



Consumer Acceptance of Chatbot Recommendations: How Chatbot Design, Product Type and Brand Personality Shape Adoption

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Abstract

Chatbots, once primarily used for customer support and FAQ handling, are increasingly deployed by brands to provide personalized product recommendations in e-commerce. This shift expands their role from problem-solving assistants to proactive advisors shaping purchase decisions. Despite this potential, consumer adoption of chatbot-generated recommendations remains inconsistent. While prior research has examined mostly psychological and emotional factors as drivers, less is known about how contextual factors shape adoption. The purpose of this dissertation is to analyze the effects of chatbot design, product type and brand personality.

A 2×2×2 experimental design tested differences between anthropomorphic and non-anthropomorphic chatbots, hedonic and utilitarian products, and modern versus traditional brands. Cognitive involvement and perceived consistency induced by the experimental conditions were also measured. Results show that recommendation adoption is higher for utilitarian products, anthropomorphic chatbots, and modern brands. However, perceived consistency emerged as the strongest predictor of adoption, mediating the effects of chatbot design and brand personality. Cognitive involvement, although higher for hedonic products, did not significantly influence adoption.

This research contributes to consumer behavior and AI adoption literature by showing that contextual alignment, rather than isolated design features, drives acceptance of chatbot recommendations. For managers, the findings emphasize that chatbot implementation should be matched with product type and brand positioning, with the greatest benefits for utilitarian goods and modern brands.

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Keywords: artificial intelligence, AI-generated recommendations, chatbots, recommendation adoption, anthropomorphism, brand personality, product type, consumer behavior, purchasing decisions

Resumo

Os chatbots, inicialmente usados sobretudo para suporte ao cliente e FAQs, estão a ser cada vez mais utilizados pelas marcas para oferecer recomendações personalizadas no e-commerce. Esta evolução amplia o seu papel, de assistentes reativos para conselheiros ativos que influenciam decisões de compra. Contudo, a adoção pelos consumidores de recomendações geradas por chatbots ainda é irregular. Enquanto estudos anteriores se focaram essencialmente em fatores psicológicos e emocionais, pouco se sabe sobre o impacto de fatores contextuais. O objetivo desta dissertação é analisar os efeitos do *chatbot design*, do tipo de produto e da personalidade da marca.

Um estudo experimental 2×2×2 avaliou diferenças entre chatbots antropomórficos e não antropomórficos, produtos hedónicos e utilitários, e marcas modernas versus tradicionais. Também foram medidas a consistência percebida e o envolvimento cognitivo. Os resultados indicam maior adoção das recomendações para produtos utilitários, chatbots antropomórficos e marcas modernas. Porém, a consistência percebida mostrou-se o preditor mais forte, mediando os efeitos do design e da personalidade da marca. O envolvimento cognitivo, apesar de mais elevado em produtos hedónicos, não influenciou significativamente a adoção.

A pesquisa contribui para a literatura de comportamento do consumidor e adoção de IA ao demonstrar que o alinhamento contextual, mais do que características isoladas, impulsiona a aceitação de recomendações. Para os gestores, as conclusões do estudo destacam que a implementação de chatbots deve ser ajustada ao tipo de produto e ao posicionamento da marca, com maiores benefícios em bens utilitários e marcas modernas.

Título: Aceitação das Recomendações dos Chatbots pelos Consumidores: Como o Design dos Chatbots, o Tipo de Produto e a Personalidade da Marca Influenciam a Adoção

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Palavras-chave: inteligência artificial, recomendações geradas por IA, chatbots, adoção de recomendações, antropomorfismo, personalidade da marca, tipo de produto, comportamento do consumidor, decisões de compra

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1. Introduction

AI has rapidly integrated into many aspects of daily life. Consumers utilize AI as personal assistant (e.g. Alexa, Siri), to plan their travels, manage their financials or control smart home applications. Businesses utilize AI's data processing capability to identify patterns, gain valuable insights, automate processes and make data driven decisions (Davenport & Ronanki 2018; Kaplan & Haenlein, 2018; Kumar et al., 2019). AI finds application in most business functions, but particularly in the domains of marketing and sales the economic potential is enormous. A McKinsey report from 2023 indicates that generative AI alone has the potential to contribute \$760 to \$1,200 billion in value through automated content creation, personalized customer interactions, optimized sales strategies and improvement of overall efficiency (Chui et al., 2023). Through these advancements, AI is not only enhancing operational effectiveness but also fostering a higher degree of customer satisfaction, which in turn influences consumer decision-making and brand loyalty. By enabling personalization along all customer touch points, companies can increase engagement, foster trust and establish stronger relationships between brands and consumers. Among these AI applications, chatbots are one of the most powerful and widely adopted tools, with the global chatbot market projected to grow at over 23% annually until 2030 (Grand View Research, 2022).

Chatbots are frequently employed in customer service settings, where they were initially designed to handle routine requests through predefined scripts, such as answering frequently asked questions or providing basic troubleshooting (Mu & Zhang, 2025). Due to the technological progression of AI tools in recent years, however, they have developed from reactive service tools to generative product advisors, guiding consumers through product choices and delivering personalized recommendations in real time (Kumar et al., 2019). This offers significant advantages, both for companies and consumers. By helping customers navigate overwhelming assortments, chatbots can reduce decision fatigue and prevent abandoned purchases, while simultaneously serving as a powerful instrument to influence purchasing decisions (Chui et al., 2023; Murtaza et al., 2024).

Despite these benefits, consumer adoption is not guaranteed. While some customers appreciate the convenience of AI-powered assistants, others remain sceptical or even resistant toward their use (Dietvorst et al., 2016; Fitzsimons & Lehmann 2004; Gomes et al., 202; Luo et al., 2019). For companies, this inconsistency presents a strategic dilemma. Firms that successfully

implement chatbots can achieve efficiency gains, cost savings, and competitive advantages. Those that fail to secure consumer acceptance, however, risk negative experiences, wasted investments, and even damage to their brand (Makarius et al., 2020). The managerial challenge is therefore no longer whether to use chatbots, but how to design and implement them in ways that foster consumer acceptance and recommendation adoption (Huang and Rust, 2018).

Previous research has primarily focused on psychological factors, such as trust and perceived competence (Longoni & Cian, 2020; Westenberger et al., 2022) or on emotions like anger and eeriness (Crolic et al., 2021; Mori, 1970). However, less is known about the contextual conditions that shape adoption. Naturally, purchasing decisions are embedded in specific product categories and brand environments. Understanding these contextual dynamics is critical, both to refine theory and to guide managerial practice.

This dissertation seeks to address this gap by examining how three contextual factors influence the adoption of chatbot-generated product recommendations: chatbot design (anthropomorphic vs. non-anthropomorphic), product type (hedonic vs. utilitarian), and brand personality (modern vs. traditional). In addition, it explores the roles of cognitive involvement and perceived consistency, two constructs well established in consumer decision-making research. Together, these factors provide a more nuanced perspective on the conditions under which consumers are likely to follow chatbot advice.

To guide this investigation, the following research questions are posed:

RQ1: Does chatbot design influence consumer adoption of chatbot-generated recommendations?

RQ2: Does product type (utilitarian vs. hedonic) affect the extent to which consumers adopt chatbot-generated recommendations?

RQ3: Does cognitive involvement influence consumer adoption of chatbot-generated recommendations?

RQ4: Does brand personality (modern vs. traditional) influence consumer adoption of chatbot-generated recommendations?

RQ5: Does consistency affect consumer adoption of chatbot-generated recommendations?

1.1 Managerial and Academic Relevance

The academic relevance of this research lies in extending the literature on AI adoption and consumer decision-making to the realm of chatbots. While prior studies have mainly emphasized individual emotions or psychological factors, this dissertation shows that consumer acceptance is also strongly shaped by contextual factors. It adds to emerging work that examines how consumers respond differently depending on the alignment between technological features, product characteristics and brand positioning. By integrating these perspectives, the study advances theoretical understanding of how consumers adopt chatbot-generated recommendations in e-commerce contexts.

From a managerial perspective, this dissertation provides guidance for companies on whether and how to implement chatbots, so that recommendation adoption is fostered rather than hindered. By examining how chatbot design, product type and brand personality interact, the study reflects the natural conditions in which purchase decisions are embedded and provides managers with insights into when customers may be more receptive to chatbot advice. These insights can help companies to evaluate whether employing chatbots as recommendation agents fits their unique product assortment and brand positioning, make more informed investment decisions and design interactions that create value for both the company and the consumer.

1.2 Dissertation Outline

This dissertation is structured as follows: Chapter 2 reviews the existing literature on artificial intelligence in business, the application of chatbots in e-commerce and critical factors influencing consumer adoption of chatbot-generated recommendations. Chapter 3 details the research methodology, including the experimental design, manipulations, sampling procedure and measurement instruments. Chapter 4 presents the results of the empirical analysis, covering descriptive statistics, reliability and manipulation checks, hypothesis testing and exploratory analyses. Chapter 5 discusses the findings in relation to the theoretical framework and prior studies and concludes with managerial implications, limitations and recommendations for future research. Chapter 6 highlights the study's limitations and suggests avenues for future research.

Chapter 7 concludes with a summary of the key findings and overall contributions.

2. Literature Review

2.1 Definition of Artificial Intelligence

AI can be defined as “programs, algorithms, systems and machines that demonstrate [human] intelligence” (Huang and Rust 2018; Shankar, 2018). It relies on various technologies, including machine learning, natural language processing, rule-based expert systems, neural networks, deep learning, physical robots and robotic process automation (Davenport, 2018). While AI can be trained to replicate certain human cognitive abilities within a defined task (Kumar et al., 2019), it lacks the ability to truly think, reason, learn and judge, nor does it possess cognitive capabilities that surpass those of humans (IBM, 2023). However, it can analyse vast amounts of data and master complex tasks with greater efficiency.

Current AI systems are typically classified into two subtypes, which represent the most advanced forms of AI available today (IBM, 2023). “Reactive Machine AI” does not have a memory and can only process real-time data. It can be encountered in applications such as computer games, smart home and wearable health monitoring devices or streaming recommendations like those of Netflix and Spotify. “Limited Memory AI” is able to recall past data like events and outcomes for some time but lacks the capability to store data long term. Chatbots are an example of this technology, among self-driving cars and generative AI tools.

2.2 Exploration of Chatbots

2.2.1 Definition and Evolution of Chatbots

Chatbots are intelligent virtual assistants that are capable of holding human-like conversations (Kumar et al., 2019). They can interact verbally, through texting and speaking and non-verbally by providing videos, images or documents. The first chatbot in existence was Eliza, a technology developed by a computer scientist in 1964 (Stryker & Scapicchio, 2024). While early chatbot models relied on basic pattern-matching techniques to simulate human interaction without true comprehension, the integration of natural language processing (NLP) and speech recognition marked a turning point. More interactive and dynamic conversations became reality, promoting chatbots to be personal assistants, exemplified by Apple’s Siri and Amazon’s Alexa. Recent

advancements in AI have revolutionized chatbot capabilities further, allowing them to understand user intent and generate highly contextual and adaptive responses. This transformation has catapulted us into the era of generative AI, driven by OpenAI's launch of their Generative Pretrained Transformer (GPT) in 2018. Since then, the progression took on speed vastly, with the realization of advanced language models GPT-3 and GPT-4 in 2020 and 2023 respectively. Today, chatbots have become almost indistinguishable from human agents in many cases.

2.2.2 Application of Chatbots in E-Commerce

Chatbots play a crucial role in modern e-commerce, as they offer a range of functionalities that improve the customer experience (Kumar et al., 2019) and optimize business operations. Their primary function is customer service and support: handling high volumes of customer inquiries, providing instant responses to frequently asked questions, troubleshooting issues and, if necessary, establishing contact to human assistants (Mu & Zhang, 2025). They can also provide information about restocks, assist with order tracking by giving shipping updates and handle returns. While previously chatbots were primarily utilized for post purchase customer service, more recently their role has been expanded into pre-purchase assistance too. Chatbots have become AI-powered personal shopping assistants, enabling consumers to actively participate in the customization process by completing detailed questionnaires about their physical attributes and product preferences or uploading photos of themselves. This heightened level of personalization not only enhances the shopping experience but also significantly boosts customer satisfaction and subsequently purchase likelihood (Al-Hyari et al., 2023; Bhattacharya et al., 2018; Gomes et al., 2025; Lee et al., 2021). Examples of such chatbots can be observed on various online shops including those of Olay and Persil (see Appendix A).

The type of chatbot currently employed by most brands still relies primarily on static algorithms. However, recent technological advancements have enabled chatbots to memorize browsing history and past purchasing data, adapt dynamically to user input and refine their suggestions in real time (Kumar et al., 2019). This shift further enhances personalization and thus potential to influence purchasing decisions (Gomes et al., 2025). Given the rapid pace of AI adoption recently, it is reasonable to expect that generative chatbots will become increasingly common on web shops in the near future.

2.2.3 Benefits of Chatbots in E-commerce

As mentioned previously, AI chatbots offer many benefits to companies and to their customers. In contrast to human agents, they are available 24/7 (Mu & Zhang, 2025), which significantly improves customer satisfaction. Their capacity to serve customers is only limited to technological boundaries. Thus, in practice, waiting times are reduced to zero and response speed is vastly increased. Additionally, chatbots can assist in any existing language, whereas humans are typically limited to speaking only a few languages. This fosters accessibility for a global customer base and decreases the risks of misunderstandings. While humans are prone to make errors due to a lack of knowledge or concentration, chatbots retain and accurately recall all the information they have been trained on, ensuring consistency and focus all the time. They can also decrease search time by helping users to navigate through product catalogues efficiently. Instead of manually searching through hundreds of product pages, customers can simply describe in detail what they are looking for and will be given relevant information and tailored suggestions in real-time. As AI tools continuously learn from user interactions, they are capable of refining their predictive accuracy regarding individual preferences. Over time, this adaptability heightens the relevance of recommendations, thereby elevating the value delivered to customers across the entire customer lifecycle (Kumar et al., 2019). Additionally, by reducing information overload, chatbots simplify decision-making which is particularly important in today's world of choice abundance and will become even more prevalent with further advancements in NLP. In the future, chatbots could be enabled to fully automate purchases based on prompts like "Find me the best monitor for my computer".

The described proactive personalization increases the likelihood of purchase completion, as each interaction feels tailored and relevant, thus leading to higher revenue generation. This effect is further amplified by the employment of generative AI, through deepened customer engagement (Hardcastle et al., 2025). Beyond that, chatbot recommendations empower companies to steer buying decisions by vastly influencing customer behaviour (Statista, 2024).

Overall, companies severely benefit from AI chatbots in terms of operational efficiency and firm performance. AI chatbots can significantly increase efficiency and achieve substantial cost savings by automating routine tasks in customer service, such as answering customer inquiries, processing orders and providing personalized recommendations (Al-Hyari et al., 2023; Kumar et al., 2019; Mu & Zhang, 2025). A study by McKinsey highlights that these services account

for 60 to 70% of employees' working time, demonstrating how AI-powered customer service spares human resources for more creative tasks (Chui et al., 2023). By reallocating human capacities more effectively, companies can reduce their dependence on large customer support teams while simultaneously improving response times. Luo et al. (2019) found, that chatbots perform equally well as trained sales assistants but are four times more effective than inexperienced ones, further underlining their transformative impact. In general, the employment of AI tools like chatbots improves business performance through increased customer satisfaction (Fitzsimons & Lehmann, 2004; Mu and Zhang, 2025).

Furthermore, AI chatbots can have a significant impact on customer acquisition and retention (Mu & Zhang, 2025). Conversations between customers and AI represent a valuable channel to gather customer data from. The chatbot's ability to store and analyze massive amounts of information allows for deeper insights into consumer preferences, needs and purchasing patterns. Thus, businesses can improve their customer segmentation and refine their marketing strategies with greater precision, resulting in significantly higher acquisition rates. Additional important factors in customer acquisition and retention include brand image and customer satisfaction. Companies that integrate AI-driven solutions into their customer service strategies are often perceived as innovative and forward-thinking, reinforcing a modern brand image. By addressing customer needs and preferences more effectively than simpler algorithms or humans, chatbots significantly increase customer satisfaction. The ability to provide highly personalized and interactive shopping experiences elevates the purchasing experience, thereby creating value and deepening customer engagement (Akdin & Casaló, 2023). Particularly generative chatbots enable more engaging and contextually relevant conversations, which strengthens the relationship between company and customer (Mu & Zhang, 2025). The enriched interactions contribute to stronger emotional and cognitive bonds, which play a vital role in fostering lasting brand loyalty (So et al., 2012).

Ultimately, chatbots are a comparatively low cost but highly impactful tool to firms (Mu & Zhang, 2025), maximizing both customer satisfaction and profitability. Heightened engagement, increased customer satisfaction and improved business performance stemming from their employment create a competitive advantage. However, as the adoption of AI tools becomes increasingly widespread, their use may no longer be a strategic differentiator but rather a baseline expectation. In this context, companies that fail to implement such technologies risk falling behind their competitors and may ultimately face a loss of market relevance. Maintaining

competitiveness in a digitally driven environment will likely require the integration of AI-driven solutions as a standard component of customer service and engagement strategies.

2.2.4 Challenges and Risks of Chatbots in E-Commerce

Despite their numerous advantages, AI chatbots in e-commerce face severe challenges and risks. One of the primary concerns is accuracy and reliability of chatbot responses (Dietvorst et al., 2016; Grewal et al., 2024). While AI chatbots have proven to be more accurate than humans, they are not error-less. In some cases, they may provide incorrect or irrelevant information or make wrong predictions. This could potentially lead to mismatched recommendations and suboptimal user experiences, ultimately resulting in customer frustration and loss of trust. Another hurdle is data privacy, although related concerns are less prevalent with customized models integrated into company websites. Furthermore, AI chatbots have limitations in handling some customer needs. While they excel at managing routine tasks, they may struggle with ambiguous or emotionally charged interactions that require human empathy and judgment. Although some AI models are already able to scan language, voice or facial expressions for emotional cues, true emotional understanding remains beyond current technological capabilities (Davenport et al., 2019). This limitation can have notable consequences for customer interaction quality: AI chatbots may fail to respond appropriately to frustration, dissatisfaction, or confusion (Zhang et al., 2024). Particularly in the cases of sensitive topics, this may lead to reduced trust and satisfaction (Gomes et al., 2025). Consequently, companies risk their relationship with the customers (Mu & Zhang, 2025).

