment with their interviews (Bloor, 1978).

The coding process generated 23 codes grouped into 17 subcategories and four categories: functional, risk-related, psychological, and individual barriers (Figure 1). Among risk barriers, five new risks were identified alongside economic and functional risks: privacy, security, time, technology obsolescence, and ethical risks (including excessive consumption and diminishing social interaction). Psychological barriers comprised new ones, such as perceived inauthenticity; and updated barriers including trust in sales assistance and preference for adventurous shopping. We extend Ram and Sheth's (1989) notion of image barriers to capture stereotypes of retailers' inferior product quality, which generate negative spillover effects on perceptions of technologies they employ. Simultaneously, tradition barriers are broadened beyond reliance on salespeople to reflect the appeal of exploration, unpredictability, and novelty inherent in shopping. Concerning individual barriers, we identified customer–technology identification alongside the existing inertia barrier. Appendix A (Table 2) provides representative quotes for each barrier.

Seventeen constructs, selected for Study 2 and defined in Appendix A (Table 2), were identified and validated, expanding the innovation-resistance literature on emerging technologies, including AR. These included usage barriers, value barriers, economic risk, functional risk, privacy risk, security risk, time risk, technological obsolescence risk, excessive consumption, diminishing social interaction, perceived inauthenticity, trust in sales assistance, preference for adventurous shopping, image barriers, technology dependence, inertia, and customer–technology identification.

[Insert Table 1 here]

Hypothesis development

This section presents the theoretical rationale and proposed hypotheses for each of the 17 constructs.

[Insert Figure 1]

Usage barriers and complexity concerns affecting usage intention

Usage barriers arise from AR technology's perceived complexity (Mani and Chouk, 2018; Ram and Sheth, 1989). AR often involves unfamiliar interfaces and functionalities, which are exacerbated when consistent or intuitive experiences are not delivered. For instance, compatibility issues with devices, or technical requirements such as specific lighting conditions, often reinforce customer frustration. While AR promises to simplify decision-making, its perceived complexity frequently contradicts this, causing disengagement before benefits are realized.

Value barriers arise when customers perceive insufficient advantages of AR (Ram and Sheth, 1989) due to the absence of unique features and failure to deliver substantive improvements in autonomy, convenience, or decision-making. An inability to address customer expectations, such as accurate product representation or enhanced control over shopping decisions, renders AR redundant or counterproductive. In online retail, AR is often marketed as an enhancement but fails to provide significant differentiation from standard product images or reviews, exacerbating resistance (da Silva and Cardoso, 2024; Ding and Keh, 2017).

Both barriers are interlinked and reflect broader challenges associated with innovation resistance (Ram, 1987). When AR technologies are perceived as complex and do not demonstrate meaningful value, they fail to encourage adoption and actively deter customers, reinforcing skepticism toward digital innovations in retail. Therefore:

H1: Concerns regarding (a) usage barriers and (b) value barriers (complexity) negatively affect AR usage intention.

Risk-related concerns affecting usage intention

Risk barriers entail customers' concerns about potential negative outcomes associated with an innovation. Such risks are inherent in any innovation due to uncertainty (Ram and Sheth, 1989). Ram and Sheth originally classified risk under functional barriers, focused primarily on the innovation's technological performance (e.g., malfunctions, usability issues) (see also Claudy et al., 2015; Heidenreich and Spieth, 2013; Kuisma et al., 2007; Laukkanen et al., 2008; Laukkanen et al., 2007; Sham et al., 2023; Uhlendorf and Uhrich, 2024). However, risk barriers have generally remained narrowly associated with technological or performance-based concerns. In this study, we consider economic, functional, privacy, security, time, technological obsolescence, and ethical concerns, which collectively discourage customer adoption. Economic risks stem from fears of high costs, hidden expenses such as data usage, and subscription fees, which increase hesitancy regarding AR use (Kleijnen et al., 2009; Lee, 2009). Functional risks involve concerns about AR reliability, such as inaccurate product representations (Park and Kang, 2022).

Privacy risks arise from the collection of sensitive (e.g., biometric or behavioral) data during AR use, fostering fears, arising from limited transparency, of misuse (Quach et al., 2022). Relatedly, security risks focus on safeguarding data, with vulnerabilities such as weak encryption undermining customer confidence (Belanger et al., 2002). Time risks reflect the effort required to learn and integrate AR into shopping routines, discouraging users in fast-paced online environments from prioritizing convenience (Featherman and Pavlou, 2003). The risk of technological obsolescence encompasses anxieties about rapid advancements rendering AR outdated, making initial investments in learning and usage seem futile (Mellal, 2020). Ethical risks highlight societal concerns, such as AR's role in promoting impulsive consumption and eroding social interactions, raising questions about long-term societal impact (Håkansson, 2014; Wright, 2011). Collectively, when AR is seen as costly, unreliable, privacy-invasive, insecure, time-consuming, prone to obsolescence, and ethically problematic, adoption can be hindered. Thus:

H2: Concerns surrounding (a) economic, (b) functional, (c) privacy, (d) security, (e) time, (f) technological obsolescence, (g) and ethical (comprising excessive consumption and diminishing social interaction) risks negatively affect AR usage intention.

Psychological and behavioral resistance affecting usage intention

Psychological barriers comprise resistance stemming from customers' perceptions that an innovation misaligns with their beliefs, values, or social norms (Kleijnen et al., 2009; Ram and Sheth, 1989). Commonly studied dimensions include tradition barriers, reflecting discomfort regarding deviation from familiar habits (Antioco and Kleijnen, 2010); and image barriers, which relate to unfavorable associations with the innovation's origin, brand, or category (Ram and Sheth, 1989). Research has expanded the concept to include technology-related unease (e.g., anxiety, fear of overdependence; Mani and Chouk, 2018). These barriers concern not the functionality of the technology itself but rather how it fits users' identity, values, or sense of autonomy.

Thus, we highlight the significant negative effects of psychological and behavioral resistance on AR technology adoption in retail, driven by factors including perceived inauthenticity of virtual experiences, technology dependence, and revived forms of tradition and image barriers. These findings reflect deeper customer tensions related to realism, control, and comfort, often shaped by individual preferences, cultural norms, and prior shopping habits. By uncovering how AR can evoke both curiosity and discomfort or skepticism, we broaden understanding of psychological barriers in the context of immersive, data-driven innovations.

Perceived inauthenticity barriers stem from customer beliefs that AR exaggerates product appearance to influence purchasing decisions (Molleda, 2010; Schallehn et al., 2014). This casts AR as manipulative rather than beneficial, fostering skepticism and dissatisfaction and deterring adoption, particularly in retail contexts where authenticity and reliability are paramount (Pérez, 2009).

Image barriers amplify resistance by linking negative perceptions of AR to stereotypes and unfavorable associations with retailer quality. Customers often project mistrust of a retailer's products onto their technological offerings, viewing their AR as unreliable or gimmicky (Ram and Sheth, 1989). This exacerbates reluctance regarding AR engagement. Previous negative experiences, such as inconsistent AR functionality or subpar products purchased via AR platforms, further entrench these biases.

Tradition barriers highlight customer reliance on established shopping practices, such as personalized advice from salespeople and in-store exploration, which AR is unable to replicate (Antioco and Kleijnen, 2010; Joachim et al., 2018; Sirdeshmukh et al., 2002). Additionally, the unpredictability and sensory appeal of physical shopping, including the thrill of product discovery and tactile evaluation, remain key drivers of customer preference (Horváth and Adıgüzel, 2018). Such barriers reinforce the appeal of traditional shopping and heighten skepticism about digital alternatives.

Concerns about technology dependence further compound resistance, as customers fear losing autonomy and critical thinking due to a reliance on AR. The shift from traditional to technology-centric shopping can diminish human connection and experiential richness, fostering apprehension about the long-term cultural and behavioral implications of AR adoption. For instance, reliance on AR may erode interpersonal interactions, such as consulting salespeople or shopping with friends, which are integral to the traditional retail experience (Mani and Chouk, 2018).

Together, these barriers underscore the complexity of psychological and behavioral resistance to AR technologies. They highlight customer skepticism about AR's authenticity, distrust toward certain retailers, attachment to sensory and cultural traditions, and fears of overdependence on technology. This resistance underscores the enduring appeal of traditional shopping practices and poses challenges to widespread AR adoption in retail. Thus:

H3: Concerns surrounding psychological and behavioral barriers i.e., (a) perceived AR inauthenticity, (b) image, (c) tradition (comprising preference for adventurous shopping and trust in sales assistance), and (d) technology dependence negatively affect AR usage intention.

Individual-specific barriers affecting usage intention

AR adoption in retail faces significant challenges from individual-specific barriers, particularly inertia and customer–technology identification. These barriers originate from enduring personal dispositions and identity-related factors, which can outweigh perceived benefits of new technologies (Kleijnen et al., 2009; Ram and Sheth, 1989). Inertia reflects resistance to change due to satisfaction with existing shopping routines, meaning customers see no compelling need to adopt AR (Mani and Chouk, 2018). Adopting AR requires breaking established routines and investing cognitive effort into learning new systems, which many view as unnecessary.

Customer–technology identification extends Pérez's (2009) concept of customer–company identification to the individual–technology relationship. Resistance occurs when customers perceive AR as misaligned with their values or self-image. For instance, those who prioritize simplicity or traditional shopping methods may feel that AR conflicts with their identity, fostering negative adoption attitudes (Schallehn et al., 2014). These barriers highlight the complex interplay between customer habits, self-concept, and identity in shaping AR resistance (El-Shamandi Ahmed et al., 2023), and addressing them requires strategies that, beyond promoting technological features, tackle underlying psychological and identity-based concerns. Therefore:

H4: Individual-specific barriers i.e., (a) inertia and (b) customer–technology identification negatively affect AR usage intention.

The mediating role of resistance in the barriers–usage intention relationship

The barriers detailed above undermine AR adoption in retail, and collectively act as antecedents to customer resistance, which mediates their negative impact on AR adoption intentions (Ram and Sheth, 1989). Resistance consolidates these barriers into a unified psychological mechanism that significantly reduces adoption likelihood.

Usage and complexity concerns (e.g., perceived difficulty using AR, unclear benefits) discourage customers from engaging with the technology (Mani and Chouk, 2018). When AR fails to deliver meaningful improvements, it is seen as unnecessary, amplifying resistance (Smink et al., 2020).

Concerns including economic, functional, privacy, security, time, technological obsolescence, and ethical risks also deter AR adoption. These risks highlight uncertainties about costs, reliability, data privacy, and long-term viability, reducing customer confidence in AR (Belanger et al., 2002; Milne and Culnan, 2004). Ethical risks, including concerns about excessive consumption and reduced social interaction, add societal dimensions to resistance, making AR adoption less appealing (Håkansson, 2014).

Psychological and behavioral resistance manifest as nuanced customer hesitations, including perceived inauthenticity, where AR is seen as exaggerating product features and undermining trust (Schallehn et al., 2014). Tradition barriers (e.g., preferences for tactile experiences and exploratory shopping) highlight gaps in AR's capacity. Image barriers regarding stereotypes about retailer quality and concerns about overreliance on AR deepen resistance by eroding trust and autonomy.

Regarding individual-specific barriers, inertia reflects satisfaction with existing shopping routines, discouraging change even when AR offers potential benefits (Mani and Chouk, 2018), while customer–technology identification emphasizes misalignment between AR technology and customers' self-identity. When AR is perceived as overly modern or inconsistent with personal values, adoption is less likely (Pérez, 2009).

Resistance acts as a central mediator, transforming these barriers into behavioral outcomes by reducing AR adoption intention. Without directly addressing resistance, efforts to mitigate individual barriers are unlikely to succeed, as resistance is the key determinant of adoption decisions (Claudy et al., 2015; Kleijnen et al., 2009). Collectively, these findings highlight the need for a holistic approach to overcoming barriers, emphasizing the interplay between customer concerns and resistance in shaping AR adoption. Thus:

H5: Resistance mediates the relationship between usage and complexity concerns, risk-related concerns, psychological and behavioral resistance, and individual-specific barriers to AR usage intention.

Intrusiveness as a moderator of the mediating role of resistance in privacy risk and usage intention

Privacy risk significantly affects AR adoption, particularly in contexts involving the collection of sensitive data, leading to resistance and reduced adoption intentions (Feng and Xie, 2019; Verhoef et al., 2015). Resistance mediates this relationship by translating privacy apprehensions into avoidance behaviors (Lapointe and Rivard, 2005), with intrusiveness moderating this dynamic. Highly intrusive AR applications, such as virtual try-ons requiring facial scans, amplify privacy concerns due to the sensitive nature of biometric data, escalating resistance and its negative effect on adoption intention (Hilken et al., 2017; Poushneh, 2018). Conversely, less intrusive applications, such as spatial AR for furniture placement, elicit less resistance, as they collect data on physical spaces rather than personal identity (Smink et al., 2020).

The degree of intrusiveness determines the strength of the mediating role of resistance. High intrusiveness intensifies the negative indirect effect of privacy risk on AR usage intention, while low intrusiveness mitigates resistance, increasing adoption likelihood. This distinction underscores the critical role of intrusiveness in moderating how privacy risk impacts customer behavior, and highlights its importance in designing AR technologies that balance data use with user comfort

(Salim et al., 2022; Shin et al., 2019). Thus:

H6: Intrusiveness moderates the mediating role of resistance in the privacy risk–usage intention relationship, such that the indirect effect of privacy risk on usage intention through resistance is amplified under high intrusiveness.

Study 2 – Quantitative method – Survey

Using a mixed-methods approach, we explore AR adoption barriers in online shopping through interviews (Study 1) and validate them in an empirical framework (Study 2). The mixed-methods approach enhances understanding by integrating explanatory insights with confirmatory evidence (Venkatesh et al., 2016).

Study 2: design and participants

This survey-based study targeted 967 British non-adopters of AR for online shopping. Seventeen constructs, identified in Study 1, were measured as independent variables using established scales. For the first category, usage and complexity barriers, usage barriers were assessed using Mani and Chouk's (2018) three-item scale; the value barrier was measured with a four-item scale adapted from Grewal et al. (1998).

For the second category, risk-related concerns, economic risk was assessed with a four-item scale by Burnham et al. (2003), while functional risk was measured using a three-item scale by Saab and Botelho (2020). Privacy and security risks were evaluated with four-item scales based on Cheng et al. (2014). Time risk was measured with a four-item scale from Pavlou (2003), and technological obsolescence risk with a four-item scale by Acikgoz et al. (2024). Ethical risk was captured through excessive consumption, measured with a four-item scale from Maccarrone-

Eaglen and Schofield (2023), and diminishing social interaction used a three-item scale from Smith et al. (2018)

For the third category, psychological and behavioral resistance, AR inauthenticity was assessed with a three-item scale by Newell et al. (1998), and image barriers with a three-item scale from Laukkanen (2016). Tradition barriers were measured through trust in sales assistance, evaluated using a four-item scale from Sirdeshmukh et al. (2002); preference for adventurous shopping was measured with Horváth and Adıgüzel's (2018) three-item scale. Technology dependence was assessed using a three-item scale by Mani and Chouk (2018).

For the fourth category, psychological and behavioral barriers, inertia was measured with a four-item scale by Mani and Chouk (1989), and customer–technology identification used a four-item scale by Pérez (2009).

Resistance was measured as a mediator using Mani and Chouk's (1989) six-item scale, while AR usage intention was assessed as the dependent variable with a four-item scale adapted from Hoehle et al. (2015). Intrusiveness was introduced as a moderator and operationalized through high intrusiveness (facial AR for sunglasses) and low intrusiveness (spatial AR for an armchair). To assess the intrusiveness manipulation, a five-item scale from Smink et al. (2020) was employed. The manipulation was successful, with significant differences between conditions (MSunglasses = 5.00 MChair = 2.50, $p < .001$), indicating that participants perceived the anticipated levels of intrusiveness.

3.5 Data analysis and results

Construct reliability and validity

Study 2 tested each scale's normal distribution. Appendix A (Table 3) reports the means, standard deviations, skewness, and kurtosis of all measures. Skewness and kurtosis values were all acceptable (Tabachnick et al., 2013). The collinearity statistics (variance inflation factor); values ranged from 1.0–3.03, evidencing no collinearity. We then ran a PLS algorithm for factor analysis using SmartPLS 4 (Ringle et al., 2024). Appendix A (Table 4) displays results of the construct reliability and validity testing. All outer loadings, ranging from 0.768–0.994, were above 0.70. All Cronbach's alphas, ranging from 0.853–0.980, were above 0.70, indicating consistency and reliability (see Appendix A, Table 4, for a summary of results).

The average variance extracted scores ranged from 0.753–0.968, suggesting strong internal convergent validity for all constructs. We also assessed discriminant validity using the heterotrait–monotrait (HTMT) ratio. All HTMT values (Appendix A, Table 5) were below 0.9, establishing discriminant validity for all constructs (Henseler et al., 2015). Finally, we assessed common method bias using Harman's single-factor test (Henseler et al., 2015). Results showed that the first factor accounted for 35.9% of the total variance explained (<50% of model variables); thus, the data did not present common method bias.

Model and hypothesis testing

We tested the measurement model with SmartPLS4 (Ringle et al, 2024), using structural equation modeling and bootstrapping tests (5,000 samples). To test H1–H6, we developed a structural model linking the 17 barriers to resistance as a mediator and resistance to usage intention. Intrusiveness (1 = high for facial AR with sunglasses, 0 = low for spatial AR with an armchair) was included as a moderator between privacy risk (one of the barriers) and resistance, and its direct effects on resistance and usage intention. The standardized root mean square residual equaled .060, with R-squared values of .421 for resistance and .863 for usage intention (see Appendix A, Table 3, for descriptive statistics results).

Results showed negative effects on AR usage intention for usage barriers (β = -.024, p = .005), technology dependence (β = -.029, p = .006), value barriers (β = -.059, p = .000), economic risk (β = -.022, p = .035), functional risk (β= -.026, p = .024), privacy risk (β = -.095, p = .000), security risk (β = -.032, p = .014), time risk (β = -.032, p = .017), technological obsolescence (β = -.034, p = .012), excessive consumption (β = -.057, p = .000), diminished social interaction (β = -.033, p = .018), perceived inauthenticity (β = -.149, p = .000), image barriers (β = -.039, p = .001), adventurous shopping (β = -.091, p = .000), trust in sales assistance (β = -.07, p = .000), inertia (β = -.062, p = .000), and customer–technology identification (β = -.042, p = .000). Thus, H1–H4 were supported.

