The impact of Shopping Assistant type and Privacy Concerns on customers' adoption of omnichannel personalization in retail stores

Anna Becságh

Dissertation written under the supervision of professor João Niza Braga.

Dissertation submitted in partial fulfilment of requirements for the MSc in International Management with specialization in Marketing, at the Universidade Católica Portuguesa, January 2025.

Abstract

Title: The impact of Shopping Assistant type and Privacy Concerns on customers' adoption of omnichannel personalization in retail stores

Author: Anna Becságh

AI has become a part of our everyday life, and with that, growing concerns around privacy and data usage are on the rise as well. In omnichannel environments, where multiple channels are integrated through technology, AI could offer significant advancements in the services retailers can provide to their customers, such as personalization. This study focuses on understanding the attitudes towards AI-enabled personalization services, and discover the potential underlying factors.

Using Causal Attribution Theory as the foundation, this study investigates the perceived capabilities and intentions consumers' associate towards different types of Shopping Assistants (AI and Human) and explores consumers' intentions about adopting personalized services provided by these shopping assistants in retail stores.

Furthermore, as Privacy Concerns were found to be the most important indicator of the adoption of such technology-driven services, the study investigated the potential moderating factor of consumers' privacy concerns in this matter through using a 2x2 between-subjects experimental design. While the moderation of privacy concerns on the intentions to adopt was not significant, AI assistants were found to trigger higher privacy concerns than humans, aligning with previous findings.

Managerial implications suggest implementing a hybrid approach to leveraging the strengths of AI and human assistants in retail environments.

Keywords: Privacy Concerns, Artificial Intelligence (AI), Shopping Assistant, Causal Attribution Theory, Personalization, Personalization-Privacy Paradox, Privacy Calculus Theory

Sumário

Título: O impacto do tipo de assistente de compras e das preocupações com a privacidade na adoção pelos clientes da personalização omnicanal em lojas de retalho

Autor: Anna Becságh

A IA tornou-se parte da nossa vida quotidiana e, com isso, as preocupações crescentes em torno da privacidade e da utilização de dados também estão a aumentar. Em ambientes omnicanal, onde vários canais são integrados através da tecnologia, a IA pode oferecer avanços significativos nos serviços que os retalhistas podem fornecer aos seus clientes, como a personalização. Este estudo centra-se na compreensão das atitudes em relação aos serviços de personalização com recurso à IA e na descoberta dos potenciais factores subjacentes. Usando a Teoria da Atribuição Causal como base, este estudo investiga as capacidades percebidas e as intenções que os consumidores associam a diferentes tipos de assistentes de compras (IA e humanos) e explora as intenções dos consumidores sobre a adoção de serviços personalizados fornecidos por estes assistentes de compras em lojas de retalho.
Além disso, uma vez que as preocupações com a privacidade foram consideradas o indicador mais importante da adoção de tais serviços tecnológicos, o estudo investigou o potencial fator moderador das preocupações com a privacidade dos consumidores nesta matéria, utilizando um desenho experimental 2x2 entre sujeitos. Embora a moderação das preocupações com a privacidade nas intenções de adoção não tenha sido significativa, verificou-se que os assistentes de IA desencadeiam maiores preocupações com a privacidade do que os seres humanos, o que está de acordo com conclusões anteriores.
As implicações para a gestão sugerem a implementação de uma abordagem híbrida para potenciar os pontos fortes da IA e dos assistentes humanos em ambientes de retalho.

Palavras-chave: Preocupações com a privacidade, Inteligência Artificial (IA), Assistente de Compras, Teoria da Atribuição Causal, Personalização, Paradoxo Personalização-Privacidade, Teoria do Cálculo da Privacidade

ACKNOWLEDGMENTS

First of all, I would like to thank my advisor, Professor João Niza Braga for the constant support and help throughout my thesis journey. Without all the valuable insights and feedback I received from him, it would not have been possible for me to complete my study.

I would also like to thank my parents for making it possible for me to go on this journey to grow professionally and as a person too. I am thankful for the support and care you provided throughout the years!

To all of my friends; to those I met during the Master's Program for making it an exceptional memory that will last for a lifetime, and especially for my friends at home, who were always very understanding and constantly cheering for me and all of my successes.

Last but definitely not least, I would like to express my deepest gratitude to the most exceptional person, Gergő, who tirelessly supported and believed in me from the very first moment of my Master's program. From the application through the endless days working on my thesis, you were always there for me. I can never be grateful enough for the constant love and energy you provided me throughout these years, even in the most difficult times. I will forever be thankful to you!

Table of Contents

TABLE OF FIGURES

TABLE OF TABLES

1. INTRODUCTION

Technology is constantly changing our everyday life from macro-, and micro perspectives as well. The retail landscape is no exception in this matter; it has undergone a complete transformation because of the technological advancements that the past few years have produced. Artificial Intelligence (AI), in particular, provided the opportunity for retailers to improve their interaction with their customers and extend the number of touchpoints as well (Verhoef et al., 2015). AI has now become an essential part of many interaction processes on various surfaces a company makes with its customers. From enabling them to provide personalized recommendations to virtual shopping assistants, AI is now deeply embedded in many services with high importance on key customer touchpoints, changing the retail experience fundamentally (Kumar et al., 2019).

This is partially due to the emerging tendency of consumers to become more familiar with and use AI increasingly in their daily lives. Companies reflecting on that incorporated this technology into their marketing platforms and services (Marinchak et al., 2018). In most cases, the main indicator is to provide personalized services to their customers. Recent McKinsey research by Gitter et al. (2020) highlighted that 71% of consumers expect companies to deliver personalized interactions. Additionally, 76% get frustrated when this does not happen (Arora et al., 2021)

The omnichannel system, however, with its personalized services, especially when AI agents provide these, could work as double-edged swords. While consumers can take various advantages from it, concerns about their data being exposed to and potentially manipulated by several parties may arise (Wetzlinger et al., 2017). The curated personalized recommendations in retail environments are enabled by analyzing the vast amounts of customer data available for AI agents to be used to predict consumer preferences and behavior (Huang & Rust, 2018).

1.1. Problem Statement

While AI-driven services can be beneficial for both sides (the consumers, as well as the retailers), these novelties in technology brought new concerns regarding privacy and trust (Martin & Murphy, 2017). This inconsistency between the perceived benefits and privacy risks is conceptualized in the term "Personalization-Privacy Paradox" (Smith et al., 2011).

The emerging amounts of surface consumers' data and information exposed to numerous entities may be a possible root cause of the concerns. Especially in cases when someone faces a situation that sheds light on the quantity and quality of data corporations own about their consumers or, in most cases, their potential customers.

In traditional retailing, whenever customers walked into a physical retail store, they should not have been concerned about their identities being revealed to any of the shopping assistants - nor the store itself. With technological advancements like smart mirrors or kiosks, especially with the integration of AI into them, this is not always the case anymore. This advancement changed the shopping experience, enabling personalized services to be diverse in a way that many of them could now be provided by either a human or an AI shopping assistant. This raises the important question of how consumers perceive-, and respond to the different types of shopping assistants (human versus AI) in personalized interactions.

1.2. Research Questions

Grounded on past research, this study aims to examine how the type of shopping assistant (human or AI) affects consumers' perceptions of the costs and benefits of personalization and their intentions about the adoption of personalized services in physical retail stores, considering privacy concerns as a potential moderating factor. Furthermore, using the Causal Attribution Theory as the theoretical foundation, this study focuses on consumers' perceptions of the different types of assistants' intentions and capabilities.

Therefore, the generic Research Question is raised as follows:

How do privacy concerns and the type of shopping assistant (AI vs. human) influence consumers' attitudes toward personalized services in omnichannel retail environments?

Following the focus of this research, there were two more specified Research Questions phrased:

RQ1: Do privacy concerns affect consumers' intention to adopt personalized services in a brick-and-mortar retail store?

RQ2: How does the type of shopping assistant (AI vs. human) affect consumers' perceptions of the perceived benefits and costs of personalization?

1.3. Relevance

The answers to the research questions and the results of this study would serve as an important addition to the existing literature in numerous ways. On the one hand, by examining privacy concerns as a potential influence of adaptation to personalized services, this research could clarify the previously found controversial results on this topic. On the other hand, addressing this matter through the lens of Causal Attribution Theory (Kelley & Michela, 1980) could provide interesting findings in the field of physical store-focused omnichannel personalization due to the perspective's novelty. This study aims to provide insights into how consumers attribute different levels of empathy and trust to human versus AI shopping assistants and how these attributions influence their acceptance of personalized services. For this, experimental research was conducted to test whether the source of personalization serves as a potential influence on the adoption of personalized services.
Thus, this study contributes to previous research on these topics. Furthermore, it also identifies managerial implications that could be of great importance for firms planning to introduce personalized services into their physical retail stores, especially, in the case of retailers who are planning on implementing AI-driven services, since it is extremely crucial for them to maintain the satisfaction and loyalty of their customers. Understanding these dynamics is crucial for developing effective personalization strategies that balance technological capabilities with consumer concerns (Puntoni et al., 2021).

1.4. Research Method

A between-subjects effect (2x2) experimental research design was conducted to understand the effects of activated privacy concerns and the impact of shopping assistant type (AI vs. human) on the adoption of personalized services in brick-and-mortar retail stores using a webrooming example to reflect on the omnichannel experience. Therefore, these conditions were manipulated by signing the participants to either activated or not activated privacy concerns conditions, and similarly, each participant was randomly assigned to an AI or human shopping assistant in the experimental research design. As for the retail store, the brand ZARA was chosen because of its popularity amongst the potential participants. In order for the perception of the brand not to influence the attitude towards the personalized services, a control condition was set up.

2. THEORETICAL REVIEW

2.1. The evolution of omnichannel retailing

According to Verhoef et al. (2015), omnichannel retailing is defined as "the synergetic management of numerous available channels and customer touchpoints in such a way that the customer experience across channels and the performance over channels is optimized". Compared to Multi-channel retailing, which is focused on optimizing each channel individually, the Omnichannel perspective instead integrates all available channels of a brand to provide a seamless customer experience across channels (Mishra et al., 2021). This form of retailing enables customers to use multiple online and offline channels combined in their user journey and switch seamlessly between them, even within the same transaction process (Melero et al., 2016). The main goal of retailers is to increase the volume of customer purchases by making their products and services available in all channels and platforms while presenting this to a consumer as part of the same design (Beck & Rygl, 2015).

2.2. In-Store Personalization

Personalization has become a critical strategy in modern retail, defined as "the ability to provide content and services that are tailored to individuals based on knowledge about their preferences and behaviors" (Adomavicius & Tuzhilin, 2005). In its essence, personalization means presenting the right product to a customer at the right place at the right time (Sheng et al., 2008). To enhance customer experience across the different touchpoints of the omnichannel design, retailers require customer data (Tyrväinen et al., 2020). As online personalization has become increasingly common, consumers are aware of their data being collected and utilized by companies, often through cookie acceptance or with the help of the numerous consents they have to make daily in order to access valuable content.

Retailers are introducing digital devices into physical retail stores so that they can better observe their customers' behavior, collect and analyze customer data, and make personalized suggestions and offers to them (Wetzlinger et al., 2017). By doing that, they bridge the gap between online and in-person shopping experiences (Wetzlinger et al., 2017).

Personalization, however, could have completely different effects. While it enhances consumer engagement with brands through the various benefits, relevant recommendations and overall improved shopping experience it offers, it also raises concerns about the companies' practices about collecting and using customer data to provide these personalized services. (Aguirre et al., 2016). Previous findings indicate that when privacy concerns are high, consumers are less likely to engage with personalized services, even though these services could provide several benefits for them (Smith et al., 2011).

These services can be available in a physical store of a retail company and could be performed both by a Human or an AI shopping assistant. AI for instance is using customer transaction history to provide personalized offers at all four P's of a customer journey, such as price, product, place, and promotion (Weber & Schütte, 2019). However, accessing consumers' personal data can raise serious privacy concerns and through that, it can impact retailers negatively (Martin et al., 2017).

2.3. AI in marketing

According to research by Davenport et al., 2020, AI is very likely to change marketing strategies from sales processes to customer service options. By that, it influences consumer behavior as well. Salespeople can easily be assisted or even completely replaced by AI agents. For example, there is a growing tendency for companies to implement AI-driven chatbots, which can sometimes function as well as human salespeople. This, however, holds a possible negative consequence: customers may become uncomfortable interacting with a bot, therefore this might trigger unintended negative consequences.

The fact that AI is able to monitor conversations, and collect vast amounts of data about the users can enhance concerns about one's data privacy and security.

AI's effects on marketing differ depending on the industry; consumer packaged goods, retail, banking, and travel are among the sectors most affected. These sectors inevitably require regular interaction with a lot of clients, which results in vast amounts of customer transaction data and customer attribute data as well (Davenport et al., 2020). These data can also be enhanced by information from outside sources, such social media or reports from data brokers. AI can then be used to evaluate this data and provide real-time, individualized recommendations (about the best pricing, the next thing to purchase, etc.) (Kumar et al. 2019). However, Davenport et al. (2020) predicted that given the issues AI raises with regard to algorithmic biases, data privacy, and ethics, it has the probability not to live up to all of its promises.

2.4. AI application in Retail

The traditional approaches of personalization were inherently transformed by the integration of AI into the physical retail environment, and new, more sophisticated technology-enabled personalization (TEP) services were introduced. For example, according to Riegger et. al, 2021), in Singapore NomadX concept store has introduced a digital solution to provide personalized offers in their store. With a facial recognition feature enables in-store personalization, with recommendations provided by both their online purchase history, and their in-store behavior (Lim, 2018, as cited by Riegger et. al, 2021).

TEP is the symbol of the evolution from online personalization and the traditional way of personalization: the in-person one. While traditional face-to-face personalization relies on sales representatives' observations and adaptations (Weitz et al., 1986), TEP advances from integrated historical- and real-time data, using automated tools without any employee intervention.