The potentially most critical challenge regarding chatbots, which shall be explored extensively throughout this thesis, is consumer adoption and acceptance (Gomes et al., 2025). While some customers appreciate the convenience of AI chatbots, others may be sceptical about them or even express a level of aversion (Dietvorst et al., 2016). Among most individuals, innovations frequently lead to increased perceptions of risk and uncertainty (Kim et al., 2021). Thus, consumer adoption of chatbots tends to be very subjective and irrational (Luo et al., 2019). For some people, knowing there is a machine behind the virtual assistant instead of a human, immediately leads to reduced perceived empathy and credibility and dramatically affects purchase behavior. In their study, the purchasing rate declined by almost 80%. Recent studies suggest that data security and usage concerns no longer represent a primary concern for most users. As AI becomes increasingly integrated into everyday life, many users now perceive the

benefits of it as outweighing the risks, namely any privacy concerns (Chen et al., 2021).

2.3 Chatbot Recommendations and Consumer Decision-Making

2.3.1 The Role of Chatbots in Shaping Consumer Decision-Making

In today's environment of unlimited choice, consumers are often overwhelmed, and decision making becomes difficult (Fitzsimons & Lehmann, 2004; Morrison & Firmstone, 2000). This can result in negative outcomes for businesses, such as shopping cart abandonment. Statistical observations in 2024 have shown that the average conversion rate in B2C E-commerce is only approximately two percent (Statista, 2025). Therefore, it has become increasingly important for companies to actively influence customer decision-making. Expert advice has long played a crucial role in shaping decisions, and its influence has been significantly amplified in the digital age (Fitzsimons & Lehmann, 2004). Virtual assistants, such as chatbots, allow firms to actively guide and influence the choices of their customers in a simple but effective way. Thereby, opportunities for upselling and cross-selling are created, making them a highly attractive instrument for brands engaging in digital commerce (Chui et al., 2023). However, they are one of the least understood online tools currently.

Kumar et al. (2019) illustrated how AI contributes to personalized engagement by expanding classic decision-making theory. They connected various elements of the customer decision-making process with AI capabilities and customer experience outcomes. According to their findings, the two critical elements influencing a decision are 1) choice criteria and 2) knowledge management and organization. Choice criteria consist of the presence of alternatives, the formation of a consideration set, the differentiation between routine and abnormal decisions and the creation of a decision plan, while knowledge management and organization focus on rule development. Here, chatbots can add value by providing curated and personalized information to customers, narrowing alternatives and organizing knowledge structures. As previously discussed, recommendations can reduce cognitive effort and reduce uncertainty.

Kim et al. (2021) found that AI-generated recommendations can serve as anchors in the customer decision-making process. They build upon the anchoring-and-adjustment heuristic introduced by Tversky and Kahneman (1974), which suggests that individuals tend to rely heavily on an initial piece of information when forming judgments, adjusting insufficiently from this reference

point. Subsequently, the comparison and perception of alternative choices is biased, actively influencing customer decisions. Wang et al. (2022) showed that in AI-assisted decision-making, individuals aggregate their own judgments with the recommendations provided by the AI. They argue, that agreement with the recommendation and confidence in personal judgement moderates their tendency. While anchoring and aggregating represent different cognitive mechanisms, they may operate simultaneously. Customers may initially be anchored by the AI's recommendation, which then serves as a reference point in a broader aggregation process.

Depending on how AI recommendations are perceived, they can either trigger compliance or resistance in customers. Thus, the following section aims to explore the conditions under which customers are more likely to adopt or reject recommendations provided by virtual assistants.

2.3.2 Critical Factors Influencing Acceptance and Resistance Toward Chatbot Recommendations

Despite the high levels of accuracy and performance that chatbots are capable of delivering, recent evidence has shown that humans remain hesitant to accept AI-generated recommendations (Castelo et al., 2019; Dietvorst et al., 2016; Longoni et al., 2019). This reluctance is primarily rooted in psychological, contextual and emotional factors that steer users either in the direction of acceptance or resistance.

Akdim and Casaló (2023) explain customer adoption of AI generated recommendations with a cost-benefit framework. In this model, perceived benefits, such as convenience, compatibility and personalization are weighed against perceived costs, including cognitive effort and intrusiveness. If the perceived benefits outweigh the costs, value is created, which fosters the intention to follow recommendations. Social presence also plays a crucial role in the value creation process. The feeling of interacting with a socially responsive agent enhances the sense of personalization, convenience and compatibility, while simultaneously reducing perceived intrusiveness. Previous research proposes that social presence is induced by anthropomorphic recommendation agents (Qiu & Benbasat, 2009).

Moreover, customer acceptance of chatbot recommendations is strongly shaped by psychological factors such as trust and perceived competence. Trust can be enhanced when recommendations are seen as objective, accurate and aligned with consumers' own tendencies

(Fitzsimons & Lehmann, 2004; Garvey et al., 2022; Kim et al., 2021) but decreases when AI lacks human qualities (Castelo, 2019; Gray, 2017) or provides unsolicited advice that triggers reactance (Fitzsimons & Lehmann, 2004; Wang et al., 2022). Consumers are more receptive when chatbots assist with analytical tasks, but resist in affective, intuitive, high-stakes, or identity-relevant decisions, where reliance on AI feels risky or inappropriate (Castelo, 2019; Davenport et al., 2019; Guszczka et al., 2017; Jarrahi, 2018; Leung et al., 2018; Longoni et al., 2019; McAfee et al., 2012; Morewedge, 2022; Wang et al., 2022). These findings reflect the perceived limit of AI's competences, particularly its lack of emotional and social intelligence. If a chatbot is perceived as incompetent in assisting in a decision, its recommendation may be rejected (Longoni & Cian, 2020).

2.3.2.1 Chatbot Design and its Influence on Recommendation Adoption

Key Dimensions and Benefits of Anthropomorphized Chatbot Design

Anthropomorphism in the context of chatbots can be defined as the “attribution of human characteristics and goals to non-human agents” (Adam et al. 2020). According to early research by Turing (1950), chatbots should resemble humans as closely as possible. Since then, perceived humanness has been a guiding design principle in chatbot development.

Anthropomorphized design can be achieved both verbally and visually. Verbal cues include natural language, self-disclosure, expressions of gratitude and personalized responses (Feine et al., 2019), while visual cues may include facial expressions and gestures expressed through avatars (Rapp et al., 2021). Prior research consistently demonstrates that such cues shape how users perceive and interact with chatbots. Reeves and Nass (1996) argue that customers respond more positively to anthropomorphized technologies, because they are perceived as more natural and less effortful to interact with (Sundar, 2008).

Gomes et al. (2025) identify five core dimensions that shape the perception of anthropomorphism in chatbots: interaction, entertainment, customization, credibility and communication. Interaction refers to the chatbot's ability to engage in a dynamic and responsive conversation style that mimics human dialogue. Entertainment captures the chatbot's potential to make interactions enjoyable, which adds hedonic value. Customization emphasizes tailoring responses to individual preferences, increasing the perception of personal relevance. Credibility

is linked to how trustworthy the chatbot is perceived and communication refers to the clarity and human-like tone of the language used. These five dimensions collectively contribute to the perception of the chatbot as a human-like entity, raising trust, engagement, satisfaction and loyalty.

Qiu and Benbasat (2009) demonstrate that anthropomorphic recommendation agents increase social presence, which is defined as the extent to which a user perceives a virtual assistant as a socially and emotionally aware entity (Rafaeli & Noy, 2005; Zhang et al., 2012). Social presence has been shown to foster a stronger emotional connection between users and chatbots, thereby enhancing trust, engagement and satisfaction (Lee & Choi, 2017; Qiu & Benbasat, 2009; Rafaeli & Noy, 2005; Zhang et al., 2012). Adam et al. (2020) offer further support for the relevance of social presence by proving that it mediates the relationship between anthropomorphic cues and user compliance. Van Doorn et al. (2016) propose that when social presence closely resembles human-to-human interaction, consumers are more inclined to attribute qualities such as warmth and competence to the virtual assistant. Subsequently, users begin to perceive AI not just as a functional tool, but as a socially intelligent entity, fostering higher levels of trust (Akdin & Casaló, 2023; Cheng et al., 2022).

Risks of Anthropomorphized Chatbot Design

While numerous studies confirm the benefits of anthropomorphic traits in chatbots, some studies have raised concerns about excessive anthropomorphism (Ciechanowski et al., 2018; Song & Shin, 2022), building upon the „uncanny valley" phenomenon by Mori (1970). This theory suggests that humanlike characteristics lead to increased AI adoption only until a certain level, after which the resemblance becomes unnerving and can decrease customer satisfaction. However, the existence and boundaries of the uncanny valley remain contested (Saygin et al., 2011; Seyama & Nagayama, 2007; Walters et al., 2007) and appear to be highly context dependent. For instance, Crollic et al. (2021) show that when customers enter chatbot interactions in an angry emotional state, anthropomorphism reduces satisfaction, firm evaluations and purchase intentions, whereas no such effect occurs in non-angry states. Mende et al. (2019) further demonstrate that in the case of humanoid service robots, adverse effects of anthropomorphism are mitigated when consumers experience a strong sense of social connectedness. By contrast, in the domain of chatbots, Sheehan et al. (2020) find no evidence of negative effects of anthropomorphism, neither among users high in need for human interaction

nor among those low in this need.

Taken together, past research highlights that anthropomorphic chatbot design fosters perceptions of humanness and social presence, which translate into greater trust, engagement and satisfaction. While potential risks such as discomfort or frustration have been noted, these appear situational and less relevant in chatbot contexts, where empirical evidence even shows no adverse effects (Sheehan et al., 2020). Although specific research on recommendation adoption in chatbot contexts is limited, prior studies indicate that trust, satisfaction and engagement are key antecedents of usage intention and compliance (Adam et al., 2020; Qiu & Benbasat, 2009). Since recommendation adoption represents a specific form of usage intention and compliance, it can be expected that anthropomorphized chatbots lead to higher adoption of chatbot generated recommendations compared to machine-like chatbots.

Thus, we hypothesize that:

H1: Chatbot design has a significant effect on consumer adoption of AI-generated recommendations, with anthropomorphized chatbots leading to higher adoption than machine-like chatbots.

2.3.2.2 Product Type and its Influence on Recommendation Adoption

The type of product a company offers is not only central to its market positioning and embedded within its brand strategy, but it also shapes how consumers evaluate and respond to AI-based interactions. Product type plays a crucial role in determining customer adoption of chatbot-generated recommendations, due to differences in the underlying decision-making process. Customers whose purchasing motives are hedonic, meaning pleasure, enjoyment and experience oriented, are more likely to engage in the peripheral route of information processing (Childers et al., 2001). In this case, affective involvement is high and cues and heuristics are relied on more often. In contrast, consumers with utilitarian motives are more likely to adopt the central route, which is characterized by high cognitive involvement and rational, attribute-based evaluation (Batra & Ahtola, 1991).

Prior research on chatbot acceptance has mainly differentiated products into material and experiential (Jin & Zhang, 2025) or functional and experiential (Ruan & Mezei, 2022). However,

this distinction overlaps considerably with the established distinction between hedonic and utilitarian products, especially in conceptual terms. Material products are generally evaluated similarly to utilitarian goods, while experiential products resemble hedonic goods in their emphasis on affective and experiential value (Batra and Ahtola, 1991; Childers et al., 2001; Van Boven & Gilovich, 2003). Building on this similarity, the present thesis adopts the distinction between utilitarian and hedonic products and transfers findings from previous research on material and experience products to this framework.

Jin and Zhang (2025) show that customers are more likely to accept chatbot recommendations for material products where competence and objectivity are prioritized. The reason for that is that users ascribe these attributes rather to AI than humans. For experiential products on the other hand, customers tended to neglect recommendations by AI, because of their shortcomings regarding affect and emotion, two factors deemed essential for evaluating experiential products. Ruan & Mezei (2022) found that for functional products, assistance by chatbots increases customer satisfaction. Conversely, for experiential products, satisfaction decreased when customers were assisted by a virtual assistant instead of a human. Longoni & Cian (2020) activated either hedonistic or utilitarian attributes of a product in consumer minds and measured the resulting preference for human versus AI assistants. They found out that AI advisors are chosen more often when functional attributes are salient. Conversely, when customers are focused on hedonic attributes, human assistance is preferred. Similarly, it was found that recommendations by humans also generate stronger purchase intentions for hedonic products than AI-generated recommendations (Wien & Peluso, 2021).

These findings indicate that in the case of utilitarian products, consumers are more likely to adopt AI-generated recommendations than for hedonic products.

Thus, we hypothesize:

H2: Product type influences consumer adoption of AI-generated recommendations, with utilitarian products leading to higher adoption than hedonic products.

2.3.2.3 Cognitive Involvement and its Influence on Recommendation Adoption

Longoni & Cian (2020) emphasized the important role of cognitive involvement. When emotional or identity-relevant aspects are salient, cognitive involvement is heightened and the preference for human advisors becomes stronger. These findings are in line with insights by Morewedge (2022) and Leung et al. (2018), who claim that consumers show aversion toward AI chatbots particularly in decisions that are central to their identity. Moreover, studies by Wang et al. (2022) and Davenport et al. (2019) reveal that when the stakes of a decision are high, individuals tend to adopt AI generated recommendations less likely. Instead, they rely more heavily on their own judgments. Wien and Peluso (2021) further support this by showing that, in the case of a hedonic product, customers experienced self-reference (the association of a product with oneself through evoked emotions) which, in turn, increased the purchase intention when the recommendation came from a human. This is explainable by the heightened involvement that occurs when consumers perceive a decision as personally meaningful (Greenwald & Leavitt, 1984; Zaichkowsky, 1985). Consequently, it can be assumed that, under high involvement, customers tend to ignore or reject chatbot-generated recommendations. Building upon these insights, we hypothesize:

H3: Cognitive involvement influences consumer adoption of AI-generated recommendations, with lower involvement leading to higher adoption than higher involvement.

2.3.2.4 Brand Personality and its Influence on Recommendation Adoption

Brand personality, defined as “a set of human characteristics associated with a brand”, plays a central role in shaping consumer perceptions (Aaker, 1997). It is a powerful predictor of positive consumer attitudes, trust and loyalty. Aaker’s framework distinguishes five core dimensions: sincerity, excitement, competence, sophistication and ruggedness. While prior research has extensively studied the impact of AI implementation on brand personality, the reverse, how brand personality influences the acceptance of AI-generated recommendations, remains largely unexplored. Addressing this gap is essential, as it is reasonable to assume that brand personality shapes how consumers evaluate interactions with AI agents.

However, consumers may evaluate the same AI interaction differently depending on whether it aligns with the brand’s perceived personality or values. In the context of frontline service,

greater alignment between service design and brand image has been shown to foster more positive brand attitudes and strengthen brand equity (Sirianni et al., 2013; Wentzel, 2009). Park (2019) extended this finding to the use of chatbots, demonstrating that inconsistency between chatbot characteristics and brand personality may harm the image of a brand. Choi et al. (2022) show that customers are more likely to respond negatively to the implementation of service robots when the brand has a sincere rather than an exciting personality. They explain this outcome with the perceived mismatch between the warm, friendly and traditional character of a sincere brand and the use of impersonal, mechanized service agents. In contrast, brands with an exciting personality (e.g. youthful, trendy, innovative) may benefit from chatbot implementation. For these brands, the adoption of new technologies like service robots, regardless of contact level, aligns well with their brand personality. In support of these findings, Yang and Hu (2021) find that customers tend to favour AI-powered customer service when a brand is perceived as competent (e.g. intelligent, efficient, reliable) but prefer human assistance when the brand is perceived as sincere.

Although Aaker's (1997) framework distinguishes five brand personality dimensions, prior research highlights especially sincerity and excitement as most relevant for evaluating technology adoption (Choi et al., 2022; Yang & Hu, 2021). For the purpose of this study, we collapse the five dimensions into a pragmatic distinction between traditional and modern brands. Building on Aaker (1997) and Choi et al., (2022), we argue that modern firms are perceived similarly as exciting brands whereas traditional companies are viewed as sincere. This contrast captures brands associated with warmth and trust versus those associated with innovation and excitement. Thus, we expect brand personality to influence chatbot recommendation adoption in such way that:

H4: Brand personality influences consumer adoption of AI-generated recommendations, with modern brands leading to higher adoption than traditional brands.