Mediation analysis showed that the barriers positively affected resistance and resistance negatively affected usage intention; indirect effects were significant for usage barriers (β = -.024, p = .005), technology dependence barriers (β = -.029, p = .006), value (β = -.059, p = .000), economic risk (β = -.022, p = .035), functional risk (β = -.026, p = .024), privacy risk (β = -.095, p = .000), security risk (β = -.032, p = .000), time risk (β = -.032, p = .017), technological obsolescence (β = -.034, p = .012), excessive consumption (β = -.057, p = .001), diminished social interaction (β = -.033, p = .018), perceived inauthenticity (β = -.149, p = .000), image barriers (β = -.039, p = .001), adventurous shopping (β = -.091, p = .001), trust in sales assistance (β = -.070, p = .000), inertia (β = -.062, p = .000), and customer–technology identification (β = -.042, p = .000), supporting H5.

For moderated-mediation analysis, privacy risk positively influenced resistance and indirectly reduced AR adoption intention through resistance. Intrusiveness moderated these relationships, with high intrusiveness significantly intensifying resistance (β = .410, p = .000) and amplifying the negative indirect effect on AR adoption intention (β = -.264, p = .000). The indirect effect was stronger under high intrusiveness, supporting H6. Table 2 summarizes the hypothesis testing results. Finally, we tested covariates; age (p = .908), education (p = .150), and gender (p = .100) were all non-significant predictors of usage intention (all p > .05), indicating that these demographic variables had no measurable effect in the model.

[Insert Table 2 here]

3.6 Discussion

Our mixed-methods research extends IRT by providing a comprehensive framework of AR adoption barriers in online retail. Study 1 identified four categories and 17 subcategories: (1) usage and complexity concerns, including usage and value barriers; (2) risk-related concerns, covering economic, functional, privacy, security, time, obsolescence, and ethical risks (e.g., overconsumption, reduced social interaction); (3) psychological and behavioral resistance, including perceived inauthenticity, image, and tradition barriers (e.g., reliance on salespeople, preference for adventurous shopping); and (4) individual-specific barriers, namely inertia and customer–technology identification. Study 2 quantified their significance and interrelations.

Study 2 revealed that usage and complexity concerns, risk-related concerns, psychological resistance, and individual-specific barriers negatively affected customers' intention to adopt AR in online retail. Usage and complexity concerns (e.g., usage and value barriers) deterred adoption, as customers perceived AR to be overly complex, requiring significant navigational effort. Furthermore, many were unclear on AR benefits, making the technology appear unnecessary (Claudy et al., 2015; Mani and Chouk, 2018; Ram and Sheth, 1989).

Risk-related concerns (economic, functional, privacy, security, time, obsolescence, and ethical risks) reduced AR adoption. Hidden costs discouraged customers, inaccurate product displays undermined trust, and privacy and security concerns (e.g., biometric data) heightened perceptions of intrusiveness (Hoffman and Novak, 2018; Rauschnabel et al., 2018). Time risks and fears of rapid obsolescence further weakened adoption, while ethical concerns (e.g., overconsumption, reduced social interaction) added societal resistance (Håkansson, 2014; Wright, 2011). Overcoming these barriers requires strong privacy protections, transparent communication, reliable functionality, and simplified interfaces (Berman and Pollack, 2021).

Psychological resistance also reduced AR adoption. Perceived inauthenticity arose when AR exaggerated product features, creating distrust (El-Shamandi Ahmed et al., 2023; C. Zhu et al., 2023). Image barriers reflected stereotypes about retailers (Ram and Sheth, 1989), while tradition barriers highlighted preferences for tactile shopping and human interaction (Horváth and Adıgüzel, 2018; Mani and Chouk, 2018). Fears of technology dependence heightened resistance. Individual barriers (e.g., inertia, reluctance to abandon familiar habits, customer–technology identification), where AR conflicted with values of simplicity or authenticity, also discouraged adoption (Mani and Chouk, 2018; Pérez, 2009).

Resistance mediated the link barriers–AR adoption link, translating concerns into reduced intentions. Intrusiveness further moderated this effect, intensifying the impact of privacy risks when high, as in facial AR try-ons using biometric scans (Mani and Chouk, 2018; Smink et al., 2020). Mitigating these factors requires transparent communication, customizable privacy settings, and opt-in mechanisms.

3.7 Theoretical contributions

First, this study extends IRT (Mani and Chouk, 2018; Ram and Sheth, 1989) to AR adoption in online retail, a rapidly growing innovation (Jayaswal and Parida, 2023a, 2023b), unlike prior IRT applications to established technologies such as mobile banking (Kuisma et al., 2007; Laukkanen, 2016; Laukkanen et al., 2007) and IoT devices (Mani and Chouk, 2018). AR in online retail introduces distinct challenges; its immersive nature, real-time engagement, and reliance on personal data raise concerns beyond conventional adoption barriers (Kowalczuk et al., 2021). We identified new risks and psychological and individual barriers to AR usage intention for online shopping. These categories uncover new drivers of resistance, enhancing understanding of why customers hesitate to adopt AR in online retail environments, and expanding existing resistance frameworks to reflect the complexities of immersive technologies in contemporary retail settings (Pfaff and Spann, 2023).

Second, we reclassified risk barriers as a distinct category, extending prior studies' view that resistance is primarily driven by functional and technical limitations, and failure to account for how AR-specific risks (e.g., privacy, security, time, technology obsolescence, ethical risks) impact customer resistance to AR adoption (Antioco and Kleijnen, 2010; Kleijnen et al., 2009; Mani and Chouk, 2018; Ram and Sheth, 1989). Ethical risk is especially important, as customers see AR as promoting impulsive buying and reducing social interaction, potentially undermining the shopping experience (Wurmser and Adrian, 2022; Wright, 2011). Moreover, technology obsolescence risk reflects concerns about AR's longevity (Acikgoz et al., 2024). Distinguishing these risk barriers clarifies their specific role in resistance, enhancing theoretical precision (Alexander and Kent, 2022; Lapointe and Rivard, 2005). We also show that AR's immersive nature may conflict with values including sustainability and social connection, extending IRT to emerging barriers relevant to today's retail technologies (Mainardes et al., 2023).

Third, we augment AR adoption literature by introducing three new psychological barriers and refining existing ones. Perceived inauthenticity shows that exaggerated AR representations can undermine trust (Wang et al., 2024), challenging the assumption that AR naturally fosters customer confidence (Erdmann et al., 2023; Trivedi et al., 2022), as overly enhanced displays may mislead customers and undermine trust (Michel et al., 2022; Pérez, 2009). We also expand traditional barriers underscoring AR limitations in replicating in-store experiences (Ram and Sheth, 1989), revealing that customers who rely on guidance from salespeople may perceive AR as less trustworthy for decision-making, while others may resist AR because they value the spontaneity and discovery of browsing physical stores. These often-overlooked factors highlight the nuanced nature of AR adoption resistance (Lee and Park, 2024; Streicher et al., 2021). We also redefine image barriers by correcting their misclassification as a usability issue (Laukkanen et al., 2008; Laukkanen, 2016; Mani and Chouk, 2017). We show that image barriers stem from spillover from low-quality brand perceptions to AR offerings. This aligns with Ram and Sheth's (1989) view that resistance is shaped by broader stereotypes, rather than just technological attributes. Lastly, customer–technology identification as a new individual barrier emphasizes that adoption depends on alignment with users' self-perceptions. Without this, AR risks being seen as an inauthentic addition, rather than a meaningful enhancement, to the shopping experience (Pérez, 2009).

To conclude, this study contributes to innovation-resistance literature by demonstrating how barriers identified within AR can be generalized to immersive technologies more broadly. Systems such as AR, VR, and mixed reality share core characteristics, including the simulation of reality, spatial interaction, and the integration of digital content into physical environments (Suh, 2024).

These features elicit resistance mechanisms that surpass functional or economic concerns, triggering authenticity, social interaction, ethical boundaries, and identity alignment questions (Heidenreich and Handrich, 2015; Hilken, Chylinski, et al., 2022). By linking customer resistance to underlying experiential qualities of immersion, we provide a framework that moves beyond single-technology explanations toward a theory of resistance that applies across immersive contexts.

3.8 Managerial implications

Study 1 and Study 2 findings underscore the importance of addressing barriers to customers' intention to adopt AR. First, usage- and complexity-related usability concerns (e.g., compatibility issues, reliance on high-speed Internet, effort required to navigate AR) deter users and underline the need for intuitive, reliable designs that simplify usage and reduce frustration (Chekembayeva et al., 2023; Riegger et al., 2021). Customers also question the added value of AR when photos, videos, or reviews seem sufficient, making it essential for retailers to clearly showcase AR's benefits (Kazmi et al., 2021; Pachoulakis and Kapetanakis, 2012). Practical incentives, such as discounts or loyalty rewards for using AR, can motivate initial engagement while reinforcing utility (Duzgun and Yamamoto, 2016).

Second, mitigating risk-related concerns is vital for AR adoption in retail. Transparent communication and improved functionality help address economic, privacy, and security risks. Clear pricing and freemium try-ons reduce fears of hidden costs, while robust data protection, opt-in privacy controls, and third-party certifications reassure customers about data security (Feng and Xie, 2019; Inman and Nikolova, 2017). To address functional concerns (e.g., unrealistic product representations), retailers should leverage advanced rendering technologies to deliver lifelike simulations that accurately reflect product details (Xu et al., 2025). Simplifying AR interfaces and offering tutorials can reduce time-related barriers. Regular updates and backward compatibility can alleviate fears of technological obsolescence, framing AR as a sustainable, long-term solution.

Third, to address psychological and behavioral resistance, retailers should focus on mitigating perceived inauthenticity, traditional shopping preferences, image concerns, and technology dependence. Perceived inauthenticity, where AR is viewed as exaggerating product displays, can be addressed by emphasizing AR as a realistic preview tool, including disclaimers, side-by-side comparisons with real product photos, and customer testimonials to manage expectations and build trust (Beerends and Aydin, 2021). For customers favoring traditional shopping, collaborative AR features that enable shopping with others, and virtual consultations with experts, can replicate social and personalized in-store experience aspects (Dah et al., 2024; Wang et al., 2023). To address image barriers stemming from perceptions of low retailer product quality that extend to their AR technology, partnerships with reputable brands, trusted endorsements, and positive customer feedback on AR accuracy can enhance the technology's credibility (Jayawardena et al., 2023). Lastly, positioning AR as a supportive tool that aids decision-making while preserving customer autonomy can alleviate technology dependence concerns (Wang et al., 2023).

To address individual-specific barriers (e.g., inertia, customer–technology identification), retailers should align AR with customers' habits and values. Inertia can be tackled by showcasing AR as an enhancement to familiar routines that saves time and reduces uncertainty. Marketing should emphasize AR as seamless integration rather than disruptive change (Mani and Chouk, 2018). Importantly, customer–technology identification reflects discomfort when AR conflicts with personal identity; customers valuing simplicity or authenticity may see it as irrelevant. Retailers should position AR as practical and user-friendly, emphasizing simplicity and everyday relevance over futuristic appeal (Ambika et al., 2023; Pérez, 2009).

Overall, this study extends understanding of AR in online retail. The identified barriers are relevant to AR and to other technologies, such as VR, mixed reality, and the metaverse, that share features including immersion, interactivity, and simulation of physical environments (Javornik, 2016; Rauschnabel et al., 2024). Thus, these findings are not AR-specific but serve as a framework to anticipate resistance across a wider range of immersive solutions. This means that lessons learned from AR (e.g., the need to address authenticity concerns, manage social interaction, and align technology use with customer identity) can inform strategies for introducing other immersive technologies in retail and beyond (Hinsch et al., 2020). By recognizing this transferability, managers can better prepare for adoption challenges in emerging digital environments and design interventions that both lower and address the unique implications of immersive experiences.

3.9 Limitations and further research

This study is subject to several limitations. First, data were collected at a single time point, restricting our ability to capture how customer resistance to AR evolves. Thus, we provide only a snapshot of resistance. Longitudinal research could explicate how attitudes shift according to technological advancements, increased familiarity with AR, or broader societal changes (Hartzel et al., 2016). Second, our exclusive focus on British non-adopters constrains the findings' cultural generalizability.

Future studies should adopt a cross-cultural perspective to examine how resistance varies across demographics and regions, since cultural context can significantly shape customer responses to new technologies (Magliocca et al., 2024). Finally, while we shed light on barriers from the perspective of non-adopters, views of adopters are not considered. Including adopters' experiences would provide a more balanced understanding of AR adoption dynamics by highlighting both enabling factors and resistance mechanisms. Together, these research extensions would provide a more nuanced and comprehensive understanding of customer barriers to AR adoption.

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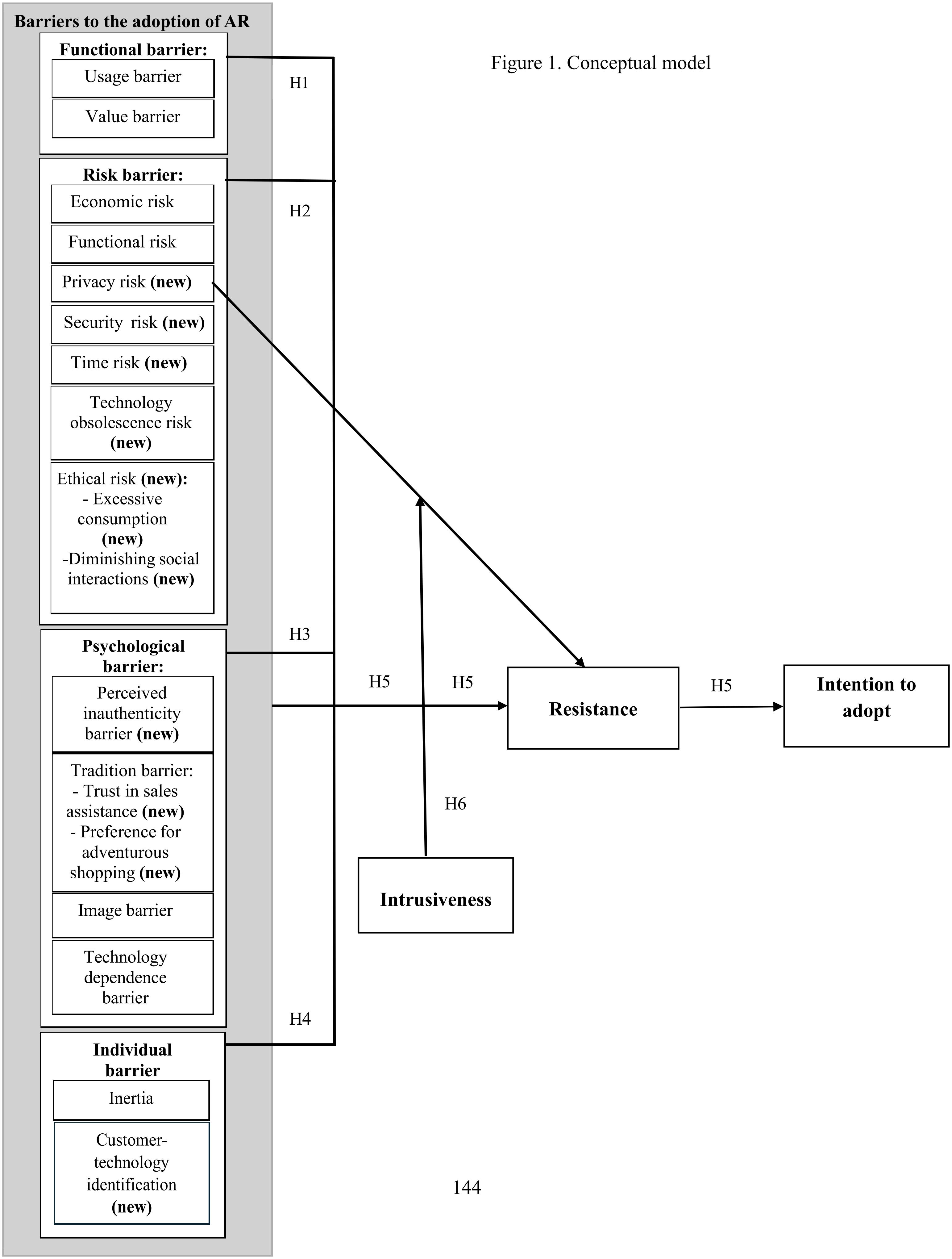

Figure 1. Conceptual model

Table 1: Study 1 sample characteristics

Non-adopter	Age	Gender	Highest level of education	Occupation
P1	42	Male	Master's degree	Product manager
P2	21	Male	Bachelor student	Student
P3	53	Male	Bachelor's degree	IT engineer
P4	39	Female	Master's degree	Radiology technologist
P5	31	Female	Bachelor's degree	Librarian
P6	33	Male	Bachelor's degree	UX designer
P7	51	Male	Bachelor's degree	Marketing professional service
P8	43	Female	Bachelor's degree	Therapist
P9	62	Male	Bachelor's degree	Nuclear health physicist
P10	53	Female	Professional degree	Management accountant
P11	36	Female	Bachelor's degree	School teacher
P12	36	Male	Bachelor's degree	Financial advisor
P13	52	Male	Master's degree	Technical project manager
P14	31	Female	Doctoral degree	Senior scientist
P15	32	Male	Bachelor's degree	Administrative assistant
P16	49	Female	Bachelor's degree	Proofreader
P17	35	Female	Bachelor's degree	Yoga teacher
P18	38	Male	Bachelor's degree	Support worker
P19	32	Male	Master's degree	Medical doctor
P20	33	Female	Vocational degree	Compliance manager