This evolution of personalized services in physical retail stores supports the relevance of our investigation on how consumers perceive and respond to the two different types of shopping assistants (human vs. AI), especially in accordance with trust and privacy concerns. To measure consumer perceptions and test the attitudes towards human and AI recommenders, two of our four research contexts include AI integration into physical retail stores.

2.5. AI vs. Human Shopping Assistant as Recommenders

Even though algorithmic models are proven to outperform humans in predictive tasks (Dawes, 1979), consumers often resist recommendations made by the algorithm (Castelo et al., 2019). Research confirms that AI is less likely to be used by customers for tasks that are associated with the need for empathy to perform them well. (Castelo et al., 2018, as cited in Puntoni et al., 2021). These tasks often involve intuition, effect, and subjectivity, but AI is perceived as lacking the capability to perform these. (Castelo et al., 2018, as cited in Puntoni et al., 2021). This might be due to several factors, such as Dawes (1979, as cited in Longoni & Cian, 2022) highlighted two important perceptions about algorithms, namely that they are not able to learn and improve, and the fear of being reduced to “mere numbers”. Longoni et al. (2019) found a consumer belief that reflects the lack of trust users have towards algorithms to be able to account for individual uniqueness.

According to Lungoni et al. (2019.), consumers tend to refuse to use services provided by AI, compared to humans. This finding supports our research direction examining how the type of shopping assistant (AI vs. human) affects consumers' perceptions of personalization benefits and costs.

This resistance towards AI recommendations is present in various fields, such as healthcare, where consumers are less willing to utilize AI-provided medical care than human providers (Longoni et al., 2019), similar to corporate settings, where professionals might trust their own judgments over algorithmic recommendations (Highhouse, 2008).

Human recommenders, however, are able to provide empathic interactions, which can positively influence customers' overall satisfaction (Zygiaris et al., 2022) and loyalty (Drollinger & Comer, 2013). Research confirms that human salespeople are able to understand customers' thoughts and intentions due to their capability of empathy, which involves both cognitive and emotional decision-making (Jones & Shandiz, 2015; Smith, 2006). Personalization in a physical retail context relies on employees' ability to reflect on consumers' individual needs and preferences and adapt their service offerings accordingly (Bock et al., 2016). Through this capability of human shopping assistants, they can provide personalized assistance by addressing customer needs (Puccinelli et al., 2013), which could result in greater customer satisfaction.

This complex dynamics between algorithmic capability and consumer perception supports this research on how the type of shopping assistant affects consumer perceptions and intentions about personalized services. The tension between AI's superior predictive capabilities and consumers' preference for human interaction provides a foundation for understanding how privacy concerns might moderate these relationships.

2.6. Privacy Concerns

Digital technology enhances privacy concerns because of the vast amount of data available, and the advanced analytics capabilities further strengthen these (Bleier et al., 2020). According to Bleier et al, (2020), there are particularly three main factors that are intensifying privacy concerns about digital technologies, namely the enormous amounts of data availability paired with low storage costs and great longevity, additionally, the data processing and transformation opportunities enabled by the advanced analytics, and lastly, the ability of information sharing with the help of networked digital devices and platforms. Through that, privacy concerns significantly influence the number of consumers open to sharing personal data (Martin & Murphy, 2017).

Additionally, technology-enabled mixed realities (AR, VR) and the integration of the Internet of Things (IoT) have further heightened these concerns about consumer surveillance. (Bleier et al. 2020).

Privacy Concerns in the Retail Personalization context refer to consumers' perceptions of the ability of retailers to keep personal information, as well as electronic records confidentially, from unauthorized access (Escobar-Rodríguez and Carvajal-Trujillo, 2014). For several reasons, these concerns have become crucial aspects of personalized service adoption in retail environments.
Prior research in Omnichannel suggests that technology has both positive and negative effects. It puts Omnichannel system into a position that it is considered a double-edged sword, as in letting its consumers have a more advanced, personalized shopping experience, it also raises their concerns about their data being used, and potentially exposed and manipulated by multiple parties. (Cheah et al., 2022)

In the context of this research, privacy concerns were found to negatively impact consumer behavior in omnichannel environments, affecting trust and engagement in particular (Shi et al., 2020 as cited in Thaichon et al., 2024).

This research aims to discover how differently consumers perceive shopping assistants (human vs. AI) in personalized contexts based on their level of perceived Privacy Concerns.

2.7. The Personalization-Privacy Paradox

The Personalization-Privacy Paradox was conceptualized by representing the tension between consumers' desire for personalized services, whilst being concerned about their privacy (Aguirre et al., 2016). This paradox is extremely relevant in omnichannel retail shopping contexts, particularly where technological advancements such as AI have been introduced, allowing retailers to collect the data of their consumers (Bleier et al., 2020). With the integration of multiple touchpoints and channels, omnichannel environments create numerous opportunities to collect and use consumer data to provide personalized services, increasing the potential privacy vulnerabilities (Aguirre et al., 2016).

Privacy Calculus Theory reflects on this dichotomy and was used in numerous studies in this field, although these revealed controversial results. According to Privacy Calculus Theory, consumers weigh the benefits against the potential privacy risks of engaging in personalized services. (Anderson and Agarwal (2011) Consumers seek to provide the least amount of personal information possible while obtaining the benefits of a personalized service (Acquisti, 2004).

Physical retail environments can be of great complexity for this evaluation due to the public space and the potential of personal data disclosure to third parties (Cas, 2005).

According to Kim (2022), it is especially present in the context of AI, due to the convenience it provides, on the other hand, it can result in unforeseen consequences, for instance, biased algorithms. Kim (2022) also suggests that incidents of data abuse incidents heightened the concerns consumers have about their privacy, which reduced their tendency to share personal data.

Thus, the Personalization-Privacy Paradox and the Privacy Calculus Theory present retailers with the challenge of balancing the provided benefits through personalization while managing consumers' privacy concerns parallelly. The Personalization-Privacy Paradox also explains the tendency of consumers who value information transparency are less likely to adopt personalized services (Awad & Krishnan, 2006, as cited by Wetzlinger et al., 2017), suggesting retailers need to implement personalization strategies in a way that enables to maintain trust amongst their consumers.

2.8. Causal Attribution Theory

Causal Attribution Theory provides the Theoretical foundation for this research to understand the causes and underlying factors of consumers' attitudes towards personalized services provided by the different types of assistants. This theory, initially developed by Fritz Heider and later expanded by Harold Kelley, explains how individuals interpret events and how these interpretations influence their behavior and judgments (Kelley & Michela, 1980).

In attribution theories, the common idea is that behavior is usually interpreted in terms of its causes. Moreover, these interpretations are of high importance in determining reactions to the behavior (Kelley & Michela, 1980).

Causal Attribution Theory posits that causes are attributed to events and behaviors considering three factors. In the context of this research, Causal Attribution Theory aims to explain how consumers may attribute different kinds of intentions and capabilities to the two types of shopping assistants (Human vs. AI) based on these three key factors.

The first one is consensus, which refers to the extent to which people behave similarly in the same situation. Interpreting this to the comparison of shopping assistants, this research aims to discover how consumers perceive the same personalized service provided by the same retailer in the most equal way possible to understand how the type of shopping assistant alters their behavior.

Distinctiveness, being the second pillar, refers to the behavior occurring in similar situations. In the context of shopping assistants, human assistants might be perceived as more distinctive in their behaviors because they adapt to each customer uniquely, whereas the perceptions of AI assistants might be different. The perceptions about AI Assistants can lean towards a less flexible and empathetic direction.

This experimental research compares behavioral patterns of similar yet different situations using a between-subject effects design.

Consistency being the third pillar of Causal Attribution Theory refers to whether a behavior is able to be detected occurring repeatedly over time. Based on previous research, consumers may perceive human assistants to be more empathic and, therefore, caring towards their interests because they are often perceived as having higher consistency, thus maintaining a caring attitude over time (Longoni & Cian, 2022; Puntoni et al., 2021). Whereas AI Shopping Assistants, in comparison to human ones, might not be seen as Assistants with high consensus, therefore, not behaving similarly across all interactions. This also suggests that AI shopping assistants may not be perceived as capable of unique adaptation to each consumer, which indicates that their empathetic skills are not as advanced as humans'. This aligns with the findings of Grove & Meehl (1996), and Castelo et al. (2019), which suggest that people prefer to receive a response from humans in several fields, such as content and recommendations or medical treatments, due to their beliefs that an AI neglects their unique, individual needs and circumstances.

These attributions may impact consumers' perceptions of personalized services, and their willingness to adopt them (Castelo et al., 2018, as cited in Puntoni et al., 2021).

2.9. Hypothesis Development

Based on the previous findings and existing literature on personalization, privacy concerns and attitudes toward the different types of recommenders, the following hypotheses are formed:

H1: Consumers will perceive human recommenders as more caring towards their interests compared to AI recommenders.

This hypothesis posits that consumers may attribute more empathy and understanding towards human shopping assistants than AI ones, suggesting a greater amount of care for the consumers' interests compared to the brands'.

When consumers attribute more positive intentions and capabilities to shopping assistants, they may be more likely to trust and act upon their recommendations.
This leads to our second hypothesis:
H2: Consumers will have more intention to adopt personalized offers when presented by human shopping assistants, than when they are presented by AI shopping assistants.

The third hypothesis includes the potential moderating factor of privacy concerns, according to Zendehdel et al. (2013), as cited in Wetzlinger et al. (2017): "privacy concerns are the most important factor for the intention to adopt innovative electronic shopping concepts."
Therefore, this hypothesis proposes that consumers' preference for human shopping assistants is more significant in cases when their perceived privacy concerns are high compared to contexts when the perceived privacy concerns are low, considering consumers might feel more comfortable with their data being exposed to a human, rather than an AI system:

H3: When perceived privacy concerns are high, consumers will perceive human recommenders as significantly more caring towards their interests compared to AI recommenders; but when perceived privacy concerns are low, the difference in the perceived intentions between human and AI recommenders will be less significant.

Through the lens of Causal attribution Theory, we examine the interactions between variables in order to test our hypothesis.

3. METHODOLOGY

In the following chapter, the research design and approach are explained in detail, as how the previously described Research Questions and Hypotheses are explored by characterizing all measures.

3.1. Introduction

As for the Research Methodology, the quantitative experimental method was chosen to explore the causal effects of AI and Human recommenders, as well as the potential moderating factors of Privacy Concerns. Experimental research designs enable the researcher to measure the impact of the manipulation, by comparing the different levels of the independent variables and examining their effects on the dependent ones. To achieve this, a between-subject effects research design was conducted, containing four unique conditions.
To ensure the balance between the groups, the conditions were randomly assigned to the participants. In order the solely measure the effects of the manipulations, the only difference between the conditions was the manipulated independent variables.
The contexts presented the users with a webrooming shopping experience, for which the brand ZARA was chosen as the retailer company due to its popularity amongst the potential participants as mentioned previously.

3.2. Participants

The survey was distributed online due to its efficiency and convenience provided for the participants, allowing them to participate in the research anonymously and voluntarily at their convenience. The survey was available both in English and Hungarian to ensure the reliability of the results by overcoming the potential misinterpretation of the questions and answers due to the language barrier. This strengthens the willingness to participate and provide honest answers, supporting the efficiency of the research. The platforms used to share the survey were different kinds of social media platforms (Instagram, Facebook, WhatsApp, Reddit, and LinkedIn) in December 2024.

273 users participated in the research, although 138 questionnaires had to be deleted due to incompletion. Therefore, only 135 valid responses were analyzed. The experimental conditions were randomly distributed among the participants, allocating 34 users to the AI Shopping Assistant – Privacy Concern scenario, and 30 participants to the AI Shopping Assistant – No Privacy Concern context. The Human Shopping Assistant – Privacy Concern scenario was completed by 38 participants validly, and in the Human Shopping Assistant – No Privacy Concern context, the total number of participants was 32.

38% of the sample consisted of men, 60% of females, and 1-1% of Non-binary/third-gender participants, and participants who preferred not to say how they would describe themselves. The majority of participants hold either a Bachelor's Degree (45%) or a Master's Degree (38%). 12% of the participants indicated a Highschool Diploma, and only 1% were Elementary. The sample consisted of 66% of participants as full-time employees, 14% were students, 9% were employed part-time, and 5% of the participants were retired. As for nationality, the vast amount of participants were Hungarian with 85%, 7% German, 2% Portuguese, 1-1% French and Austrian, and 4% indicated Other nationalities.

3.3. Materials

To comply with the aim of the research, Privacy Concerns were manipulated as one of the independent variables. Participants were either assigned to a high-risk condition where Privacy Concerns were directly raised or to a low-risk condition where this independent variable was not manipulated directly.

In the high-risk condition, participants were assigned to read an article from Bitdefender, a global cyber security software's online portal about a recent data breach incident. The article explained how PII (Personal Identifiable Information) was stolen from over 60.000 customers of Neimann Marcus, a Dallas-based luxury retailer. The article was chosen to highlight the possibility of data breaches even at companies this size and prestige. The aim was to directly manipulate privacy concerns. Given the example that a luxury retailer can be a victim of cyber-attacks as well, when later on the participants were faced with an imaginary shopping situation, similarly at a retailer, it was expected that they would be actively concerned about their personal data's security. Due to the previously read article, participants instantly perceive the shopping context as a high-risk one. More detailed information is presented in Appendix 1.

In order to provide the same structure and for participants to be exposed to the same amount of time and effort to complete the survey, an article was also displayed in the low-risk perception condition. To ensure that it did not impact the perceived risk in any way, the article was about the weather around Thanksgiving, published in USA TODAY.

By directly manipulating the Privacy Concerns, with these two different levels of perceived risk, it is expected for participants to deviate in their behavior when assigned to the two types of Shopping Assistant conditions. Appendix 1 presents the exact manipulations.

As for the second independent variable, participants were assigned to two different treatment levels regarding the Type of Shopping Assistants, either an AI-, or a Human one.