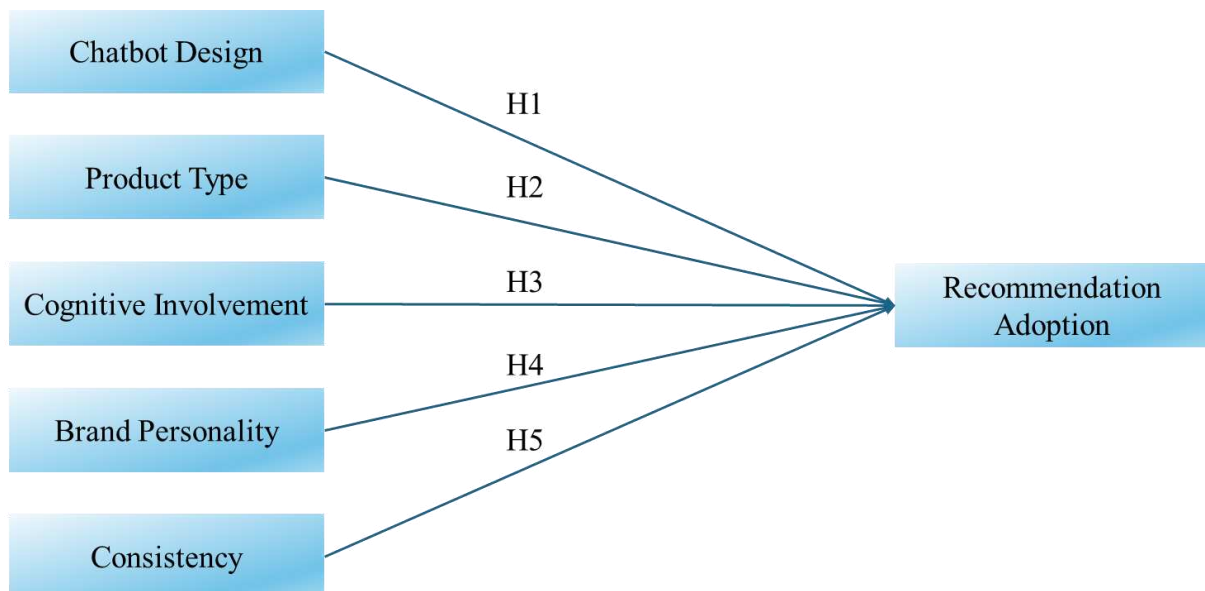
Beyond the direct influence of brand personality, prior studies highlight the importance of congruence. Misalignment can undermine trust, while alignment strengthens favourable consumer responses (Choi et al. 2022; Park, 2019; Sirianni et al., 2013). Therefore, we propose:

H5: Consistency influences consumer adoption of AI-generated recommendations, with higher consistency conditions leading to higher adoption than lower consistency conditions

Table 1: Research Questions and Hypotheses

Research Question	Hypothesis
RQ1: Does chatbot design influence consumer adoption of chatbot-generated recommendations?	H1: Chatbot design has a significant effect on consumer adoption of chatbot-generated recommendations, with anthropomorphized chatbots leading to higher adoption than machine-like chatbots.
RQ2: Does product type (utilitarian vs. hedonic) affect the extent to which consumers adopt chatbot-generated recommendations?	H2: Product type influences consumer adoption of chatbot-generated recommendations, with utilitarian products leading to higher adoption than hedonic products.
RQ3: Does cognitive involvement influence consumer adoption of chatbot-generated recommendations?	H3: Cognitive involvement influences consumer adoption of chatbot-generated recommendations, with lower involvement leading to higher adoption than higher involvement.
RQ4: Does brand personality (modern vs. traditional) influence consumer adoption of chatbot-generated recommendations?	H4: Brand personality influences consumer adoption of chatbot-generated recommendations, with modern brands leading to higher adoption than traditional brands.
RQ5: Does consistency affect consumer adoption of chatbot-generated recommendations?	H5: Consistency influences consumer adoption of chatbot-generated recommendations, with higher consistency conditions leading to higher adoption than lower consistency conditions.

To represent the formulated hypotheses, the following model was designed:



The model proposes that chatbot design, product type, cognitive involvement, brand personality and consistency (independent variables) predict recommendation adoption (dependent

variable). In the context of this thesis, recommendation adoption is understood as the consumer's likelihood and willingness to act upon AI-generated product suggestions by purchasing the recommended product.

3. Methodology

3.1 Research Design

To test the hypotheses derived from prior research, a quantitative research approach was employed. This approach was deemed suitable because it allows for the systematic investigation of causal relationships between clearly defined independent variables (chatbot design, product type, brand personality, cognitive involvement and perceived consistency) and the dependent variable (recommendation adoption). The study followed a 2 (Chatbot Design: anthropomorphized vs. non-anthropomorphized) \times 2 (Product Type: hedonic vs. utilitarian) \times 2 (Brand Personality: traditional vs. modern) between-subjects experimental design, resulting in eight unique experimental conditions. In addition to these manipulations, cognitive involvement and perceived consistency were measured as continuous variables to capture further influences on recommendation adoption. The between-subjects design was chosen to avoid potential carryover or contrast effects that could occur if participants were exposed to multiple chatbot or brand types. Random assignment was applied to allocate participants to the experimental conditions. This procedure is a standard practice in between-subjects designs, as it ensures that individual differences such as demographic characteristics, prior experiences, or motivational factors are distributed evenly across groups. By minimizing systematic bias and pre-existing group differences, random assignment increases the internal validity of the experiment and strengthens the causal interpretation of observed effects (Shadish et al., 2002). This experimental setup enabled the systematic testing of both main effects and interaction effects of the manipulated variables on recommendation adoption.

Table 2: Experimental Conditions

		Experimental Condition							
		1	2	3	4	5	6	7	8
Chatbot Design	Anthropomorphic	x	x	x	x				
	Non-Anthropomorphic					x	x	x	x
Product Type	Hedonic (Perfume)	x	x			x	x		
	Utilitarian (Laundry Detergent)			x	x			x	x
Brand Personality	Traditional (Guerlain / Persil)	x		x		x		x	
	Modern (Glossier / Blueland)		x		x		x		x

3.2 Data Collection Method and Sample Definition

A survey-based experiment was selected as the data collection method, as it allows for the efficient gathering of standardized quantitative data at scale. This approach makes it possible to identify patterns, examine correlations, and test potential causal relationships. To gather participants, a convenience sampling strategy was employed, complemented by a snowball technique in which respondents were encouraged to share the survey link within their own networks. These techniques were chosen due to their practicality in reaching individuals who were readily available, within close proximity and open to participating during the designated data collection period. While such methods do not support statistical generalization to the broader population, they are commonly applied in experimental research where the primary focus is on examining theoretical constructs and relationships rather than population-level inference.

Data collection was carried out in two stages. First, a pilot test involving 13 participants was conducted to evaluate the clarity of the survey items and confirm the effectiveness of the experimental manipulations. Following this, the main study was launched to test the proposed hypotheses. The survey was created and administered using Qualtrics and remained published for a total of 12 days. The survey link was distributed anonymously through social media platforms, various personal and academic networks and direct contact. This approach allowed for broad and efficient participant reach, offering respondents the flexibility to complete the survey at a time and place of their convenience.

This study focused on consumers in general, therefore no specific population was targeted by this study and no characteristics were prerequisites for participating in the survey. However, a certain degree of familiarity with the internet was deemed useful, which was ensured by the online nature of the survey and its exclusively digital distribution. Participants needed to be comfortable navigating digital platforms to access and complete the questionnaire. An adequate sample size was calculated by using the GPower 3.1 tool, developed by the Heinrich-Heine-University of Düsseldorf. By assuming a medium effect size ($f=0.25$), $\alpha = 0.05$ and a desired power of 0.80, the minimum required sample size for detecting main effects was calculated to be 158 participants. To enhance reliability and allow for subgroup comparisons, a target of 30 to 40 participants per experimental condition was set, yielding a total planned sample size of 240 to 320 participants. This sample size provides adequate power to detect medium-sized effects in factorial ANOVA and regression analyses.

3.3 Study Materials

As mentioned before, participants were assigned to one of eight experimental conditions. Each experimental condition incorporated two stimuli in the form of screenshots to manipulate perceived chatbot design, product type and brand personality. The first stimulus that participants were exposed to showed a conversation between a customer and a chatbot. The conversation was about a perfume in the hedonic condition and about a laundry detergent in the utilitarian shopping scenario. The virtual assistant was either framed as Claire (anthropomorphic communication style and appearance) or as ScentBot or WashBot (machinelike communication style and appearance). The second stimulus pictured the online shop of a brand alongside a description of its personality. The brands chosen in the hedonic conditions were Guerlain for the traditional scenario and Glossier in the modern scenario and in the utilitarian condition Persil for the traditional scenario and Blueland for the modern scenario.

The visual stimuli can be seen in the survey in Appendix B.

3.4 Survey Design

A fully structured questionnaire was developed, consisting of close ended, occasionally bipolar questions and statements with pre-defined response options. Most constructs were measured utilizing 7-point Likert scales ranging from 7 (“Strongly Agree”) to 1 (“Strongly Disagree”). The survey was structured into thirteen thematic sections (see Table 3), each designed to systematically capture the relevant variables of the study.

Table 3: Questionnaire Structure

Section	Subject
1	Survey Introduction & Consent
2	Previous Chatbot Experience
3	Experimental Scenario (Chatbot Design x Product Type)
4	Chatbot Design Manipulation Check
5	Product Type Definition
6	Product Type Manipulation Check
7	Cognitive Involvement
8	Recommendation Adoption Pre Brand Introduction
9	Brand Introduction
10	Brand Personality Manipulation Check
11	Perceived Consistency
12	Recommendation Adoption Post Brand Introduction
13	Demographic Information
14	Thank You & Closing

The initial section presented participants with a brief introduction explaining the purpose of the study, emphasizing voluntary participation, data anonymity and estimated completion time. This introductory section also served as an informed consent statement. The second section assessed participants’ prior experience with chatbots and AI-generated product recommendations. These covariates were included to account for potential individual differences in prior exposure to chatbots.

The third section exposed participants to one of the eight randomly assigned experimental conditions. To ensure unbiased allocation across conditions, a randomizer was employed. In this section, participants were only shown a combination of chatbot design (anthropomorphic vs. non-anthropomorphic) and product type (hedonic vs. utilitarian). Brand personality (traditional vs. modern) was only introduced in section nine, to enable a differentiation between the effects of product type and brand personality. Participants were exposed to the first stimulus.

Afterwards they were instructed to place themselves in the described scenario, imagining they were browsing for the assigned product while engaging in a real-time conversation with the chatbot.

Following the scenario, participants completed a series of manipulation check items in section four to assess whether they perceived the chatbot as intended. Because of the previously discussed importance of social presence, the construct of anthropomorphism was assessed using the *Perceived Online Recommender Anthropomorphism* scale developed by Trzebiński et al. (2023). While Trzebiński et al. do not explicitly refer to social presence, their scale includes items (e.g., warmth, human-like qualities) that overlap with dimensions commonly used to capture social presence in prior research. Therefore, this scale was considered appropriate and was slightly adapted to the context of this study.

However, this scale lacks items explicitly measuring machine-likeness, which was essential for capturing participants' perceptions in both experimental conditions (anthropomorphic vs. non-anthropomorphic design). To address this gap, the study incorporated an additional item from Powers and Kiesler (2006), which directly targeted the concept of machine-likeness. Since this scale consisted of only one item, its internal consistency could not be evaluated. To enhance the reliability and psychometric robustness, several complementary items were developed by the researchers. These new items were constructed in a bipolar format, mirroring the structure of Trzebiński et al.'s anthropomorphism measures, to allow for conceptual consistency and balanced assessment across chatbot design dimensions.

In Section Five, participants were presented with a definition of the respective product type, depending on their assigned scenario. This was done to ensure a consistent baseline understanding across respondents. Section Six followed with a short comprehension check, in which participants were asked to confirm their understanding of the product classification and its relevance to the assigned shopping scenario (“According to the definition, would you categorize perfume (laundry detergent) as hedonic (utilitarian) product?”). Participants then completed a second set of manipulation check items to assess their perception of the product’s hedonic or utilitarian nature. These measures were adapted from Voss et al. (2003), whose *HED/UT* scale has been widely used to distinguish between emotional and functional product attributes. Items were slightly modified in wording to reflect the specific products used in this study (perfume and laundry detergent) and to fit the simulated online shopping context.

In section seven, cognitive involvement (the extent to which participants engaged thoughtfully with the product decision) was assessed. To capture this construct comprehensively, a combination of established scales was used. Items were adapted from Vaughn's (1980) Elaboration Likelihood Model framework and Zaichkowsky's (1985) *Personal Involvement Inventory* scale, both of which are frequently applied in consumer behaviour research. One attention-check item was embedded within this section to ensure high quality responses. Participants who failed this attention-check were excluded from the final analysis to maintain data integrity. While this scale demonstrated strong validity in its original context, adaptation was necessary to align with the particular e-commerce setting. Modifications were made to ensure contextual relevance and clarity for participants who were evaluating a simulated interaction with a product-recommending chatbot rather than a general AI agent.

Section eight introduced the study's dependent variable: recommendation adoption. This variable measured the degree to which participants were inclined to accept the product recommendation made by the chatbot prior to the introduction of any brand-related information. Items were borrowed from Yen and Chiang's *Purchase Intention* scale (2020). The original items capture consumers' likelihood of purchasing goods from a website (e.g., "I will purchase goods from this site"). Since recommendation adoption in the context of this study similarly reflects consumers' willingness to act upon technological advice and no dedicated scale was available, the items were adapted to explicitly measure consumers' intention to follow chatbot recommendations. This adaptation maintained the original construct focus while aligning the wording with the context of this study.

In section nine, participants were introduced to the assigned brand through a description of its personality and a screenshot of the brand's online shop. This manipulation aimed to convey either a traditional or modern brand personality. In section ten, participants responded to manipulation check items to assess how they perceived the brand's personality. These items were adapted from Aaker's (1997) widely recognized brand personality framework, revised to suit the binary classification (traditional vs. modern) employed in this study.

The subsequent section measured the perceived congruence between the chatbot's design, particularly in terms of visual appearance and communication style and the brand's personality by employing measures of the *Perceived Fit* scale developed by Choi et al., (2022). The

wording of the items was adapted to enhance comprehensibility and accessibility for a general consumer sample, without altering their conceptual meaning.

In section twelve, the recommendation adoption after the brand introduction was assessed, using the same measurement scale as previously.

In section thirteen, participants were asked to provide demographic information, including gender, age, education level and country of residence.

The final section served as a conclusion and thank you message, providing closure to the study and offering participants contact information for follow-up questions or feedback. The full survey including the stimuli is available in Appendix B. All scales and respective items used in the survey can be found in Table 4.

Table 4: Questionnaire's Variables and Measurement Items

Variable	Item	Source
	[Q2] Have you ever interacted with a chatbot while shopping online (e.g., for product questions, support, or order help)?	Self-developed
	[Q2] How many times have you interacted with a chatbot while shopping online (e.g., for product questions, support, or order help)?	Self-developed
	[Q3] Have you ever consulted a chatbot for product recommendations before making a purchase?	Self-developed
Chatbot Design	[Q6] The chatbot seems humanlike. [Q6] The chatbot has human-like traits. [Q6] The chatbot seems warm and friendly. [Q6] The chatbot gives me the feeling of interacting with a human being. [Q6] The chatbot responds like a human being.	Adapted from Trzebiński et al. (2023)
	[Q6] The chatbot seems machine-like.	Adapted from Powers & Kiesler (2006)
	[Q6] The chatbot has robotic characteristics. [Q6] The chatbot seems emotionless and impersonal. [Q6] The chatbot gives me the feeling of interacting with a machine. [Q6] The chatbot responds like a machine.	Self-developed

Product Type	[Q8] According to the definition, would you categorize perfume (laundry detergent) as a hedonic (utilitarian) product?	Self-developed
	<p>[Q9] I enjoy using this type of product. [Q9] Using this type of product is pleasurable. [Q9] This type of product feels emotionally appealing. [Q9] This type of product helps me to express my personality. [Q9] This product is purchased primarily for enjoyment.</p> <p>[Q9] This product is practical. [Q9] This type of product is used to solve a problem. [Q9] This type of product is used to accomplish tasks or chores. [Q9] This product is purchased primarily for functionality.</p>	Adapted from Voss et al. (2003)
Cognitive Involvement	<p>[Q10] I would put a lot of thought into the decision which product to purchase. [Q10] I would carefully compare this product to alternatives before deciding.</p>	Adapted from Vaughn (1980)
	<p>[[Q10] The decision which product to purchase would matter to me. [Q10] I would be genuinely interested in choosing the right product. [Q10] I would be concerned with finding the right product.</p>	Adapted from Zaichkowsky (1985)
Recommendation Adoption	<p>[Q11 / Q16] I would seriously consider purchasing the product recommended by the chatbot. [Q11 / Q16] I would be willing to purchase the product recommended by the chatbot. [Q11 / Q16] I would probably purchase the product recommended by the chatbot. [Q11 / Q16] I would likely accept the product recommendation from the chatbot.</p>	Adapted from Yen & Chiang (2020)
Brand Personality	<p>[Q13] The brand seems traditional. [Q13] The brand seems classic. [Q13] The brand seems conservative. [Q13] The brand seems timeless. [Q13] The brand seems modern. [Q13] The brand seems progressive. [Q13] The brand seems trendy. [Q13] The brand seems contemporary.</p>	Adapted from Aaker (1997)
Consistency	<p>[Q15] The chatbot's appearance and communication style are appropriate for the brand. [Q15] The chatbot's appearance and communication style align well with the brand. [Q15] The chatbot's appearance and communication style are consistent with the brand.</p>	Adapted from Choi et al., (2022)

3.5 Analytical Approach

The data analysis was conducted using IBM SPSS Statistics Version 30.0.0. In addition, the PROCESS macro for SPSS (Hayes, 2018) was applied to test mediation effects with bootstrapping procedures. Prior to hypothesis testing, the data was screened for missing values, outliers, and distributional assumptions. Reliability analyses were performed using Cronbach's Alpha and corrected item-total correlations were inspected to ensure internal consistency of all multi-item scales. To confirm the effectiveness of the experimental manipulations, independent-samples t-tests were conducted. To test hypotheses, factorial ANOVAs examined the main and interaction effects of chatbot design, product type, and brand personality on recommendation adoption. An ANCOVA was additionally performed to control for cognitive involvement and consistency as covariates. Mediation was tested with PROCESS Model 4 using 5,000 bootstrap samples and 95% confidence intervals.

4. Data Analysis

The present study was based on a sample of 334 individuals, of which 268 completed the survey and passed the attention-check. Therefore, 66 responses were excluded from the analysis due to invalidity. The data was screened for univariate outliers within each composite scale using boxplots (Appendix C). Three mild outliers were identified for the Cognitive Involvement scale. However, these values fell within the plausible range of the scale and were therefore retained, in line with recommendations to preserve natural variance and avoid unnecessary loss of data. Thus, no further responses were excluded. The final sample slightly exceeded the minimum required size of 240 respondents. Participants were distributed evenly across the experimental conditions of product type (hedonic vs. utilitarian), chatbot design (anthropomorphic vs. non-anthropomorphic) and brand personality (traditional vs. modern). Allocation across the eight experimental groups was relatively balanced, with group sizes ranging from 30 to 38 participants. This lies within the recommended range of 20 to 40 participants per cell for between-subjects comparisons, supporting the robustness and reliability of the statistical analyses. The detailed distribution of participants across conditions is provided in Appendix D.