Table 2: Hypothesis testing using SmartPLS

Hypothesis/Relationship	Coefficient	t-Value	p-Value
Direct effect of each barrier on AR usage intention (without considering the mediator and moderator)			
Usage barrier (UB) → AR usage intention (INTENT)	-.024	2.791	.005
Value barrier (VB) → INTENT	-.059	4.363	.000
Economic risk (ER) → INTENT	-.022	2.104	.035
Functional risk (FR) → INTENT	-.026	2.263	.024
Privacy risk (PR) → INTENT	-.095	7.659	.000
Security risk (SR) → INTENT	-.032	2.457	.014
Time risk (TR) → INTENT	-.032	2.390	.017
Technological obsolescence risk (TOR) → INTENT	-.034	2.507	.012
Excessive consumption (EC) → INTENT	-.057	5.167	.000
Diminishing social interaction (DSI) → INTENT	-.033	5.167	.000
Perceived AR inauthenticity barrier (PIB) → INTENT	-.149	6.752	.000
Image barrier (IB) → INTENT	-.039	3.387	.001
Preference for adventurous shopping (PADV) → INTENT	-.091	4.950	.000
Trust in sales assistance (TSA) → INTENT	-.070	5.297	.000
Technology dependence barrier (TD) → INTENT	-.029	2.754	.006
Inertia (INERT) → INTENT	-.062	4.313	.000
Customer-technology identification (CTI) → INTENT	-.042	3.687	.000
Direct effect of each barrier on AR usage intention (considering the whole model)			
Usage barrier (UB) → AR usage intention (INTENT)	–.015	–1.211	.226

Value barrier (VB) → INTENT	–.020	–1.352	.178
Economic risk (ER) → INTENT	–.015	–1.101	.271
Functional risk (FR) → INTENT	–.018	–1.251	.211
Privacy risk (PR) → INTENT	–.030	–1.662	.098
Security risk (SR) → INTENT	–.015	–1.182	.238
Time risk (TR) → INTENT	–.010	–0.882	.380
Technological obsolescence risk (TOR) → INTENT	–.012	–0.941	.347
Excessive consumption (EC) → INTENT	–.020	–1.403	.162
Diminishing social interaction (DSI) → INTENT	–.008	–0.611	.542
Perceived AR inauthenticity barrier (PIB) → INTENT	–.020	–0.962	.338
Image barrier (IB) → INTENT	–.010	–0.691	.491
Preference for adventurous shopping (PADV) → INTENT	–.030	–1.701	.090
Trust in sales assistance (TSA) → INTENT	–.025	–1.502	.135
Technology dependence barrier (TD) → INTENT	–.012	–0.894	.374
Inertia (INERT) → INTENT	–.018	–1.283	.202
Customer-technology identification (CTI) → INTENT	–.010	–1.526	.413
Mediating effect of resistance			
UB → Resistance (RESIST) → INTENT	-.024	2.791	.005
VB → RESIST → INTENT	-.059	4.363	.000
ER → RESIST → INTENT	-.022	5.167	.000
FR → RESIST→ INTENT	-.026	2.263	.024
PR → RESIST → INTENT	-.095	7.659	.000
SR → RESIST → INTENT	-.032	2.457	.014
TR → RESIST → INTENT	-.032	2.390	.017
TOR → RESIST → INTENT	-.034	2.507	.012
EC → RESIST→ INTENT	-.057	5.167	.000
DSI → RESIST → INTENT	-.033	2.357	.018
PIB → RESIST → INTENT	-.149	6.752	.000
IB → RESIST → INTENT	-.039	3.387	.001
PADV → RESIST → INTENT	-.091	4.950	.000
TSA → RESIST → INTENT	-.070	5.297	.000
TD → RESIST → INTENT	-.029	2.754	.006
INERT → RESIST → INTENT	-.062	4.313	.000
CTI → RESIST → INTENT	-.042	3.687	.000
Moderated mediating effect of intrusiveness			
PR x Intrusiveness → RESIST → INTENT	-.264	10.598	.000

3.11 Appendix A

Table 1. Comparison of findings from the existing literature on innovation resistance

Author(s)	**Technology type**	**Functional barriers**	**Risk barriers**	**Psychological barriers**	**Individual barriers**	**Methods**
Ram and Sheth (1989)	General	**Usage barrier**: Complexity and difficulties associated with using new technology **Value barrier:** when Consumers believe the new technology does not offer sufficient value	**Risk barrier:** Uncertainties and potential negative outcomes, such as financial loss or privacy issues	**Tradition barrier:** Reluctance to adopt new technology due to a preference for established methods **Image barrier:** Innovations acquire a certain identity from their origin, the country they are manufactured.		Conceptual
Laukkanen et al. (2007)	Mobile banking	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Survey
Kuisma et al. (2007)	Internet banking	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Interview & survey
Laukkanen et al. (2008)	Internet banking	Usage barrier Value barrier Risk barrier		Tradition barrier Image barrier		Survey
Heidenreich and Spieth (2013)	Notebook, camera, laser projector	Usage barrier Value barrier Complexity barrier Observability barrier Trialability barrier	Risk barrier			Survey
Talke and Heidenreich (2014)	General	Value barrier Complexity barrier Trialability barrier Compatibility barrier Co-dependence barrier Visibility barrier Communicability barrier Amenability barrier Realization barrier	Social risk barrier	Norm barrier Image barrier Usage barrier Information barrier Personal risk barrier Functional risk barrier Economic risk barrier		Conceptual
Claudy et al. (2015)	Micro wind turbines and car sharing	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Survey
Laukkanen (2016)	Internet and mobile banking	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Survey
Heidenreich et al. (2016)	Mobile phone	Value barrier Complexity barrier Usage barrier Observability barrier	Risk barrier			Experiment

		Trialability barrier				
Heidenreich and Kraemer (2016)	Mobile phone	Value barrier Complexity barrier Usage barrier Observability barrier Trialability barrier	Risk barrier			Experiment
Mani and Chouk (2018)	Internet of Things (IoT)	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier Perceived technological Dependence Technology anxiety	Inertia	Survey
Joachim et al. (2018)	Service innovation: New mobile services SleepBot, MomentCam, AgingBooth and a pedometer application called Moves. Product innovation: Dual tablet Toshiba Libretto, the 3-D camera Fujifilm Finepix 3D, and the holographic laser projector Blueoptics Light Touch	Value barrier Complexity barrier Trialability barrier Compatibility barrier Co-dependence barrier Visibility barrier Communicability barrier Amenability barrier Realization barrier		Norm barrier Image barrier Usage barrier Information barrier Personal risk barrier Functional risk barrier Economic risk barrier Social risk barrier		Survey Experiment
Chakraborti et al. (2022)	The reasons why start-ups have not yet adopted digital marketing tools	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Survey
Chen et al. (2022)	Mobile ticketing Application	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Survey
Iyanna et al. (2022)	E-health/m-health	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Qualitative; open-ended essay
Agarwal et al. (2023)	OTT streaming platforms	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Interview
Sham et al. (2023)	Drone delivery services	Usage barrier Value barrier	Risk barrier	Tradition barrier Image barrier		Fuzzy set qualitative comparative analysis (fsQCA)
Uhlendorf and Uhrich (2024)	AR for sport spectators in stadiums	Usage barrier Value barrier	Social risk barrier	Tradition barrier Image barrier		Interview & survey
This study	**AR virtual try-on in online retailer**	Usage barrier Value barrier	Economic risk Functional risk Privacy risk (new) Security risk (new) Time risk (new) Technology obsolescence risk (new) Ethical risk (new):	Perceived inauthenticity barrier (new) Tradition barrier: – Trust in sales assistance (new) – Preference for adventurous shopping (new)	Inertia Customer–Technology identification (new*)*	**Interview & survey**

			– Excessive consumption (new) – Diminishing social interactions (new)	Image barrier Technology dependence barrier		

Table 2. Study 1: Literature review and findings

Barriers	**Findings of this study** **Type of technology: AR in online retailers** (findings are divided based on themes)	**Representative verbatim**
Functional barrier	**Theme 1: Usage and complexity concern** **Usage barrier** → Complexity and difficulties associated with using new technologies (Ram & Steth, 1989).	**Usage barrier:** "I'm always concerned about technical issues when using AR, such as the wrong camera connection or the mobile phone lacking the necessary drivers to run the app. On top of that, slow Internet can make AR very frustrating, with endless loading and nothing working properly, which makes me hesitant to trust or use it" (P3, IT engineer, 53-year-old male)
	Value barrier → When customers believe the new technology does not offer sufficient value (Ram & Steth, 1989).	**Value barrier:** "I think there is little value added in using AR because, again, there are videos, photos, reviews, and so on; they are enough for me to decide to buy something. I didn't find it that useful for me; it has no value in my purchase decision. It wasn't clear what kind of advantages it would bring to my purchase decision" (P14, senior scientist, 31-year-old female)
Risk barrier	**Theme 2: Risk-related concern** **Economic risk** → Concerns about potential financial loss (Ram & Steth, 1989). **Functional risk** → Fears of unrealistic product representation (Ram & Steth, 1989). **Privacy risk (new)** → Unwillingness to disclose personal data (Malhotra et al., 2004). **Security risk** → Technological and procedural safeguards to prevent data theft or loss (H.-F. Cheng et al., 2014). **Time risk** → Loss of time incurred while learning and using a new technology (Pavlou, 2003). **Technology obsolescence risk** → From the customer's perspective, there is a perceived risk that AR technology may soon become obsolete as newer and more advanced innovations emerge (Acikgoz et al., 2024). **Ethical risk (new)** → Innovations causing societal harm. It consists of: • **Excessive consumption (new)** → Impulsive or unnecessary purchases (Maccarrone-Eaglen and Schofield, 2023).	**Economic risk:** "I can't help but worry about the potential costs associated with using AR in retail apps. It seems like everything these days comes with a subscription fee or hidden charges. The idea of having to pay more just to use a feature that might not even be worth it is off-putting. It feels like retailers are just trying to squeeze more money out of customers" (P1, product manager, 42-year-old male) **Functional risk:** "I can't rely on my decision based on what I've seen through AR only; I wouldn't do that for my purchase; I don't think it accurately represents the real product that I want to buy" (P13, technical project manager, 52-year-old male) **Privacy risk:** "It's probably okay to upload pictures of the room. I think that just seems less personal, or you can control what's in the background of the picture more easily than, say, your face. I don't want to use AR that requires me to take picture of my face, my face is my identity. Sharing personal information, such as face or body, it raises serious concerns" (P17, yoga teacher, 35-year-old female) **Security risk** "As far as I know, if I were to try on spectacles using AR, I would have to upload a picture of myself. However, I realize that the image is stored by the company, supposedly in an encrypted manner, but still held for a long time. The idea of my information and image being stored online is unsettling. This makes me even more wary of using AR, as I'm concerned about the security of my data" (P10, management accountant, 53-year-old female) **Time risk** "I think it might take more time. I'm not quite sure because if it's something that I'm browsing for; I could spend a few hours on the Internet anyway. Adding AR to help me search for something would make my online

	• **Diminishing social interaction (new) →** Reduced opportunities for meaningful human connections (Smith et al., 2018b).	shopping process even longer, requiring more time to adapt to how to use AR, learn to navigate it, and so on—yeah very time-consuming" (P20, compliance manager, 33-year-old female) **Technology obsolescent risk** "With how fast tech evolves, I'm concerned that AR could become obsolete before I really get the hang of it. I don't want to adopt something that might be irrelevant soon, especially when new and better versions are always around the corner" (P12, financial advisor, 36-year-old male) **Ethical risk (excessive consumption)** "I think from an ethical standpoint, promoting excessive consumerism in a world already facing significant challenges is problematic. This is what I see in AR. It raises questions about the social impact of making shopping experiences more engaging at a time when we should be considering sustainability and responsible consumption" (P5, librarian, 31-year-old female) **Ethical risk (diminishing social interaction)** "We risk losing those vital social interactions that come with shopping. Shopping is often a way for people to connect and engage with their community. If AR makes it too easy to buy everything online, we might see social spaces shrink, especially for vulnerable groups like the elderly, who rely on those outings not just for shopping but for socialising or refreshing" (P11, school teacher, 36-year-old female)
Psychological barrier	**Theme 3: Psychological and behavioral resistance** **Perceived inauthenticity barrier (new) →** The perception that AR exaggerates product features (Schallehn et al., 2014). **Tradition barrier →** When innovation is incompatible with customers' existing traditions, values, norms, or culture. This barrier often stems from a desire for human interaction (Antioco & Kleijnen, 2010; Joachim et al., 2018; Ram & Sheth, 1989). It consists of: • **Trust in sales assistance (SA) →** consumer trust in SA expertise to provide reliable guidance (Antioco and Kleijnen, 2010; Sirdeshmukh et al., 2002). • **Preference for adventurous shopping (new) →** The desire for the unpredictability of exploratory shopping (Horváth & Adıgüzel, 2018).	**Perceived inauthenticity barrier** "I just can't see myself using AR to try on clothes. It feels like such an inauthentic experience, where everything might have been portrayed in a way that looks much better than reality, just to entice you into making a purchase. They employ all this clever technology to make the fit and style appear flawless, which creates a false sense of confidence" (P7, librarian, 31-year-old female) **Tradition barrier (Trust in SA)** "I still trust sales assistants for their expertise. The salesperson is usually an expert in that area. They match the makeup according to your skin type and tone, so you can get advice from them. They can actually see you in person to offer that advice, while AR can't do the same" (P4, radiology technologist, 39-year-old female) **Tradition barrier (Preference for adventurous shopping)** "My favourite physical shop is TK Maxx. I think that is because of the unpredictability of what I'll find in there. I guess it's almost like an amusement to have the novelty of things, and it can be quite a short dopamine loop because I can go, "oh, that looks interesting." So all of these things can't be replaced by AR" (P8, therapist 43-year-old female)
	Image barrier → Stereotypes about a retailer's low product quality can create negative spillover effects, leading consumers to assume that the retailer's shopping technologies are also of low quality and unreliable (Ram & Steth, 1989).	**Image barrier** "I've always been a bit wary of buying from Chinese retailers because I've had some bad experiences in the past with their product quality. When I saw that this Chinese retailer was offering AR to try on clothes virtually. If their basic products often lack quality, how can I believe that their advanced tech like AR would work any better? It makes me hesitate to even try it" (P6, UX designer, 33-year-old male)
	Technology dependence barrier → When users fear becoming overly reliant on technology, leading to a loss of autonomy and self-reliance (Mani & Chouk, 2018)	**Technology dependence barrier** "The idea of using AR makes me uneasy because I worry it might make me less self-reliant. I've always prided myself on being able to figure things out on my own. It's important to me to maintain control over my decisions and actions without feeling like I need technology to guide me" (P18, support worker, 38-year-old male)
Individual barrier	**Theme 4: Individual-specific barrier** **Inertia barrier →** Reluctance to change due to satisfaction with existing methods of shopping (Mani & Chouk, 2018)	**Inertia** "I've always shopped online the same way, and it works fine for me. I'm comfortable with the way things are, browse things with my phone, and I don't feel the need to complicate it with all this new technology. I'm not really interested in changing how I shop just because there's a new feature available" (P15, administrative

	Consumer-Technology Identification (new) → How individuals perceive a connection between their self-identity and a technology's characteristics (Pérez, 2009).	assistant, 32-year-old male) **Customer-Technology Identification** "Using AR makes me feel like I'm trying to adopt a technology that doesn't align with who I am. I've always prided myself on keeping things simple and not getting caught up in flashy, tech-driven solutions. When I think about using AR, it feels misaligned with my identity, which values real-world experiences over digital simulations" (P19, medical doctor, 32-year-old male)

Table 3: Descriptive statistics

	Mean Statistics	**Std. Deviation Statistics**	**Skewness Statistics**	**Kurtosis Statistics**	**Std. Errors**
Usage barrier	4.313	1.097	-0.007	-1.436	0.068
Value barrier	4.376	1.545	-0.102	-0.796	0.050
Economic risk	3.740	1.558	0.027	-0.620	0.050
Functional risk	4.617	1.562	-0.518	-0.498	0.050
Privacy risk	3.788	0.979	-0.889	0.988	0.032
Security risk	4.574	1.971	-0.178	-1.266	0.063
Time risk	3.258	1.485	0.456	-0.440	0.048
Technology obsolescent risk	4.378	1.067	-0.122	-1.249	0.067
Excessive consumption	4.130	1.040	-0.024	-0.983	0.066
Diminishing social interaction	4.988	1.954	-0.537	-0.951	0.063
Perceived inauthenticity barrier	3.832	1.313	0.183	-0.173	0.042
Trust in sales assistant	3.744	1.768	0.159	-0.901	0.057
Preference for adventurous shopping	3.631	1.232	0.043	-0.613	0.040
Image barrier	3.793	1.437	0.064	-0.255	0.046
Technology dependence	2.704	1.609	0.893	-0.170	0.052
Inertia	4.216	1.154	-0.009	-1.370	0.069
Customer–technology identification	3.715	1.501	0.174	-0.505	0.048
Intrusiveness	3.498	0.500	0.006	-2.004	0.157
Resistance	3.570	1.583	0.326	-0.613	0.051
Intention to use	3.474	1.587	0.052	-0.945	0.051

Table 4: Construct reliability and validity

Constructs and measures	Loadings
Usage barrier (AVE = .968; Rho A = .919; Cronbach's α = .953)	
Learning to use AR technology will be difficult for me	0.948
AR technology will be difficult to use	0.958
It isn't easy to achieve results that I desire from using AR technology	0.953
Value barrier (AVE = .791; Rho A = .931; Cronbach's α = .911)	
I believe there are other tools (e.g., photos, videos, reviews) that provide sufficient information for my purchase decisions without the need for AR technology.	0.768
After evaluating the available AR technology, I am unsure if it provides meaningful value to my shopping process.	0.920
I think this AR technology adds little to no value in helping me make better purchase decisions.	0.945
Given the features of this AR technology, I find it unclear how it would improve my ability to make informed choices.	0.915
Economic risk (AVE = .774; Rho A = .910; Cronbach's α = .902)	
Using AR technology will probably involve hidden costs and subscription fees	0.905
I am likely to end up with a bad financial deal if I use AR technology	0.858
Using AR technology will probably result in some unexpected costs	0.927
I expect that using AR technology will not remain free forever	0.825
Functional risk (AVE = .849; Rho A = .913; Cronbach's α = .911)	
I am concerned about how reliable AR technology is	0.889
I worry about whether AR technology inaccurately represents the product	0.949
I am concerned that AR technology will not provide a realistic image of the product	0.925
Privacy risk (AVE = .849; Rho A = .913; Cronbach's α = .911)	
AR technology presents its privacy protection policy clearly	0.935
AR technology collects personal information with the consent of consumers	0.909
AR technology guarantees that the personal information of consumers will be handled in accordance with a third party's privacy protection regulations	0.932
AR technology will collect consumers' personal information (e.g., facial images, weight, height, age, and personal space) with their consent.	0.932
Security risk (AVE = .860; Rho A = .948; Cronbach's α = .946)	
AR technology guarantees that it observes a third party's transactional security protection regulations	0.977
AR technology safely stores my data	0.976
AR technology guarantees that transmission of transactional data will be protected without any unauthorized modification or sabotage	0.948
AR technology ensures secure handling of consumer information during interactions, with a clear and understandable security policy	0.856