The study had two different types of shopping situations, where participants were either assisted by an AI-, or a Human Shopping Assistant. Participants were told to imagine a scenario where they wanted to purchase a t-shirt. To resonate with an Omnichannel shopping experience, an emphasis was placed on the role of the different channels. In both conditions (assisted shopping by an AI-, or a Human Agent), participants were told that they were first looking at ZARA's website to find the right t-shirt for them. An additional element of the omnichannel approach was integrated into the situational description, namely, the fact that they already possess a customer account. Therefore, since in the described situation, they were not sure about their product choice, they saved it on their wish list and visited a physical store a couple of days later. Next, participants were presented with an in-store situation, which differed based on the condition.

In the AI Shopping Assistant condition, participants were exposed to a kiosk at the storefront, that had a facial recognition system built in it. With the help of this technology, the system automatically recognised the customer, and an AI Shopping Assistant offered personalized help right away. Since the main objective is to examine the intention to adapt to a personalised

service in-store and how it is influenced by the type of recommender, the personalized service was not optional to choose at the beginning of the survey but rather a given factor. This way, participants' attitudes and intentions toward the personalised service could be measured.
The survey included a further element to enhance the imagination of a shopping situation: in this condition, smart mirrors were introduced to the changing rooms. Through these, the AI Shopping Assistants were able to give further personalised outfit and accessory suggestions to the customers.

In the Human Shopping Assistant condition, the only differences made were in the way how the two types of agents are able to provide the specific services. Such as navigating the customer through the store: whereas in the AI condition, the only guidance provided was regarding the t-shirt's location, in the Human condition, the salesperson could lead the customer to the item. In this condition, the shopping journey included the same number of touchpoints. Therefore, in the changing room, the same personalized recommendations were provided by the Shopping Assistant. A more detailed overview can be found in Appendix 1.

Thus, the four conditions were (1) High Risk – AI Shopping Assistant, (2) High Risk – Human Shopping Assistant, (3) Low Risk – AI Shopping and (4) Low Risk – Human Shopping Assistant.

3.4. Dependent variables

Privacy concerns: The first variable measured was Privacy Concerns by using the scale adapted from Wetzlinger et al. (2017). The original scale consists of five duplicable items, from these, the four applicable ones were adapted to this study measuring the concerns about participants' personal data security (e.g.: "When faced with this scenario, it bothers me that the service provider is able to track information about me.", "When faced with this scenario, it bothers me that the service provider has too much information about me."). On a scale of one to seven, where one represented "Strongly Disagree" and seven represented "Strongly Agree," respondents indicated how much they agreed with the sentences.

Intention to Adopt: To measure participants' intention to adopt, a scale was adapted from the research of Wetzlinger et al. (2017). With items such as "When faced with this scenario, I intend to adopt the personalized service.” and “When faced with this scenario, I predict I will use the personalized service”, this scale directly measured consumers’ intentions to adopt in-store personalized services on a scale of (1) Strongly disagree to (7) Strongly Agree. However, according to Gefen et al. (2003), as cited by Wetzlinger et al. (2017), Trust, Perceived Usefulness, and Perceived Ease of Use are the main indicators for the adoption of online shopping services. Although all three variables were found to have higher levels in online contexts, to follow the structure of Wetzlinger et al. (2017), these dependent variables were measured individually in this research as well.

Trust in the recommender: Trust is measured as a key element of the adoption of technology-enabled systems, such as AI-driven services. Furthermore, when consumers trust an AI assistant, they are more likely to attribute positive outcomes to the assistant's internal characteristics rather than external factors (Gu et al. 2024) This internal attribution enhances the perception that an AI assistant has benevolent intentions and is capable of providing personalized recommendations.
Emotional Trust in the recommender was measured particularly, with a scale adapted from Zhou and Tong (2022) in order to differentiate from the Brand Trust scale, providing valuable insights about attitudes toward the different recommenders (Human vs. AI). The scale included elements such as “You believe that the information of the product recommended by AI/Sales Person is true.” and “You have confidence in AI's/the Sales Person’s knowledge about clothes.” The original scale was developed by Koufaris et al. (2004).

Perceived Usefulness: One of the key pillars of the Technology Acceptance Model (TAM), Perceived Usefulness is an important indicator of consumers’ intentions to adopt the personalization services provided by retailers. With a scale adapted from Koufaris and Hampton-Sosa (2004), with items such as “The (AI) Shopping Assistant can improve my shopping performance” and “I find the help of the AI Shopping Assistant useful”.

Perceived Ease of Use: The other element of TAM, the Perceived Ease of Use was also measured by a scale adapted from Koufaris and Hampton-Sosa (2004). Some of the items were “My interaction with the (AI) Shopping Assistant is clear and understandable.” and “I find the (AI) Shopping Assistant easy to use.”

Trust in the brand: In order to measure attitudes towards the brand, Brand Trust was measured separately by a scale adapted from Koufaris et al. (2003). Respondents' trust in the brand was evaluated and measured on a scale from 1 (Strongly Disagree) to 7 (Strongly Agree), with measures like "This company is trustworthy" and I trust this company keeps my best interests in mind".

Perceived value of the brand: Perceived brand value was measured with the original scale developed by Cronin et al. (2020) and Zeithaml and Zeithaml (1988), adapted from Alimamy and Gnoth (2022), with items such as “Overall, I believe that the value I get from ZARA will be good” and “Overall, I believe that ZARA will satisfy my expectations”. All items were evaluated on a scale from 1 (Strongly Disagree) to 7 (Strongly Agree).

Perceived transparency: Perceived transparency plays a vital role in building trust and reducing privacy concerns (Cramer et al., 2022).
Furthermore, according to Pomfret et al. (2020), the success of personalization initiatives depends on retailers' ability to demonstrate transparent data practices and provide clear value propositions that justify the collection of consumer data. Therefore, Perceived Transparency is measured with a scale adapted from Montecchi et al. (2024) with items like “ZARA provides sufficient information about its operations.” and “I believe that ZARA communicates honestly with its stakeholders”. The items were evaluated on a scale from 1 (Strongly Disagree) to 7 (Strongly Agree) according to the participants’ perceived transparency towards the brand.

Personalization: In order to have a clear vision of the perceived personalization provided by the Shopping Assistants in the contexts, Personalization was measured with the help of a scale adapted from Alimamy and Gnoth (2022). Items such as “The AI Shopping Assistant understands my needs” and “The AI Shopping Assistant knows what I want” were presented to the participants, and all items were evaluated on a scale from 1 (Strongly Disagree) to 7 (Strongly Agree).

Personalization value: To get an understanding of consumers’ evaluation of the perceived personalization, Personalization Value was measured directly. The scale was adapted from Evans et al. (2023), and items like “I am sufficiently rewarded for providing information online.” and “I feel that the benefits I receive for providing information online are fair.” These were measured on a scale from 1 (Strongly Disagree) to 7 (Strongly Agree).

Empathy: Consumers are more likely to attribute positive intentions to AI assistants when they show signs of empathy, enhancing that the assistant genuinely cares about providing services in the customers' interests (Gu et al. 2024). Therefore, serving as the key indicator of the perceived capabilities and intentions of the different kinds of Shopping Assistants, Empathy was measured with a scale adapted from Schmidmaier et al. (2024). The scale contained items like "The (AI) Shopping Assistant sympathized with me." or "The (AI) Shopping Assistant supported me by putting my interest before the brands'.". The original scale was developed by Ball et al. (2006).

Brand familiarity: We measure brand familiarity to control it to avoid potential moderating effects on the relationship between personalization and trust. (Kim & Ahn, 2017). Studies show that consumers are more likely to accept personalization from familiar brands they perceive as valuable (Keller, 2016).

Perceived benefits and costs of personalization: Personalized services can offer customers numerous advantages, such as enhanced customer experience, improved product recommendations, and reduced search costs (Bleier et al., 2020).
Perceived Benefits were measured through a scale adapted from Treiblmaier and Pollach (2007) that contained items such as "Personalized communication helps me make purchasing decisions." and "I enjoy personalized communication since it reduces communication because companies advertise in a more targeted manner.".
Perceived Costs of Personalization were also measured by a scale adapted from Treiblmaier and Pollach (2007). This scale consisted of items like "I am poorly informed about the use of my data." or "Personalization leads to an increase in unsolicited advertising messages since companies know what I am interested in.". All items were evaluated on a scale from 1 (Strongly Disagree) to 7 (Strongly Agree) for Perceived Benefits and Costs of Personalization.

3.5. Procedure

Participants were first directed to an informed consent page, then they were randomly assigned to one shopping assistant conditions and one of the privacy concerns conditions.

They were asked to imagine that they were shopping at a ZARA store, with either the help of an AI-, or a human Shopping Assistant, then they had to rate how concerned they were about the amount of information the service provider has about them, reflecting on their concerns about privacy. Next, they were asked about to what extent they were willing to use the personalized service in the store, aiming to indicate their intentions to adopt it. In the following question, participants were presented with a brand trust scale, measuring how trustworthy they perceived the brand to be, and in the next one, they were asked about the value they perceived to be getting from the brand. The following question reflected on the level of trust towards the Shopping Assistants, and then their perceived transparency about the brand was measured. After that, one of the primary dependent variables, empathy regarding the shopping assistants, was measured, as well as the level of participants' perceived personalization they got from the assistants in imaginary shopping situations. The following question presented the participants with the manipulation check, asking them about the type of assistant their context provided, and the next question was about their brand familiarity with ZARA to control for it. Later, the two other indicators of Intention to Adopt, alongside Trust, Perceived Usefulness, and Perceived Ease of Use of the personalized services, were measured. Then, participants were asked about the value they perceived from the customized service. Lastly, they had to indicate how strongly they agree with personalization's potential benefits and costs.
Demographics were collected at the end of the questionnaire. The detailed Questionnaire can be found in Appendix 1.

3.6. Design

The experiment followed a 2 type of assistant x 2 concerns between-subjects experimental design, with Privacy Concerns, Intention to Adopt, Trust, Empathy, and Personalization Costs and Benefits as the main dependent variables. Perceived Transparency, Perceived Usefulness, Perceived Ease of Use, Perceived Personalization, Personalization Value, Brand Trust, and Perceived Brand Value were also measured.
Participants were randomly assigned to one of the four conditions, ensuring that each participant was only assigned to one of the assistant types and privacy concern levels. This between-subject effects setup enabled the comparison of responses from different groups of participants, ensuring a clear understanding of each participant's attitudes toward the personalized services under the assigned manipulation they were exposed to.

4. RESULTS

4.1. Data Preparation

The experimental research design used multi-item scales to measure the dependent variables. Therefore, new variables had to be computed using the means of the items for the analysis. The Cronbach Alpha was calculated for all scales to test the scales' reliability. An ANOVA was used for hypothesis testing, considering a 5% significance level in all analyses completed.

4.2. Manipulation Checks

A manipulation check question was implemented in the questionnaire to ensure participants understood the condition they were assigned to and that the manipulation was effective. Participants had to indicate what type of shopping assistant is helping them in the imaginary shopping situation by choosing between “AI” or “Human” as an answer. The manipulation check analysis revealed significant issues with the effectiveness of the manipulations. In the AI condition, only 59.4% of participants (38) identified the AI assistant, while in the human condition (N=71), only 53.5% of the participants (38) indicated correctly that a human assisted them. These results suggest that participants did not have a clear understanding of the condition they were assigned to. Despite both chi-square tests showing statistical significance (AI condition: $\chi^2 = 64.000$, $p < .001$; Human condition: $\chi^2 = 71.000$, $p < .001$), these results highlight that participants struggled to distinguish between AI and human shopping assistants in both conditions. This suggests a potential limitation in the strength of the manipulation that should be considered when interpreting the study's findings.

4.3. Control Conditions

No significant differences were found between the AI- ($M = 1.07$, $SD = 0.27$) and Human Shopping Assistant ($M = 1.04$, $SD = 0.20$) groups for the control variable Brand Familiarity ($F(3, 131) = 0.396$, $p = .756$). This suggests that Brand Familiarity does not play a role in the effect of the independent variables (assistant type and privacy concerns) on the main dependent variables, as indicated by the minimal R-squared value of .009 (adjusted R-squared = -.014).

4.4. Main Dependent Variables

4.4.1. Reliability Test

Variable	Scale	Number of Items	Cronbach's Alpha	Literature
Privacy Concerns	7-point Likert scale	4	.900	Wetzlinger et al. (2017)
Intention to Adopt	7-point Likert scale	3	.948	Wetzlinger et al. (2017)
Emotional Trust	7-point Likert scale	5	.900	Zhou and Tong (2022), Koufaris et al. (2004)
Perceived Usefulness	7-point Likert scale	3	.948	Koufaris and Hampton-Sosa (2004)
Perceived Ease of Use	7-point Likert scale	3	.910	Koufaris and Hampton-Sosa (2004)
Brand Trust	7-point Likert scale	5	.935	Koufaris et al. (2003)
Perceived Brand Value	7-point Likert scale	3	.940	Alimamy and Gnoth (2022)
Perceived Transparency	7-point Likert scale	3	.932	Montecchi et al. (2024)
Personalization	7-point Likert scale	3	.908	Alimamy and Gnoth (2022)
Personalization Value	7-point Likert scale	3	.887	Evans et al. (2023)
Empathy	7-point Likert scale	3	.871	Schmidmaier et al. (2024), Ball et al. (2006)
Perceived Benefits	7-point Likert scale	3	.913	Treiblmaier and Pollach (2007)
Perceived Costs	7-point Likert scale	3	.825	Treiblmaier and Pollach (2007)

Table 1 - Cronbach Alpha's of the Dependent Variables

4.4.2. Privacy Concerns

An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed a significant main effect of the Assistant Type ($F(1, 131) = 9.337$, $p = .003$), indicating that the AI Shopping Assistant group leads to higher levels of Privacy Concerns ($M = 5.73$, $SD = 1.36$), than the Human Shopping Assistant group ($M = 4.94$, $SD = 1.53$). We did not find a significant main effect of Privacy Concerns ($M_{privacy\ concerns} = 5.30$, $SD_{privacy\ concerns} = 1.51$; $M_{no\ privacy\ concerns} = 5.34$, $SD_{no\ privacy\ concerns} = 1.48$; $F(1, 131) = .010$, $p = .919$).