4.1 Sample Characterization

In terms of socio-demographic characteristics, there was a slight imbalance of gender. The sample consisted of 57.1% female, 40.1% male and 1.9% non-binary or third gender respondents. Only one participant preferred not to disclose their gender. This distribution indicates that female respondents were slightly overrepresented in the sample. Regarding age, the largest proportion of participants (42.2%) were between 25 and 34 years old, followed by 19.0% aged 18 to 24, 14.2% aged 35 to 44, 11.2% aged 55 to 64, 10.4% aged 45 to 54 and 3.0% aged 65 or older. The educational profile was relatively high, with 42.2% holding a master's degree, 25.0% a bachelor's degree and 5.2% a doctoral degree. A further 20.9% had completed a high school diploma (Abitur), while smaller proportions reported a diploma (4.1%), less than high school education (1.5%), or another qualification (1.1%). Participants were predominantly based in Germany (41.8%) and the United Kingdom (25.4%), with smaller groups from Austria (8.2%), Portugal (8.2%), Poland (3.7%), Italy (3.4%), Spain (2.6%), France (2.2%) and other European countries including Belgium, the Netherlands, Luxembourg, Sweden and Finland. This distribution reflects a primarily European sample, with a notable concentration in German-speaking countries. Further socio-demographic information can be viewed in Table 5.

Table 5: Socio-demographic Characteristics of Respondents

Classification	Categories	% (out of 268)
Gender	Male	40,7
	Female	57,1
	Non-binary / third gender	1,9
	Prefer not to say	0,4
Age	18–24 years	19,0
	25–34 years	42,2
	35–44 years	14,2
	45–54 years	10,4
	55–64 years	11,2
	65 years or older	3,0
Education	Less than high school diploma / Abitur	1,5
	High school diploma / Abitur	20,9
	Bachelor's degree	25,0
	Master's degree	42,2
	Doctorate	5,2
	Diploma	4,1
	Other	1,1

Country of Residence	Germany	41,8
	Portugal	8,2
	Spain	2,6
	United Kingdom	25,4
	Sweden	0,4
	France	2,2
	Finland	0,4
	Other	1,5
	Poland	3,7
	Italy	3,4
	Belgium	0,7
	The Netherlands	1,1
	Austria	8,2
	Luxembourg	0,4
Prior Chatbot Interaction	Yes	72,4
	No	21,6
	Not sure	6,0
Number of Prior Chatbot Interactions	More than 10 times	13,4
	6 to 10 times	12,7
	3 to 5 times	20,1
	2 to 3 times	23,9
	Once	3,7
	Never	19,0
	Not sure	7,1
Used Chatbot for Product Recommendation	Yes	29,9
	No	62,3
	Not sure	7,8

4.2 Descriptive statistics

The descriptive statistics for the three constructs representing the central continuous variables are presented in Table 6. On average, participants reported a moderate level of recommendation adoption ($M = 4.34$, $SD = 1.54$). Cognitive involvement was relatively high, with a mean of 5.26 ($SD = 1.44$), suggesting that respondents generally engaged with the recommendations on a relatively high cognitive level. Perceived consistency has a mean of 4.46 ($SD = 1.67$), indicating moderate perceptions of the fit between chatbot design and brand personality. An inspection of skewness values showed that all distributions were approximately symmetric (Recommendation Adoption = -0.29 , Cognitive Involvement = -0.93 , Consistency = -0.39) and did not deviate substantially from normality (Appendix D). Overall, the data met the assumptions for subsequent parametric analyses. The manipulated variables (chatbot design, product type and brand personality) are categorical and are therefore examined separately in the manipulation checks and hypothesis testing.

Table 6: Descriptive Statistics for Main Study Variables

	N	Minimum	Maximum	Mean	Std. Deviation
Recommendation Adoption	268	1.00	7.00	4.34	1.54
Cognitive Involvement	268	1.00	7.00	5.26	1.44
Consistency	268	1.00	7.00	4.46	1.67

4.3 Reliability of Measures

Prior to hypotheses testing, a reliability analysis was conducted for each of the six constructs: Anthropomorphism, anti-anthropomorphism, hedonism, utilitarianism, cognitive involvement and traditionality. Cronbach’s alpha and the Corrected item-total correlation of each variable were calculated to assess internal consistency, indicating the extent to which the items within a scale measure the same underlying concept (Nunnally, 1978). All constructs in this study demonstrated Cronbach’s alpha values well above .90, indicating excellent reliability and confirming strong internal consistency (Bland & Altman, 1997). While for some items, alpha values would have increased slightly if deleted, the improvement was negligible and did not justify removal given the theoretical importance of retaining these items. Corrected item-total correlations were consistently above .59, further supporting the reliability of the measures (Nurosis, 1994). Overall, the results confirm each scale exhibited sufficient homogeneity and no single item reduced reliability substantially (Table 7). Further details of the reliability analysis can be viewed in Appendix E.

Table 7: Internal Consistency of Constructs

Constructs and correspondent items	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach’s Alpha
Recommendation Adoption (4 items)			,959
I would seriously consider purchasing the product recommended by the chatbot.	,911	,943	
I would be willing to purchase the product recommended by the chatbot.	,911	,943	
I would probably purchase the product recommended by the chatbot.	,915	,942	
I would likely accept the product recommendation by the chatbot.	,863	,957	

Anthropomorphism (5 items)			,914
The chatbot seems human-like.	,833	,884	
The chatbot has human-like characteristics.	,831	,884	
The chatbot seems warm and friendly.	,595	,929	
The chatbot gives me the feeling of interacting with a human being.	,816	,888	
The chatbot responds like a human being.	,833	,884	
Anti-Anthropomorphism (5 items)			,945
The chatbot seems machine-like.	,865	,929	
The chatbot has robotic characteristics.	,856	,931	
The chatbot seems emotionless and impersonal.	,728	,953	
The chatbot gives me the feeling of interacting with a machine.	,904	,922	
The chatbot responds like a machine.	,900	,923	
Hedonism (5 items)			,921
I enjoy using this type of product.	,711	,920	
Using this type of product is pleasurable.	,823	,899	
This type of product feels emotionally appealing.	,822	,898	
This type of product is purchased primarily for enjoyment.	,797	,906	
This type of product helps me to express my personality.	,856	,891	
Utilitarianism (4 items)			,913
This type of product is practical.	,705	,921	
This type of product is used to solve a problem.	,848	,871	
This type of product is used to accomplish tasks or chores.	,827	,881	
This type of product is purchased primarily for functionality.	,861	,865	

Cognitive Involvement (5 items)			,938
I would put a lot of thought into the decision of which product to purchase.	,831	,924	
I would carefully compare the product to alternatives before deciding.	,829	,924	
The decision which product to purchase would matter to me.	,855	,919	
I would be genuinely interested in choosing the right product.	,849	,921	
I would be concerned with finding the right product.	,804	,928	
Traditionality (4 items)			,925
The brand seems traditional.: The brand seems modern.	,850	,895	
The brand seems classic.: The brand seems trendy.	,891	,879	
The brand seems conservative.: The brand seems progressive.	,809	,909	
The brand seems timeless.: The brand seems progressive.	,762	,923	
Consistency (3 items)			,960
The chatbot's appearance and communication style are appropriate for the brand.	,884	,962	
The chatbot's appearance and communication style align well with the brand.	,935	,925	
The chatbot's appearance and communication style are appropriate are consistent with the brand.	,924	,933	

4.4 Manipulation Checks

Independent-samples *t*-tests were carried out for chatbot design, product type, brand personality, and cognitive involvement (Appendix F), to assess whether the manipulation of these variables had been successful by determining if there was a statistically significant difference in the mean scores between the groups (Gerald, 2018).

Chatbot design

Participants in the anthropomorphic chatbot design condition reported significantly higher anthropomorphism ($M = 4.71$, $SD = 1.32$) compared to those in the machine-like design condition ($M = 3.72$, $SD = 1.41$), $t(266) = 5.89$, $p < .001$, Cohen's $d = 1.37$, 95% CI [0.47, 0.97]. Conversely, participants in the machine-like design condition reported higher anti-anthropomorphism ($M = 4.71$, $SD = 1.40$) than those in the anthropomorphic design condition ($M = 3.92$, $SD = 1.38$), $t(266) = -4.29$, $p < .001$, Cohen's $d = -0.52$, 95% CI [-0.77, -0.28]. These results confirm that the manipulation of chatbot design was successful.

Product type

Perfume was rated significantly higher on hedonic attributes ($M = 5.76$, $SD = 1.07$) than laundry detergent ($M = 3.17$, $SD = 1.02$), $t(266) = 18.03$, $p < .001$, Cohen's $d = 2.20$, 95% CI [1.90, 2.50]. Conversely, laundry detergent was rated higher on utilitarian attributes ($M = 6.24$, $SD = 0.92$) than perfume ($M = 3.24$, $SD = 1.11$), $t(266) = -22.95$, $p < .001$, Cohen's $d = -2.80$, 95% CI [-3.14, -2.47]. Thus, the manipulation of product type was highly effective.

Brand personality

Participants in the traditional brand condition rated the brand as significantly more traditional ($M = 5.52$, $SD = 1.12$) compared to those in the modern brand condition ($M = 2.39$, $SD = 1.21$), $t(266) = 22.12$, $p < .001$, Cohen's $d = 2.70$, 95% CI [2.37, 3.03]. This confirms that the manipulation of brand personality was successful.

Overall, all manipulations were successful, producing strong and statistically significant differences in the expected directions with large effect sizes. This provides confidence in the integrity of the experimental design and its suitability for testing the hypotheses. For detailed results see Appendix F.

4.5 Hypotheses Testing

To examine the effects of product type, chatbot design and brand personality on recommendation adoption, a three-factor between-subjects ANOVA was conducted (Appendix G). Assumption checks confirmed that the requirements for parametric testing were met. Levene's test of equality of variances was non-significant, $F(7,260) = 0.87$, $p = .532$ and the Breusch–Pagan test indicated that the variance of residuals did not depend on the predictors, $\chi^2(1) = 0.52$, $p = .473$. Accordingly, the analysis proceeded under the assumption of equal error variances. The overall model was statistically significant, $F(3,264) = 15.64$, $p < .001$, $\eta^2_p = .151$, explaining 15.1% of the variance in recommendation adoption ($R^2 = .151$, Adjusted $R^2 = .141$).

4.5.1 Effects of Chatbot Design on Recommendation Adoption

Hypothesis 1 predicted that chatbot design would influence recommendation adoption, such that recommendations provided by anthropomorphic chatbots would be adopted more likely than those of non-anthropomorphic chatbots. The ANOVA revealed a significant main effect of chatbot design $F(1, 264) = 5.19$, $p = .023$, $\eta^2_p = .019$. Participants in the anthropomorphic condition reported higher recommendation adoption ($M = 4.54$, $SD = 1.43$) than those in the non-anthropomorphic condition ($M = 4.13$, $SD = 1.63$). These findings provide support for H1.

4.5.2 Effects of Product Type on Recommendation Adoption

Hypothesis 2 proposed that product type would affect recommendation adoption. The analysis confirmed a strong main effect of product type, $F(1, 264) = 35.60$, $p < .001$, $\eta^2_p = .119$. Participants exposed to the utilitarian product (laundry detergent) reported higher recommendation adoption ($M = 4.85$, $SD = 1.39$) than those in the hedonic product condition (perfume; $M = 3.82$, $SD = 1.52$). Thus, H2 is supported.

4.5.3 Effects of Cognitive Involvement on Recommendation Adoption

Hypothesis 3 proposed that cognitive involvement would be associated with differences in recommendation adoption, such that lower involvement would lead to higher adoption compared to higher involvement. To test this, an extended ANCOVA was conducted in which cognitive involvement and perceived consistency were included as covariates alongside product type, chatbot design and brand personality. The results showed that cognitive involvement did

not significantly predict recommendation adoption, $F(1,262) = 0.96$, $p = .327$, $\eta^2_p = .004$. The parameter estimate was negative ($B = -0.05$, $SE = 0.05$), consistent with the hypothesized direction, but the effect size was negligible and statistically non-significant. This suggests that, although the trend pointed towards lower cognitive involvement being linked with slightly higher adoption, the relationship was too weak to draw reliable conclusions. Accordingly, H3 was not supported.

4.5.4 Effects of Brand Personality on Recommendation Adoption

Hypothesis 4 predicted that brand personality would influence recommendation adoption, with modern brands expected to yield higher recommendation adoption than traditional brands. The ANOVA revealed a significant main effect of brand personality, $F(1, 264) = 6.78$, $p = .010$, $\eta^2_p = .025$, 95% CI [.004, .06]. Participants in the modern brand condition reported higher adoption ($M = 4.55$, $SD = 1.53$) than those in the traditional brand condition ($M = 4.12$, $SD = 1.53$). These results support H4.

4.5.5 Effects of Consistency on Recommendation Adoption

In hypothesis 5 we expected perceived consistency to affect recommendation adoption. An extended ANCOVA including cognitive involvement and consistency as covariates demonstrated that consistency was indeed a strong predictor of recommendation adoption, $F(1,262) = 185.04$, $p < .001$, $\eta^2_p = .414$. Parameter estimates showed that for each one-point increase in perceived consistency, recommendation adoption increased by approximately 0.60 scale points ($B = 0.60$, $SE = 0.04$). Thus, H5 is supported. Notably, when consistency was added to the model, the previously significant effects of chatbot design and brand personality became non-significant ($p = .413$ and $p = .818$, respectively), whereas the effect of product type remained significant, $F(1,262) = 14.48$, $p < .001$, $\eta^2_p = .052$. These findings indicate that perceived consistency mediates the effects of chatbot design and brand personality on recommendation adoption. A deeper examination of this mediation effect is provided in the exploratory analysis section.

4.6 Exploratory Analysis

Origin of Consistency

In an exploratory follow-up analysis, we examined where perceptions of consistency originated. Specifically, an ANOVA with consistency as the dependent variable was conducted to assess whether the manipulations of product type, chatbot design, and brand personality systematically influenced consistency. Levene's test indicated a violation of the homogeneity of variances assumption, $F(7, 260) = 3.69, p < .001$. To address this, Welch's ANOVAs were conducted for each factor, which confirmed all main effects and thus strengthen confidence in the robustness of the findings. The analysis revealed significant main effects of chatbot design, Welch's $F(1, 250.24) = 21.35, p < .001, \eta^2_p = .078$, product type, Welch's $F(1, 262.04) = 7.78, p = .006, \eta^2_p = .038$, and brand personality, Welch's $F(1, 254.96) = 16.59, p < .001, \eta^2_p = .063$. Anthropomorphic chatbots, modern brands, and utilitarian products were associated with higher consistency ratings. No interactions reached statistical significance, indicating that perceived consistency was shaped independently by these factors.

Mediating Effect of Consistency

To further examine the mediating role of consistency, three mediation models were conducted using Hayes PROCESS Model 4 with 5,000 bootstrapped samples (Hayes, 2018) with recommendation adoption as the dependent variable, consistency as the mediator and each manipulated factor (chatbot design, product type, brand personality) as independent variables. For chatbot design, results showed that chatbot design significantly predicted perceived consistency ($B = -0.91, SE = 0.20, p < .001$) and consistency strongly predicted recommendation adoption ($B = 0.63, SE = 0.04, p < .001$). The direct effect of chatbot design on adoption was non-significant when controlling for consistency ($B = 0.16, SE = 0.15, p = .27, 95\% CI [-0.13, 0.45]$), while the indirect effect through consistency was significant ($B = -0.58, 95\% CI [-0.86, -0.32]$). These findings indicate that consistency fully mediated the effect of chatbot design on adoption.

For product type, results revealed that product type significantly predicted consistency ($B = 0.56, SE = 0.20, p = .006$), which in turn, predicted adoption ($B = 0.58, SE = 0.04, p < .001$). Both the direct effect ($B = 0.70, SE = 0.14, p < .001, 95\% CI [0.43, 0.97]$) and the indirect effect ($B = 0.33, 95\% CI [0.09, 0.57]$) were significant, indicating a partial mediation. Thus, product type affected adoption both directly and indirectly through perceived consistency.

For brand personality, results showed that brand personality significantly predicted consistency ($B = 0.81$, $SE = 0.20$, $p < .001$) and consistency again predicted adoption ($B = 0.62$, $SE = 0.04$, $p < .001$). The direct effect of brand personality on adoption was non-significant ($B = -0.07$, $SE = 0.14$, $p = .61$, 95% CI $[-0.36, 0.21]$), while the indirect effect through consistency was significant ($B = 0.51$, 95% CI $[0.26, 0.77]$). These results indicate that consistency fully mediated the effect of brand personality on adoption.

Effects of Product Type on Cognitive Involvement

In an exploratory analysis, it was examined whether cognitive involvement differed depending on the product type. The independent samples t-test revealed that participants in the hedonic product condition (perfume) reported significantly higher involvement ($M = 5.98$, $SD = 1.00$) than those in the utilitarian product condition (laundry detergent; $M = 4.53$, $SD = 1.45$). This difference was highly significant, $t(236.1) = 9.54$, $p < .001$, $d = 1.24$, 95% CI $[0.90, 1.42]$ and corresponded to a large effect size. These findings indicate that the hedonic product condition was associated with greater cognitive involvement. However, as this analysis was not guided by a specific hypothesis, it is reported here as an exploratory additional result.