Time risk (AVE = .848; Rho A = .948; Cronbach's α = .940)	
If I begin to use AR technology, I will lose time	0.878
Using AR features would lead to a loss of convenience because I would have to waste a lot of time	0.927
It would be risky to adopt AR due to the considerable time investment to set up and use AR	0.936
It is risky to use AR due to the time loss involved in setting it up and learning how to use it	0.940
Technology obsolescent risk (AVE = .925; Rho A = .930; Cronbach's α = .974)	
I think AR technology is a kind of technology that can easily get worn out over time, leading to it become obsolete	0.913
AR technology will likely have functional defects over time	0.983
Over time, AR technology is unlikely to be compatible with the latest devices and software	0.992
AR technology is likely to be outdated over time	0.957
Excessive consumption (AVE = .887; Rho A = .910; Cronbach's α = .969)	
I think it is risky to use AR technology because it could increase my urge to buy something.	0.872
I'm worried that the immersive features of AR technology (e.g., virtual try-ons, real-time visualizations) may stimulate my urge to buy too many products	0.941
I think it is risky to use AR technology because it might make me more prone to impulsive shopping	0.977
I am concerned that relying on AR technology for shopping might lead me to excessive buying behavior	0.926
Diminishing social interaction (AVE = .960; Rho A = 0.921; Cronbach's α = .980)	
Using AR technology is risky because it will be difficult to relate to other people	0.965
When using AR technology, my concern is that I don't have someone to share my feelings with	0.994
I believe that the use of AR technology carries the risk of losing human interactions	0.981
Perceived inauthenticity barrier (AVE = .914; Rho A = 0.953; Cronbach's α = .953)	
I find AR technology is misleading because it projects an image that is better than reality	0.963
AR technology seems to distort the product	0.952
I find AR technology is not truly authentic	0.953
Trust in sales assistant (AVE = .839; Rho A = 0.936; Cronbach's α = .936)	
I find sales assistants to be more dependable compared to AR technology	0.915
I consider sales assistants to be more competent than AR technology.	0.916
I believe sales assistants have higher integrity than AR technology	0.914
Sales assistants are much more responsive to my needs than AR technology	0.918
Preference for adventurous shopping (AVE = .923; Rho A = 0.972; Cronbach's α = .972)	
I see shopping in the store as more of an adventure than using AR technology.	0.968
I find the thrill of exploring the store more stimulating than shopping with AR technology	0.951
I enjoy the unpredictability of finding unique items in-store rather than relying on AR technology	0.952
Shopping in the store makes me feel like I am in my own universe rather than using AR technology	0.972
Image barrier (AVE = .841; Rho A = 0.918; Cronbach's α = .906)	
I have a very negative image of AR technology offered by certain retailers	0.899
In my opinion, AR technology in certain retailers is not reliable due to their poor product quality	0.915
I have a negative perception of AR technology from certain retailers because I do not trust their product quality.	0.938
Technology dependence (AVE = .801; Rho A = 0.928; Cronbach's α = .878)	

I'm afraid of becoming dependent on AR technology	0.823
AR technology will reduce my autonomy	0.938
I think using AR will make me less capable of making my own judgment	0.919
Inertia (AVE = .929; Rho A = .923; Cronbach's α = .975)	
I often view the introduction of AR technology as a negative shift.	0.931
I'd prefer to stick with my existing shopping methods rather than experimenting with AR technology	0.977
In my view, previous shopping technologies have been satisfactory, and I don't see a compelling reason to switch to AR technology	0.991
Overall, I feel that my needs in the online shopping experience have been sufficiently met by existing methods and technologies	0.954
Customer–technology identification (AVE = .942; Rho A = .953; Cronbach's α = .853)	
The way I see myself conflicts with how I perceive AR technology	0.863
I feel that my values and preferences do not align with what AR technology represents	0.942
My self-identity differs from how I perceive the use of AR technology for shopping	0.940
The image I have of AR technology does not resonate with my personal values and self-image	0.946
Intrusiveness (AVE = .921; Rho A = .983; Cronbach's α = .978)	
Disturbing	0.949
Interfering	0.958
Intrusive	0.969
Unpleasant	0.961
Invasive	0.961
Resistance (AVE = .753; Rho A = .938; Cronbach's α = .934)	
I believe the possible use of AR technology would cause problems that I don't need	0.839
I would be making a mistake by using AR technology	0.882
The use of AR technology would be connected with too many uncertainties	0.877
AR technology is not for me	0.835
I'm likely to be opposed to the use of AR technology	0.903
I'm likely to be opposed to the discourses extolling the benefits of AR technology	0.867
Intention to use (AVE = .855; Rho A = .948; Cronbach's α = .943)	
I intend to use AR technology for shopping	0.944
I predict that I will use AR technology for shopping	0.944
I plan to use AR technology in the future for shopping	0.958
In the future, I will use AR technology significantly more often than I will use previous shopping methods	0.849

Table 5: Heterotrait-Monotrait Ratio (HTMT)

	CTI	DSI	EC	ER	FR	IB	INERT	INTENT	INTRUS	PADV	PIB	PR	RESIST	SR	TD	TOR	TR	TSA	UB	VB
CTI																				
DSI	0.378																			
EC	0.331	0.540																		
ER	0.401	0.246	0.179																	
FR	0.460	0.321	0.322	0.517																
IB	0.578	0.395	0.357	0.412	0.584															
INERT	0.374	0.582	0.396	0.281	0.257	0.330														
INTENT	0.336	0.700	0.680	0.184	0.346	0.404	0.586													
INTRUS	0.167	0.265	0.071	0.166	0.027	0.103	0.518	0.123												
PADV	0.348	0.616	0.607	0.247	0.379	0.426	0.497	0.877	0.075											
PIB	0.413	0.651	0.649	0.274	0.422	0.481	0.542	0.800	0.097	0.832										
PR	0.242	0.019	0.120	0.225	0.170	0.187	0.042	0.287	0.234	0.128	0.115									
RESIST	0.608	0.647	0.616	0.475	0.600	0.642	0.556	0.676	0.122	0.730	0.793	0.267								
SR	0.115	0.244	0.159	0.061	0.107	0.127	0.211	0.255	0.246	0.218	0.226	0.029	0.224							
TD	0.469	0.286	0.243	0.479	0.469	0.455	0.242	0.175	0.085	0.248	0.304	0.302	0.535	0.091						
TOR	0.380	0.618	0.395	0.254	0.288	0.370	0.598	0.589	0.381	0.521	0.550	0.082	0.581	0.282	0.247					
TR	0.527	0.378	0.332	0.595	0.551	0.471	0.325	0.356	0.074	0.406	0.444	0.186	0.629	0.079	0.564	0.337				
TSA	0.357	0.567	0.603	0.251	0.430	0.396	0.457	0.786	0.066	0.728	0.764	0.057	0.722	0.213	0.262	0.508	0.428			
UB	0.216	0.226	0.053	0.194	0.166	0.221	0.304	0.121	0.505	0.092	0.122	0.129	0.195	0.154	0.156	0.255	0.184	0.123		
VB	0.471	0.610	0.594	0.337	0.541	0.512	0.487	0.758	0.083	0.707	0.753	0.025	0.765	0.240	0.330	0.531	0.535	0.670	0.140	

CHAPTER 4 : INVESTIGATING THE EFFECTS OF AUGMENTED REALITY ON CUSTOMER EXPERIENCE AND ADOPTION INTENTION IN ONLINE RETAIL

The effects of augmented reality on customer experience and adoption intention in online retail

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Status: *Submitted to Electronic Commerce Research*

4.1 Abstract

Augmented reality (AR) has the potential to transform online customer experiences by enhancing product visualization and fostering engagement. Yet, AR adoption remains limited. Prior studies have largely taken a technological characteristics perspective in explaining AR usage; however, this overlooks the value-driven perspective, leaving the role of values in AR adoption insufficiently understood. Using a mixed-methods approach, we analyze 20 semi-structured interviews and reveal additional subdimensions of consumption values: cognitive offloading, shopping personalization, virtual self-expression, and sustainability. A subsequent quantitative survey incorporating these subdimensions demonstrates that customer experience mediates their effects on AR adoption intentions. This research provides a comprehensive framework that identifies the values s associate with AR, and explains how these values drive adoption in e-retail. We offer actionable guidance for retailers to align AR with customer expectations.

Keywords: Augmented reality (AR), adoption, customer experience, consumption value, immersive experience, online shopping

4.2 Introduction

Augmented reality (AR) is becoming an increasingly attractive technology for e-retailers. For example, IKEA's AR app, *IKEA Place*, has been reported to have reduced product returns by 20% while increasing online sales by 35% since its launch in 2017 (Appify Commerce, 2023). For s, AR enriches the shopping journey by making virtual product evaluation more engaging and personalized, thereby strengthening confidence in online purchases (Xu et al., 2024). Despite these advantages, AR adoption remains limited, with as few as 13% of s reporting that they have used it (The Interline, 2024; Wurmser & Adrian, 2022). Studies on AR have emphasized technological characteristics, showing that interactivity, immersion, and usability enhance engagement (Huang & Chung, 2024; Lin et al., 2025; McLean & Wilson, 2019). Beyond technological aspects, AR research has identified utilitarian, hedonic, and social usage drivers (Hilken et al., 2017; Hilken et al., 2020; McLean & Wilson, 2019; Yim et al., 2017). Yet, these categories have been treated unevenly across disciplines. Marketing research has emphasized hedonic and social benefits, while information systems and HCI (Human-Computer Interaction) research has focused on utilitarian aspects such as usability and system quality (Hilken et al., 2017; Huang & Chung, 2024). This disciplinary divide has reinforced fragmentation and left explanations of AR adoption inconsistent (Hoffmann & Mai, 2022; Du et al., 2022).

Moreover, much of the research has prioritized technological or experiential characteristics while neglecting integrative, value-based perspectives that could explain why these drivers matter for adoption (Du et al., 2022). As a result, existing studies have provided only partial understanding of adoption behavior, underscoring the need for frameworks that capture the broader consumption values shaping decisions. Importantly, Jayaswal and Parida (2023) highlighted the need to move beyond the predominant reliance on TAM (Technology Acceptance Model) in AR research in order to examine alternative theoretical perspectives. In particular, understanding the different types of value that s seek from AR-enabled online retail platforms is critical for explaining adoption behavior. However, values-driven approaches, that examine which values AR delivers to users, remain scarce (Schultz & Kumar, 2024; Wang et al., 2023). Given that values fundamentally drive user behavior (Gutman, 1982), and that s tend to choose offerings they perceive as most valuable, uncovering the value dimensions of AR is critical (Armstrong et al., 2018). Doing so would deepen our theoretical understanding of AR adoption and help firms better design and implement their AR strategies.

Thus, this paper investigates AR adoption from a values-based perspective (Sheth et al., 1991). The study makes three contributions. First, it extends application of the theory of consumption values (TCV) to the context of AR adoption. While Schultz and Kumar (2024) also employed TCV in this domain, their framework did not incorporate epistemic value or conditional value. These two values are particularly important in AR adoption, as novelty-seeking and situational factors, such as sustainability, may strongly influence s' willingness to adopt. By integrating all five consumption values and introducing AR-specific subdimensions, this paper provides a comprehensive application of TCV to AR adoption. The study extends TCV by theorizing how AR adoption is shaped not only by functional, emotional, and social value but also by epistemic and conditional value. This broader conceptualization enriches the AR adoption literature and offers retailers clearer guidance on designing AR that reduces cognitive effort, supports self-expression, and aligns with sustainability expectations or technologies to support responsible consumption (Thandayuthapani & Thirumoorthi, 2025).

Second, this study contributes to the literature by investigating whether s adopt AR not simply because they perceive value in it, but because such value is made tangible through their actual AR consumption experience. Previous studies in AR and technology adoption have primarily focused on underlying mechanisms such as telepresence (Baytar et al., 2020), cognitive fluency (Fan et al., 2020), or spatial presence (Wang et al., 2022). In contrast, customer experience represents a comprehensive, multidimensional framework that reflects cognitive, affective, relational and symbolic experience with the technology use. Customer experience acts as a key mechanism through which value perceptions are translated into adoption decisions, and captures the complexity of decisions to engage with AR (Chylinski et al., 2020). This shows that AR adoption is shaped less by psychological constructs—such as telepresence or cognitive fluency, which are abstract and difficult for retailers to act upon—and more by outcomes such as product evaluation confidence (cognitive), shopping enjoyment (emotional), social connection (relational), and personal value fit (symbolic), which represent levers that retailers can actively design for.

Third, this study investigates how product involvement shapes the relationship between perceived values and AR adoption. Jayaswal and Parida (2023) identified product involvement as an underexplored area in AR research, underscoring the need to examine how this factor influences responses. Prior research has often assumed that positive value perceptions lead to adoption; however, we argue that product involvement levels may alter how cuatomers respond to different value dimensions (Burucuoglu & Erdogan, 2016; Wang et al., 2013). For instance, when product involvement is high, appeals such as sustainability or enjoyment may hold less importance, as s prioritize accuracy and follow a more deliberate decision-making process (Ha & Lennon, 2010; Zhang et al., 2024). This highlights the need to consider product involvement when aligning AR's value propositions with the motivations and expectations inherent in different product categories.

4.3. Literature Review

4.3.1 Theory of consumption value (TCV)

TCV (Sheth et al., 1991) offers a multidimensional framework for understanding choice, positing that decisions are shaped by functional, emotional, social, epistemic, and conditional value dimensions. It argues that five distinct types of value—functional, emotional, social, epistemic, and conditional, jointly shape how s evaluate technology. Functional value refers to the perceived utility and performance of a technology (Burucuoglu & Erdogan, 2016), while emotional value encompasses the affective responses elicited by usage and consumption, such as enjoyment, pleasure, and excitement (Bettiga et al., 2017). Social value is derived from the perceived benefits of social identity and recognition. It becomes highly relevant in contexts such as online communities and peer-to-peer platforms, where group belonging and status signaling influence participation and loyalty (Kaur et al., 2018; Sung, 2021). Epistemic value captures customers' desire for novelty and curiosity. This value is especially salient when customers are motivated to explore technology that is innovative or intellectually stimulating (Hur et al., 2012; Wang et al., 2023). Finally, conditional value refers to the perceived importance of a technology under specific circumstances or situational factors, such as sustainability concerns. This dimension is particularly relevant in situations where needs vary over time (White et al., 2019; Yang & Lin, 2017).

4.3.2 TCV and its applications

TCV (Sheth et al., 1991) has been applied in relation to several digital and service technologies, as shown in Table 1. In convergence products and mobile applications, functional and epistemic value strongly shape adoption (Hur et al., 2012; Wang et al., 2013). In mobile banking, conditional, emotional, and functional value are significant in determining adoption (Burucuoglu & Erdogan, 2016). In more hedonic or socially embedded contexts, studies of brand communities and streaming apps have emphasized enjoyment and belonging as drivers of continued use (Bettiga & Lamberti, 2017; Kaur et al., 2018; Oyedele & Simpson, 2018). Research on online brand experiences and metaverse applications has shown the importance of emotional and social value as drivers of adoption, though their influence can be shaped by contextual factors such as information overload, or mediated by attitudes and trust (Chakraborty et al., 2022; Fathima et al., 2023; Yang & Lin, 2017).

In AR research, applications of TCV are emerging but remain at different stages of development. Wang et al. (2023) examined satisfaction with AR by linking Schwartz's (1992) value orientations to perceived AR outcomes such as playfulness, social interaction, usability, and visual appeal. These outcomes can be associated with several TCV dimensions, for example, playfulness and visual appeal with emotional value, social interaction with social value, and usability with functional value—yet, the framework does not explicitly capture epistemic or conditional value. Wang et al. (2023) also focused on satisfaction rather than adoption, which represents a different outcome dimension. Schultz and Kumar (2024) employed TCV more directly in the context of AR adoption, highlighting the role of functional, emotional, and social value. Their framework, however, does not extend to epistemic or conditional value, both of which are central to Sheth et al.'s (1991) original conceptualization. Taken together, these studies demonstrate the potential of TCV to explain AR-related outcomes while also suggesting opportunities for further extension by considering the full set of consumption values.

[Insert Table 1 here]

4.3.3 Customer experience of AR

AR in e-retail may enhance the cognitive experience by replacing imagination with direct visualization, thereby improving clarity in decision-making. AR also may foster emotional experience through enjoyment and immersion, while social sharing of virtual try-ons may reduce uncertainty, build confidence, and strengthen the relational dimension of customer experience (Vaidyanathan & Henningsson, 2023). Customers may respond more favorably if interactions preserve a sense of control, and they tend to report higher satisfaction when virtual adjustment aligns with the product type, such as automatic placement for larger items (Alexander et al., 2025; Heller et al., 2023). Beyond usability, AR activates the symbolic dimension of customer experience by aligning with broader values, such as reducing returns and enabling more sustainable, informed shopping decisions (Nadeem et al., 2025). Taken together, customers perceive AR not just as a functional tool but as a multidimensional experience that engages cognitive, affective, relational, and symbolic dimensions of online shopping.

4.3.4 TCV, customer experience of AR, and intention to use

Understanding AR adoption requires a values-based perspective. TCV identifies functional, emotional, epistemic, social, and conditional value as key drivers of choice (Sheth et al., 1991), and has been applied to mobile and financial technologies (Burucuoglu & Erdogan, 2016). In the AR context, these values extend beyond functionality to include curiosity, self-expression, and situational relevance. Importantly, value perceptions are realized through customer experience, which develops as s engage with AR touchpoints during their shopping journey. These touchpoints often occur in stages, such as during product exploration, option evaluation, or purchase, and influence how s process information, experience enjoyment, connect with others, and align their choices with broader personal or societal values, such as sustainability (De Keyser et al., 2020). In this way, AR interactions shape the responses that determine how value is perceived and whether adoption follows.

Building on this view, prior research has also shown that ensuring the quality of the AR experience is critical for value realization. Seamless AR interactions enhance functional, emotional, and epistemic value, whereas disruptions due to instability or poor rendering undermine them (Gahler et al., 2023; Hilken et al., 2022; Kim et al., 2023). Moreover, behavioral intentions increase when AR is experienced as useful, engaging, and novel (Barta et al., 2025; Heller et al., 2023). Together, TCV and CX provide a comprehensive lens for understanding AR adoption by linking motivations with experiential evaluations that ultimately shape intention to use the technology.