The interaction between Assistant Type and Privacy Concerns was not significant ($F(1, 131) = 1.914$, $p = .169$). However, examining the means reveals interesting patterns in how AI and human assistants were perceived across privacy conditions. For the AI assistant condition with privacy concerns, the analysis showed higher levels of privacy concerns ($M = 5.88$, $SD = 1.30$) than the condition where privacy concerns were not manipulated directly ($M = 5.56$, $SD = 1.42$). Still, for human assistants, the means for the directly manipulated privacy concern condition is lower ($M = 4.77$, $SD = 1.52$) than for the context where privacy concerns were not manipulated at all ($M = 5.14$, $SD = 1.54$).

These results could occur for several reasons, further discussed in the “Main findings” section below.

The interaction suggests that while AI assistants consistently received higher Privacy Concern scores than human assistants, this difference was more observable when privacy concerns were present. The results of independent samples T-tests supported the findings of the ANOVA’s main effect by showing a significant difference between the assistant types ($t(133) = -3.18$, $p = .002$) with a moderate to large effect size (Cohen's $d = -0.548$), indicating AI assistants’ consistent association with higher privacy concerns ($M = 5.73$, $SD = 1.35$) compared to human assistants ($M = 4.94$, $SD = 1.52$). The results of a comparison between the two levels of privacy concerns showed no significant difference ($t(133) = .16$, $p = .873$), with similar means for the high privacy concern condition ($M = 5.3014$, $SD = 1.51151$) and no privacy concern condition ($M = 5.3427$, $SD = 1.48368$), with a small effect size (Cohen's $d = .028$).

The assumption of homogeneity of variances was met since Levene's test for equality of variances was non-significant for both comparisons (privacy concerns: $F = .760$, $p = .385$; assistant type: $F = 1.834$, $p = .178$).

4.4.3. Personalization

As predicted, the AI Assistant group led to significantly lower levels of Perceived Personalization ($M = 3.37$, $SD = 1.49$, $t(131) = 6.977$, $p = .009$) than the Human group ($M = 4.10$, $SD = 1.61$). An ANOVA 2 Privacy concerns x 2 Assistant Type revealed a significant main effect of Assistant Type ($F(1, 131) = 6.977$, $p = .009$), indicating that the human group leads to higher levels of Perceived Personalization ($M = 4.10$, $SD = 1.61$) than the AI group ($M = 3.37$, $SD = 1.49$). We did not find a significant main effect of Privacy Concerns ($M_{no\ pc} = 3.90$, $SD_{no\ pc} = 1.57$; $M_{pc} = 3.62$, $SD_{pc} = 1.60$; $F(1, 131) = 1.181$, $p = .279$). The interaction between Assistant Type and Privacy Concerns was not significant ($F(1, 131) = 1.276$, $p = .261$). Looking at the means across conditions: For human assistants, with privacy concerns: $M = 4.11$, $SD = 1.60$, and without privacy concerns: $M = 4.09$, $SD = 1.65$. For AI assistants, with privacy concerns: $M = 3.10$, $SD = 1.46$, and without privacy concerns: $M = 3.69$, $SD = 1.48$. The interaction suggests that human assistants generally received higher personalization scores than AI assistants.

4.4.4. Intention to Adopt

Contrary to previous findings and predictions, the AI Shopping Assistant condition led to higher levels of Intention to Adopt ($M = 3.76$, $SD = 1.82$, $F(131) = .268$, $p = .606$) than the Human Shopping Assistant group ($M = 3.63$, $SD = 1.82$). Thus, the difference was only marginal, and the results were not statistically significant.

An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed no significant main effect of Assistant Type ($F(1, 131) = .268$, $p = .606$), indicating that the AI Shopping Assistant group ($M = 3.76$, $SD = 1.82$) and the Human Shopping Assistant group ($M = 3.63$, $SD = 1.82$) had similar levels of Intention to Adopt. We did not find a significant main effect of Privacy Concerns ($M_{pc} = 3.73$, $SD_{pc} = 1.91$; $M_{no\ pc} = 3.66$, $SD_{no\ pc} = 1.70$; $F(1, 131) = .035$, $p = .852$). The interaction between Assistant Type and Privacy Concerns was not significant ($F(1, 131) = 1.111$, $p = .294$). Looking at the means across conditions, the condition including AI assistants with manipulated privacy concerns revealed lower levels of Intention to Adopt ($M = 3.64$, $SD = 2.01363$) than the control condition group without activated privacy concerns ($M = 3.91$, $SD = 1.57$). However, for Human Shopping Assistants in the Privacy Concern condition, the Intention to Adopt showed higher results ($M = 3.80$, $SD = 1.83$) than in the no Privacy Concern condition ($M = 3.42$, $SD = 1.81$).

None of the differences between conditions reached statistical significance at $p < .005$. The interaction suggests that while AI and human assistants were perceived similarly overall, there were slight variations in how they were evaluated under different privacy conditions. However, these differences were not statistically significant.

According to the indications of Davenport et al. (2020), Trust, Perceived Usefulness, and Perceived Ease of Use are the variables explaining a significant amount of the variety of the expected extent of adoption of online shopping services; therefore, these variables were measured individually.

4.4.5. Trust

As predicted, the AI Assistant group led to significantly lower levels of Trust (M = 4.00, SD = 1.57, $t(131) = 9.767$, $p = .002$) than the Human Assistant group (M = 4.81, SD = 1.32). An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed a significant main effect of Assistant Type ($F(1, 131) = 9.767$, $p = .002$), indicating that the human group leads to higher levels of Trust (M = 4.80, SD = 1.32), than the AI group (M = 4.01, SD = 1.57). We did not find a significant main effect of Privacy Concerns ($M_{no\ pc} = 4.42$, $SD_{no\ pc} = 1.45$; $M_{pc} = 4.42$, $SD_{pc} = 1.54$; $F(1, 131) = .004$, $p = .950$). The interaction between Assistant Type and Privacy Concerns was not significant ($F(1, 131) = 2.027$, $p = .157$). Looking at the means across conditions: For human assistants, with privacy concerns: M = 4.97, SD = 1.29, and without privacy concerns: M = 4.63, SD = 1.36. For AI assistants, with privacy concerns: M = 3.83, SD = 1.60, and without privacy concerns: M = 4.20, SD = 1.54. The interaction suggests that human assistants consistently received higher trust scores than AI assistants, which is statistically significant at $p < .005$, regardless of privacy conditions.

4.4.6. Perceived Usefulness

The AI Assistant group led to significantly lower levels of Perceived Usefulness (M = 3.72, SD = 1.68, $t(131) = 8.313$, $p = .005$) than the Human Assistant group (M = 4.55, SD = 1.62). An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed a significant main effect of Assistant Type ($F(1, 131) = 8.313$, $p = .005$), indicating that the human group leads to higher levels of Perceived Usefulness (M = 4.55, SD = 1.62), than the AI group (M = 3.72, SD = 1.68). We did not find a significant main effect of Privacy Concerns ($M_{no\ pc}$ = 4.38, $SD_{no\ pc}$ = 1.63; M_{pc} = 3.96, SD pc = 1.74; F (1, 131) = 2.215, p = .139). The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 131) = .061, p = .806). Looking at the means across conditions: For human assistants, with privacy concerns: M = 4.39, SD = 1.69, and without privacy concerns: M = 4.74, SD = 1.55. For AI assistants, with privacy concerns: M = 3.50, SD = 1.70, and without privacy concerns: M = 3.99, SD = 1.64. The interaction suggests that human assistants consistently received higher perceived usefulness scores than AI assistants, with this difference being statistically significant at p = .005.

4.4.7. Perceived Ease of Use

There was no significant difference in Perceived Ease of Use between the AI Assistant group (M = 4.21, SD = 1.62) and the Human Assistant group (M = 4.41, SD = 1.68), t(131) = .347, p = .557. An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed no significant main effect of Assistant Type (F (1, 131) = .347, p = .557), indicating that the human group (M = 4.41, SD = 1.68) and the AI group (M = 4.21, SD = 1.62) had similar levels of perceived ease of use. We did not find a significant main effect of privacy concerns ($M_{no\ pc}$ = 4.46, $SD_{no\ pc}$ = 1.54; M_{pc} = 4.18, SD_{pc} = 1.75; F (1, 131) = 1.106, p = .295). The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 131) = 2.830, p = .095). Looking at the means across conditions: For human assistants, with privacy concerns: M = 4.49, SD = 1.73, and without privacy concerns: M = 4.31, SD = 1.64. For AI assistants, with privacy concerns: M = 3.85, SD = 1.70, and without privacy concerns: M = 4.62, SD = 1.44. The interaction suggests that while there were some variations in perceived ease of use between AI and human assistants under different privacy conditions, none of these differences reached statistical significance at $p < .005$.

4.4.8. Personalization Value

As predicted, the AI Assistant group led to significantly lower levels of Personalization Value (M = 2.94, SD = 1.73, t (131) = 45.191, $p < .001$) than the Human Assistant group (M = 4.75, SD = 1.35). An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed a significant main effect of Assistant Type (F (1, 130) = 45.191, $p < .001$), indicating that the human group leads to higher levels of Personalization Value (M = 4.75, SD = 1.35), than the AI group (M = 2.94, SD = 1.73). We did not find a significant main effect of Privacy Concerns ($M_{no\ pc}$ = 4.04, $SD_{no\ pc}$ = 1.84; M_{pc} = 3.73, SD_{pc} = 1.73; F (1, 130) = 1.451, p = .231). The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 130) = .332, p = .566). Looking at the means across conditions: For human assistants, with privacy concerns: M = 4.68, SD = 1.36, and without privacy concerns: M = 4.84, SD = 1.35. For AI assistants, with privacy concerns: M = 2.72, SD = 1.51, and without privacy concerns: M = 3.20, SD = 1.94. The interaction suggests that human assistants consistently received higher personalization value scores than AI assistants, with this difference being highly statistically significant at p < .001, regardless of privacy conditions.

4.4.9. Perceived Benefits of Personalization

As predicted, the AI Assistant group led to significantly higher levels of Personalization Benefits (M = 4.38, SD = 1.48, t (131) = 8.729, p = .004) than the control group (M = 3.49, SD = 1.94). An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed a significant main effect of Assistant Type (F (1, 131) = 8.729, p = .004), indicating that the AI group leads to higher levels of Personalisation Benefits (M = 4.38, SD = 1.47), than the human group (M = 3.49, SD = 1.94). We did not find a significant main effect of Privacy Concerns ($M_{no\ pc}$ = 4.03, $SD_{no\ pc}$ = 1.64; M_{pc} = 3.83, SD_{pc} = 1.90; F (1, 131) = .428, p = .514). The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 131) = .000, p = .983). Looking at the means across conditions: For human assistants, with privacy concerns: M = 3.40, SD = 2.02, and without privacy concerns: M = 3.59, SD = 1.86. For AI assistants, with privacy concerns: M = 4.29, SD = 1.66, and without privacy concerns: M = 4.49, SD = 1.24. The interaction suggests that AI assistants consistently received higher personalization benefits scores than human assistants, with this difference being statistically significant at p < .005, regardless of privacy conditions.

4.4.10. Perceived Costs of Personalization

As predicted, there was no significant difference in Personalization Costs between the AI- (M = 5.38, SD = 1.37, t (131) = .508, p = .477) compared to the Human Assistant group (M = 5.55, SD = .98). An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed no significant main effect of Assistant Type (F (1, 131) = .508, p = .477) indicating that the human group (M =

5.55, SD = .98) and the AI group (M = 5.38, SD = 1.37) had similar levels of perceived costs. We did not find a significant main effect of privacy concerns ($M_{no\ pc}$ = 5.43, $SD_{no\ pc}$ = 1.13; M_{pc} = 5.50, SD_{pc} = 1.23; F (1, 131) = .103, p = .749). The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 131) = 1.276, p = .261). Looking at the means across conditions: For human assistants, with privacy concerns: M = 5.68, SD = .79, and without privacy concerns: M = 5.39, SD = 1.16. For AI assistants, with privacy concerns: M = 5.31, SD = 1.56, and without privacy concerns: M = 5.47, SD = 1.12. The interaction suggests that there were no significant differences in perceived costs between AI and human assistants under different privacy conditions, with none of the effects reaching statistical significance at p < .005.

4.4.11. Brand Trust

As predicted, the AI Assistant group led to lower levels of Brand Trust (M = 3.56, SD = 1.63, t (131) = 4.484, p = .036) than the Human Assistant group (M = 4.18, SD = 1.52), though this difference was not significant at p < .005. An ANOVA Privacy Concerns x 2 Assistant Type revealed no significant main effect of Assistant Type (F (1, 131) = 4.484, p = .036), indicating that while the human group had higher levels of brand trust (M = 4.18, SD = 1.52) compared to the AI group (M = 3.56, SD = 1.63), this difference did not reach statistical significance at p < .005. We did not find a significant main effect of Privacy Concerns ($M_{no\ pc}$ = 4.07, $SD_{no\ pc}$ = 1.58; M_{pc} = 3.75, SD pc = 1.60; F (1, 131) = 1.488, p = .225). The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 131) = .800, p = .373). Looking at the means across conditions: For human assistants, with privacy concerns: M = 4.14, SD = 1.50, and without privacy concerns: M = 4.23, SD = 1.56. For AI assistants, with privacy concerns: M = 3.32, SD = 1.62, and without privacy concerns: M = 3.89, SD = 1.61. The interaction suggests that while human assistants generally received higher brand trust scores than AI assistants, none of these differences reached statistical significance at the p < .005 level.

4.4.12. Perceived Value of the Brand

As predicted, the AI Assistant group led to significantly lower levels of Perceived Value of the Brand (M = 3.41, SD = 1.63, t (134) = 8.866, p = .003) than the Human Assistant group (M = 4.27, SD = 1.58).