Effects of Prior Chatbot Experience on Recommendation Adoption

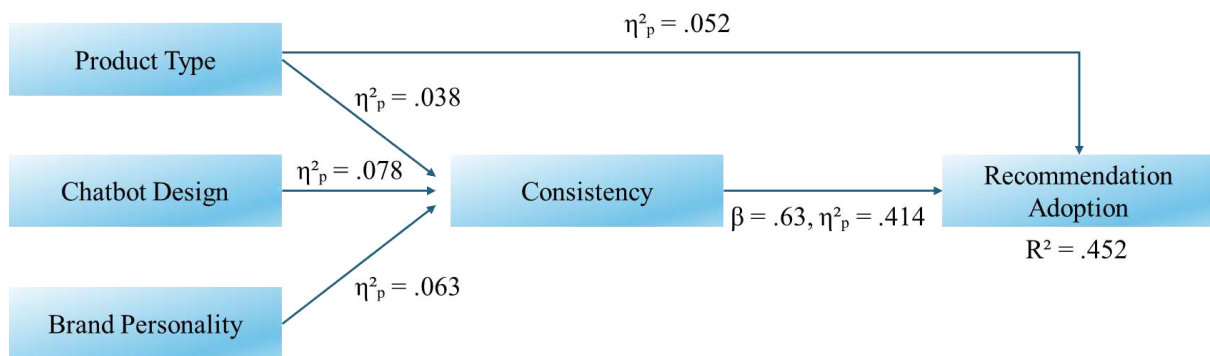
To explore whether prior chatbot experience influenced recommendation adoption, an ANCOVA was conducted including three covariates related to participants' experience with chatbots in addition to the previously tested variables of chatbot design, product type, and brand personality. Specifically, Q2 ("Have you ever interacted with a chatbot while shopping online?") and Q4 ("Have you ever used a chatbot to receive product recommendations before making a purchase decision?") were treated as fixed factors and Q3 ("How many times have you interacted with a chatbot while shopping online?") was entered as a continuous covariate. Levene's test indicated that the assumption of homogeneity of variances was met, $F(45, 222) = 0.87$, $p = .702$. The results showed that product type, chatbot design and brand personality remained significant predictors of recommendation adoption (all $p < .05$). In contrast, none of the prior chatbot experience variables reached significance (Q2: $F(2, 259) = 1.39$, $p = .252$, $\eta^2_p = .011$; Q4: $F(2, 259) = 1.84$, $p = .161$, $\eta^2_p = .014$; Q3: $F(1, 259) = 0.64$, $p = .425$, $\eta^2_p = .002$). These very small effect sizes suggest that participants' previous interactions with chatbots, including their use of chatbots for product recommendations, did not systematically affect their adoption behaviour in the present study.

Detailed output of the exploratory analyses can be viewed in Appendix H.

Table 8: Hypotheses and Results

Hypotheses	Results
H1: Chatbot design has a significant effect on consumer adoption of chatbot-generated recommendations, with anthropomorphized chatbots leading to higher adoption than machine-like chatbots.	Supported
H2: Product type influences consumer adoption of chatbot-generated recommendations, with utilitarian products leading to higher adoption than hedonic products.	Supported
H3: Cognitive involvement influences consumer adoption of chatbot-generated recommendations, with lower involvement leading to higher adoption than higher involvement.	Not supported
H4: Brand personality influences consumer adoption of chatbot-generated recommendations, with modern brands leading to higher adoption than traditional brands.	Supported
H5: Consistency influences consumer adoption of chatbot-generated recommendations, with higher consistency conditions leading to higher adoption than lower consistency conditions.	Supported

The previously described findings lead to the following final model:



5. Main Findings and Discussion

The aim of this study was to explore how different factors affect consumer adoption of chatbot-generated product recommendations. Specifically, the roles of chatbot design, product type, brand personality, cognitive involvement and perceived consistency were examined in an online shopping scenario. Since these factors are mostly rooted in a brand's business strategy and can therefore not be altered easily, it is crucial to understand how they shape consumer responses.

With AI rapidly advancing and becoming a standard tool in customer service, particularly in pre-purchase contexts, companies must ensure that chatbot employment does not harm consumer trust or reduce adoption. Instead, AI should ideally support or even increase recommendation acceptance and subsequently revenue.

Our findings show that participants are more likely to adopt recommendations from anthropomorphic chatbots compared to non-anthropomorphic ones. This is consistent with research by Qiu and Benbasat (2009), who emphasized that in online shopping environments the intention to use agents as a decision aid is significantly heightened by anthropomorphic cues. Similarly, Lee (2021) demonstrated in the context of virtual try-ons that anthropomorphic features improve user acceptance of augmented reality. Our findings are also in line with those by Adam et al. (2020), who found that anthropomorphic design cues, such as human-like language and avatars, significantly increase user compliance with chatbot requests. These findings suggest that consumers respond more favourably to technology when it mimics human characteristics. However, the effect of anthropomorphism on recommendation adoption turned out to be mediated by consistency. This finding indicates that anthropomorphic design alone may not be sufficient to increase recommendation adoption.

There was also a significantly stronger adoption of chatbot-generated recommendations for utilitarian products than for hedonic products. This result aligns with prior findings by Wien and Peluso (2021), who showed that AI advisors were equally effective as humans in utilitarian product conditions but less effective in hedonic ones. Longoni and Cian (2020) likewise demonstrated that consumers prefer AI advisors over human ones when utilitarian product goals are salient. Our study extends the findings by showing that this preference also holds when comparing utilitarian (laundry detergent) and hedonic (perfume) products, rather than by framing the same product differently. Similarly, Jin and Zhang (2025) found that AI recommendations are more readily accepted for material products, whereas humans are preferred for experiential products, a pattern explained by differences in competence versus emotion-based evaluations. As hypothesized, our findings mirror this logic, suggesting that chatbots are particularly effective for utilitarian products where rationality and performance dominate, but less so for hedonic products where emotional and sensory value is central.

Contrary to expectations, cognitive involvement did not significantly predict adoption. Literature suggests that high involvement, which arises particularly when products are central to the consumer's identity or evoke emotions, reduces reliance on AI advice (Morewedge, 2022;

Leung et al., 2018; Wien & Peluso, 2021). In our case, although hedonic products triggered higher involvement, this did not translate into significant differences in adoption. One explanation may lie in the artificial nature of the survey setting. Participants were explicitly asked to reflect on the recommendation and imagine a purchase decision, which likely increased cognitive elaboration beyond what would occur in a natural shopping situation. As a result, involvement was elevated across both conditions, creating a ceiling effect that limited its ability to distinguish between hedonic and utilitarian products as a predictor of adoption. Another possible reason may lie in the sample characteristics. Given that most participants were young and digitally literate, they may not have perceived high involvement as conflicting with reliance on AI.

The higher adoption rate in the modern versus traditional brand conditions of our study supports findings that consumers evaluate AI technologies more positively when implemented by exciting or competent brands (Choi et al., 2022; Yang & Hu, 2021). Those brands align more naturally with technological solutions, whereas traditional or sincere brands evoke expectations of warmth and human contact, making mechanized service appear less fitting (Sirianni et al., 2013). Our findings extend those results by showing that this effect persists also when differentiating between traditional and modern brands. However, when consistency was considered in the model, the direct effect of brand personality disappeared. This suggests, in line with Park (2019), that congruence between all factors is more decisive than brand type alone.

Once consistency was included in the analysis, the direct effects of chatbot design and brand personality became non-significant. This indicates that the effect of these manipulations on recommendation adoption was fully mediated through perceived consistency. In the study of Park (2019), consistency was largely conceptualized as the alignment between chatbot design and brand personality. By contrast, in the present study perceived consistency was independently shaped by anthropomorphism, product type, and brand personality, without reliable interaction effects. Instead, it was shaped independently by anthropomorphism, product type and brand personality. Descriptive statistics showed that, the anthropomorphic-hedonic-modern condition yielded the highest consistency ratings. Whereas anthropomorphic design and hedonic products were expected to drive high consistency ratings due to their shared emphasis on emotional appeal, a modern brand personality was assumed to decrease perceived consistency, due to its association with innovativeness rather than warmth (Aaker, 1997). One

possible explanation may lie in the perception of chatbots as innovative and contemporary tool, regardless of their specific design. Employing chatbots as product advisors may have been interpreted by participants as a signal of modernity, with anthropomorphic chatbots in particular reinforcing this impression because their human-like qualities might be seen as even more advanced than traditional, non-anthropomorphic alternatives. These findings extended the results of Park (2019), Sirianni et al., (2013) and Wentzel (2009) by suggesting that perceived consistency may be shaped by a combination of contextual factors, rather than chatbot-brand congruence alone.

The lack of significant effects from prior chatbot experience suggests that even first-time or infrequent users are responsive to chatbot recommendations if the design and brand fit are appropriate. The findings further suggest that adoption behavior was primarily shaped by the experimental manipulations, while prior chatbot experience did not exert a meaningful effect. This implies that design, product and brand-related cues can effectively shape consumer responses to chatbot recommendations regardless of whether users have extensive or limited prior experience with chatbots.

In summary, the results of this study demonstrate that the adoption of chatbot-generated recommendations is not determined by a single factor but emerges from the interplay of chatbot design, product type, brand personality as well as their perceived consistency. While anthropomorphism, modern brand positioning and utilitarian product categories each increased recommendation adoption, their effects were ultimately mediated through consistency. This highlights that congruence across contextual factors is more decisive than any single element by itself.

5.1 Theoretical Implications

The present study contributes to the literature on AI adoption, consumer decision-making and chatbot research. Specifically, we provided deeper understanding on artificial intelligence in customer service settings and how the complex interplay of factors inherent to a brand's strategy affect the adoption of chatbot-generated product recommendations.

First, the results extend prior research on anthropomorphism by confirming that human-like design cues increase recommendation adoption. At the same time, the analysis revealed that this effect is fully mediated by perceived consistency, indicating that anthropomorphic chatbot

design is only effective when it aligns with contextual factors such as product type and brand personality. Second, the present study enriches the literature on product types by confirming that utilitarian products are associated with significantly higher adoption of chatbot recommendations than hedonic products. Unlike previous studies that typically relied on hedonic versus utilitarian framing of the same product or on the distinction between experiential and material goods, this research directly contrasts distinct utilitarian and hedonic products. In doing so, it provides strong empirical support for product type as a determinant of adoption. Notably, the effect of product type remained significant even after controlling for perceived consistency, indicating that product type exerts both a direct effect on adoption and an indirect effect through consistency. Third, while previous work emphasized the role of cognitive involvement in shaping consumers' reliance on AI, our findings indicate that it did not significantly affect recommendation adoption. This challenges existing assumptions and suggests that in digitally literate consumer groups, involvement may not act as a strong determinant of recommendation adoption in AI-assisted decision-making. Fourth, the present study adds to the brand personality literature by confirming that modern brands foster higher adoption of chatbot recommendations than traditional brands. However, this direct effect becomes non-significant once perceived consistency is accounted for, indicating that the influence of brand personality on adoption is fully mediated by consistency and that congruence between chatbot design, brand positioning, and product type is more decisive than brand personality alone. Lastly, the present study advances theoretical understanding by identifying perceived consistency as a central mediating mechanism. Rather than being driven by isolated variables, consumer adoption of chatbot-generated recommendations emerges from the perceived alignment of technological, product-related and brand-related cues. This perspective offers a more integrative explanation of AI acceptance in customer service contexts and adds nuance to existing models of consumer trust and compliance with AI-generated advice

5.2 Practical Implications

Based on the findings of this study, we recommend that chatbots should generally be designed with anthropomorphic features, as these increase recommendation adoption. However, the effectiveness of chatbot design depends on whether it is coherent with the product type and the brand's personality. Firms should therefore avoid a one-size-fits-all approach and instead ensure that chatbot communication style, visual design and interaction patterns are consistent with their broader brand strategy.

Furthermore, companies offering utilitarian products may particularly benefit from chatbot recommendations, as consumers are more receptive to AI advice in functional decision-making contexts. For hedonic products, however, managers should exercise caution, as chatbot-driven recommendations tend to be less persuasive. Moreover, traditional brands, commonly associated with heritage, warmth and sincerity may risk dissonance among consumers if chatbots cannot embody these values (Yang & Hu, 2021). Chatbots should therefore rather be employed by modern brands, as such brands can integrate chatbots more seamlessly. However, traditional brands may consider softening resistance by presenting chatbots as support for human advisors, not as replacements. Overall, the baseline against which chatbots are introduced must be considered. The absence of low recommendation adoption levels across conditions, indicates that chatbots can still have positive effects for hedonic products and traditional brands in contexts where no product advisor currently exists. However, when human advisors are already in place, fully substituting them with AI may reduce recommendation adoption and risk harming business outcomes. Moreover, in the present study we identified perceived consistency as the strongest determinant of recommendation adoption. Managers should therefore prioritize a coherent design strategy in which the chatbot's appearance, language and level of personalization align with the brand personality and the type of product offered. Inconsistent signals risk undermining trust and reducing adoption, even when individual elements are designed effectively. Importantly, prior chatbot experience did not significantly affect adoption, indicating that even first-time users can be positively influenced if contextual alignment is achieved. This highlights the opportunity for companies to shape consumer attitudes from the very first interaction, making careful deployment strategies essential. Finally, the presented implications should be treated as guiding principles rather than universally applicable solutions. Managers should carefully evaluate whether the implementation of chatbot advisors aligns with their specific brand strategy and customer expectations. Since consumer preferences are not homogeneous, segmentation can help identify which customer groups are most receptive to chatbot-based recommendations and which may require additional human support. The implementation of chatbots should always be tested and evaluated in the context of each brand's unique positioning, customer base and touchpoints first, before any large-scale rollout. A suitable tool to test the effect of chatbots or different chatbot designs for a specific brand could be A/B-Testing, because it parallelly compares two different conditions to each other based on predefined KPIs and is unnoticed by customers.

6. Limitations and Future Research

While this study provides valuable insights into the factors that influence consumer adoption of chatbot-generated product recommendations, it is equally important to acknowledge its limitations and to point out opportunities for future research.

This study used a between-subjects experimental design. This choice helped to prevent potential carryover or contrast effects that might have occurred if participants had been exposed to multiple conditions. At the same time, it limited the possibility of directly comparing how the same individuals respond across different scenarios. A within-subjects design could therefore be a valuable approach for future research, as it would allow for stronger insights into how participants evaluate chatbot recommendations for different product types or brand personalities.

It should also be considered, that although the manipulations generally worked as intended, some product-related characteristics may have influenced the results. Perfume, which was chosen as the hedonic product, is by nature more personal than laundry detergent. Additionally, even though an effort was made to present the perfume as unisex by describing it as “fresh and citrusy,” the brands used in the scenario tend to have a more feminine image. This may have lowered recommendation adoption among male participants. Future studies could therefore benefit from selecting hedonic products that are less identity-driven and more gender-neutral. Furthermore, the artificial survey environment may have heightened cognitive involvement across conditions. This may have created a ceiling effect that masked natural differences between hedonic and utilitarian products, which could partly explain why cognitive involvement did not significantly predict adoption in this study. Future studies could investigate other product categories, for example expensive versus inexpensive products, to potentially achieve stronger contrasts in involvement and reveal more pronounced effects. Another constraint of the experimental design is that adoption of chatbot recommendations could only be measured as intention rather than actual purchase behavior. However, intentions do not always translate into real-world outcomes (Flores & Jansson, 2021). To address these limitations, cognitive involvement and recommendation adoption could be investigated by replicating this study in a real e-commerce setting by employing A/B. Through the incorporation of adequate behavioral measures, such as conversion rate, dwell time and number of clicks, researchers could obtain a more accurate picture of how chatbot recommendations affect purchasing decisions in practice.

Moreover, the sample consisted primarily of young, digitally literate university students. Although this group is highly relevant for online shopping contexts, it may not fully represent the broader consumer population. Future research should include more diverse demographic groups to assess whether factors such as age, digital literacy, or cultural background influence chatbot adoption.

Finally, the most important limitation lies in the complexity of contextual factors influencing recommendation adoption. This study examined key variables such as product type, brand personality and chatbot design, yet it is likely that many additional factors also play a decisive role. Since adoption has shown to be highly dependent on the congruence of these factors, it may be difficult to capture the full picture within a controlled experimental design. For this reason, future research should investigate chatbot implementation using real brands in their natural market environments. Case studies could provide valuable insights into how chatbot adoption interacts with unique brand strategies and how congruence across multiple contextual elements shapes consumer responses.

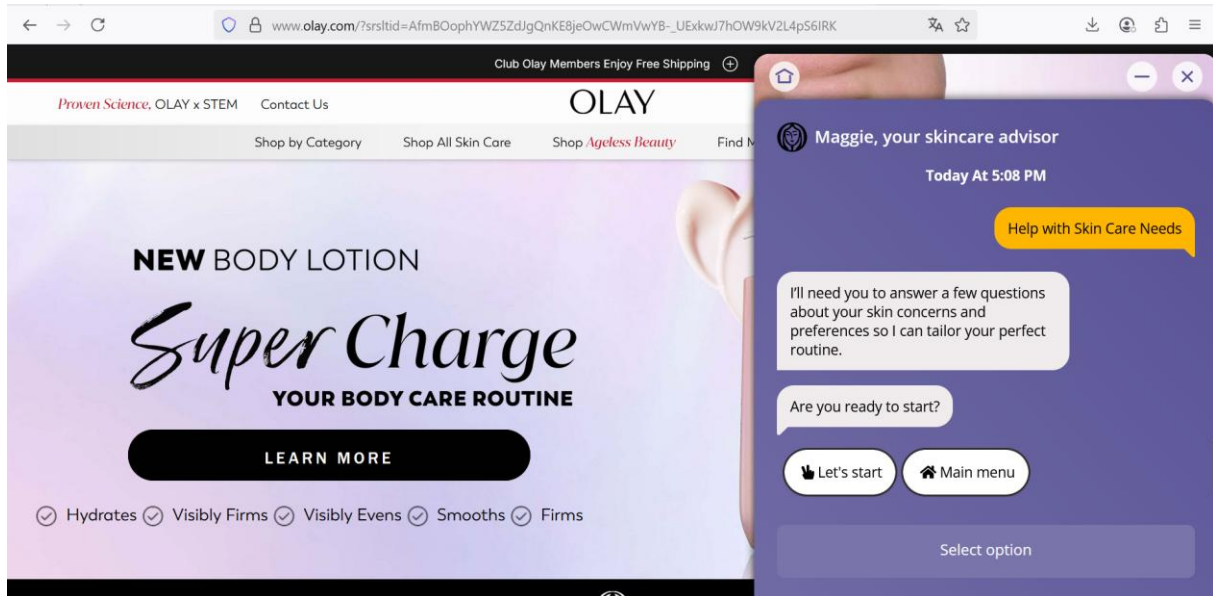
7. Conclusion

This thesis examined the influence of chatbot design, product type, brand personality, consistency and cognitive involvement on the adoption of chatbot-generated product recommendations. A central finding is that anthropomorphism and brand personality affected adoption only through perceived consistency, whereas product type persisted as a direct predictor. Adoption was significantly higher for anthropomorphized design, utilitarian products and modern brands than for non-anthropomorphized design, hedonic products and traditional brands. Perceived consistency emerged as the strongest determinant but contrary to expectations, cognitive involvement did not play a significant role. Overall, the study shows that adoption is shaped by both robust product effects and the congruence of contextual factors, underscoring the importance of coherence in theory and practice.