4.4 Methodology

Using a mixed-methods design, this research investigates the consumption values driving AR adoption in online shopping. Study 1 uses interviews to inductively identify relevant value dimensions, while Study 2 validates these dimensions within an empirical framework. This combination strengthens the contribution of the research by capturing context-specific nuances through qualitative insights and confirming their effects with generalizable quantitative evidence. Following Venkatesh et al. (2016), this integration enhances both explanatory depth and confirmatory rigor, offering a more comprehensive understanding of AR adoption.

4.4.1 Study 1: Qualitative method – In-depth interview

Study design and participants

Study 1 aimed to identify the consumption values that drive s to adopt AR for online shopping. We conducted semi-structured qualitative interviews with 20 British AR adopters, with each interview lasting an average of 70 minutes. Participants were recruited through online panels and social media posts. Table 2 summarizes participant details. The interview guide was designed to capture both the breadth and depth of adopters' experiences with AR. They were asked about a recent occasion when they used AR while shopping online, their motivations for using AR, the features they found appealing or useful, the perceived benefits compared to traditional online shopping, and the extent to which AR influenced their purchase decisions. This approach allowed us to explore how s articulate the values they associate with AR use in real purchase contexts.

We define AR adopters as customers who use AR technology to evaluate products and finalize purchase decisions in online shopping (Rogers, 2003, p.22). This operationalization is stricter than that used in much of the AR literature, where participants are often treated as adopters after mere exposure or experimental use (Poushneh & Vasquez-Parraga, 2017). By focusing on customers who have used AR in actual shopping contexts leading to purchase, this study captures values that are consumption-related rather than superficial impressions.

[Insert Table 2 here]

Study 1: Data analysis and qualitative results

After completing the interviews with the 20 adopters, the interview transcripts were analyzed using NVivo 14, incorporating a thematic analysis approach (Braun & Clarke, 2006). The data were rigorously reviewed several times, and coded by organizing and refining into transparent categories. The consumption values related to AR adoption were grouped by similarity into themes and subthemes, with irrelevant codes discarded. Member-checking was conducted to assess validity, with participants reviewing and confirming written summaries of emerging categories. All participants concurred with the identified themes and subthemes, which ensured alignment with their interviews (Cho & Trent, 2006).

The final coding process generated five themes (shown in Figure 1): (1) functional value, (2) social value, (3) emotional value, (4) epistemic value, and (5) conditional value. Functional value emerged as an important theme in participants' accounts of AR in e-retail. Many emphasized convenience, describing AR as reducing the time and effort required for visiting physical stores, while enabling realistic product exploration and decision-making. Beyond this established dimension, two new insights extended the understanding of functional value. First, participants highlighted cognitive offloading, which pertains to AR's ability to reduce mental effort by taking over tasks such as remembering measurements, checking reviews, or visualizing product fit. Second, interviewees highlighted shopping personalization, where AR adapts to individual preferences by recalling past choices and incorporating biometric data, which in turn leads users to perceive the recommendations as more accurate (Li & Qing, 2021; Wahn et al., 2023).

Social value was identified as the second theme in participants' perceptions of AR in e-retail. This value was reflected in online social interactivity, where participants can share their virtual try-ons with friends and family through messaging apps or social media. Interviewees reported seeking opinions on product choices; several emphasized that AR made it easier to involve others instantly, and that this collaborative element enhanced their confidence in making the right choice. These findings highlight how AR extends shopping beyond individual experience, creating opportunities for conversation, validation, and social connection (Sung, 2021).

Emotional value was identified as the third theme in participants' perceptions of AR in e- retail.

This value was reflected in two dimensions: enjoyment and virtual self-expression. Participants described AR as making the shopping experience more playful and engaging, with features such as virtual try-ons enhancing enjoyment by allowing them to interact with products in a fun and exploratory way. Beyond enjoyment, participants also highlighted virtual self-expression as a new aspect of emotional value. They noted that AR enabled them to experiment with styles and makeup looks that reflected different moods or their identity. Together, these findings suggest that AR contributes not only to the pleasure of the shopping process but also to the expressive freedom customers experience (Javornik et al., 2023).

Epistemic value was identified as the fourth theme in participants' perceptions of AR in e- retail. This value reflects how AR stimulates curiosity and offers novel ways to learn about products. Participants described experimenting with AR, such as placing virtual furniture or testing products in different contexts, as a way to explore possibilities they had not initially considered. In doing so, interviewees stated that they were able to learn new information about product attributes, including dimensions, layout, and even the effects of lighting. Several also noted that the process enhanced their understanding of AR itself, as they became more familiar with how technology functioned. These findings indicate that AR supports epistemic value by combining interactive exploration with knowledge acquisition, enabling customers to satisfy their desire for discovery and learning in the shopping process (Teng, 2018; Zhu et al., 2025).

Conditional value was identified as the fifth theme in participants' perceptions of AR in e-retail. This value was linked to sustainability, a new dimension in the context of AR. Participants emphasized that AR reduces the need to over-order products or return items, and allows them to better assess fit, size, and appearance of the product before purchase. They associated this with lowering waste, cutting down on packaging and delivery emissions, and contributing to more eco-conscious shopping practices by avoiding unnecessary returns. These findings highlight how AR not only supports more efficient consumption but also aligns with customers' growing concerns for environmental sustainability (Johnson & Chattaraman, 2021; Nadeem et al., 2025). Table 3 provides representative quotes for each identified theme and subtheme.

[Insert Table 3 here]

4.4.2 Study 2 – Quantitative survey

Hypothesis development

The following section presents the theoretical rationale and proposed hypotheses for each of the eight constructs derived from the subthemes identified in study 1.

[Insert Figure 1 here]

Functional values affecting cognitive experience

Functional value refers to the utility derived from a product or service's ability to fulfill practical and utilitarian needs (Sheth et al., 1991). In the context of AR in e-retail, functional value is reflected through three key components: convenience, cognitive offloading, and shopping personalization. These elements shape how customers interact with AR, particularly in terms of their cognitive engagement during the experience.

Cognitive experience is defined as the extent to which customers are mentally stimulated and actively process information while interacting with a digital environment (Gahler et al., 2023). Convenience contributes to cognitive experience by simplifying the product evaluation process. AR allows users to examine and compare products virtually without the need to visit the store. By reducing external distractions and task complexity, AR enables customers to concentrate more effectively on evaluating product features and making comparisons.

Cognitive offloading further enhances cognitive experience by reducing the internal mental workload. Rather than requiring customers to imagine how a product might look or fit, AR provides visual simulations that externalize complex judgments. This supports clearer and more confident information processing, which in turn encourages greater cognitive engagement with the interface and the content presented (Chylinski et al., 2020; Wahn et al., 2023).

Shopping personalization increases the relevance and clarity of the information customers are presented with. When AR tools personalize product options based on user-inputted characteristics, such as size or style preferences, the interaction becomes more targeted and easier to navigate. This focused presentation of relevant options encourages more purposeful information processing and contributes to a more cognitively engaging experience (Alimamy & Gnoth, 2022).

Convenience, cognitive offloading, and shopping personalization help customers complete shopping tasks easily, and with less mental effort compared to traditional shopping (Wahn et al., 2023; Weis & Wiese, 2019). When customers see that a technology simplifies decision-making, they become more mentally engaged in the shopping process (Chylinski et al., 2020). AR that supports these functional benefits allows users to process shopping-related information more effectively, leading to higher cognitive experience. Therefore, functional value is expected to positively affect cognitive experience. Thus, we hypothesize:

H1: Functional value; (H1a) convenience, (H1b) cognitive offloading, and (H1c) shopping personalization positively relates to cognitive experience with the retailer.

Social values affecting relational experience

Social value refers to the benefit customers gain when a product or service enhances social approval or facilitates interaction with others (Sheth et al., 1991). In e-retail, AR creates social value when it allow users to share experiences or connect with others during the shopping journey. For example, virtual try-on tools allow users to generate images or videos of themselves using products such as clothing or cosmetics, which can then be shared through messaging apps or social media platforms. These interactions allow customers to invite feedback, express preferences, and engage socially while shopping (Hilken et al., 2020).

Thus, AR helps to create a sense of mutual participation and social presence. This aligns with the concept of relational experience, which refers to the interaction, connection, and relationship-building that occurs during service encounters (Gahler et al., 2023). When a retailer facilitates this kind of meaningful social exchange, customers may perceive the retailer as more socially responsive and interactive. Research has shown that socially enriched experiences foster relational outcomes by allowing customers to feel seen, heard, and supported in co-creating their shopping journey (Hilken et al., 2020). Therefore, when AR enhances customers' ability to engage in social interaction and share their experiences with others, it also strengthens the relational experience between the customer and the retailer. Thus, we hypothesize:

H2. Social value (online social interactivity) positively relates to the customer's relational experience with the retailer.

Emotional values affecting affective experience

Emotional value refers to the positive emotional rewards customers associate with a consumption experience, such as pleasure or emotional connection. In AR settings, particularly in e-retail, this value primarily manifests through enjoyment and opportunities for virtual self-expression (Sheth et al., 1991). Enjoyment, as a central dimension of emotional value in AR, reflects the perception of these technologies as entertaining, motivating customers to engage with virtual try-on tools. Once engaged, this perception translates into affective experience, expressed through actual feelings of joy, excitement, and emotional stimulation during the interaction (Gahler et al., 2023). In this way, emotional value serves as a precursor to affective experience, which subsequently strengthens customers' intention to use AR (Poushneh & Vasquez-Parraga, 2017).

Virtual self-expression also contributes to affective experience by allowing customers to explore and express their identity. AR tools that let users visualize how certain styles, colors, or products look on them help to foster personal connection to the shopping experience. This opportunity to experiment with a temporary self-image can lead to emotionally meaningful experiences. As shown in prior studies, when digital interfaces support self-expression, users are more likely to feel emotionally fulfilled and connected during their engagement with the technology (Ambika et al., 2023; Lavoye et al., 2023).

Together, enjoyment and virtual self-expression make the AR experience emotionally richer, leading to heightened affective responses throughout the interaction. Rather than serving merely as background elements, these emotional drivers help to shape how customers feel during the retail experience. Thus, we hypothesize:

H3. Emotional value; (H3a) enjoyment and (H3b) virtual self-expression positively relates to an affective experience with the retailer.

Epistemic values affecting cognitive and affective experience

Epistemic value derives from curiosity, novelty, and the desire for knowledge acquisition (Sheth et al., 1991). In e-retail environments using AR, epistemic value becomes relevant as customers engage with novel, immersive, and interactive features such as virtual try-ons and spatial product visualizations (Schultz & Kaiser, 2025). Curiosity, conceptualized as the arousal of interest and pursuit of novel sensory experiences (Zhu et al., 2025), drives customers to explore AR. This process contributes to cognitive experience, defined as the extent to which customers are mentally stimulated and actively process information (Gahler et al., 2023). Through these interactions, customers go beyond passive browsing; they compare options and evaluate features, which leads to deeper cognitive involvement (Barta et al., 2025; Poushneh & Vasquez-Parraga, 2017).

At the same time, epistemic value is closely tied to affective experience. While often associated with learning and evaluation, curiosity also elicits emotional responses such as anticipation, fascination, or even joy when customers encounter something novel (Schultz & Kaiser, 2025). These emotions emerge from the process of discovery; they differ from hedonic enjoyment, which is rooted in personal expression or entertainment value. For example, a user may feel excitement not because using AR is fun, but because it offers a new perspective or uncovers unexpected possibilities (Chakraborty & Zhang, 2025; Pandey & Pandey, 2025).

Thus, while both emotional and epistemic value can generate affective responses, the underlying mechanisms differ. Epistemic value leads to emotionally engaging experiences through curiosity-driven exploration, whereas emotional value does so through pleasure or identity alignment. Taken together, these arguments suggest that epistemic value enhances both cognitive and affective dimensions of customer experience with the retailer. Therefore, we hypothesize:

H4: Epistemic value (curiosity) positively relates to the customer's (a) cognitive experience and (b) affective experience with the retailer.

Conditional values affecting symbolic experience

Conditional value refers to the benefit a customer perceives from using a product or service under specific circumstances or conditions that are external to the product itself (Sheth et al., 1991).

In the case of AR in e-retail, one such situational condition is the technology's perceived potential to support sustainable consumption. As environmental awareness continues to influence customer decision-making, individuals increasingly evaluate technologies not only for their efficiency or novelty but also for their alignment with ecological values (Johnson & Chattaraman, 2021).

AR helps in minimizing returns, over-ordering, and resource use by enabling accurate product visualization before purchase (Nadeem et al., 2025). In this way, AR's value increases when viewed in relation to the broader environmental context (Joerss et al., 2021). Symbolic experience refers to the personal meaning that customers attach to a retailer based on how well it reflects their identity, values, or social image (Gahler et al., 2023). When customers see AR as aligning with their ethical standards, it reinforces not just practical goals, but also moral or identity-based expressions.

Customers practice environmentally responsible behaviors both to make better choices and to express their values (Johnson & Chattaraman, 2021). In this context, AR's ability to reduce environmental impact elevates the symbolic meaning of using it. Customers may feel they are making a values-aligned choice, not just using a tool. When conditional value is shaped by perceived sustainability, it reinforces symbolic experience through value expression. Thus, we hypothesize:

H5. Conditional value (perceived sustainability) positively relates to the customer's symbolic experience with the retailer.

The mediating role of cognitive experience in the relationship between functional values and intention to use.

In the context of AR in e-retail, functional value, which includes convenience, cognitive offloading, and shopping personalization, facilitates customers' ability to achieve their goals more efficiently and make better-informed decisions. However, the influence of functional value on usage intention is be limited to a direct evaluation of utility. Rather, it is shaped by the internal cognitive processes that are activated during interaction with the technology while shopping (Gahler et al., 2023).

When functional value is present, it stimulates these mental processes by making the interaction more informative, clear, and mentally engaging. Customer are not only able to complete tasks more easily but also actively think and learn throughout the AR experience. Prior research suggests that technologies that support cognitive structuring of information tend to improve comprehension and decision confidence, thus leading to adoption (Chylinski et al., 2020).

In summary, functional value initiates the customer–technology interaction by delivering instrumental support. Cognitive experience then acts as the mechanism through which this support is interpreted and evaluated. As customers mentally process the benefits of AR, their motivation to continue using it becomes stronger. Accordingly, cognitive experience is expected to mediate the relationship between functional value and usage intention. Therefore, we hypothesize:

H6. Cognitive experience mediates the relationship between functional value; (a) convenience, (b) cognitive offloading, and (c) shopping personalization and intention to use AR.

The mediating role of relational experience in the relationship between social value and intention to use.

In AR-enabled online shopping, social value emerges when customers engage with features that allow them to share their experiences and also seek feedback from others (Sung, 2021; Wang et al., 2023), which leads to relational experience.

Gahler et al. (2023) described relational experience as the dimension of customer experience that captures perceptions of emotional closeness with the retailer. Studies have shown that relational experience in co-creative and socially rich service environments plays a central role in shaping behavioral intentions, particularly in technology-mediated contexts. When customers feel socially and emotionally aligned with a retailer, they are more likely to continue using its services and platforms (Jaakkola et al., 2015).

When AR enables social interaction and connection, it generates social value for customers. This social value fosters a relational experience, which deepens users' sense of connection and belonging with the retailer. Based on this, the effect of social value on usage intention is expected to be mediated by relational experience. Therefore, we hypothesize:

H7. Relational experience mediates the relationship between social value (online social interactivity) and intention to use AR.

The mediating role of affective experience in the relationship between emotional value and intention to use.

In the context of AR in e-retail, emotional value arises when customers find the technology enjoyable or when it enables expressive, self-reflective experiences. Emotional value shapes behavioral intention indirectly, as it is expressed through customers' affective experience during their interaction with the retailer or platform. Affective experience refers to the emotional states triggered during the customer journey. It includes both immediate affective responses, such as excitement; and more enduring emotional impressions, such as joy, comfort, or personal resonance (Gahler et al., 2023).

When AR generates emotional value by offering pleasurable or expressive moments, these moments shape customer' overall affective experience with the retailer (Soon et al., 2023). Affective experience is a central aspect of the retail experience, as it shapes behavioral intention and decision-making. Thus, emotional value reflects the customer's perception that the technology is emotionally rewarding, and the affective experience captures how that value is felt in real time through the shopping journey. Affective experience, therefore, serves as the mechanism by which emotional value exerts its influence on behavioral intention (Chekembayeva et al., 2023). Therefore, we hypothesize:

H8. Affective experience mediates the relationship between emotional value; (a) enjoyment, and (b) virtual self-expression and intention to use AR.

The mediating role of cognitive and affective experience in the relationship between epistemic value and intention to use AR

According to TCV (Sheth et al., 1991), epistemic value refers to the benefit customers gain from experiencing curiosity, novelty, and the pursuit of new knowledge. In AR-based e-retail, epistemic value is activated when customers interact with virtual try-ons. These features stimulate exploration and activate both cognitive and affective processes, which also stimulate cognitive and affective experience (Poushneh & Vasquez-Parraga, 2017).

Cognitive experience with the retailer refers to the mental processing, reflection, and learning that occur during interaction with the retailer's digital offerings (Gahler et al., 2023). Customers who are driven by curiosity engage in evaluating product details and judging the functionality and relevance of AR. This cognitive experience increases their intention to use AR because it enables customers to process information more effectively and reach better purchase decisions (Barta et al., 2025).

Moreover, affective experience with the retailer refers to the emotional states experienced during the interaction, such as excitement, fascination, and curiosity-induced enjoyment. In the case of AR, these emotions result from engaging with novel and stimulating technology that supports exploration. When the retailer's AR interface elicits these specific emotional states, customers form an emotionally charged interaction that strengthens their intention to use the technology (Gahler et al., 2023). These emotions are driven not by hedonic pleasure, but by the customer's psychological response to novelty and discovery.

Cognitive and affective experiences with the retailer transmit the effect of epistemic value to usage intention. Curiosity leads to both mental stimulation and emotionally charged reactions during AR interaction, which strengthens customers' intention to use the technology (Pandey & Pandey, 2025). These findings support the mediating roles of both cognitive and affective experience in translating epistemic value into technology adoption. Therefore, we hypothesize:

H9. (a) Cognitive experience and (b) affective experience mediate the relationship between epistemic value (curiosity) and intention to use AR.