An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed a significant main effect of Assistant Type (F (1, 130) = 8.866, p = .003), indicating that the human group leads to higher levels of Perceived Brand Value (M = 4.27, SD = 1.58), than the AI group (M = 3.41, SD = 1.63). We did not find a significant main effect of Privacy Concerns ($M_{no\ pc}$ = 3.95, $SD_{no\ pc}$ = 1.61; M_{pc} = 3.77, SD_{pc} = 1.71; F (1, 130) = .445, p = .506).

The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 130) = 2.708, p = .102). Looking at the means across conditions: for human assistants with privacy concerns (M = 4.40, SD = 1.55), without privacy concerns (M = 4.13, SD = 1.63). For AI assistants with privacy concerns (M = 3.11, SD = 1.63), without privacy concerns (M = 3.76, SD = 1.59). The interaction suggests that while human assistants consistently received higher perceived value scores than AI assistants, this difference was most pronounced when privacy concerns were present, though this interaction did not reach statistical significance at $p < .005$.

4.4.13. Empathy

As predicted, the Human Assistant group led to significantly higher levels of Empathy (M = 3.78, SD = 1.55) than the control group (M = 2.95, SD = 1.65, t (131) = 8.894, p = .003). An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed a significant main effect of Assistant Type (F (1, 131) = 8.894, p = .003), indicating that the human group leads to higher levels of Empathy (M = 3.78, SD = 1.55), than the AI group (M = 2.960, SD = 1.65226). We did not find a significant main effect of Privacy Concerns ($M_{no\ pc}$ = 3.51, $SD_{no\ pc}$ = 1.70; M_{pc} = 3.27, SD_{pc} = 1.61; F (1, 131) = .790, p = .376). The interaction between Assistant Type and Privacy Concerns was not significant (F (1, 131) = .039, p = .845). Looking at the means across conditions: For human assistants, with privacy concerns: M = 3.69, SD = 1.55, and without privacy concerns: M = 3.89, SD = 1.57. For AI assistants, with privacy concerns: M = 2.81, SD = 1.57, and without privacy concerns: M = 3.11, SD = 1.76. The interaction suggests that human assistants consistently received higher empathy scores than AI assistants regardless of privacy conditions, with the main effect of assistant type being the only significant finding at $p < .005$.

4.4.14. Perceived Transparency

As predicted, the AI Assistant group did not show significantly different levels of Perceived Transparency (M = 3.46, SD = 1.70, t (131) = .693, p = .407) compared to the Human Assistant group ($M = 3.72$, $SD = 1.69$). An ANOVA 2 Privacy Concerns x 2 Assistant Type revealed no significant main effect of Assistant Type ($F(1, 131) = .693$, $p = .407$), indicating that the human group ($M = 3.72$, $SD = 1.69$) and the AI group ($M = 3.46$, $SD = 1.70$) had similar levels of perceived transparency. We did not find a significant main effect of Privacy Concerns ($M_{no\ pc} = 3.83$, $SD_{no\ pc} = 1.82$; $M_{pc} = 3.39$, $SD\ pc = 1.57$; $F(1, 131) = 2.438$, $p = .121$). The interaction between Assistant Type and Privacy Concerns was not significant ($F(1, 131) = .821$, $p = .367$). Looking at the means across conditions: For human assistants, with privacy concerns: $M = 3.63$, $SD = 1.61$, and without privacy concerns: $M = 3.82$, $SD = 1.80$. For AI assistants, with privacy concerns: $M = 3.12$, $SD = 1.51$, and without privacy concerns: $M = 3.84$, $SD = 1.86$. The interaction suggests that while there were some variations in perceived transparency scores between AI and human assistants under different privacy conditions, none of these differences reached statistical significance at $p < .005$.

4.5. Hypothesis testing

The research evaluated three key hypotheses examining the relationship between shopping assistant type, privacy concerns, and consumer behavior in omnichannel retail environments, with a focus on physical retail stores.

4.5.1. Hypothesis 1 Evaluation

The first hypothesis predicted that consumers would perceive human recommenders as more caring towards their interests compared to AI recommenders. This hypothesis was supported by the experimental results:
Human Shopping Assistants received significantly higher empathy scores ($M = 3.789$, $SD = 1.55198$) compared to AI assistants ($M = 2.960$, $SD = 1.65226$). Trust levels were also significantly higher for Human Shopping Assistants ($M = 4.795$, $SD = 1.32068$) compared to AI Shopping Assistants ($M = 4.014$, $SD = 1.56901$).

4.5.2. Hypothesis 2 Evaluation

The second hypothesis proposed that consumers would show greater intention to adopt personalized offers when presented by human versus AI shopping assistants. This hypothesis was not supported by the experimental research:

Contrary to predictions, AI Shopping Assistants led to slightly higher adoption intentions (M = 3.7641, SD = 1.81499) compared to human assistants (M = 3.6286, SD = 1.81472), though this difference was not statistically significant. However, human assistants scored significantly higher on perceived usefulness (M = 4.548, SD = 1.62413) compared to AI assistants (M = 3.723, SD = 1.67453)

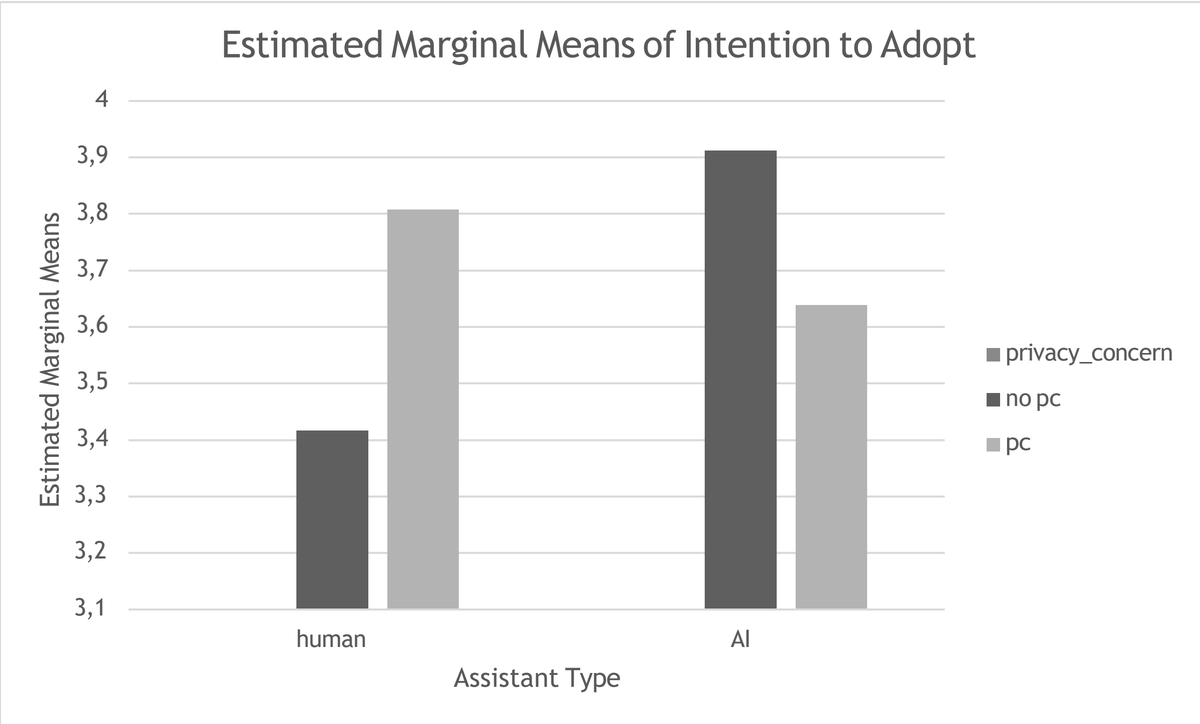

Figure 1 - Estimated Marginal Means of "Intention to Adopt" comparing Human and AI assistant types in High- and Low Privacy Concern Conditions

4.5.3. Hypothesis 3 Evaluation

The third hypothesis suggested that privacy concerns would moderate the relationship between assistant type and perceived caring intentions. To understand if moderation arises and to test this hypothesis, a moderation analysis was run using Process by Andrew F. Hayes with Model 1. The results suggested that the relationship between the Assistant Type and the Intention to Adopt personalized services is not significant (p = .2872). This suggests that the type of assistant alone does not significantly influence the Intention to Adopt. The effect of Privacy Concerns is not significant either (p = .3732), indicating that privacy concerns alone also do not significantly influence adoption intentions. The interaction between Assistant Type and Privacy

Concerns shows a negative coefficient (b = -.6634), but it is also non-significant (p = .2937). The results of the interaction suggest that the relationship between assistant type and adoption intentions does not significantly differ between people with high and low privacy concerns. Based on the results of the moderation analysis, hypothesis 3 was therefore rejected.

However, a significant main effect was found for assistant type (F(1, 131) = 8.894, p = .003), with human assistants receiving higher empathy scores (M = 3.789, SD = 1.55198) compared to AI assistants (M = 2.960, SD = 1.65226). There was no significant main effect found for privacy concerns nor for the interaction between assistant type and privacy concerns.

The predicted main effect of the assistant type was confirmed, with humans consistently being perceived as more empathetic than AI. However, the hypothesized interaction with privacy concerns was not statistically significant, therefore, it is not supported. The difference in empathy ratings between human and AI assistants remained relatively stable regardless of privacy concern conditions. These results also suggest that while consumers consistently tribute higher levels of caring intentions to humans - compared to AI shopping assistants - this preference is not significantly moderated by privacy concerns, as originally hypothesized.

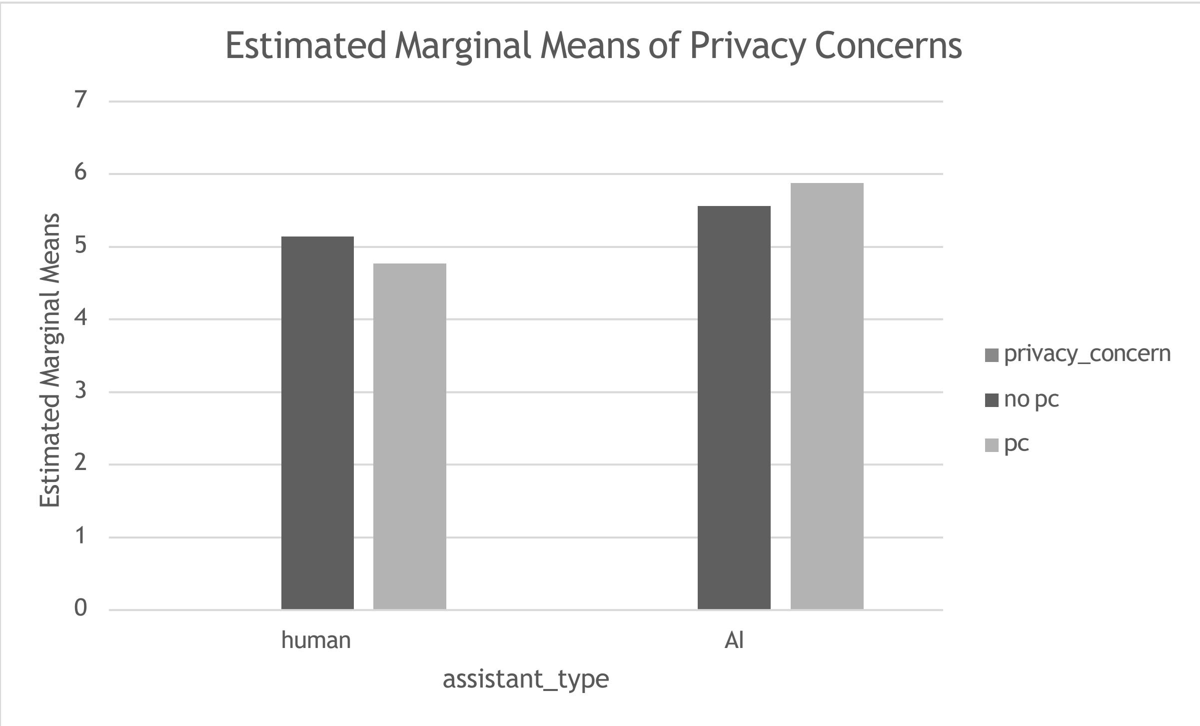

Figure 2 - Estimated Marginal Means of "Privacy Concerns" comparing Human and AI assistant types in High- and Low Privacy Concern Conditions

4.6. Additional findings

The research revealed several noteworthy secondary findings: Human assistants consistently received higher personalization value scores ($M = 4.754$, $SD = 1.34511$) compared to AI assistants ($M = 2.944$, $SD = 1.72559$), while AI assistants were perceived as offering greater personalization benefits ($M = 4.380$, $SD = 1.47535$) than human assistants ($M = 3.491$, $SD = 1.93678$). Furthermore, perceived ease of use showed no significant differences between human and AI assistants.

5. GENERAL DISCUSSION

5.1. Main Findings

The purpose of the study was to inspect how consumers are likely to adopt personalized services in physical retail stores, and how this tendency is influenced by the type of shopping assistant they are receiving the personalized service from. Furthermore, we examined how privacy concerns interfere with these intentions. Additionally, based on the Causal Attribution Theory, the study focused on the perceived capabilities consumers attribute to the different types of assistants. Therefore, the study included the manipulation of two key independent variables, Privacy Concerns with two levels, and Assistant type, also with two levels. These manipulations enabled the researcher to understand how these impact consumers' intentions to adopt these services and their perceptions about AI and human shopping assistants. However, based on the results of the manipulation check, the manipulations might not have been completely successful, which can limit the conclusions we can draw from the results of this study. Understanding the underlying factors for the unsuccessful manipulation results exceeds this study's limits and would indicate a detailed follow-up study. However, this may also be due to the undesirable quality of respondents and their lack of dedication towards the questionnaire. The first hypothesis was confirmed, indicating that consumers attribute higher empathy and trust toward human assistants, as predicted.