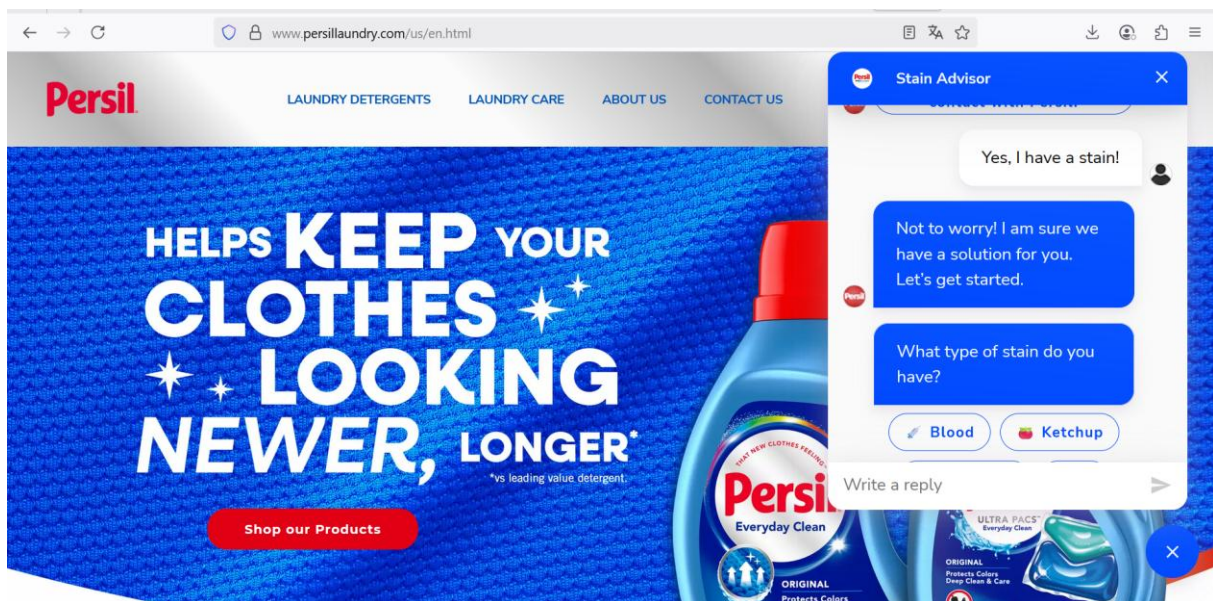
Appendices

Appendix A

Website of Olay (*OLAY Official Site, 2025*)



Website of Persil US (*Persil Official Website, 2025*)



Appendix B: Qualtrics Survey

Start of Block: Introduction and Consent

Welcome and thank you for participating in this research for my master thesis at Católica Lisbon School of Business and Economics. This study aims to understand consumer reactions to chatbot-generated product recommendations. The survey will take approximately 5 minutes to complete. Your responses will remain completely anonymous and will be used solely for academic purposes. There are no right or wrong answers, so please be as honest and candid as possible. If you have any questions or feedback regarding the survey, feel free to reach out to me at s-sallekotte@ucp.pt. Thank you for your time and participation! By proceeding with this survey, you consent to participate in this study.

End of Block: Introduction and Consent

Start of Block: Previous Chatbot Experience

Have you ever interacted with a chatbot while shopping online (e.g., for product questions, support or order help)?

- Yes
- No
- Not sure

How many times have you interacted with a chatbot while shopping online before (e.g., for product questions, support or order help)?

- More than 10 times
- 6 to 10 times
- 3 to 5 times
- 2 to 3 times
- Once
- Never
- Not sure

Have you ever used a chatbot to receive product recommendations before making a purchase decision?

- Yes
- No
- Not sure

End of Block: Previous Chatbot Experience

Start of Block: Chatbot Design x Product Type

Anthropomorphized x Hedonic Product for Groups 1 & 2
Or Anthropomorphized x Utilitarian Product for Groups 3 & 4

Please imagine the following scenario. You are browsing an online store in search of a new **perfume (laundry detergent)**. You come across a chatbot named Claire, that offers to assist you with your decision.

User: Welcome, my name is Claire. May I assist you in discovering a scent that resonates with your personality? 😊

Claire: Hi there! 🙋 My name is Claire. Looking for something special? I'd love to assist you. 😊

User: Yes, I'd love that.

Claire: I am looking for laundry detergent.

User: Wonderful. To begin, may I ask what notes you find most captivating? Are you drawn to the fresh, citrusy, woody or aromatic blends? 🌿

Claire: Great! 🙌 I'll help you find a laundry detergent that matches your needs. Can you tell me what kind of fabrics you want to clean with it? ✨

User: I like something fresh and citrusy.



Claire: I need something for sports clothing.

User: Thank you for sharing. I believe this scent would suit you perfectly. It is clean and energizing, with bright citrus notes 🍊 that uplift your spirits. Would you like me to add it to your cart? 🛒

Claire: Thanks for sharing! Based on that, I think this detergent could be a great fit — it's specially designed for activewear, fights tough odours and stains, and helps keep fabrics breathable and fresh 🌿 after every wash. Would you like me to add it to your cart? 🛒

Or Start of Block: Non-Anthropomorphized x Hedonic Product for Groups 5 & 6
Or Start of Block: Non-Anthropomorphized x Utilitarian Product for Groups 7 & 8

Please imagine the following scenario. You are browsing an online store in search of a new **perfume (laundry detergent)**. You come across a chatbot named ScentBot (WashBot), that appears on the screen and offers to assist you with your decision.

 ScentBot Chatting	 WashBot Chatting
Hello, how can I assist you?	Hello, how can I assist you?
I am looking for a perfume.	I am looking for a laundry detergent.
Sure. Please specify your preferences.	Sure, do you have any preferences regarding this product?
I would like something fresh and citrusy.	I need something for sports clothing.
Thank you for specifying! Based on that, I think this product is the most suitable. Scent: Fresh Top note: Citrus Shall I proceed to cart?	Thank you for specifying! Based on that, I think this product is the most suitable. Scent: Fresh Strength: 4.5/5. Developed for active wear. Shall I proceed to cart?

End of Block: Chatbot Design x Product Type

Start of Block: Chatbot Design Manipulation Check

Please indicate how you feel about the interaction with the chatbot. To what extent do you agree with the following statements? - Likert Scale from 7 (Strongly Agree) to 1 (Strongly Disagree)

- The chatbot seems human-like
- The chatbot has human-like characteristics.
- The chatbot seems warm and friendly.
- The chatbot gives me the feeling of interacting with a human being.
- The chatbot responds like a human being.
- The chatbot seems machine-like.
- The chatbot seems machine-like.
- The chatbot has robotic characteristics.

- The chatbot seems emotionless and impersonal.
- The chatbot gives me the feeling of interacting with a machine.
- The chatbot responds like a machine.

End of Block: Chatbot Design Manipulation Check

Start of Block: Product Type Definition

Please read the following definition:

Hedonic products are consumed for pleasure and sensory enjoyment rather than for their usefulness and functionality. They offer experiential value and appeal to emotions and personal gratification. Examples include luxury items, chocolate, designer clothes and video games.

(Utilitarian products are goods bought for their practical or problem-solving functions. They meet basic needs or help complete tasks efficiently, offering value through usefulness rather than emotional appeal. Examples include cleaning supplies, household tools and personal care products.)

According to the definition, would you categorize **perfume (laundry detergent)** as a hedonic (utilitarian) product?

- Yes
- No
- Not sure

End of Block: Product Type Definition

Start of Block: Product Type Manipulation Check

To what extent do you agree with the following statements about perfume (laundry detergent)?
- Likert Scale from 7 (Strongly Agree) to 1 (Strongly Disagree)

- I enjoy using this type of product.
- Using this type of product is pleasurable.
- This type of product is practical.
- This type of product is practical.
- This type of product is used to solve a problem.
- Please select 'Agree' to show you are paying attention.
- This type of product is used to accomplish tasks or chores.
- This type of product feels emotionally appealing.
- This type of product helps me to express my personality.

End of Block: Product Type Manipulation Check

Start of Block: Cognitive Involvement

When deciding on which **perfume (laundry detergent)** to purchase, to what extent do you agree with the following statements? - Likert Scale from 7 (Strongly Agree) to 1 (Strongly Disagree)

- I would put a lot of thought into the decision of which product to purchase.
- I would carefully compare this product to alternatives before deciding.
- The decision which product to purchase would matter to me.
- I would be genuinely interested in choosing the right product.
- I would be concerned with finding the right product.

End of Block: Cognitive Involvement

Start of Block: Recommendation Adoption Pre Brand Introduction

Please indicate how you feel about the chatbot's product recommendation. To what extent do you agree with the following statements? - Likert Scale from 7 (Strongly Agree) to 1 (Strongly Disagree)

- I would seriously consider purchasing the product recommended by the chatbot.
- I would be willing to purchase the product recommended by the chatbot.
- I would probably purchase the product recommended by the chatbot.
- I would likely accept the recommendation given by the chatbot.

End of Block: Recommendation Adoption Pre Brand Introduction

Start of Block: Brand Introduction

Traditional Brand (Groups 1, 3, 5, 7)

Or Start of Block: Modern Brand (Groups 2, 4, 6, 8)

For Groups 1 & 5

Please imagine that the online store you are browsing for the perfume belongs to the brand Guerlain. Established in Paris in 1828, Guerlain is one of the oldest and most prestigious perfume houses in the world. Known for its unwavering dedication to tradition, refinement and exceptional quality, the house has created signature scents cherished across generations. Every scent is the result of nearly two centuries of expertise, time-honoured methods and rare, natural ingredients. Guerlain's creations are steeped in history and elegance, reflecting the enduring values of its storied past.

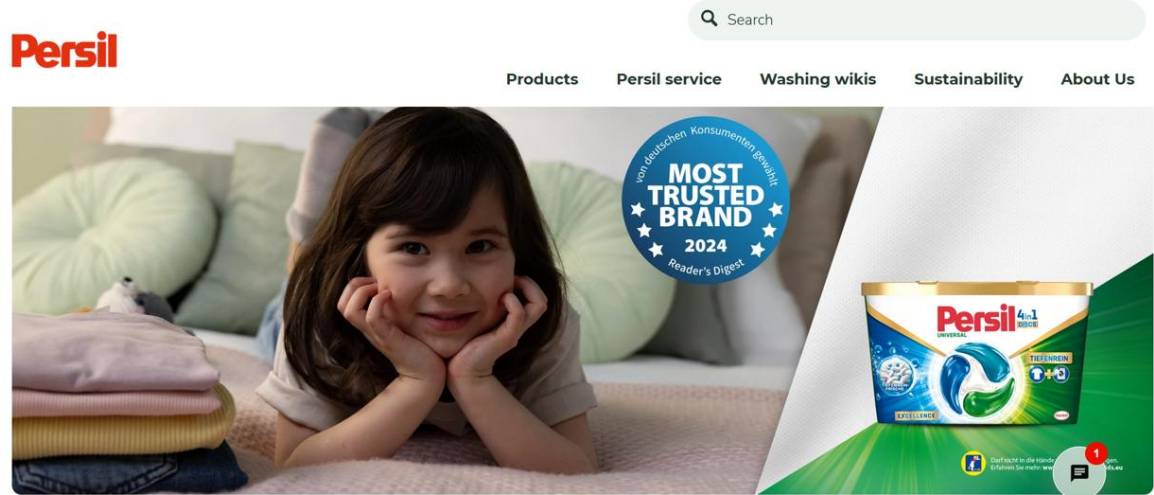


End of Block: Recommendation Adoption

End of Block: Brand Introduction

For Groups 3 & 7

Please imagine that the online store you are browsing for laundry detergent belongs to the brand Persil. Established in 1907, Persil has built a longstanding reputation as one of the most respected names in household care. Known for its consistent quality and dependable performance, Persil is a brand that many families have trusted across generations. Its formulas are carefully crafted to uphold high standards, focusing on cleanliness, fabric care and effectiveness. Persil’s visual identity and product design reflect its heritage — emphasizing familiarity, simplicity and reliability. Rather than following fleeting trends, the brand remains dedicated to time-honoured values and a no-nonsense approach to laundry.

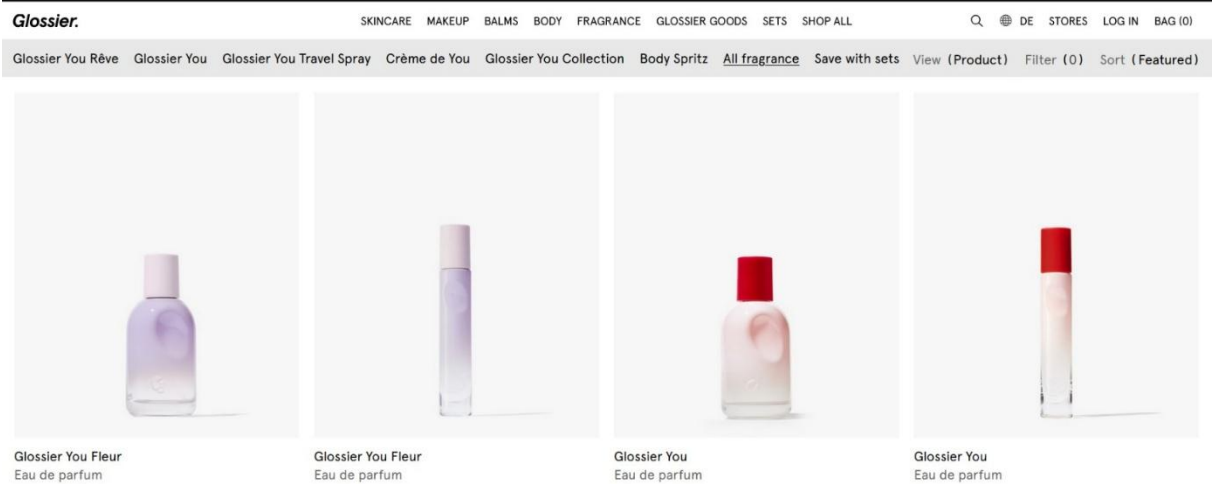


Persil for hygienically pure laundry

For Groups 2 & 6

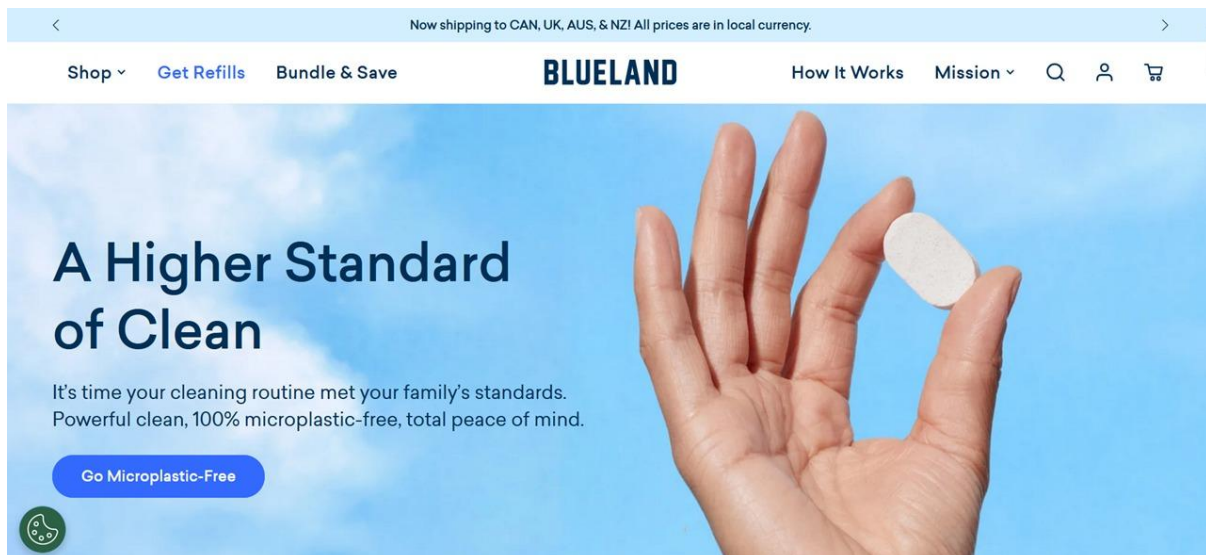
Please imagine that the online store you are browsing for a perfume belongs to the brand Glossier. Glossier is a forward-thinking beauty brand designed for the digital generation —

fresh, inclusive and community-driven. Founded in 2014, Glossier challenges traditional beauty standards by putting individuality and self-expression at the center of everything it does. Its fragrance line reflects a new approach to scent: lightweight, skin-adapting and personal. With its unique design, minimalist packaging and a focus on how fragrance feels rather than how it's worn, Glossier speaks to a culture that values authenticity over convention. Through collaborations with artists, influencers and creative voices, Glossier positions itself at the intersection of beauty, lifestyle and culture — bold, current and always evolving.



For Groups 4 & 8

Please imagine that the online store you are browsing for laundry detergent belongs to the brand Blueland. Founded in 2019, Blueland set out to completely rethink everyday cleaning: Eliminating over a billion single-use plastic bottles by introducing tablet-based formulas and sleek reusable bottles wrapped in minimalist packaging. Blueland's approach is straightforward yet innovative: no water or plastic — just concentrated cleaning tablets and stylish glass or metal “forever” bottles that reduce shipping impact and clutter. The brand blends aesthetic appeal with eco-conscious efficacy. Their digital-first presence—featuring viral TikTok tips, artist collaborations and bold seasonal launches—positions Blueland at the intersection of sustainability and lifestyle.