The mediating role of symbolic experience in the relationship between conditional value and intention to use.

Conditional value, as outlined in TCV (Sheth et al., 1991), refers to the perceived utility of a product or service under specific circumstances. In the context of AR in retail, one situational factor that can enhance conditional value is the perception of sustainability. When customers view AR as a tool that supports sustainable consumption practices, such as reducing unnecessary returns or facilitating informed decision-making, it increases the perceived situational relevance of the technology (White et al., 2019). Symbolic experience is the meaning customers attach to a technology based on its alignment with their values (Gahler et al., 2023). When customers see AR as supporting environmentally conscious actions (conditional value), it aligns with their personal values and reinforces their self-image as responsible individuals. Using AR then becomes not only practical, but also a way to express and affirm their values, creating a symbolic experience.

Previous studies have shown that sustainable consumption often fulfills value-related functions. Customers adopt sustainable practices not only for their practical value but also as a form of self-expression (Johnson & Chattaraman, 2021; Nadeem et al., 2025). As a result, when AR is seen as contributing to sustainable retail practices, the symbolic meaning associated with its use can strengthen customers' motivation to adopt it. This symbolic meaning becomes a key pathway through which the perceived conditional value of AR translates into usage intention. Thus, we hypothesize:

H10. Symbolic experience mediates the relationship between conditional value (perceived sustainability) and intention to use AR.

The moderating role of product involvement in the relationship between emotional value (enjoyment) and affective experience

Enjoyment reflects the intrinsic pleasure customers derive from interacting with a technology (Sheth et al., 1991; Soon et al., 2023). In e-retail, AR that enables playful interaction or sensory stimulation, such as virtual try-ons, can evoke pleasurable emotional responses that contribute to the affective experience with the retailer (Gahler et al., 2023). This affective experience encompasses the emotional states customers associate with the retailer during the interaction, and contributes to their evaluation of the brand or service context. However, the strength and direction of this effect are not universal. Enjoyment may not always enhance affective experience, especially when the customer is highly involved with the product. Product involvement is the product's perceived relevance or importance to the customer (Ha & Lennon, 2010); it shapes how information is processed, such that highly involved customers adopt a goal-oriented, information-driven mindset rather than focusing on enjoyment (Petty & Cacioppo, 1986).

This higher involvement increases cognitive elaboration and reduces reliance on emotional cues, thereby diminishing the impact of hedonic elements on affective experience (Zhang et al., 2024).When emotional value is high but the customer is also highly involved with the product, affective experience with the retailer is weakened. This weaker emotional response leads to a lower intention to use AR (Ha & Lennon, 2010). The interplay between enjoyment and product involvement negatively affects intention by diminishing the customer's affective experience with the retailer, which acts as a mediator in this relationship. Therefore, we hypothesize:

H11. Product involvement negatively moderates the effect of emotional value (enjoyment) on intention to use AR through affective experience, such that when product involvement is higher, emotional value has a weaker negative relationship with intention to use AR.

The moderating role of product involvement in the relationship between conditional value (sustainability) and affective experience

Conditional value refers to the utility customers derive from a product or service under specific contextual conditions (Sheth et al., 1991). In AR retail environments, sustainability increasingly serves as a source of conditional value. Retailers often promote AR as a sustainable shopping solution by highlighting its ability to reduce over-purchasing, minimize product returns, and support more conscious consumption (Hou et al., 2024). When customers value sustainability, they develop a symbolic experience with the retailer, perceiving the interaction as a reflection of their personal values or broader ideals (Thandayuthapani & Thirumoorthi, 2025)

However, the formation of symbolic experience is contingent upon how customers process value-related cues. Product involvement, defined as the perceived importance or relevance of the product to the customers (Zhang et al., 2024), plays a central role in shaping this processing. When involvement is low, customers are more receptive to peripheral cues, such as sustainability messaging. In contrast, highly involved customers focus on product fit and technical functionality, often viewing symbolic cues, such as sustainability, as less relevant to their purchasing goals (Ha & Lennon, 2010; Petty & Cacioppo, 1986).

According to the elaboration likelihood model, high involvement triggers central route processing, leading customers to focus on core attributes and disregard peripheral cues such as symbolic appeals (Petty & Cacioppo 1986). In this context, sustainability fails to enhance symbolic experience, weakening the value-based connection with the retailer and reducing intention to use AR. This means that product involvement plays a negative moderating role in the relationship between sustainability and intention to use AR through symbolic experience. Thus, we hypothesize that:

H12. Product involvement negatively moderates the effect of conditional value (sustainability) on intention to use AR through symbolic experience such that when product involvement is higher, conditional value (sustainability) has a weaker negative relationship with intention to use AR.

4.4.1 Study design and participants

This survey-based study targeted 1,255 British adopters of AR for online shopping. Eight constructs, as identified in Study 1, were measured as independent variables using established scales. For the first theme, functional value, convenience was assessed using a three-item scale from Hwang et al. (2024), while cognitive off-loading was measured with a four-item scale adapted from Bechwati and Xia (2003). Shopping personalization was measured with a six-item scale adapted from Gao et al. (2023). For the second theme, social value, online social interaction was assessed with a three-item scale developed by Kaur et al. (2018). For the third theme, emotional value, enjoyment was assessed with a three-item scale from Kim and Hall (2019), and virtual self-expression was measured with a three-item scale from Jo et al. (2025). For the fourth theme, epistemic value, curiosity was measured with a three-item scale adapted from Teng (2018). Finally, for the fourth theme, conditional value, sustainability was measured with a five-item scale developed by Molla et al. (2014).

Customer experience was assessed as a mediating variable using scales developed by Gahler et al. (2023). It comprised four dimensions: cognitive experience (measured with a five-item scale), affective experience (three items), relational experience (three items), and symbolic experience (three items). The dependent variable, intention to use AR, was measured using a three-item scale adapted from Venkatesh et al. (2012). Product involvement was included as a moderating variable and measured with a five-item scale adapted from Beatty and Talpade (1994).

4.5 Data analysis and results

4.5.1 Construct reliability and validity

In Study 2, we tested the normal distribution of each scale. Table 4 reports the descriptive statistics. All skewness and kurtosis values were within acceptable ranges (Tabachnick et al., 2013). For the collinearity statistics (variance inflation factor [VIF]), values ranged from 1.26 to 2.99, evidencing no collinearity (Tabachnick et al., 2013). We then proceeded to run a PLS algorithm for factor analysis using SmartPLS 4 (Ringle et al., 2022). Table 5 displays the results of the construct reliability and validity testing. All outer loadings, ranging from 0.707 to 0.920, were above the threshold value of 0.70. All scores for Cronbach's alpha, ranging from 0.749 to 0.908, were above the threshold value of 0.70, indicating consistency and reliability. A complete summary of the construct reliability and validity test results is provided in Table 5.

[Insert Table 4]

[Insert Table 5]

The average variance extracted (AVE) scores ranged from 0.561 to 0.819, suggesting strong internal convergent validity for all constructs. We also checked the discriminant validity of the constructs using the heterotrait–monotrait (HTMT) ratio of correlations. All HTMT values (Table 6) were lower than the suggested value of 0.9, thereby establishing discriminant validity for all constructs (Henseler et al., 2015). Finally, we assessed common method bias using Harman's single factor test (Henseler et al., 2015). The results showed that the first factor accounted for 23.30% of the total variance explained, indicating that the data did not present common method bias, as the first component accounted for less than 50% of all the variables in the model.

[Insert Table 6 here]

4.5.2 Model and hypothesis testing

We tested the measurement model with SmartPLS4 (Ringle et al., 2022), using structural equation modelling and bootstrapping tests (based on 5,000 samples). To test H1 to H12, we developed a structural model linking the eight consumption values identified in Study 1 to customer experience, which in turn were posited to predict intention to use AR. Customer experience was expected to serve as a mediator in the relationship between consumption values and usage intention. Additionally, product involvement was included as a moderator of the relationship between consumption values and customer experience. The standardized root mean square residual was .061, indicating good model fit. The R-squared values were .306 for cognitive experience, .471 for affective experience, .172 for relational experience, .406 for symbolic experience, and .302 for intention to use AR.

The results indicate that functional value had a significant positive effect on cognitive experience, specifically for convenience ($\beta = 0.122$, $p < .001$), cognitive offloading ($\beta = 0.056$, $p = .046$), and shopping personalization ($\beta = 0.195$, $p < .001$). Social value, measured by online social interactivity, also showed a significant positive effect on relational experience ($\beta = 0.230$, $p < .001$). Emotional value, reflected in enjoyment ($\beta = 0.323$, $p < .001$) and virtual self-expression ($\beta = 0.110$, $p < .001$), was positively associated with affective experience. Epistemic value, represented by curiosity, had a strong positive effect on both cognitive experience ($\beta = 0.242$, $p < .001$) and affective experience ($\beta = 0.251$, $p < .001$). Finally, conditional value, indicated by sustainability, showed a highly significant positive effect on symbolic experience ($\beta = 0.558$, $p < .001$). Thus, H1a–c, H2, H3a and b, H4a and b, and H5 were all supported.

The mediation analysis revealed that all four customer experience dimensions significantly influenced intention to use AR. Specifically, cognitive experience had the strongest effect ($\beta =

0.276, $p < .001$), followed by affective experience ($\beta = 0.210$, $p < .001$), relational experience ($\beta = 0.136$, $p < .001$), and symbolic experience ($\beta = 0.099$, $p = .001$). Overall, each consumption value positively influenced customer experience, which, in turn, positively shaped intention to use through all customer experience dimensions. The indirect effects of functional value—convenience ($\beta = 0.033$, $p < .001$), cognitive offloading ($\beta = 0.019$, $p = .025$), and shopping personalization ($\beta = 0.053$, $p < .001$) on intention to use through cognitive experience—were significant. The effect of social value, measured by online social interactivity, on intention to use through relational experience was also significant ($\beta = 0.031$, $p < .001$). Emotional value, including enjoyment ($\beta = 0.068$, $p < .001$) and virtual self-expression ($\beta = 0.023$, $p = .001$), had significant indirect effects on intention to use through affective experience. Furthermore, epistemic value, operationalized as curiosity, had significant indirect effects on intention to use through both cognitive experience ($\beta = 0.067$, $p < .001$) and affective experience ($\beta = 0.053$, $p < .001$). Conditional value, represented by sustainability ($\beta = 0.055$, $p < .001$), had a significant indirect effect on intention to use through symbolic experience. Thus, H6a–c, H7, H8a and b, H9a and b, and H10 were all supported.

Finally, in the moderated mediation analysis, the interaction between conditional value (sustainability) and product involvement had a significant negative indirect effect on intention to use AR through symbolic experience ($\beta = -0.013$, $p = .008$). Similarly, the interaction between emotional value (enjoyment) and product involvement resulted in a significant negative indirect effect on intention to use AR through affective experience ($\beta = -0.026$, $p < .001$). These findings indicate that higher product involvement reduces the positive impact of both sustainability and enjoyment on intention to use AR via their respective customer experience dimensions. Thus, H11 and H12 were supported. A comprehensive summary of the hypothesis testing results is provided in Table 7.

[Insert Table 7 here]

4.6 Discussion

Study 1 identified five key themes and eight usage values: functional (convenience, cognitive offloading, personalization), social (online interactivity), emotional (enjoyment, virtual self-expression), epistemic (curiosity), and symbolic (sustainability). These findings laid the foundation for Study 2 by clarifying how these values shape customer experience and intention to use AR.

Study 2 demonstrated that multiple value dimensions positively affect customers' intention to use AR in e-retail. Functional value (convenience, cognitive offloading, and shopping personalization) increases adoption by reducing effort, simplifying decisions, and personalizing experiences. Social value (social interactivity) leads to adoption as it enables peer validation and shared experiences. Emotional value (enjoyment, virtual self-expression) supports intention to use by fulfilling hedonic and identity needs. Epistemic value (curiosity) motivates customers to explore AR's novel features. Conditional value (sustainability) reinforces usage intention by enabling more informed and responsible consumption (Johnson & Chattaraman, 2021; Nadeem et al., 2025).

Together, the two studies demonstrate that customer experience mediates how different values influence intention to use AR in e-retail. Functional value improves cognitive experience by making shopping more efficient and relevant (Li & Qing, 2021; Sharma et al., 2023). Social value enhances relational experience by enabling shared experiences, while emotional value deepens affective experience through enjoyment and virtual self-expression, strengthening emotional engagement (McLean & Wilson, 2019). Epistemic value, driven by curiosity, boosts cognitive and affective experiences by encouraging active exploration and excitement (Strzelecki et al., 2024). Conditional value, linked to sustainability, shapes symbolic experience when AR supports responsible consumption, aligning with personal values and strengthening intention (Foroudi et al., 2020; Joerss et al., 2021). Overall, these findings show that value shapes intention not only through practical benefits but also through the experiential quality of AR.

The results also reveal that high product involvement weakens the effect of certain values on customer experience and AR usage intention. In particular, it reduces the impact of conditional value on symbolic experience, as customers focus more on product attributes than on benefits such as sustainability (Ha & Lennon, 2010). Even if AR enables sustainable consumption, its symbolic value is less salient for customers who are deeply engaged in product evaluation. Similarly, high product involvement weakens the effect of aspects of emotional value such as enjoyment on affective experience (Ha & Lennon, 2010; Petty & Cacioppo, 1986). For customers with high product involvement, the hedonic appeal of AR may be secondary to functional or informational concerns, which reduces the emotional engagement typically driven by enjoyment. These findings suggest that customers with high product involvement may adopt a more goal-oriented and utilitarian approach to AR.

4.7 Theoretical contributions

This paper's theoretical contributions are derived from its reframing of AR adoption through a value-based perspective. Whereas prior studies have primarily emphasized technological features or treated utilitarian, hedonic, and social drivers in fragmented ways across disciplines, this study consolidates these insights within an integrative framework. Building on critiques of fragmentation (Du et al., 2022; Hoffmann & Mai, 2022) and calls to move beyond TAM toward richer theoretical explanations (Jayaswal & Parida, 2023), it applies and extends the TCV to capture the broader set of values shaping adoption behavior. In doing so, the paper provides the first comprehensive value-based account of AR adoption in online retail. We thereby make three key contributions.

First, this study extends TCV in two ways: it specifies how consumption values operate when applied to an immersive technological context within an e-retail setting, and it provides AR research with a mechanism-based account of adoption that goes beyond identifying system characteristics only (Huang & Chung, 2024; Lin et al., 2025; McLean & Wilson, 2019). While such perspectives have identified features that elicit customer responses, they have failed to account for the value-based mechanisms through which these features translate into adoption. By applying TCV, this study clarifies these pathways, demonstrating that consumption values represent the core motivations driving customers to adopt AR in e-retail (Schultz & Kumar, 2024; Wang et al., 2023).

Second, this study demonstrates that customer experience (cognitive, affective, relational, and symbolic) constitutes the mediating process through which consumption values shape AR adoption. Each value dimension connects to a distinct form of customer experience. This matters theoretically because it demonstrates that values acquire behavioral relevance only when they are expressed through distinct dimensions of customer experience; without this translation, values remain detached from behavior and cannot drive adoption. Prior studies that have relied on isolated constructs, such as telepresence, cognitive fluency, or spatial presence (Baytar et al., 2020; Fan et al., 2020; Wang et al., 2022), have thus provided only partial accounts. By foregrounding customer experience as the underlying mechanism, this study delivers a more comprehensive theoretical explanation of AR adoption that captures the multiplicity of customer experience and establishes it as the pathway through which AR adoption decisions in e-retail are formed (Fan et al., 2020; Gahler et al., 2023).

Third, this study contributes to the literature by establishing product involvement as a boundary condition in AR adoption. In doing so, it addresses Jayaswal and Parida's (2023) call to investigate product involvement as an underexplored factor in AR research. The findings advance theory by challenging prior assumptions that positive value experiences consistently drive adoption (Burucuoglu & Erdogan, 2016; Wang et al., 2013), showing instead that the influence of value on AR adoption varies with the level of product involvement (Ha & Lennon, 2010). In such contexts, sustainability or enjoyment cues may diminish symbolic or affective experiences and lower adoption intentions, as customers with high product involvement prioritize accuracy and deliberate decision-making (Liao et al., 2017; Petty & Cacioppo, 1986). This advances the literature by moving beyond generalized accounts of value impacts toward a more nuanced framework that incorporates boundary conditions and offers guidance for tailoring AR design to distinct customer contexts (Bruni & Galvagno, 2025). Overall, the findings extend Vaidyanathan and Henningsson's (2023) call for AR that aligns with customer needs. Specifically, this study shows that adoption cannot be explained through technological characteristics alone, but requires recognition of how multiple value dimensions shape customer experience and how their salience shifts with situational factors such as product involvement.

4.8 Managerial implications

First, to advance meaningful AR adoption, managers should develop features that provide accurate visualizations while also meeting customers' broader experiential needs, as technical fidelity alone does not guarantee user adoption, especially in visually sensitive categories such as makeup and eyewear (Javornik, Duffy, et al., 2021; Javornik, Marder, et al., 2021). Managers are encouraged to implement AR that enables social sharing, supports self-expression through personalized options, and helps customers make more informed and sustainable choices. For example, realistic AR try-ons can reduce purchase errors and lower product return rates, thereby contributing to more sustainable consumption patterns (Ambika et al., 2023; Hou et al., 2024; Thandayuthapani & Thirumoorthi, 2025).

Second, our mediation analysis shows that AR's influence is not uniform but occurs through specific pathways, such as affective, cognitive, relational, and symbolic experience (Gahler et al., 2023). However, in practice, many AR systems fail to fully support these dimensions because they are not sufficiently aligned with customer motivations (Becker & Jaakkola, 2020; Gahler et al., 2023). For example, sustainability claims such as "reduce returns with virtual try-ons" do not clearly demonstrate the user's impact. To enhance relevance, AR should connect functionalities to specific value dimensions. One way to achieve this is by providing immediate, personalized feedback, such as quantifying the reduction in an individual's shopping-related carbon footprint when using AR try-ons. By making the benefits of AR both tangible and personally meaningful, such design choices can strengthen customers' engagement with the technology (Hilken et al., 2022; Vaidyanathan & Henningsson, 2023).