The second hypothesis was rejected due to the lack of significant results supporting the idea that a higher intention to adopt is associated with human shopping assistants compared to the AI one. Trust, Perceived Usefulness, and Perceived Ease of Use were also measured to support the direct measure of the Intention to Adopt, as indicated by Wetzlinger et al. (2017). However,

Trust and Perceived Usefulness showed significantly higher results for human assistants in total (M_{Trust}= 4.8095, M_{PEU}= 4.5476), and there was a slight difference between the assistant types for Perceived Ease of Use as well, also for the human assistants' advantage ($M_{human\ assistant}$=4.4095, $M_{AI\ assistant}$= 4.2051), although these results were not significant. This might occur due to the poor quality of the measure used in the research because of its incapability to detect the intentions of adoption. Another possible reason for the non-significant result could be the lack of predicting capability of the variables found in previous research to indicate the adoption intentions in the context of personalized services provided by a shopping assistant.
The third hypothesis focused on the interaction between the assistant type and the level of privacy concerns, measured for empathy. Although the interaction did not turn out to be significant, there is a pattern visible in the analysis, which would indicate the relevancy of this hypothesis.

5.2. Discussion

The experimental findings extend our understanding of consumer behavior about AI-driven personalization in retail environments.

As discussed before, when smart retail environments integrate digital personalization into physical retail stores through Technology-Enabled Personalization (TEP) and, through that, offer a sophisticated form of personalization that enhances shopping experiences, they must also consider privacy concerns raised with them parallelly. Although the results of the analysis turned out to be non-significant in many cases, the pattern of consumers exhibiting different responses to TEP based on the type of shopping assistant and their privacy concerns is demonstrated in this research.
This pattern strongly supports Causal Attribution Theory's application to AI and human interactions. As indicated by Gu et al. (2024), alongside perceived Empathy, Trust in an AI assistant increases the likelihood of consumers' positive attributing intentions towards them, indicating their perceptions about the AI assistants' honest intentions toward their advantages. Consumers attribute different levels of intentions to the AI and human assistants, with human assistants receiving significantly higher trust scores (M = 4.795) compared to AI assistants (M = 4.014). This aligns with previous research, demonstrating consumers' preference for human interaction in contexts that require emotional understanding and subjective judgment.

Therefore, the findings support the Causal Attribution Theory applied to the context of this research, suggesting that consumers attribute more positive intentions and caring capabilities to human assistants.
AI assistants triggered significantly higher privacy concerns compared to human assistants, as expected, and this heightened concern aligns with previous findings about consumers' reservations regarding AI's data collection and usage practices. However, the results indicated an unexpected relationship between privacy concerns and the human assistants. Privacy concerns for human assistants were higher in the context where this variable was manipulated to be low compared to the high privacy concern context; in the context of AI shopping assistants, the manipulation resulted in the expected pattern. The surprising result in the human condition might be due to the psychological mechanism of Overcompensation. Conceptualized by Adler (1959), it represents the psychological mechanism of excessive compensation in situations with high perceived inferiority to pursue superiority. In the context of the results, it suggests that when one becomes aware of the manipulation attempt about their privacy concerns, it might trigger compensating mechanisms, which may turn into overcorrection. This might be the reason for the unexpected results in their responses. However, this is only speculative because this interaction is non-significant.

The Personalization-Privacy Paradox framework is also recognizable in the results of the respondents' behavior: Human assistants generated overall higher empathy scores (M = 3.789) and trust levels (M= 4.8095), resulting in higher trust and perceived values towards the brand and an overall higher personalization value (M= 4.7536), but also higher personalization costs (M= 5.5476) were associated with human assistants. Meanwhile, AI assistants turned out to be perceived as offering greater personalization benefits (M = 4.380) with lower overall personalization costs. This dichotomy supports previous findings about consumers resisting algorithmic recommendations despite their superior capabilities in various fields. These findings also enhance Privacy Calculus Theory by revealing how the assistant type influences the privacy cost-benefit evaluation process. This extends our understanding with a novel perspective about how consumers weigh personalization benefits against privacy risks.

5.3. Managerial Implications

Based on the findings of this research, retailers should consider implementing in-store personalization strategies with a hybrid approach that leverages both AI and human assistants' strengths and capabilities by using AI for data gathering, analysis, and data-driven personalized approaches, represented by a human assistant, enabling their high levels of empathy, subjective judgment capability, and overall personal touch to enhance the shopping experience for the consumers.
With the implementation of personalized services into retailers' sales strategies, it is crucial to aim for a clearly communicated and transparent data usage and privacy protection policy to maintain and strengthen their consumers' trust in the company.
From a service design perspective, retailers should aim to balance the amount of automation in the implemented services with human touch and interactions across all channels and touchpoints and create clear and understandable protocols about when and how to transition between the AI and human shopping assistants on the different platforms included in their Omnichannel strategy.

5.4. Limitations and Future Research Directions

The study had several limitations, such as the obvious difference between the experimental setting and real-world behavior. This partially indicated the lack of success of the manipulations' effectiveness regarding privacy concerns, as well as the manipulations of the shopping assistant types. Future studies should aim for a clearer distinction between the kinds of assistants in different contexts to achieve more effective manipulations. Furthermore, in a longitudinal experiment, studies should examine how consumer perceptions of AI assistants evolve and how multiple interactions with the widespread AI technology implementation vary.

Furthermore, although the study was spread internationally, 85% of the participants were Hungarians. This limited geographical scope may indicate a preference for AI assistants due to different cultural and socio-economic patterns. To confirm this, further research is needed to explore how cultural differences influence consumer responses to AI versus human assistants. This would provide valuable insights for international retail operations.
Another limitation of the research was the focus on a single brand. However, the analysis of the control condition measuring Brand Familiarity did not reveal significant results that would

influence respondents' attitudes toward the personalized services, future research should aim for various brand integration into the experimental settings.

Additionally, further investigation is needed on how the different types of AI and human integration models affect consumer trust and adoption of personalized services.

REFERENCES

1. Acquisti, A. (2004). Privacy in electronic commerce and the economics of immediate gratification. In Proceedings of the 5th ACM conference on Electronic commerce (pp. 21-29).DOI:10.1145/988772.988777
2. Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6), 734-749. https://doi.org/10.1109/TKDE.2005.99
3. Aguirre, E., Roggeveen, A.L., Grewal, D. and Wetzels, M. (2016), "The personalization-privacy paradox: implications for new media", Journal of Consumer Marketing, Vol. 33 No. 2, pp. 98-110. https://doi.org/10.1108/JCM-06-2015-1458
4. Alimamy, S., & Gnoth, J. (2022). I want it my way! The effect of perceptions of personalization through augmented reality and online shopping on customer intentions to co-create value. Computers in Human Behavior, 127, 107105. https://doi.org/10.1016/j.chb.2021.107105
5. Anderson, C. L., & Agarwal, R. (2011). The digitization of healthcare: boundary risks, emotion, and consumer willingness to disclose personal health information. Information Systems Research, 22(3), 469-490. https://doi.org/10.1287/isre.1100.0335
6. Arora, N., Ensslen, D., Fiedler, L., Liu, W. W., Robinson, K., Stein, E., & Schüler, G. (2021). The value of getting personalization right—or wrong—is multiplying. McKinsey & Company. Retrieved from https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-value-of-getting-personalization-right-or-wrong-is-multiplying
7. Awad, N.F., Krishnan, M.S.: The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization. MIS Q. 30, 13–28 (2006) https://doi.org/10.2307/25148715
8. Beck, N., Rygl, D.: Categorization of multiple channel retailing in multi-, cross-, and omni-channel retailing for retailers and retailing. J. Retail. Consum. Serv. 27, 170–178 (2015)
9. Bleier, A., Goldfarb, A., & Tucker, C. (2020). Consumer privacy and the future of data-based innovation and marketing. International Journal of Research in Marketing, 37(3), 466-480. https://doi.org/10.1016/j.ijresmar.2020.03.006
10. Bock, D. E., Mangus, S. M., & Folse, J. A. G. (2016). The road to customer loyalty paved with service customization. Journal of Business Research, 69(10), 3923-3932. DOI:10.1016/j.jbusres.2016.06.002
11. Cai Y. J., Lo C. K. Y. (2020). Omnichannel management in the new retailing era: A systematic review and future research agenda. International Journal of Production Economics, 229, 107729.

12. Cas, J. (2005). Privacy in pervasive computing environments - a contradiction in terms? IEEE Technology and Society Magazine, 24(1), 24-33. DOI:10.1109/MTAS.2005.1407744

13. Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. Journal of Marketing Research, 56(5), 809–825. https://doi.org/10.1177/0022243719851788

14. Cheah, J.-H., Lim, X.-J., Ting, H., Liu, Y., & Quach, S. (2022). Are privacy concerns still relevant? Revisiting consumer behaviour in omnichannel retailing. Journal of Retailing and Consumer Services, 65, 102242. https://doi.org/10.1016/j.jretconser.2021.102242

15. Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

16. Dawes Robyn M. (1979), "The Robust Beauty of Improper Linear Models in Decision Making," American Psychologist, 34 (7), 571–82.

17. Drollinger, T., & Comer, L. B. (2013). Salesperson's listening ability as an antecedent to relationship selling. Journal of Business & Industrial Marketing, 28(1), 50-59. Retrieved from https://www.emerald.com/insight/content/doi/10.1108/08858621311285714/full/html

18. Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2014). Online purchasing tickets for low cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. Tourism Management, 43, 70–88. https://doi.org/10.1016/j.tourman.2014.01.017

19. Evans, R., Hajli, N., & Nisar, T. M. (2023). Privacy-Enhancing Factors and Consumer Concerns: The Moderating Effects of the General Data Protection Regulation. British Journal of Management, 34(4), 2075-2092. https://doi.org/10.1111/1467-8551.12685

20. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in Online Shopping: An Integrated Model. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

21. Gitter, J., Leibowitz, J., Swinford, R., & Toma, B. (2020). The value of getting personalization right—or wrong—is multiplying. McKinsey & Company Digital Report. Retrieved from
McKinsey & Company

22. Grove William M., Meehl Paul E. (1996), "Comparative Efficiency of Informal (Subjective, Impressionistic) and Formal (Mechanical, Algorithmic) Prediction Procedures: The Clinical-Statistical Controversy," Psychology, Public Policy, and Law, 2 (2), 293–323.

23. Gu, C., Zhang, Y. & Zeng, L. Exploring the mechanism of sustained consumer trust in AI chatbots after service failures: a perspective based on attribution and CASA theories. Humanit Soc Sci Commun 11, 1400 (2024). https://doi.org/10.1057/s41599-024-03879-5

24. Highhouse, S. (2008). Stubborn reliance on intuition and subjectivity in employee selection. Industrial and Organizational Psychology, 1(3), 333–342. https://doi.org/10.1111/j.1754-9434.2008.00058.x
25. https://doi.org/10.1509/jm.15.0497
26. Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155-172. https://doi.org/10.1177/1094670517752459
27. Jones, M. A., & Shandiz, M. (2015). Service quality expectations: Exploring the importance of SERVQUAL dimensions from different nonprofit constituent groups. Journal of Nonprofit & Public Sector Marketing, 27(1), 48-69. https://doi.org/10.1080/10495142.2014.925762
28. Kelley, H. H., & Michela, J. L. (1980). Attribution theory and research. Annual Review of Psychology, 31, 457-501. https://doi.org/10.1146/annurev.ps.31.020180.002325
29. Kim, W. (2022). Shopping with AI: Consumers' perceived autonomy in the age of AI. In S. Saqr & T. Wasson (Eds.), Human-Centered Artificial Intelligence (pp. 187-202). Academic Press.
30. Koufaris, M., & Hampton-Sosa, W. (2004). The development of initial trust in an online company by new customers. Information & Management, 41(3), 377-397. https://doi.org/10.1016/j.im.2003.08.004
31. Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. California Management Review, 61(4), 135-155. https://doi.org/10.1177/0008125619859317
32. Lee, M. K., & Baykal, S. (2017). Algorithmic Mediation in Group Decisions: Fairness Perceptions of Algorithmically Mediated vs. Discussion-Based Social Division. Proceedings of the ACM on Human-Computer Interaction, 1(CSCW), Article 91, 1-21. https://doi.org/10.1145/3134726
33. Lim, S. (2018). NomadX at Plaza Singapura is Singapore's first 'phygital' store – here's what it's like inside. Business Insider Singapore.
34. Longoni, C., & Cian, L. (2022). Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The "Word-of-Machine" Effect. Journal of Marketing, 86(1), 91-108. https://doi.org/10.1177/0022242920957347
35. Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. Journal of Consumer Research, 46(4), 629–650. https://doi.org/10.1093/jcr/ucz013
36. Marinchak, C. M., Forrest, E., & Hoanca, B. (2018). Artificial intelligence: Redefining marketing management and the customer experience. International Journal of E-Business Research, 14(4), 35-47. DOI:10.4018/IJEEI.2018070102
37. Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. Journal of the Academy of Marketing Science, 45(2), 135-155. https://doi.org/10.1007/s11747-016-0495-4
38. Martin, K. D., Borah, A., & Palmatier, R. W. (2017). Data privacy: Effects on customer and firm performance. Journal of Marketing, 81(1), 36-58.

39. Melero, I., Sese, F. J., & Verhoef, P. C. (2016). Recasting the Customer Experience in Today's Omni-channel Environment. Universia Business Review, (50), 18-37.

40. Mishra, R., Singh, R. K., & Koles, B. (2021). Consumer decision-making in omnichannel retailing: Literature review and future research agenda. International Journal of Consumer Studies, 45(4), 664-686. https://doi.org/10.1111/ijcs.12617

41. Puccinelli, N. M., Andrzejewski, S. A., Markos, E., Noga, T., & Motyka, S. (2013). The value of knowing what customers really want: The impact of salesperson ability to read non-verbal cues of affect on service quality. Journal of Marketing Management, 29(3-4), 356-373.https://doi.org/10.1080/0267257X.2013.76

42. Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. Journal of Marketing, 85(1), 131-151. https://doi.org/10.1177/0022242920953847

43. Schmidmaier, M., Rupp, J., Cvetanova, D., & Mayer, S. (2024). Perceived Empathy of Technology Scale (PETS): Measuring empathy of systems toward the user. In Proceedings of the ACM CHI Conference on Human Factors in Computing Systems (CHI 2024). https://doi.org/10.1145/3613904.3642035

44. Sheng, H., Nah, F. F.-H., & Siau, K. (2008). An experimental study on ubiquitous commerce adoption: Impact of personalization and privacy concerns. In Proceedings of the 14th Americas Conference on Information Systems (AMCIS 2008) (pp. [insert page range]).