End of Block: Brand Introduction

Start of Block: Brand Personality Manipulation Check

How would you describe the brand you just read about? Please indicate your perception of the brand on the following scales. – Likert Scale 7 to 1

- The brand seems traditional (7) – The brand seems modern (1)
- The brand seems classic (7) – The brand seems trendy (1)
- The brand seems conservative (7) – The brand seems progressive (1)
- The brand seems timeless (7) – The brand seems contemporary (1)

End of Block: Brand Personality Manipulation Check

Start of Block: Chatbot Design x Brand Personality

Please take another look at the interaction with the chatbot. Focus on the chatbot's **appearance** and the way it **communicates**, as this will help you answer the next questions.

Please indicate how well the chatbot's appearance and communication style match the brand you read about earlier. - Likert Scale from 7 (Strongly Agree) to 1 (Strongly Disagree)

- The chatbot's appearance and communication style are appropriate for the brand.
- The chatbot's appearance and communication style align well with the brand.
- The chatbot's appearance and communication style are consistent with the brand.

End of Block: Chatbot Design x Brand Personality

Start of Block: Recommendation Adoption Post Brand Introduction

Thinking about the brand you read about previously, please tell us how you feel about the chatbot's product recommendation now. To what extent do you agree with the following statements? - Likert Scale from 7 (Strongly Agree) to 1 (Strongly Disagree)

- I would seriously consider purchasing the product recommended by the chatbot.
- I would be willing to purchase the product recommended by the chatbot.
- I would probably purchase the product recommended by the chatbot.
- I would likely accept the recommendation given by the chatbot.

End of Block: Recommendation Adoption Post Brand Introduction

Start of Block: Demographics

You are almost finished! To conclude, we ask you only four simple questions to let us know a bit more about you.

What gender do you identify with?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

What is your age?

- Younger than 18
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65 or older

What is your highest level of education completed?

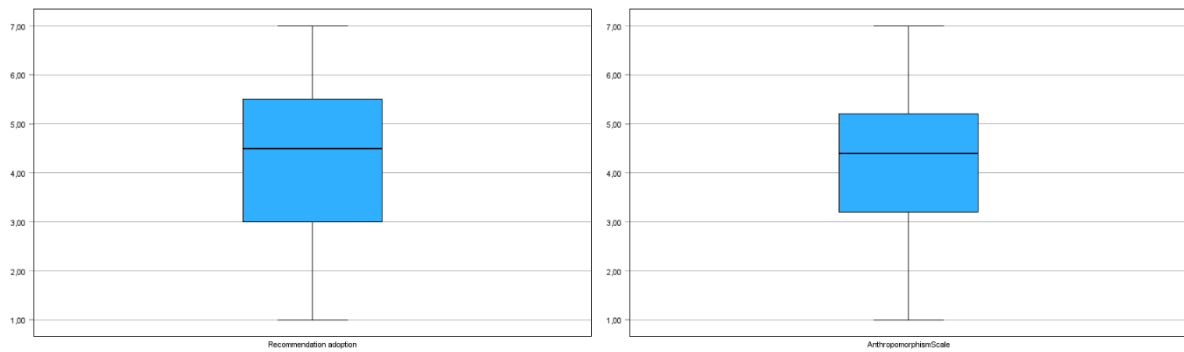
- Less than high school diploma / Abitur
- High school diploma / Abitur
- Bachelor's degree
- Master's degree
- Diploma
- Doctorate
- Other

In which country do you currently reside?

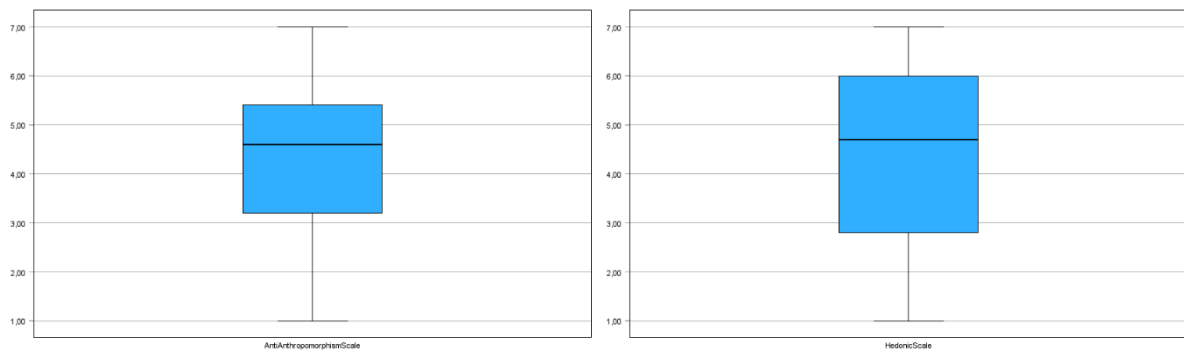
▼ Germany (1) ... Other (11)

Appendix C: Data Preparation

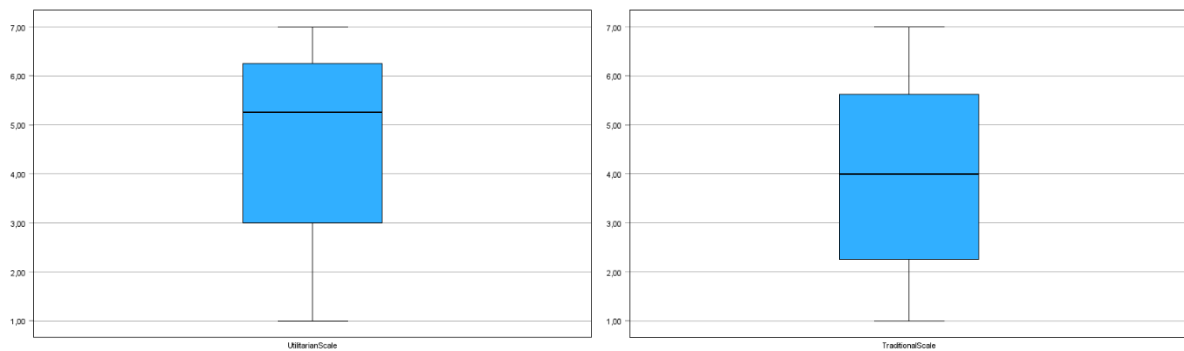
Boxplot for Recommendation Adoption (l.); Boxplot for Anthropomorphism (r.)



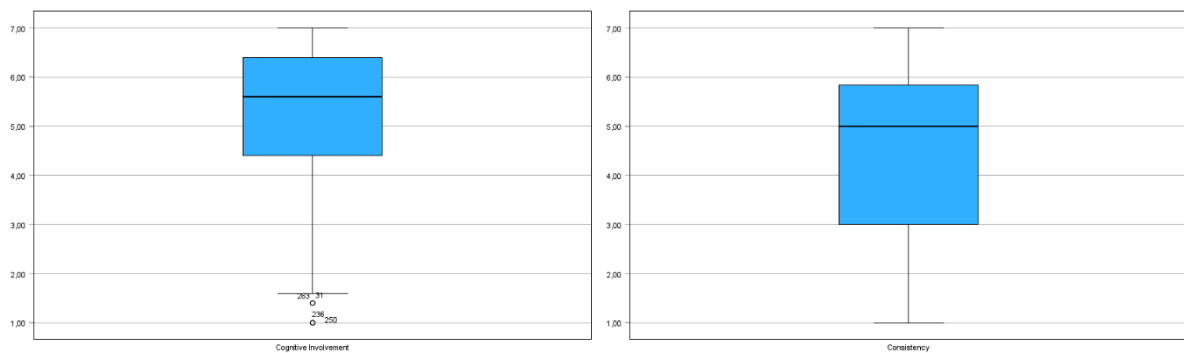
Boxplot for Anti-Anthropomorphism (l.); Boxplot for Hedonism (r.)



Boxplot for Utilitarianism (l.); Boxplot for Traditionality (r.)



Boxplot for Cognitive Involvement (l.); Boxplot for Consistency (r.)



Appendix D: Between Subjects Factors and Descriptive Statistics of Main Variables

Between-Subjects Factors

		Value Label	N
Chatbot Design	1	anthropomorphic	136
	2	anti-anthropomorphic	132
Product Type	1	hedonistic	134
	2	utilitarian	134
Brand Personality	1	traditional	133
	2	modern	135

Between-Subjects Factors

		Value Label	N
Chatbot design	1	anthropomorphic	136
	2	anti-anthropomorphic	132
Product type	1	hedonistic	134
	2	utilitarian	134
Brand	1	traditional	133
	2	modern	135
Have you ever interacted with a chatbot while shopping online (e.g., for product questions, support or order help)?	1	Yes	194
	2	No	58
	3	Not sure	16
Have you ever used a chatbot to receive product recommendations before making a purchase decision?	1	Yes	80
	2	No	167
	3	Not sure	21

Descriptive Statistics

Dependent Variable: Recommendation adoption

Product type	Chatbot design	Brand	Mean	Std. Deviation	N
hedonistic	anthropomorphic	traditional	3.8667	1.44248	30
		modern	4.3816	1.50532	38
		Total	4.1544	1.48941	68
	anti-anthropomorphic	traditional	3.1912	1.42497	34
		modern	3.7891	1.51486	32
		Total	3.4811	1.48862	66
Total	traditional	3.5078	1.46179	64	
	modern	4.1107	1.52790	70	
	Total	3.8228	1.52141	134	
utilitarian	anthropomorphic	traditional	4.7500	1.32565	35
		modern	5.1136	1.17774	33
		Total	4.9265	1.26008	68
	anti-anthropomorphic	traditional	4.6176	1.43183	34
		modern	4.9297	1.61674	32
		Total	4.7689	1.52057	66

Total		traditional	4.6848	1.37041	69
		modern	5.0231	1.40293	65
		Total	4.8489	1.39144	134
Total	anthropomorphic	traditional	4.3423	1.43992	65
		modern	4.7218	1.40252	71
		Total	4.5404	1.42797	136
	anti-anthropomorphic	traditional	3.9044	1.58939	68
		modern	4.3594	1.65704	64
		Total	4.1250	1.63236	132
Total		traditional	4.1184	1.52832	133
		modern	4.5500	1.53346	135
		Total	4.3358	1.54326	268

Descriptive Statistics

Dependent Variable: Consistency

Chatbot design	Product type	Brand	Mean	Std. Deviation	N
anthropomorphic	hedonistic	traditional	4,2778	1,67259	30
		modern	5,3421	1,02955	38
		Total	4,8725	1,44212	68
	utilitarian	traditional	4,6857	1,57169	35
		modern	5,2020	1,19006	33
		Total	4,9363	1,41334	68
	Total	traditional	4,4974	1,61925	65
		modern	5,2770	1,10121	71
		Total	4,9044	1,42286	136
anti-anthropomorphic	hedonistic	traditional	2,9216	1,65767	34
		modern	4,0208	1,69743	32
		Total	3,4545	1,75376	66
	utilitarian	traditional	4,3137	1,73096	34
		modern	4,7604	1,56630	32
		Total	4,5303	1,65584	66
	Total	traditional	3,6176	1,82235	68
		modern	4,3906	1,66249	64
		Total	3,9924	1,78271	132
Total	hedonistic	traditional	3,5573	1,78674	64
		modern	4,7381	1,51736	70
		Total	4,1741	1,74848	134
	utilitarian	traditional	4,5024	1,65053	69
		modern	4,9846	1,39497	65
		Total	4,7363	1,54524	134

Total	traditional	4,0476	1,77532	133
	modern	4,8568	1,45954	135
	Total	4,4552	1,67080	268

Descriptive Statistics

	N	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Std. Error
Recommendation adoption	268	4,3358	1,54326	-,293	,149
Cognitive Involvement	268	5,2582	1,43646	-,926	,149
Consistency	268	4,4552	1,67080	-,386	,149
Valid N (listwise)	268				

Appendix E: Scale Assessment and Reliability

Reliability Statistics for Recommendation Adoption

Cronbach's Alpha	N of Items
,959	4

Item Statistics for Recommendation Adoption

	Mean	Std. Deviation	N
I would seriously consider purchasing the product recommended by the chatbot.	4,36	1,607	268
I would be willing to purchase the product recommended by the chatbot.	4,38	1,590	268
I would probably purchase the product recommended by the chatbot.	4,26	1,671	268
I would likely accept the product recommendation from the chatbot	4,34	1,669	268

Item-Total Statistics for Recommendation Adoption

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I would seriously consider purchasing the product recommended by the chatbot.	,911	,943
I would be willing to purchase the product recommended by the chatbot.	,911	,943
I would probably purchase the product recommended by the chatbot.	,915	,942
I would likely accept the product recommendation from the chatbot	,863	,957

Reliability Statistics for Anthropomorphism

Cronbach's Alpha	N of Items
,914	5

Item Statistics for Anthropomorphism

	Mean	Std. Deviation	N
The chatbot seems human-like.	4,19	1,712	268
The chatbot has human-like characteristics.	4,23	1,691	268
The chatbot seems warm and friendly.	4,96	1,508	268
The chatbot gives me the feeling of interacting with a human being.	3,64	1,809	268
The chatbot responds like a human being.	4,10	1,682	268

Item Statistics for Recommendation Adoption

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
The chatbot seems human-like.	,833	,884
The chatbot has human-like characteristics.	,831	,884
The chatbot seems warm and friendly.	,595	,929
The chatbot gives me the feeling of interacting with a human being.	,816	,888
The chatbot responds like a human being.	,833	,884

Reliability Statistics for Anti-Anthropomorphism

Cronbach's Alpha	N of Items
,945	5

Item Statistics for Anti-Anthropomorphism

	Mean	Std. Deviation	N
The chatbot seems machine-like.	4,39	1,705	268
The chatbot has robotic characteristics.	4,44	1,713	268
The chatbot seems emotionless and impersonal.	4,01	1,748	268
The chatbot gives me the feeling of interacting with a machine.	4,46	1,714	268
The chatbot responds like a machine.	4,25	1,770	268

Item-Total Statistics for Anti-Anthropomorphism

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
The chatbot seems machine-like.	,865	,929
The chatbot has robotic characteristics.	,856	,931
The chatbot seems emotionless and impersonal.	,728	,953
The chatbot gives me the feeling of interacting with a machine.	,904	,922
The chatbot responds like a machine.	,900	,923

Reliability Statistics for Hedonism

Cronbach's Alpha	N of Items
,921	5

Item Statistics for Hedonism

	Mean	Std. Deviation	N
I enjoy using this type of product.	5,12	1,709	268
Using this type of product is pleasurable.	4,83	1,848	268
This type of product feels emotionally appealing.	4,29	1,911	268
This type of product is purchased primarily for enjoyment.	4,07	2,318	268
This type of product helps me to express my personality.	4,00	2,189	268

Item-Total Statistics for Hedonism

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I enjoy using this type of product.	,711	,920
Using this type of product is pleasurable.	,823	,899
This type of product feels emotionally appealing.	,822	,898
This type of product is purchased primarily for enjoyment.	,797	,906
This type of product helps me to express my personality.	,856	,891

Reliability Statistics for Utilitarianism

Cronbach's Alpha	N of Items
,913	4

Item Statistics for Utilitarianism

	Mean	Std. Deviation	N
This type of product is practical.	5,31	1,660	268
This type of product is used to solve a problem.	4,74	2,007	268
This type of product is used to accomplish tasks or chores.	4,20	2,350	268
This type of product is purchased primarily for functionality.	4,70	2,184	268

Item-Total Statistics for Utilitarianism

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
This type of product is practical.	,705	,921
This type of product is used to solve a problem.	,848	,871
This type of product is used to accomplish tasks or chores.	,827	,881
This type of product is purchased primarily for functionality.	,861	,865

Reliability Statistics for Traditionality

Cronbach's Alpha	N of Items
,925	4

Item Statistics for Traditionality

	Mean	Std. Deviation	N
The brand seems traditional.:The brand seems modern.	3,88	2,311	268
The brand seems classic.:The brand seems trendy.	4,01	2,256	268
The brand seems conservative.:The brand seems progressive.	3,58	1,992	268
The brand seems timeless.:The brand seems contemporary.	4,30	2,045	268

Item-Total Statistics for Traditionality

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
The brand seems traditional.:The brand seems modern.	,850	,895
The brand seems classic.:The brand seems trendy.	,891	,879
The brand seems conservative.:The brand seems progressive.	,809	,909
The brand seems timeless.:The brand seems contemporary.	,762	,923

Reliability Statistics for Cognitive Involvement

Cronbach's Alpha	N of Items
,938	5

Item Statistics for Cognitive Involvement

	Mean	Std. Deviation	N
I would put a lot of thought into the decision of which product to purchase.	5,00	1,706	268
I would carefully compare this product to alternatives before deciding.	5,22	1,586	268
The decision which product to purchase would matter to me.	5,28	1,606	268
I would be genuinely interested in choosing the right product.	5,66	1,510	268
I would be concerned with finding the right product.	5,14	1,617	268

Item-Total Statistics for Cognitive Involvement

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I would put a lot of thought into the decision of which product to purchase.	,831	,924
I would carefully compare this product to alternatives before deciding.	,829	,924
The decision which product to purchase would matter to me.	,855	,919
I would be genuinely interested in choosing the right product.	,849	,921
I would be concerned with finding the right product.	,804	,928

Reliability Statistics for Consistency

Cronbach's Alpha	N of Items
,960	3

Item Statistics for Consistency

	Mean	Std. Deviation	N
The chatbot's appearance and communication style are appropriate for the brand.	4,53	1,697	268
The chatbot's appearance and communication style align well with the brand.	4,42	1,756	268
The chatbot's appearance and communication style are consistent with the brand.	4,41	1,758	268

Item-Total Statistics for Consistency

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
The chatbot's appearance and communication style are appropriate for the brand.	,884	,962
The chatbot's appearance and communication style align well with the brand.	,935	,925
The chatbot's appearance and communication style are consistent with the brand.	,924	,933