Third, our findings show that symbolic and affective experiences have less impact on AR usage intention when product involvement is high (Ha & Lennon, 2010). In high-involvement categories, such as appliances or professional electronics, customers place greater emphasis on precision and decision support over emotional or ethical features. By contrast, in low-involvement categories such as fashion accessories, AR designs that emphasize enjoyment, creativity, and social sharing are more effective (Soon et al., 2023). To accommodate these variations, retailers should adopt involvement-contingent AR strategies. For high-involvement products, AR strategies should prioritize more utilitarian benefits, such as interactive comparisons, zoom capabilities, and high-fidelity visualizations that enhance decision confidence (Hilken et al., 2022; Javornik, Duffy, et al., 2021). For low-involvement products, AR can instead emphasize playful visual effects, avatar customization, and easy shared-experience options (Sung, 2021).

4.9 Limitations and further research

Despite its contributions, this study is subject to several limitations that should be considered when interpreting the findings. First, the use of a cross-sectional design, where data were collected at a single point in time, limited our ability to capture the evolving nature of AR adoption. This made it difficult to observe how usage patterns, frequency, or enthusiasm for AR may change as users gain experience, AR technologies advance, or societal perceptions shift (Fan et al., 2020). For instance, initial adopters may alter their usage or attitudes over time, and improvements in AR could lead to new patterns of adoption. Future research that employs longitudinal designs would enable the observation of these temporal changes and provide a more nuanced understanding of the dynamics influencing AR adoption (Khashan et al., 2023).

Second, the study's focus on British adopters may limit the generalizability of the findings to other cultural or national contexts. Adoption drivers and barriers can vary across countries due to differences in technological infrastructure, cultural values, and market maturity. Future studies should incorporate cross-cultural comparisons and broader geographic samples to clarify how cultural and technological environments shape AR adoption, thereby strengthening the external validity and applicability of the results (Magliocca et al., 2024)

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Figure 1. Conceptual model

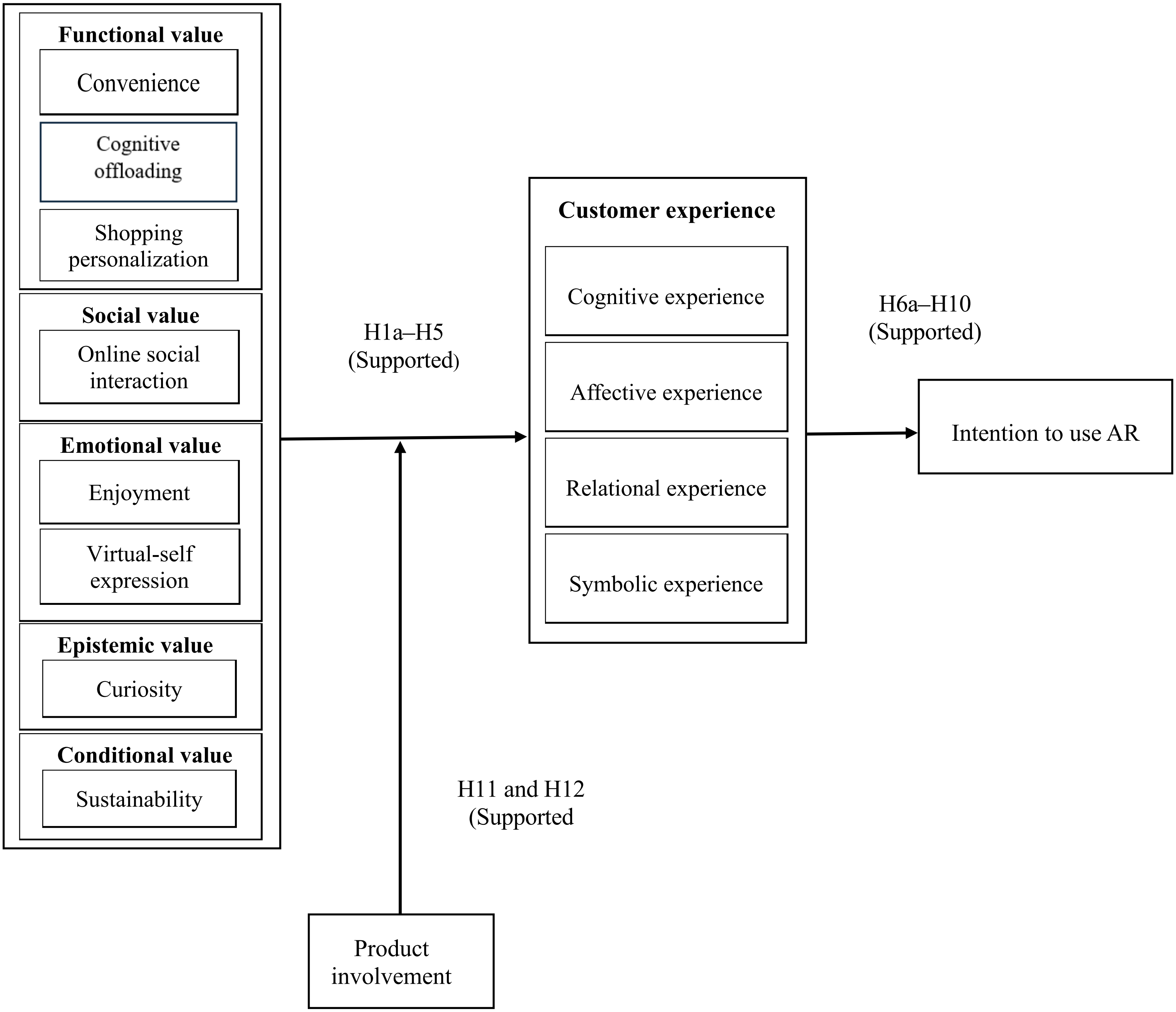

Table 1. Applications of TCV in prior research

Study	Technology Type	Independent Variable	Conditional Mechanism		Theory	Dependent Variable	Key Findings
			Moderator	**Mediator**			
Hur et al. (2012)	Convergence home robots	Functional value Social value Emotional value Conditional value Epistemic value	Consumer innovativeness	-	TCV	Purchase intention	Functional, epistemic, and emotional value are important factors affecting intention to purchase convergence home robots. Consumer innovativeness shows a moderating effect on the relationship between emotional value and purchase intentions.
. Wang et al. (2013)	Mobile pay-per-use service apps	Conditional value	-	Functional value Social value Emotional value Epistemic value	TCV	Behavioral intention	Consumption values significantly affect consumer behavioral intention to use mobile apps. Epistemic and emotional value have stronger relationships with behavioral intention. Moreover, conditional value influences mobile app users' behavioral intention via the mediation of other consumption values (functional, social, emotional, and epistemic value).
Burucuoglu and Erdogan (2016)	Mobile banking services	Functional value Conditional value Emotional value Epistemic value Social value	-	-	TCV	Adoption	Conditional value, emotional value, epistemic value, and consumption value have a positive and statistically meaningful effect on adoption to mobile banking, and social value has a negative and statistically meaningful effect.
Yang and Lin (2017)	Social mobile services	Functional value Social value Emotional value Epistemic value Fashion value		Information overload Social overload	TCV	Intention to continue using social mobile services	Functional value (usefulness, efficiency), epistemic value (novelty, curiosity), and conditional value (situational relevance) significantly influence users' intention to continue using social mobile services. Social value and emotional value are not significant predictors of continued use. Overload weakens the effects of value dimensions on continuance intention.
Kaur et al. (2018)	Online social media	Epistemic value (social influence and problem solving) Emotional value (playfulness) Social value (social enchantment and social interaction)	Activity level	-	TCV	Continuation intention	Emotional and social value exert partial influence in predicting users' intention to continue using online social media brand communities. Social enhancement and playfulness predict users' continuation intentions. The influence of the investigated constructs (except playfulness) is consistent across users with various activity levels.
Oyedele & Simpson (2018).	Streaming apps	Cognitive, monetary, emotional, social, convenience value	-	Identity salience mediates social values to recommend and hours of use	TCV	Hours of use	All consumption values, as well as identity salience, impact recommendation likelihood.

Chakraborty et al., (2022)	Food delivery app	Functional value Conditional value Emotional value Epistemic value Social value	Visibility	-	TCV	Purchase intention	Except for emotional value, there is a significant association between functional, social, conditional, and epistemic value and usage intention. Furthermore, visibility mediates the relationship between consumption values and usage intention.
Fathima et al. (2023)	Website-based construct of online brand experience	Online brand experience	Consumption value and flow	-	TCV and flow theory	Satisfaction and purchase intention	TCV and flow are critical drivers of online brand experience, and online brand experience positively influences satisfaction and purchase intention.
Wang et al. (2023)	AR	Openness to change Conservation Self-transcendence Self-enhancement	-	Playfulness value Social value Usability value Visual appeal value	Human value orientation theory and TCV	Consumer satisfaction	Each human value orientation is associated with its unique perceived AR values; various perceived AR values influence customer satisfaction differently.
Chakraborty et al. (2025)	Metaverse	Functional value Conditional value Emotional value Epistemic value Social value	Perceived security risk	Attitude toward metaverse	TCV and SOR	Trust toward metaverse Intention to use metaverse	Individual attitudes to the metaverse and trust in metaverse technologies significantly impact intention to use the metaverse.
Schultz and Kumar (2024)	AR	Hedonic value Convenience value Monetary value Informational value Social value	Perceived ease of use Perceived usefulness Attitude	Previous experience	TCV and TAM	Behavioral intention	Informational and convenience value are significant, emotional hedonic value is only significant for female consumers, and there is no statistical support for monetary value and social value in driving behavioral intention.
This study	AR	Functional value - Convenience - Cognitive offloading (new) - Shopping personalization (new) Social value - Online social interactivity - Emotional values - Enjoyment - Virtual self-expression (new) Epistemic value - Curiosity Conditional value - Sustainability (new)	Product involvement	Customer experience (cognitive, affective, relational, symbolic)	TCV	Intention to use	Each value dimension (functional, social, emotional, epistemic, conditional) positively influences intention to use AR, acting through different types of customer experience (cognitive, affective, relational, symbolic). High product involvement weakens the impact of conditional and emotional values on AR adoption, as consumers focus on product attributes over sustainability or enjoyment.

Table 2: Characteristics of the Study 1 sample

Adopter	Age	Gender	Highest level of education	Occupation
P1	31	Male	Bachelor’s degree	IT technician
P2	52	Female	Secondary school	Retired administrator
P3	23	Female	Master’s degree	Student
P4	44	Female	Master’s degree	Trauma therapist
P5	34	Female	Bachelor’s degree	Student
P6	55	Male	Professional degree	Charity worker
P7	46	Male	Associate degree	IT technician
P8	32	Male	Bachelor’s degree	Business coach
P9	24	Female	Master’s degree	Student
P10	40	Female	Bachelor’s degree	Executive assistant
P11	42	Female	Master degree	Charity worker
P12	53	Male	Bachelor’s degree	Business analyst
P13	40	Female	Master’s degree	Nurse
P14	60	Female	Professional degree	English teacher
P15	36	Female	Master’s degree	Lecturer
P16	49	Female	Bachelor’s degree	Nurse
P17	39	Female	Secondary school	Entrepreneur
P18	35	Female	Bachelor’s degree	PR Manager
P19	24	Female	Bachelor’s degree	Teacher
P20	31	Male	Secondary school	Tech start-up executive

Table 3. Study 1: Literature review and findings

Theme	Subtheme	Description	Example Quote
1. Functional value	Convenience	An individual’s perception of reducing time and effort is associated with the shopping experience, enabling access to realistic product exploration and confident decision-making without the hassle of physically visiting stores (S. Li & Qing, 2021).	“I do enjoy going into shops to get a proper look at things, but sometimes I just can’t be bothered. With AR, I can stay at home and still get a real sense of what something will look like. It’s like being in the shop without the hassle of actually going out. I can just pull out my phone, place the item, and see instantly if it fits. It’s so much easier than trudging around the high street.” (P13, nurse, 40-year-female)

	Cognitive offloading (new)	AR reduces mental effort or cognitive load by allowing users to visualize products instead of making abstract judgments. AR does the thinking for them, removing the burden of remembering measurements, checking reviews, or imagining product fit (Wahn et al., 2023; Weis & Wiese, 2019).	"I used to go back and forth between websites, checking measurements and still feeling unsure if something would fit. With AR, I don't have to think about any of that. AR takes all the effort out of shopping. I don't have to check measurements or compare endless reviews anymore. No messing around with a tape measure or stressing over whether I've misread the dimensions, it just makes the whole process effortless." (P1, technician, 30-year-male)
	Shopping personalization (new)	AR is able to adapt to individual user preferences by using both behavioral data (past interactions and choices) and biometric information (e.g., body measurements or skin tones) to deliver tailored product recommendations and realistic try-on experiences (Alimamy & Gnoth, 2022).	"One of the things I love about the AR try-on feature is how personalized it feels. It remembers my previous sizes, styles, and even favorite colors, and it also matches the clothes to my body shape so I can see how they really fit. Instead of scrolling endlessly, the app suggests outfits that suit me, almost like having a personal stylist built in. I actually trust the recommendations more because they're tailored to me." (P17, entrepreneur, 39-year-female)
2.Social value	Online social interactivity	AR enables shareable experiences, where users capture and share virtual try-ons or product interactions to gather feedback and involve others in shopping decisions (Sung, 2021).	"I used Ray-Ban's virtual try-on share button. I sent a few photos of myself wearing different sunglasses to my friends on WhatsApp, and I also posted them on my Instagram story to get their opinions. With AR, I could just get their opinions instantly and I ended up buying a pair that really suited me." (P3, student, 23-year-female)
3. Emotional value	Enjoyment	The degree of pleasure and intrinsic satisfaction experienced when using AR in online shopping (Chakraborty et al., 2025).	"What I've enjoyed the most is using AR for home stuff, like placing a sofa in my living room or trying out different paint colors on my walls. It feels like I'm exploring options interactively and playfully, which makes the whole online shopping experience a lot more enjoyable for me." (P8, business coach, 32-year-male)
	Virtual self-expression (new)	AR allows users to creatively represent their identity. This links to emotional value, as it is driven by the pleasure and expressive freedom users experience when connecting with themselves when using the try-on feature (Ambika et al., 2023; Javornik et al., 2021; Soon et al., 2023).	"When I use AR while shopping online, it's not just about seeing if something fits; it's a way to express myself digitally. I'll try out bold red lipstick when I'm feeling confident, or go for soft, natural tones when I want something more subtle. With clothes, I use AR try-ons to switch between sleek minimalist styles, or something a bit edgy, just to see what feels like 'me' that day. It's really interesting to explore different personalities in what I try virtually." (P16, nurse, 49-year-female)
4. Epistemic value	Curiosity	AR stimulates curiosity and offers users novel ways to learn about products. By enabling interactive exploration and virtual try-ons, AR helps users discover new product information and satisfy their desire for learning and discovery (Teng, 2018; Zhu et al., 2025).	"I was curious to see how it worked, so I started experimenting with AR by placing sofas and even watching a machine in different corners of my home. I found myself exploring all sorts of options I wouldn't have considered before. For example, I realized that a smaller dining table would fit better in the space than the one I had in mind. I ended up learning so much both about AR itself and the products." (P12, business analyst, 53-year-male)
5. Conditional value	Sustainability (new)	AR try-ons promote sustainability by reducing unnecessary purchases and returns, thus lowering the carbon footprint and supporting eco-conscious consumption (O. Johnson & Chattaraman, 2021; Nadeem et al., 2025).	"Normally, I'd order several items just to see if they fit and end up returning half of them. It's such a waste, think of all the packaging and delivery emissions. With AR, I can see exactly how something will look before I even place the order. I didn't have to return the Nike sneakers I bought, because the color and size were spot on. It feels good knowing that I'm reducing waste and doing my bit for the planet." (P19, teacher, 24-year-female)

Table 4 : Descriptive statistics

Descriptive statistics	Mean Statistics	Std. Deviation Statistics	Skewness Statistics	Kurtosis Statistics	Std. Errors
Functional value (convenience)	6.033	0.872	1.353	3.097	0.025
Functional value (cognitive offloading)	5.432	1.105	-0.895	0.069	0.031

Functional value (shopping personalization)	5.016	1.199	-0.895	-0.087	0.034
Social value (online social interactivity)	4.914	0.988	-0.335	-0.309	0.028
Emotional value (enjoyment)	5.432	1.192	-0.964	0.869	0.034
Emotional value (virtual self-expression)	4.854	1.440	-0.619	-0.100	0.041
Epistemic value (curiosity)	5.696	1.026	-1.362	3.337	0.029
Conditional value (sustainability)	4.900	1.196	0.443	-0.195	0.034
Cognitive experience	5.878	1.077	1.026	0.972	0.030
Affective experience	5.622	0.947	-1.047	2.011	0.027
Symbolic experience	5.844	1.221	1.004	0.417	0.034
Relational experience	4.254	1.415	0.170	-0.571	0.040
Product involvement	4.879	1.612	0.351	-0.671	0.046
Intention to use	5.585	1.225	0.490	-0.626	0.035

Table 5: Construct reliability and validity

Constructs and measures	**Loading**
Functional value (convenience) (AVE = .728; Rho A = .918; Cronbach's α = .827)	
It is convenient to use AR when shopping online.	0.878
Using AR for online shopping does not take much time.	0.846
Using AR for online shopping does not require much effort.	0.837
Functional value (cognitive offloading) (AVE = .567; Rho A = .755; Cronbach's α = .749)	
Using AR saved me a lot of mental effort when shopping online.	0.727
Without AR, shopping would have been much more mentally demanding	0.734
AR performed tasks for me (e.g., matching shades to my skin tone, checking clothing fit, or visualizing product size and placement) that would have taken a lot of mental effort to do manually**.**	0.772
I think AR reduced the mental effort I needed to make online shopping decisions	0.779
Functional value (shopping personalization) (AVE = .644; Rho A = .885; Cronbach's α = .864)	
AR offers me suggestions based on the information that AR detects through the camera (e.g., skin tone, facial shape, body size, room dimension, and lighting conditions).	0.771
The AR experience feels tailored to my personal needs and preferences.	0.775
AR helps me better understand what suits my needs when shopping online.	0.815
AR can be customized to fit my preferences (e.g., skin tone, facial shape, body size, room dimension, and lighting conditions).	0.832
AR personalizes the virtual experience to match what I'm looking for.	0.820
Social value (online social interactivity) (AVE = .563; Rho A = .761; Cronbach's α = .753)	
I enjoy talking about AR shopping experiences online with my friends.	0.797
AR in online shopping gives me interesting content to share with others on social media.	0.749
Using AR helps me interact more with others online (e.g., through comments, reviews, or social media).	0.707