45. Shi, S., Wang, Y., Chen, X., & Zhang, Q. (2020). Conceptualization of omnichannel customer experience and its impact on shopping intention: A mixed-method approach. International Journal of Information Management, 50, 325-336. https://doi.org/10.1016/j.ijinfomgt.2019.09.001

46. Smith, A. (2006). Cognitive empathy and emotional empathy in human behavior and evolution. The Psychological Record, 56(1), 3-21. Retrieved from https://link.springer.com/article/10.1007/BF03395534

47. Smith, H. J., Dinev, T., & Xu, H. (2011). Information privacy research: An interdisciplinary review. MIS Quarterly, 35(4), 989-1015. DOI:10.2307/41409970

48. Sunikka, A., & Bragge, J. (2012). Applying text-mining to personalization and customization research literature–Who, what and where?. Expert Systems with Applications, 39(11), 10049-10058.

49. Supramaniam, S., John, S. P., & Gaur, S. S. (2024). The Role of Sales Personnel Empathy and Customer-oriented Behaviour on Female Consumers' Emotions and Satisfaction: An Empirical Analysis. FIIB Business Review, 0(0). https://doi.org/10.1177/23197145241241956

50. Thaichon, P., Quach, S., Barari, M., & Nguyen, M. (2024). Exploring the Role of Omnichannel Retailing Technologies: Future Research Directions. Australasian Marketing Journal, 32(2), 162-177. https://doi.org/10.1177/14413582231167664

51. Tyrväinen, O., Karjaluoto, H., & Saarijärvi, H. (2020). Personalization and hedonic motivation in creating customer experiences and loyalty in omnichannel retail. Journal of Retailing and Consumer Services, 57, 102233. https://doi.org/10.1016/j.jretconser.2020.102233

52. Verhoef, P., Kannan, P. K., & Inman, J. (2015). From multi-channel retailing to omni-channel retailing: Introduction to the special issue on multi-channel retailing. Journal of Retailing, 91(2), 174–181. https://doi.org/10.1016/j.jretai.2015.02.005

53. Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. Digital Policy, Regulation and Governance, 21(3), 264-279. https://doi.org/10.1108/DPRG-09-2018-0050

54. Weitz, B. A., Sujan, H., & Sujan, M. (1986). Knowledge, motivation, and adaptive behavior: A framework for improving selling effectiveness. Journal of Marketing, 50(4), 174–191. https://doi.org/10.1177/002224298605000404

55. Wetzlinger, W., Auinger, A., Kindermann, H., & Schönberger, W. (2017). Acceptance of personalization in omnichannel retailing. In F. H. Nah & C. H. Tan (Eds.), HCI in Business, Government and Organizations. Supporting Business (Lecture Notes in Computer Science, Vol. 10294). Springer, Cham. https://doi.org/10.1007/978-3-319-58484-3_10

56. Zendehdel, M., & Paim, L. (2013). Predicting consumer attitude to use online shopping: context of Malaysia. Life Science Journal, 10, 497-501.

57. Zhou, R., & Tong, L. (2022). A Study on the Influencing Factors of Consumers' Purchase Intention During Livestreaming e-Commerce: The Mediating Effect of Emotion. Frontiers in Psychology, 13, 903023. https://doi.org/10.3389/fpsyg.2022.903023Koufaris, M., & Hampton-Sosa, W. (2004). The development of initial trust in an online company by new customers. Information Management, 41(3), 377-397. https://doi.org/10.1016/j.im.2003.08.004

58. Zygiaris, S., Hameed, Z., Alsubaie, M. A., & Rehman, S. U. (2022). Service quality and customer satisfaction in the post-pandemic world: A study of Saudi auto care industry. Frontiers in Psychology, 13, Article 842141. https://doi.org/10.3389/fpsyg.2022.842141

Appendices

Appendix 1: Survey transcript – AI Shopping Assistant + high Privacy Concerns condition

English

Dear participant,

Welcome and thank you for participating in this research as part of my Master's Thesis at Católica Lisbon School of Business and Economics!

This survey is about personalized recommendations and is expected to take around 5 minutes to complete. Your participation is completely voluntary and anonymous. The data collected will be kept confidential and only used within this research. There are no right or wrong answers, only your personal opinion counts.
If you have any questions or comments, please do not hesitate to contact me via email: s-abecsagh@ucp.pt

By proceeding with the survey, you acknowledge agreeing to participate in the research. If you are willing to complete this survey, please click the button on the bottom right to begin. ➡️

Magyar verzióért kérlek, válaszd ki a jobb felső sarok legördülő menüjében a "Magyar" opciót!

Thank you for your valuable contribution!
Anna

Please read the following paragraphs of an article from Bitdefender carefully:

Data breach affects over 60,000 customers of luxury retailer Neiman Marcus

Alina BÎZGĂ

June 28, 2024

Dallas-based luxury retailer Neiman Marcus is one of the latest companies impacted by the security incident at Snowflake, a US-based cloud-based data storage and analytics company.

What happened?
According to a data breach letter sample filed with the Office of the Maine Attorney General, Neiman Marcus was made aware of unauthorized access to its database in May 2024. The breach impacted 64,472 people.

What information did the hackers steal from Neiman Marcus?
The data notification letter says the type of PII (*Personal Identifiable Information)* compromised in the breach "varied by individual, and included names, contact info such email address and phone number, date of birth, and Neiman Marcus or Bergdorf Goodman gift card numbers (without PINs).

Stolen data was put up for sale online for $150,000 The breach notice was issued following a for-sale ad posted by a threat actor using the handle "Sp1d3r" online, with the user even suggesting Neiman Marcus did not give in to any ransom demands.

The threat actor also mentioned additional stolen data, not present in the data breach filling from Neiman Marcus, specifically:
- Last 4 digits of Social Security Numbers
- Info on 70 million transactions with full customer details
- 50 million customer emails and IP addresses
- Info on 12 million gift cards (with names, gift card numbers, balances and more)
- 6 billion rows of customer shopping records, employee data and store information

Now please imagine that you want to buy a new T-shirt. When you first start looking for T-shirts, you browse the website of the brand ZARA. As you frequently buy apparel from ZARA, you already have a customer account and app on your phone. You put one T-shirt on your online wish list. As you are not sure about this T-shirt, you leave the online store without buying it, and visit ZARA's physical store a couple of days later.

You enter a ZARA store, and instantly see that a new tool has been introduced in the store: a kiosk, that has a built-in facial recognition system.

Since you have a ZARA account, it automatically recognizes you, and an AI Shopping Assistant instantly offers you help by guiding you towards the T-shirt you saved to your wish list a few days ago. Based on your previous purchase (and return) history, it also recommends the perfect size for you.

When you enter the changing room, you can see that AI-driven smart mirrors were newly introduced to them.

Here you can also communicate with the AI Shopping Assistant. When you try on the T-shirt, it recommends you matching outfit and accessory suggestions, based on your previous preferences and the style of the new T-shirt you are now considering buying.

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
When faced with this scenario, it bothers me that the service provider is able to track information about me	○	○	○	○	○	○	○
When faced with this scenario, I am concerned that the service provider has too much information about me	○	○	○	○	○	○	○
When faced with this scenario, it bothers me that the service provider is able to access information about me	○	○	○	○	○	○	○
When faced with this scenario, I am concerned that my information could be used in ways I cannot foresee	○	○	○	○	○	○	○

Please rate your agreement with the following sequence:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
When faced with this scenario, I intend to adopt the personalized service	○	○	○	○	○	○	○
When faced with this scenario, I predict I will use the personalized service	○	○	○	○	○	○	○
When faced with this scenario, I plan to use the personalized service	○	○	○	○	○	○	○

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
This company is trustworthy	○	○	○	○	○	○	○
I trust this company keeps my best interests in mind	○	○	○	○	○	○	○
This company will keep promises it makes to me	○	○	○	○	○	○	○
I believe in the information that this vendor provides me	○	○	○	○	○	○	○
This company wants to be known as one who keeps promises and commitments	○	○	○	○	○	○	○

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
Overall, I believe that the value I get from ZARA will be good	○	○	○	○	○	○	○
Overall, I believe that I will receive more than what I will give up	○	○	○	○	○	○	○
Overall, I believe that ZARA will satisfy my expectations	○	○	○	○	○	○	○

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
You believe that the information of the product recommended by AI is true							
You believe that the information of the product recommended by AI is accurate							
You have confidence in AI's knowledge about clothes							

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
ZARA provides sufficient information about its operations.							
ZARA is open about its decision-making processes.							
I believe that ZARA communicates honestly with its stakeholders							

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
The AI Shopping Assistant sympathized with me.							
The AI Shopping Assistant showed interest in me.							
The AI Shopping Assistant supported me by putting my interest before the brands'.							

Please indicate what kind of Shopping Assistant is helping you at in the given imaginary situation:

- AI
- Human

Are you familiar with the brand ZARA?

- Yes
- No

Please indicate the likelihood of yours for the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
My interaction with the AI Shopping Assistant is clear and understandable							
It would be easy for me to become skillful at using this AI Shopping Assistant							
I find the AI Shopping Assistant easy to use							

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
Personalized communication helps me make purchasing decisions.							
Personalized recommendations enable me to save time.							
I enjoy personalized communication since it reduces communication because companies advertise in a more targeted manner.							

Please indicate to what extent do you agree with the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
I am poorly informed about the use of my data.							
If I divulge personal data, I lose control over how companies use my data.							
Personalization leads to an increase in unsolicited advertising messages, since companies know what I am interested in.							

Please indicate the likelihood of yours for the following statements:

	1 - Strongly disagree	2	3	4	5	6	7 - Strongly agree
The AI Shopping Assistant can improve my shopping performance							
The AI Shopping Assistant can increase my shopping productivity							
I find the help of the AI Shopping Assistant useful							

Appendix 2 – Statictical analysis

*Human_pcnopc * Human_aggr Crosstabulation*

Count

		Human_aggr		
		AI	Human	Total
Human_pcnopc	AI	33	0	33
	Human	0	38	38
Total		33	38	71

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	71.000[a]	1	<.001		
Continuity Correction[b]	67.037	1	<.001		
Likelihood Ratio	98.074	1	<.001		
Fisher's Exact Test				<.001	<.001
Linear-by-Linear Association	70.000	1	<.001		
N of Valid Cases	71				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 15.34.

b. Computed only for a 2x2 table

*AI_pcnopc * AI_aggr Crosstabulation*

Count

		AI_aggr		
		AI	Human	Total
AI_pcnopc	AI	38	0	38
	Human	0	26	26
Total		38	26	64

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	64.000[a]	1	<.001		
Continuity Correction[b]	59.921	1	<.001		
Likelihood Ratio	86.459	1	<.001		
Fisher's Exact Test				<.001	<.001
Linear-by-Linear Association	63.000	1	<.001		
N of Valid Cases	64				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.56.

b. Computed only for a 2x2 table

Table 2 - Manipulation check

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

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

**************************************************************************
Model  : 1
    Y  : meanIntA
    X  : AT
    W  : PC

Sample
Size:  135

**************************************************************************
OUTCOME VARIABLE:
 meanIntA

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1009      .0102     3.3146      .4495     3.0000   131.0000      .7180

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.4167      .3218    10.6161      .0000     2.7800     4.0533
AT            .4944      .4627     1.0687      .2872     -.4208     1.4097
PC            .3904      .4368      .8936      .3732     -.4738     1.2545
Int_1        -.6634      .6293    -1.0542      .2937    -1.9082      .5815

Product terms key:
 Int_1    :        AT       x        PC

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0084     1.1113     1.0000   131.0000      .2937

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

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Table 3 - Moderation analysis of "Privacy Concerns" on "Intention to Adopt"

Descriptive Statistics

Dependent Variable: BrandFam_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	1.0625	.24593	32
	pc	1.0263	.16222	38
	Total	1.0429	.20400	70
AI	no pc	1.0667	.25371	30
	pc	1.0857	.28403	35
	Total	1.0769	.26854	65
Total	no pc	1.0645	.24768	62
	pc	1.0548	.22915	73
	Total	1.0593	.23699	135

Tests of Between-Subjects Effects

Dependent Variable: BrandFam_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.068[a]	3	.023	.396	.756
Intercept	150.562	1	150.562	2644.556	<.001
assistant_type	.034	1	.034	.594	.442
privacy_concern	.002	1	.002	.043	.836
assistant_type * privacy_concern	.026	1	.026	.448	.504
Error	7.458	131	.057		
Total	159.000	135			
Corrected Total	7.526	134			

a. R Squared = .009 (Adjusted R Squared = -.014)

Table 4 - Control analysis for "Brand Familiarity"

Descriptive Statistics

Dependent Variable: PC_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	5.1406	1.53578	32
	pc	4.7697	1.51499	38
	Total	4.9393	1.52482	70
AI	no pc	5.5583	1.41982	30
	pc	5.8786	1.29673	35
	Total	5.7308	1.35375	65
Total	no pc	5.3427	1.48368	62
	pc	5.3014	1.51151	73
	Total	5.3204	1.49335	135

Tests of Between-Subjects Effects

Dependent Variable: PC_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	25.160[a]	3	8.387	4.014	.009
Intercept	3814.378	1	3814.378	1825.850	<.001
assistant_type	19.506	1	19.506	9.337	.003
privacy_concern	.021	1	.021	.010	.919
assistant_type * privacy_concern	3.998	1	3.998	1.914	.169
Error	273.672	131	2.089		
Total	4120.188	135			
Corrected Total	298.831	134			

a. R Squared = .084 (Adjusted R Squared = .063)