Appendix F: Manipulation Check
Independent sample t-test for Anthropomorphism

Group Statistics

	Chatbot design	N	Mean	Std. Deviation	Std. Error Mean
Anthropomorphism Scale	anthropomorphic	136	4,7074	1,32327	,11347
	anti-anthropomorphic	132	3,7227	1,41349	,12303

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
AnthropomorphismScale	Equal variances assumed	,716	,398	5,889	266	<,001	<,001	,98463	,16720	,65542	1,31383
	Equal variances not assumed			5,883	263,583	<,001	<,001	,98463	,16737	,65508	1,31417

Independent Samples Effect Sizes

		Standardizer ^a	Point Estimate	95% Confidence Interval	Lower	Upper
Anthropomorphism Scale	Cohen's d	1,36845	,720	,472	,966	
	Hedges' correction	1,37232	,717	,470	,963	
	Glass's delta	1,41349	,697	,442	,949	

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Independent sample t-test for Anti-Anthropomorphism

Group Statistics

	Chatbot design	N	Mean	Std. Deviation	Std. Error Mean
AntiAnthropomorphism Scale	anthropomorphic	136	3,9176	1,59173	,13649
	anti-anthropomorphic	132	4,7121	1,43697	,12507

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
AntiAnthropomorphismScale	Equal variances assumed	1,849	,175	-4,285	266	<,001	<,001	-,79447	,18541	-1,15954	-,42941
	Equal variances not assumed			-4,291	264,624	<,001	<,001	-,79447	,18513	-1,15899	-,42996

Independent Samples Effect Sizes

				95% Confidence Interval	
				Lower	Upper
	Standardizer ^a	Point Estimate			
AntiAnthropomorphism Scale	Cohen's d	1,51749	-,524	-,767	-,280
	Hedges' correction	1,52179	-,522	-,764	-,279
	Glass's delta	1,43697	-,553	-,801	-,303

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Independent sample t-test for Hedonism

Group Statistics

	Product type	N	Mean	Std. Deviation	Std. Error Mean
HedonicScale	hedonic	134	5,7582	1,07468	,09284
	utilitarian	134	3,1672	1,26994	,10971

Independent Samples Test

Levene's Test for Equality of Variances				t-test for Equality of Means							
				Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference			
				One-Sided p	Two-Sided p			Lower	Upper		
HedonicScale	Equal variances assumed	7,404	,007	18,029	266	<,001	<,001	2,59104	,14372	2,30808	2,87401
	Equal variances not assumed			18,029	258,916	<,001	<,001	2,59104	,14372	2,30804	2,87405

Independent Samples Effect Sizes

				95% Confidence Interval	
				Lower	Upper
	Standardizer ^a	Point Estimate			
HedonicScale	Cohen's d	1,17637	2,203	1,897	2,505
	Hedges' correction	1,17970	2,196	1,892	2,498
	Glass's delta	1,26994	2,040	1,696	2,381

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Independent sample t-test for Utilitarianism

Group Statistics

	Product type	N	Mean	Std. Deviation	Std. Error Mean
UtilitarianScale	hedonic	134	3,2425	1,32072	,11409
	utilitarian	134	6,2351	,73049	,06310

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
UtilitarianScale	Equal variances assumed	37,119	<,001	-22,952	266	<,001	<,001	-2,99254	,13038	-3,24925	-2,73583
	Equal variances not assumed			-22,952	207,410	<,001	<,001	-2,99254	,13038	-3,24958	-2,73549

Independent Samples Effect Sizes

		Standardizer ^a	Point Estimate	95% Confidence Interval	
				Lower	Upper
UtilitarianScale	Cohen's d	1,06722	-2,804	-3,140	-2,465
	Hedges' correction	1,07024	-2,796	-3,132	-2,458
	Glass's delta	,73049	-4,097	-4,642	-3,548

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Independent sample t-test for Traditionality / Modernity

Group Statistics

	Brand	N	Mean	Std. Deviation	Std. Error Mean
Trad_ModScale	traditional	133	5,5188	1,11745	,09690
	modern	135	2,3907	1,19569	,10291

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
Trad_ModScale	Equal variances assumed	,917	,339	22,119	266	<,001	<,001	3,13806	,14142	2,84961	3,40650
	Equal variances not assumed			22,130	265,266	<,001	<,001	3,13806	,14135	2,84975	3,40636

Independent Samples Effect Sizes

		Standardizer ^a	Point Estimate	95% Confidence Interval	
				Lower	Upper
Trad_ModScale	Cohen's d	1,15753	2,702	2,369	3,033
	Hedges' correction	1,16080	2,695	2,363	3,024
	Glass's delta	1,19569	2,616	2,220	3,008

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Appendix G: Hypotheses Testing

ANOVA for Recommendation Adoption

Levene's Test of Equality of Error Variances^a

Dependent Variable: Recommendation adoption

F	df1	df2	Sig.
.869	7	260	.532

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + ProductType + ChatbotDesign + BrandPersonality

Breusch-Pagan Test for Heteroskedasticity^{a,b,c}

Chi-Square	df	Sig.
.516	1	.473

a. Dependent variable: Recommendation adoption

b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.

c. Predicted values from design: Intercept + ProductType + ChatbotDesign + BrandPersonality

Tests of Between-Subjects Effects

Dependent Variable: Recommendation adoption

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Squared	Eta
Corrected Model	95.979 ^a	3	31.993	15.643	.000	.151	
Intercept	5026.007	1	5026.007	2457.515	.000	.903	
ProductType	72.801	1	72.801	35.597	.000	.119	
ChatbotDesign	10.622	1	10.622	5.194	.023	.019	
BrandPersonality	13.873	1	13.873	6.783	.010	.025	
Error	539.922	264	2.045				
Total	5674.125	268					
Corrected Total	635.901	267					

a. R Squared = ,151 (Adjusted R Squared = ,141)

Parameter Estimates

Dependent Variable: Recommendation adoption

Parameter	B	Std. Error	Sig.	95% Confidence Interval		Partial Squared	Eta
				Lower Bound	Upper Bound		
Intercept	4.881	.178	.000	4.530	5.233	.739	
[ProductType=1]	-1.043	.175	.000	-1.387	-.699	.119	
[ProductType=2]	0 ^a	
[ChatbotDesign=1]	.398	.175	.023	.054	.743	.019	
[ChatbotDesign=2]	0 ^a	
[BrandPersonality=1]	-.456	.175	.010	-.800	-.111	.025	
[BrandPersonality=2]	0 ^a	

a. This parameter is set to zero because it is redundant.

ANCOVA for Recommendation Adoption with Cognitive Involvement and Consistency as Covariates

Levene's Test of Equality of Error Variances^a

Dependent Variable: Recommendation adoption

F	df1	df2	Sig.
1.182	7	260	.314

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + ProductType + BrandPersonality+ ChatbotDesign + CI_total + Cons_total

Breusch-Pagan Test for Heteroskedasticity^{a,b,c}

Chi-Square	df	Sig.
1.275	1	.259

a. Dependent variable: Recommendation adoption

b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.

c. Predicted values from design: Intercept + ProductType + BrandPersonality + ChatbotDesign + CI_total + Cons_total

Tests of Between-Subjects Effects

Dependent Variable: Recommendation adoption

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Squared	Eta
Corrected Model	319.669 ^a	5	63.934	52.969	.000	.503	
Intercept	39.884	1	39.884	33.044	.000	.112	
ProductType	17.472	1	17.472	14.475	.000	.052	
BrandPersonality	.064	1	.064	.053	.818	.000	
ChatbotDesign	.810	1	.810	.671	.413	.003	
CI_total	1.163	1	1.163	.964	.327	.004	
Cons_total	223.342	1	223.342	185.040	.000	.414	
Error	316.232	262	1.207				
Total	5674.125	268					
Corrected Total	635.901	267					

a. R Squared = ,503 (Adjusted R Squared = ,493)

Parameter Estimates

Dependent Variable: Recommendation adoption

Parameter	B	Std. Error	Sig.	95% Confidence Interval		Partial Squared	Eta
				Lower Bound	Upper Bound		
Intercept	2.289	.327	.000	1.644	2.933	.157	
[ProductType=1]	-.609	.160	.000	-.924	-.294	.052	
[ProductType=2]	0 ^a	
[BrandPersonality=1]	.032	.139	.818	-.242	.307	.000	
[BrandPersonality=2]	0 ^a	
[ChatbotDesign=1]	-.115	.140	.413	-.391	.161	.003	
[ChatbotDesign=2]	0 ^a	
CI_total	-.054	.055	.327	-.163	.054	.004	
Cons_total	.601	.044	.000	.514	.688	.414	

a. This parameter is set to zero because it is redundant.

Appendix H: Exploratory Analysis

ANOVA Results: Consistency by Product Type, Chatbot Design and Brand Personality

Levene's Test of Equality of Error Variances^{a,b}

		Levene Statistic	df1	df2	Sig.
Consistency	Based on Mean	3,691	7	260	<,001
	Based on Median	3,083	7	260	,004
	Based on Median and with adjusted df	3,083	7	248,903	,004
	Based on trimmed mean	3,691	7	260	<,001

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Dependent variable: Consistency

b. Design: Intercept + ChatbotDesign + ProductType + Brand + ChatbotDesign * ProductType + ChatbotDesign * Brand + ProductType * Brand + ChatbotDesign * ProductType * Brand

Tests of Between-Subjects Effects

Dependent Variable: Consistency

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	140,768 ^a	7	20,110	8,648	<,001	,189
Intercept	5261,544	1	5261,544	2262,718	<,001	,897
ChatbotDesign	50,814	1	50,814	21,852	<,001	,078
ProductType	24,007	1	24,007	10,324	,001	,038
Brand	40,757	1	40,757	17,528	<,001	,063
ChatbotDesign*	14,485	1	14,485	6,229	,013	,023
ProductType						
ChatbotDesign * Brand	,005	1	,005	,002	,963	,000
ProductType * Brand	6,010	1	6,010	2,584	,109	,010
ChatbotDesign*	,046	1	,046	,020	,889	,000
ProductType * Brand						
Error	604,583	260	2,325			
Total	6064,889	268				
Corrected Total	745,352	267				

a. R Squared = ,189 (Adjusted R Squared = ,167)

Oneway ANOVA for Chatbot Design

Robust Tests of Equality of Means

Consistency

	Statistic ^a	df1	df2	Sig.
Welch	21,347	1	250,243	<,001
Brown-Forsythe	21,347	1	250,243	<,001

a. Asymptotically F distributed.

Oneway ANOVA for Product Type

Robust Tests of Equality of Means

Consistency

	Statistic ^a	df1	df2	Sig.
Welch	7,778	1	262,039	,006
Brown-Forsythe	7,778	1	262,039	,006

a. Asymptotically F distributed.

Oneway ANOVA for Brand Personality

Robust Tests of Equality of Means

Consistency

	Statistic ^a	df1	df2	Sig.
Welch	16,586	1	254,960	<,001
Brown-Forsythe	16,586	1	254,960	<,001

a. Asymptotically F distributed.

PROCESS Macro Results: Mediating Effects of Consistency

***** PROCESS Procedure for SPSS Version 5.0 *****

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
 Documentation available in Hayes (2022). www.guilford.com/p/hayes3

Model: 4
 Y: RA_total
 X: ChatbotD
 M: Cons_tot

Sample Size: 268

OUTCOME VARIABLE: Cons_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2734	,0747	2,5926	21,4890	1,0000	266,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	5,8164	,3097	18,7826	,0000	5,2067	6,4261
ChatbotD	-,9120	,1967	-4,6356	,0000	-1,2993	-,5246

OUTCOME VARIABLE: RA_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,6723	,4520	1,3151	109,2676	2,0000	265,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1,2774	,3364	3,7974	,0002	,6151	1,9397
ChatbotD	,1613	,1457	1,1075	,2691	-,1255	,4481
Cons_total	,6324	,0437	14,4826	,0000	,5465	,7184

***** TOTAL EFFECT MODEL *****

OUTCOME VARIABLE: RA_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,1348	,0182	2,3471	4,9256	1,0000	266,0000	,0273

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,9559	,2946	16,8199	,0000	4,3758	5,5360
ChatbotD	-,4154	,1872	-2,2194	,0273	-,7840	-,0469

***** TOTAL, DIRECT and INDIRECT EFFECTS OF X ON Y *****

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
-,4154	,1872	-2,2194	,0273	-,7840	-,0469

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
,1613	,1457	1,1075	,2691	-,1255	,4481

Indirect effect(s) of X on Y:

Effect	BootSE	BootLLCI	BootULCI
Cons_total	-,5768	,1354	-,8574

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output: 95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals: 5000

***** PROCESS Procedure for SPSS Version 5.0 *****

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

Model: 4

Y: RA_total
 X: ProductT
 M: Cons_total

Sample Size: 268

OUTCOME VARIABLE: Cons_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,1686	,0284	2,7225	7,7782	1,0000	266,0000	,0057

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,6119	,3187	11,3325	,0000	2,9844	4,2395
ProductT	,5622	,2016	2,7889	,0057	,1653	,9591

OUTCOME VARIABLE: RA_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,7066	,4993	1,2016	132,1120	2,0000	265,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	,6875	,2578	2,6662	,0081	,1798	1,1951
ProductT	,6978	,1359	5,1363	,0000	,4303	,9653
Cons_tot	,5839	,0407	14,3357	,0000	,5037	,6641

***** TOTAL EFFECT MODEL *****

OUTCOME VARIABLE: RA_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3331	,1109	2,1254	33,1918	1,0000	266,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2,7966	,2816	9,9308	,0000	2,2422	3,3511
ProductT	1,0261	,1781	5,7612	,0000	,6754	1,3768

***** TOTAL, DIRECT and INDIRECT EFFECTS OF X ON Y *****

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
1,0261	,1781	5,7612	,0000	,6754	1,3768

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
,6978	,1359	5,1363	,0000	,4303	,9653

Indirect effect(s) of X on Y:

Effect	BootSE	BootLLCI	BootULCI	
Cons_total	,3283	,1189	,0963	,5703

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output: 95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals: 5000

***** PROCESS Procedure for SPSS Version 5.0 *****

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
 Documentation available in Hayes (2022). www.guilford.com/p/hayes3

Model: 4
 Y: RA_total
 X: BrandPersonality
 M: Cons_total

Sample Size: 268

OUTCOME VARIABLE: Cons_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2426	,0589	2,6372	16,6339	1,0000	266,0000	,0001

Model

	coeff	se	t	p	LLCI	ULCI
constant	3,2384	,3144	10,3004	,0000	2,6194	3,8575
BrandPersonality	,8092	,1984	4,0785	,0001	,4185	1,1998

OUTCOME VARIABLE: RA_total

Model Summary

R	R-sq	MSE	F	df1	df2	p
,6708	,4500	1,3199	108,3901	2,0000	265,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
--	-------	----	---	---	------	------

constant 1,6642 ,2631 6,3259 ,0000 1,1462 2,1821
 BrandPersonality -,0738 ,1447 -,5102 ,6104 -,3587 ,2111
 Cons_total ,6246 ,0434 14,3988 ,0000 ,5392 ,7100

***** TOTAL EFFECT MODEL *****

OUTCOME VARIABLE: RA_total

Model Summary

R R-sq MSE F df1 df2 p
 ,1401 ,0196 2,3437 5,3244 1,0000 266,0000 ,0218

Model

coeff se t p LLCI ULCI
 constant 3,6868 ,2964 12,4391 ,0000 3,1033 4,2704
 Brand ,4316 ,1870 2,3075 ,0218 ,0633 ,7998

***** TOTAL, DIRECT and INDIRECT EFFECTS OF X ON Y *****

Total effect of X on Y

Effect se t p LLCI ULCI
 ,4316 ,1870 2,3075 ,0218 ,0633 ,7998

Direct effect of X on Y

Effect se t p LLCI ULCI
 -,0738 ,1447 -,5102 ,6104 -,3587 ,2111

Indirect effect(s) of X on Y:

Effect BootSE BootLLCI BootULCI
 Cons_total ,5054 ,1303 ,2646 ,7747

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output: 95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals: 5000

Independent-Samples t-test: Effects of Product Type on Cognitive Involvement

Group Statistics

	Product type	N	Mean	Std. Deviation	Std. Error Mean
Cognitive Involvement	hedonistic	134	5,9821	,99698	,08613
	utilitarian	134	4,5343	1,44655	,12496

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
Cognitive Involvement	Equal variances assumed	22,879	<,001	9,539	266	<,001	<,001	1,44776	,15177	1,14894	1,74658
	Equal variances not assumed			9,539	236,092	<,001	<,001	1,44776	,15177	1,14877	1,74675

Independent Samples Effect Sizes

	Standardizer ^a	Point Estimate	95% Confidence Interval	
			Lower	Upper
Cognitive InvolvementCohen's d	1,24227	1,165	,905	1,424
Hedges' correction	1,24578	1,162	,903	1,420
Glass's delta	1,44655	1,001	,731	1,267

a. The denominator used in estimating the effect sizes.

Cohen's d uses the pooled standard deviation.

Hedges' correction uses the pooled standard deviation, plus a correction factor.

Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Effect of Prior Chatbot Experience

Levene's Test of Equality of Error Variances^a

Dependent Variable: Recommendation adoption

F	df1	df2	Sig.
,872	45	222	,702

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + ChatbotDesign + ProductType + Brand + Q2 + Q4 + Q3

Tests of Between-Subjects Effects

Dependent Variable: Recommendation adoption

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Squared	Eta
Corrected Model	112,424 ^a	8	14,053	6,953	<,001	,177	
Intercept	201,179	1	201,179	99,537	<,001	,278	
ChatbotDesign	12,888	1	12,888	6,377	,012	,024	
ProductType	66,445	1	66,445	32,875	<,001	,113	
Brand	14,457	1	14,457	7,153	,008	,027	
Q2	5,605	2	2,803	1,387	,252	,011	
Q4	7,444	2	3,722	1,842	,161	,014	
Q3	1,288	1	1,288	,637	,425	,002	
Error	523,477	259	2,021				
Total	5674,125	268					
Corrected Total	635,901	267					

a. R Squared = ,177 (Adjusted R Squared = ,151)

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