Emotional value (enjoyment) (AVE = .794; Rho A = .874; Cronbach's α = .870)	
The process of using AR while shopping online is enjoyable.	0.876
I find using AR in online shopping to be a pleasurable experience.	0.915
I have fun when I use AR during online shopping.	0.881
Emotional value (virtual self-expression) (AVE = .795; Rho A = .998; Cronbach's α = .879)	
I want to express myself through AR by experimenting with different products on myself or visualizing them in my space.	0.920
I aim to convey my desires by using AR to experiment with different products on myself or visualizing them in my space.	0.885
I aspire to nurture my creativity by using AR to experiment with different products on myself or visualizing them in my space.	0.869
Epistemic value (curiosity) AVE = .734; Rho A = .861; Cronbach's α = .820)	
I feel curious when I use AR while shopping online.	0.878
Using AR in online shopping offers me a sense of novelty.	0.903
AR in online shopping satisfies my desire to explore or try something new.	0.785
Conditional value (sustainability) (AVE = .561; Rho A = .810; Cronbach's α = .805)	
Because AR enables virtual try-ons before purchase and potentially reduces product returns, I believe that…	
…using AR for online shopping can help reduce greenhouse gas emissions	0.735
…AR technology is contributing to minimizing environmental impact.	0.743
…AR can contribute to reducing the overall carbon footprint of online shopping.	0.708
…AR can play a significant role in making online shopping more environmentally friendly.	0.815
…AR technology should be a key part of a retailers' sustainability strategy	0.741
Cognitive experience (AVE = .706; Rho A = .901; Cronbach's α = .896)	
The experience with [retailer] piqued my curiosity.	0.791
I learned something beneficial during the experience with [retailer].	0.844
I obtained positive insights during my experience with [retailer].	0.887
The experience with [retailer] helped me make a better decision.	0.819
The experience with [retailer] helped me to find what I was looking for.	0.856
Affective experience (AVE = .767; Rho A = .854; Cronbach's α = .849)	
The experience with [retailer] induced good emotions.	0.867
I had positive feelings while interacting with [retailer].	0.887
The experience I had with [retailer] put me in a good mood.	0.874
Symbolic experience (AVE = .797; Rho A = .874; Cronbach's α = .872)	
The contact with [retailer] was in line with my personal values.	0.874
My personal beliefs were confirmed during my contact with [retailer].	0.905
My contact with [retailer] was in line with my self-image.	0.898
Relational experience (AVE = .819; Rho A = 0.893; Cronbach's α = .890)	
I established a personal relationship with [retailer].	0.897
I felt positively connected with [retailer].	0.908
My contact with [retailer] made me feel like I belonged to a community.	0.911
Product involvement (AVE = .730; Rho A = 0.911; Cronbach's α = .908)	
In general, I am very interested in [product].	0.815

Compared to other products, [product] is very important to me.	0.857
Compared to other products, [product] matters a lot to me.	0.867
I enjoy it when other people talk to me about [product].	0.866
When I buy [product], I choose it very carefully.	0.866
Intention to use (AVE = .680; Rho A = .769; Cronbach's α = .760)	
I intend to continue using AR for online shopping in the future.	0.728
I will always try to use AR when shopping online in my daily life.	0.882
I plan to frequently use AR for online shopping.	0.855

Table 6: Heterotrait-Monotrait Ratio (HTMT)

	AFFX	**COGX**	**CV_ SUS**	**EPVAL_ CUR**	**EV_ ENJO**	**EV_ VSE**	**FV_ COL**	**FV_ CONV**	**FV_ SP**	**INTEN**	**INVOL**	**RELX**	**SV_ OSI**	**SYMX**
AFFX_														
COGX_	0.524													
CV_SUS	0.340	0.292												
EPVAL_CUR	0.633	0.474	0.309											
EV_ENJO	0.684	0.488	0.317	0.627										
EV_VSE	0.442	0.335	0.303	0.579	0.408									
FV_COL	0.136	0.224	0.223	0.119	0.206	0.228								
FV_CONV	0.440	0.356	0.242	0.382	0.467	0.268	0.218							
FV_SP	0.575	0.442	0.899	0.476	0.510	0.412	0.210	0.366						
INTEN_	0.560	0.538	0.315	0.452	0.493	0.336	0.227	0.380	0.490					
PINVOL_	0.395	0.408	0.172	0.321	0.371	0.284	0.344	0.283	0.303	0.477				
RELX_	0.625	0.336	0.459	0.459	0.446	0.445	0.143	0.360	0.591	0.461	0.381			
SV_OSI	0.156	0.150	0.258	0.097	0.182	0.110	0.200	0.071	0.312	0.209	0.133	0.296		
SYMX_	0.438	0.358	0.696	0.316	0.402	0.379	0.211	0.240	0.666	0.401	0.319	0.530	0.211	

Table 7: Hypotheses testing using SmartPLS

Hypothesis	**Coefficient**	**t-Value**	**p-Value**
H1a: Functional value (convenience) → Cognitive experience	0.122	4.027	.000
H1b: Functional value (cognitive offloading) → Cognitive experience	0.056	2.001	.046
H1c: Functional value (shopping personalization) → Cognitive experience	0.195	6.346	.000
H2: Social value (online social interactivity) → Relational experience	0.230	9.808	.000
H3a: Emotional value (enjoyment) → Affective experience	0.323	10.271	.000

H3b: Emotional value (virtual self-expression) → Affective experience	0.110	4.366	.000
H4a: Epistemic value (curiosity) → Cognitive experience	0.242	7.693	.000
H4b: Epistemic value (curiosity) → Affective experience	0.251	8.030	.000
H5: Conditional value (sustainability) → Symbolic experience	0.558	31.393	.000
H6a: Functional value (convenience) → Cognitive experience → Intention to use AR	0.033	3.660	.000
H6b: Functional value (cognitive offloading) → Cognitive experience → Intention to use AR	0.019	2.238	.025
H6c: Functional value (shopping personalization) → Cognitive experience → Intention to use AR	0.053	5.264	.000
H7: Social value (online social interactivity) → Relational experience → Intention to use AR	0.031	3.720	.000
H8a: Emotional value (enjoyment) → Affective experience → Intention to use AR	0.068	5.057	.000
H8b: Emotional value (virtual self-expression) → Affective experience → Intention to use AR	0.023	3.423	.001
H9a: Epistemic value (curiosity) → Cognitive experience → Intention to use AR	0.067	5.601	.000
H9b: Epistemic value (curiosity) → Affective experience → Intention to use AR	0.053	4.628	.000
H10: Conditional value (sustainability) → Symbolic experience → Intention to use AR	0.055	3.731	.001
H11: Conditional value (sustainability) x Product involvement → Symbolic experience → Intention to use AR	-0.013	2.668	.008
H12: Emotional value (enjoyment) x Product involvement → Affective experience → Intention to use AR	-0.026	3.731	.000

CHAPTER 5: CONCLUDING REMARKS

5.1 Concluding remarks

Online retail is at a turning point as firms adopt technologies such as generative AI chatbots and augmented reality (AR) to enhance shopping experiences, while facing ongoing uncertainty about how customers will react. This dissertation explores these technologies across three studies, offering fresh insights into customer engagement, resistance, and adoption, and demonstrating how these dynamics shape technology use in e-retail (Alexander & Kent, 2022b). The contributions are both theoretical and managerial; the research advances understanding of customer responses to emerging retail technologies by identifying the mechanisms and boundary conditions that shape technology responses, and it offers guidance for managers on how to provide the technologies that empower customers, reduce barriers, and deliver meaningful experiences across different purchase contexts. At the same time, the studies acknowledge limitations, such as reliance on scenario-based and cross-sectional designs, which invite future research using field and longitudinal approaches to capture the evolving nature of technology use in e-retail. In doing so, the dissertation not only enriches theory but also provides a foundation for more effective and responsible implementation of emerging technologies in practice (Berg et al., 2024; Hoyer et al., 2020).

5.2 Theoretical contributions

This dissertation advances theoretical understanding of how emerging technologies shape customer engagement, resistance, and adoption in online retail by challenging dominant assumptions in existing literature, namely that technology adoption is primarily functionally driven and context-independent, and by developing a more nuanced and context-sensitive understanding of customer responses, this dissertation reveals the mechanisms through which customers engage with, resist, and ultimately adopt technological innovations in retail settings (Mühlburger &

Krumay, 2024). Across the studies of generative AI chatbots and AR, the findings demonstrate that adoption is not the inevitable outcome of technological novelty or functionality, but a conditional process shaped by psychological mechanisms, value priorities, and situational factors (Chylinski et al., 2020a; Zeng et al., 2023).

In relation to customer engagement, the findings from paper 1 move beyond the dominant anthropomorphism paradigm in chatbot research, which has emphasized human-like qualities as the defining driver of effectiveness (Sheehan et al., 2020; Sun et al., 2024; Van Esch et al., 2019). Generative AI chatbots advance understanding not because they mimic human conversation, but because they enhance customers' perceptions of control and decision quality when choices are complex. This perspective demonstrates the limits of the assumption that automation reliably improves outcomes, showing instead that chatbot effectiveness is contingent on contextual factors such as product type and choice complexity (Sembada & Koay, 2021; Weathers et al., 2007; Whang et al., 2021). By theorizing customer engagement as shaped by psychological mechanisms and conditioned by contextual factors, this dissertation challenges the prevailing tendency to portray AI as an inherently beneficial solution and advances a more nuanced understanding of how interactive technologies influence consumer behavior in online retail. It emphasizes that customer responses are contingent rather than automatic. By identifying perceived control as the key psychological mechanism and product type as the contextual boundary, the dissertation reframes AI engagement research around the conditions under which technology fosters, rather than guarantees, customer engagement (Fazal-e-Hasan et al., 2021; Grewal et al., 2021).

Regarding resistance, the findings reposition it as a central construct rather than a transitional hurdle. Much of the literature assumes that barriers fade once usability improves, yet in a study on barriers of AR adoption, our findings show that immersive technologies trigger barriers tied to privacy, authenticity, overconsumption, and social interaction. These barriers are not incidental but structural, reflecting the ways customers negotiate the alignment of technology with their values and identities (de Bellis & Venkataramani Johar, 2020; Foroudi et al., 2020). This dissertation reconceptualizes customer resistance to AR by challenging the assumption that improved design or greater familiarity inevitably leads to adoption. It extends innovation resistance theory (IRT) by positioning resistance as a psychological and moral response embedded in human–technology interaction rather than as an interim reaction to design flaws (Foroudi et al., 2020). From this perspective, it highlights the need to recognize the boundaries of IRT in capturing the ongoing experiential and ethical tensions that immersive technologies evoke. Accordingly, it proposes that resistance should be understood as a process of consumer sensemaking that exposes the moral and existential dimensions underlying technology adoption (Claudy et al., 2015; Koch et al., 2021; Ram & Sheth, 1989).

In relation to adoption, Paper 3 contributes to a deeper theorization of how consumption values drive technology use. Prior research often treats value as a stable predictor of intention, assuming that higher perceived value naturally leads to adoption. The findings challenge this view by showing that, in the context of AR, value is not evaluated but experienced; it takes shape through cognitive, affective, relational, and symbolic encounters that link technological features to personally meaningful outcomes (Fathima MS et al., 2023; Gahler et al., 2023; Sheth et al., 1991). This reconceptualization refines consumption value theory by clarifying how values are enacted through experience rather than simply assessed before choice. It further conceptualizes product involvement as a contextual lens that explains how situational relevance moderates the translation of value into experiential and behavioral outcomes (Celsi & Olson, 1988; Cowan & Ketron, 2019; Ha & Lennon, 2010). These findings demonstrates that positive value experiences do not automatically translate into adoption, and it introduces situational boundaries that qualify when and how value motivates customer action. By doing so, the dissertation enriches research on consumption values, customer experience, and technology adoption with a more contextualized and dynamic account of how technological features are converted into behavior (Chen & Lin, 2022; Sharma et al., 2023; Zhu et al., 2025).

Overall, these contributions move adoption theory beyond deterministic accounts that equate technological advancement with improved outcomes. They show that the impact of emerging technologies depends on whether they empower customers, address structural sources of resistance, and align with situational demands. In this way, the dissertation advances a more critical and theoretically grounded understanding of how technologies such as generative AI chatbots and AR interact with consumer psychology, values, and decision contexts in e-retail.

5.3 Managerial implications

Viewed collectively, the three papers show that the value of generative AI chatbots and AR in e-retail depends on how these technologies are designed and aligned with customer needs, product characteristics, and usage contexts. They offer managers guidance on how to deploy these tools in ways that improve decision-making, reduce resistance, and create meaningful shopping experiences. First, managers need to approach generative AI chatbots and AR with selective and strategic investment. Generative AI chatbots are not equally beneficial across all products. For search goods, where product features can be easily evaluated, detailed product descriptions, photos, and reviews can be more cost-effective than complex chatbot systems (Girard & Dion, 2010; Jiménez & Mendoza, 2013; Lim et al., 2015). Similarly, AR should be implemented where it clearly adds value. For example, try-on functions for eyewear, furniture placement in a room, or makeup shades can directly reduce uncertainty and returns. Retailers should therefore map their product portfolios and identify categories where these technologies can make a tangible difference, ensuring that investment aligns with expected returns (Sahli & Lichy, 2024; Schultz & Kumar, 2024).

Second, the effective implementation of generative AI chatbots and AR depends on how well retailers anticipate risks and overcome resistance. For chatbots, the main risks lie in misinformation, biased recommendations, or irrelevant outputs, which can quickly erode customer trust. To mitigate these risks, retailers should build in fact-checking mechanisms and create seamless escalation pathways to human agents when the chatbot cannot resolve an issue. Such safeguards preserve credibility and help customers view generative AI chatbots as reliable sources of support rather than frustrating barriers (Agnihotri & Bhattacharya, 2024; Behera et al., 2024). For AR, resistance often stems from privacy concerns, perceptions of inauthenticity, and broader ethical issues such as overconsumption. Retailers can address these barriers by making data practices transparent, offering opt-in privacy controls, and clarifying how images are stored and used (Scarpi et al., 2022). To counter perceived inauthenticity, AR previews should be supported with real product photos, customer testimonials, or side-by-side comparisons that help set realistic expectations. Together, these measures show that adoption depends not only on technical design but also on building trust through responsible and transparent practices (Rauschnabel et al., 2024; Xu et al., 2024).

Third, there is the need to design meaningful and context-sensitive experiences. Technologies should be built to support multiple pathways of customer experience. For generative AI chatbots, this means features that give customers control, such as personalized recommendations, interactive decision guides, and the ability to compare products in real time (Korzynski et al., 2023; Ooi et al., 2023). For AR, meaningful design involves personalization (body measurement–based try-on or style matching), self-expression (customizable avatars or styling options), and sustainability cues (showing how AR virtual try-on reduces returns and waste). Crucially, these features should be tailored to the product involvement level (Ha & Lennon, 2010; Hwang et al., 2020; Kumar et al., 2024). In high product involvement categories such as appliances or professional electronics, AR should emphasize accuracy, interactive demonstrations, and detailed side-by-side comparisons to support careful evaluation. In low product involvement categories such as accessories or fashion items, playful filters, social sharing tools, and creative customization are more effective in increasing customer intention to involve such technology in their shopping journey. By aligning design choices with the stakes of the purchase, retailers can ensure that chatbots and AR enhance rather than frustrate the shopping journey (Plotkina et al., 2022; Romano et al., 2021).

As a whole, these findings suggest that managers should view generative AI chatbots and AR not as universal solutions but as tools whose value depends on fit with context. Retailers that invest selectively, address customer concerns with transparency and safeguards, and tailor design to product involvement can move beyond experimentation and turn these technologies into reliable drivers of customer engagement, trust, and long-term business value.

5.4 Limitations and further research

Across the three studies, several common limitations emerge that also suggest avenues for future inquiry. A first limitation concerns method and time horizon. Study 1, which examined generative AI chatbots with US participants, relied on scenario-based experiments. While this design offered strong control and internal validity, it cannot fully capture how customers engage with chatbots in actual retail environments. Studies 2 and 3, both conducted with UK participants, used cross-sectional surveys, providing only snapshots of customer resistance and adoption at a single point in time (Hartzel et al., 2016; Venkatesh & Davis, 2000). These approaches are valuable for identifying mechanisms but cannot track how attitudes and behaviors shift as customers gain experience, technologies advance, or societal expectations evolve. Future research should employ longitudinal and field designs, embedding chatbots and AR in live retail platforms and following users over time to capture the dynamics of engagement, resistance, and adoption (Jayaswal & Parida, 2023b; Skjuve et al., 2022).

A second limitation relates to scope and perspective. Study 1 focused on customers' engagement responses in controlled scenarios, Study 2 on UK non-adopters of AR, and Study 3 on UK adopters of AR. Each perspective offers valuable insights, yet on their own they capture only facets of the broader adoption process. A fuller picture of technology adoption requires integrating the views of adopters and non-adopters, as well as examining customers across different cultural contexts (Hoehle et al., 2015). Cross-cultural research would help clarify how technological infrastructure, cultural values, and market maturity shape adoption and resistance patterns, extending the applicability of these findings beyond single-country contexts (Magliocca et al., 2024).

A third limitation concerns risks and governance. Study 1 highlighted that generative AI chatbots, while engaging, may also produce inaccurate or biased outputs, creating risks of misinformation, unfairness, and erosion of customer trust (Christou et al., 2024; Følstad et al., 2021; Sigala et al., 2024). Study 2 revealed that AR adoption is constrained not only by functional risks but also by deeper concerns, including privacy, perceived inauthenticity, and ethical issues such as overconsumption and reduced social interaction. These findings emphasize that adoption cannot be explained by technical functionality alone. Future research should therefore investigate how transparency, oversight, and responsible design can address both operational risks and ethical concerns, ensuring that emerging technologies foster confidence and long-term acceptance (Murtarelli et al., 2021; Wright, 2011).

Overall, these limitations highlight the importance of future research that is longitudinal, cross-cultural, and multi-perspective, while also addressing governance and ethical issues. Such work would build a more comprehensive and dynamic understanding of how generative AI chatbots and AR shape customer engagement, resistance, and adoption in online retail.

5.5 References

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