Table 5 - 2 way ANOVA about the variable "Privacy Concerns"

Group Statistics

	privacy_concern	N	Mean	Std. Deviation	Std. Error Mean
PC_mean	no pc	62	5.3427	1.48368	.18843
	pc	73	5.3014	1.51151	.17691

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
PC_mean	Equal variances assumed	.760	.385	.160	133	.437	.873	.04137	.25885	-.47063	.55338
	Equal variances not assumed			.160	130.217	.437	.873	.04137	.25846	-.46995	.55270

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
PC_mean	Cohen's d	1.49881	.028	-.311	.366
	Hedges' correction	1.50733	.027	-.309	.364
	Glass's delta	1.51151	.027	-.311	.366

Table 6 - Independent samples T-test of "Privacy Concerns" – Privacy Concern condition

Group Statistics

	assistant_type	N	Mean	Std. Deviation	Std. Error Mean
PC_mean	human	70	4.9393	1.52482	.18225
	AI	65	5.7308	1.35375	.16791

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
PC_mean	Equal variances assumed	1.834	.178	-3.180	133	<.001	.002	-.79148	.24891	-1.28381	-.29915
	Equal variances not assumed			-3.194	132.741	<.001	.002	-.79148	.24781	-1.28165	-.30132

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
PC_mean	Cohen's d	1.44503	-.548	-.891	-.203
	Hedges' correction	1.45324	-.545	-.886	-.202
	Glass's delta	1.35375	-.585	-.935	-.230

Table 7 - Independent samples T-test of "Privacy Concerns" - Assistant Type condition

Descriptive Statistics

Dependent Variable: PPErsonaliz_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	4.0938	1.64880	32
	pc	4.1053	1.59599	38
	Total	4.1000	1.60850	70
AI	no pc	3.6889	1.48281	30
	pc	3.0952	1.45874	35
	Total	3.3692	1.48852	65
Total	no pc	3.8978	1.57113	62
	pc	3.6210	1.60373	73
	Total	3.7481	1.58897	135

Tests of Between-Subjects Effects

Dependent Variable: PPErsonaliz_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	23.694[a]	3	7.898	3.288	.023
Intercept	1879.078	1	1879.078	782.372	<.001
assistant_type	16.756	1	16.756	6.977	.009
privacy_concern	2.837	1	2.837	1.181	.279
assistant_type * privacy_concern	3.065	1	3.065	1.276	.261
Error	314.632	131	2.402		
Total	2234.889	135			
Corrected Total	338.326	134			

a. R Squared = .070 (Adjusted R Squared = .049)

Table 8 - 2 way ANOVA about the variable "Personalization"

Descriptive Statistics

Dependent Variable: mean_IntA

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	3.4167	1.80799	32
	pc	3.8070	1.82514	38
	Total	3.6286	1.81472	70
AI	no pc	3.9111	1.57308	30
	pc	3.6381	2.01363	35
	Total	3.7641	1.81499	65
Total	no pc	3.6559	1.70285	62
	pc	3.7260	1.90625	73
	Total	3.6938	1.80934	135

Tests of Between-Subjects Effects

Dependent Variable: mean_IntA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	4.470[a]	3	1.490	.450	.718
Intercept	1826.712	1	1826.712	551.117	<.001
assistant_type	.887	1	.887	.268	.606
privacy_concern	.115	1	.115	.035	.852
assistant_type * privacy_concern	3.683	1	3.683	1.111	.294
Error	434.208	131	3.315		
Total	2280.667	135			
Corrected Total	438.678	134			

a. R Squared = .010 (Adjusted R Squared = -.012)

Table 9 - 2 way ANOVA about the variable "Intention to Adopt"

Descriptive Statistics

Dependent Variable: Trust_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	4.6250	1.35929	32
	pc	4.9649	1.28467	38
	Total	4.8095	1.32068	70
AI	no pc	4.2000	1.53528	30
	pc	3.8286	1.59937	35
	Total	4.0000	1.56901	65
Total	no pc	4.4194	1.45100	62
	pc	4.4201	1.54363	73
	Total	4.4198	1.49624	135

Tests of Between-Subjects Effects

Dependent Variable: Trust_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	26.323[a]	3	8.774	4.200	.007
Intercept	2598.222	1	2598.222	1243.717	<.001
assistant_type	20.405	1	20.405	9.767	.002
privacy_concern	.008	1	.008	.004	.950
assistant_type * privacy_concern	4.235	1	4.235	2.027	.157
Error	273.669	131	2.089		
Total	2937.111	135			
Corrected Total	299.992	134			

a. R Squared = .088 (Adjusted R Squared = .067)

Table 10 - 2 way ANOVA about the variable "Trust"

Descriptive Statistics

Dependent Variable: PU_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	4.7396	1.54904	32
	pc	4.3860	1.68820	38
	Total	4.5476	1.62413	70
AI	no pc	3.9889	1.63881	30
	pc	3.4952	1.69461	35
	Total	3.7231	1.67453	65
Total	no pc	4.3763	1.62459	62
	pc	3.9589	1.73823	73
	Total	4.1506	1.69367	135

Tests of Between-Subjects Effects

Dependent Variable: PU_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	29.023[a]	3	9.674	3.566	.016
Intercept	2309.199	1	2309.199	851.266	<.001
assistant_type	22.552	1	22.552	8.313	.005
privacy_concern	6.009	1	6.009	2.215	.139
assistant_type * privacy_concern	.164	1	.164	.061	.806
Error	355.359	131	2.713		
Total	2710.111	135			
Corrected Total	384.382	134			

a. R Squared = .076 (Adjusted R Squared = .054)

Table 11 - 2 way ANOVA about the variable "Perceived Usefulness"

Descriptive Statistics

Dependent Variable: PEU_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	4.3125	1.63943	32
	pc	4.4912	1.72899	38
	Total	4.4095	1.67886	70
AI	no pc	4.6222	1.43501	30
	pc	3.8476	1.70225	35
	Total	4.2051	1.61986	65
Total	no pc	4.4624	1.53923	62
	pc	4.1826	1.73476	73
	Total	4.3111	1.64775	135

Tests of Between-Subjects Effects

Dependent Variable: PEU_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	11.655[a]	3	3.885	1.445	.233
Intercept	2497.487	1	2497.487	929.022	<.001
assistant_type	.933	1	.933	.347	.557
privacy_concern	2.972	1	2.972	1.106	.295
assistant_type * privacy_concern	7.607	1	7.607	2.830	.095
Error	352.167	131	2.688		
Total	2872.889	135			
Corrected Total	363.822	134			

a. R Squared = .032 (Adjusted R Squared = .010)

Table 12 - 2 way ANOVA about the variable "Perceived Ease of Use"

Descriptive Statistics

Dependent Variable: PersValue_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	4.8438	1.34667	32
	pc	4.6757	1.35739	37
	Total	4.7536	1.34511	69
AI	no pc	3.2000	1.94089	30
	pc	2.7238	1.51136	35
	Total	2.9436	1.72559	65
Total	no pc	4.0484	1.84346	62
	pc	3.7269	1.73009	72
	Total	3.8756	1.78393	134

Tests of Between-Subjects Effects

Dependent Variable: PersValue_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	113.803[a]	3	37.934	15.936	<.001
Intercept	1984.440	1	1984.440	833.645	<.001
assistant_type	107.574	1	107.574	45.191	<.001
privacy_concern	3.454	1	3.454	1.451	.231
assistant_type * privacy_concern	.790	1	.790	.332	.566
Error	309.457	130	2.380		
Total	2436.000	134			
Corrected Total	423.260	133			

a. R Squared = .269 (Adjusted R Squared = .252)

Table 13 - 2 way ANOVA about the variable "Personalization Value"

Descriptive Statistics

Dependent Variable: PersBenef_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	3.5938	1.85830	32
	pc	3.4035	2.02115	38
	Total	3.4905	1.93678	70
AI	no pc	4.4889	1.24024	30
	pc	4.2857	1.66302	35
	Total	4.3795	1.47535	65
Total	no pc	4.0269	1.64000	62
	pc	3.8265	1.89794	73
	Total	3.9185	1.78043	135

Tests of Between-Subjects Effects

Dependent Variable: PersBenef_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	27.933[a]	3	9.311	3.074	.030
Intercept	2082.117	1	2082.117	687.328	<.001
assistant_type	26.441	1	26.441	8.729	.004
privacy_concern	1.296	1	1.296	.428	.514
assistant_type * privacy_concern	.001	1	.001	.000	.983
Error	396.837	131	3.029		
Total	2497.667	135			
Corrected Total	424.770	134			

a. R Squared = .066 (Adjusted R Squared = .044)

Table 14 - 2 way ANOVA about the variable "Personalization Benefits"

Descriptive Statistics

Dependent Variable: PersCosts_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	5.3854	1.15504	32
	pc	5.6842	.79392	38
	Total	5.5476	.97972	70
AI	no pc	5.4713	1.11810	29
	pc	5.3048	1.56425	35
	Total	5.3802	1.37227	64
Total	no pc	5.4262	1.12896	61
	pc	5.5023	1.23118	73
	Total	5.4677	1.18196	134

Tests of Between-Subjects Effects

Dependent Variable: PersCosts_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2.928[a]	3	.976	.694	.557
Intercept	3956.497	1	3956.497	2812.520	<.001
assistant_type	.715	1	.715	.508	.477
privacy_concern	.145	1	.145	.103	.749
assistant_type * privacy_concern	1.795	1	1.795	1.276	.261
Error	182.877	130	1.407		
Total	4191.778	134			
Corrected Total	185.804	133			

a. R Squared = .016 (Adjusted R Squared = -.007)

Table 15 - 2 way ANOVA about the variable "Personalization Costs"

Descriptive Statistics

Dependent Variable: mean_BrandTrust

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	4.2250	1.56226	32
	pc	4.1368	1.49602	38
	Total	4.1771	1.51611	70
AI	no pc	3.8933	1.60579	30
	pc	3.3200	1.62060	35
	Total	3.5846	1.62685	65
Total	no pc	4.0645	1.57928	62
	pc	3.7452	1.59974	73
	Total	3.8919	1.59248	135

Tests of Between-Subjects Effects

Dependent Variable: mean_BrandTrust

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	17.278[a]	3	5.759	2.339	.076
Intercept	2030.510	1	2030.510	824.686	<.001
assistant_type	11.041	1	11.041	4.484	.036
privacy_concern	3.663	1	3.663	1.488	.225
assistant_type * privacy_concern	1.970	1	1.970	.800	.373
Error	322.543	131	2.462		
Total	2384.600	135			
Corrected Total	339.821	134			

a. R Squared = .051 (Adjusted R Squared = .029)

Table 16 - 2 way ANOVA about the variable "Brand Trust"

Descriptive Statistics

Dependent Variable: PerceivedValueBrand_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	4.1250	1.63244	32
	pc	4.3964	1.54728	37
	Total	4.2705	1.58142	69
AI	no pc	3.7556	1.59004	30
	pc	3.1143	1.63288	35
	Total	3.4103	1.63275	65
Total	no pc	3.9462	1.60962	62
	pc	3.7731	1.70503	72
	Total	3.8532	1.65763	134

Tests of Between-Subjects Effects

Dependent Variable: PerceivedValueBrand_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	32.677[a]	3	10.892	4.255	.007
Intercept	1971.099	1	1971.099	770.030	<.001
assistant_type	22.696	1	22.696	8.866	.003
privacy_concern	1.138	1	1.138	.445	.506
assistant_type * privacy_concern	6.931	1	6.931	2.708	.102
Error	332.770	130	2.560		
Total	2355.000	134			
Corrected Total	365.447	133			

a. R Squared = .089 (Adjusted R Squared = .068)

Table 17 - 2 way ANOVA about the variable "Perceived Brand Value"

Tests of Between-Subjects Effects

Dependent Variable: Empathy_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	25.456[a]	3	8.485	3.281	.023
Intercept	1525.262	1	1525.262	589.752	<.001
assistant_type	23.003	1	23.003	8.894	.003
privacy_concern	2.043	1	2.043	.790	.376
assistant_type * privacy_concern	.100	1	.100	.039	.845
Error	338.802	131	2.586		
Total	1906.778	135			
Corrected Total	364.258	134			

a. R Squared = .070 (Adjusted R Squared = .049)

Descriptive Statistics

Dependent Variable: Empathy_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	3.8854	1.57172	32
	pc	3.6930	1.55071	38
	Total	3.7810	1.55198	70
AI	no pc	3.1111	1.75803	30
	pc	2.8095	1.56824	35
	Total	2.9487	1.65226	65
Total	no pc	3.5108	1.69615	62
	pc	3.2694	1.61078	73
	Total	3.3802	1.64874	135

Table 18 - 2 way ANOVA about the variable "Empathy"

Tests of Between-Subjects Effects

Dependent Variable: PersTransp_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	11.350[a]	3	3.783	1.325	.269
Intercept	1741.146	1	1741.146	609.652	<.001
assistant_type	1.979	1	1.979	.693	.407
privacy_concern	6.961	1	6.961	2.438	.121
assistant_type * privacy_concern	2.345	1	2.345	.821	.367
Error	374.132	131	2.856		
Total	2127.889	135			
Corrected Total	385.481	134			

a. R Squared = .029 (Adjusted R Squared = .007)

Descriptive Statistics

Dependent Variable: PersTransp_mean

assistant_type	privacy_concern	Mean	Std. Deviation	N
human	no pc	3.8229	1.80200	32
	pc	3.6316	1.61038	38
	Total	3.7190	1.69078	70
AI	no pc	3.8444	1.86053	30
	pc	3.1238	1.50617	35
	Total	3.4564	1.70433	65
Total	no pc	3.8333	1.81549	62
	pc	3.3881	1.57136	73
	Total	3.5926	1.69609	135

Table 19 - 2 way ANOVA about the variable "Perceived Transparency"