MYIN, MON THU A. Ph.D. Exploring the Behavioral Intentions to Use AI-Based Chatbots for Apparel Shopping. (2024)
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In the retail industry, AI chatbots have played a vital role by offering 24/7 customer services, enhancing sales through prompt and accurate responses to customers' questions, and providing personalized product recommendations based on customers' preferences (Ashfaq et al., 2020). Despite the significant impact of AI chatbot technology on the apparel retail industry, its coverage is still nascent in existing apparel and retail literature. Specifically, the lack of studies has hindered our understanding of consumers' antecedents (reasons for and reasons against) and consequences (willingness to buy and eWOM) regarding attitudes toward using AI chatbots, along with the moderating effect of technology familiarity. To address this gap, this dissertation developed and tested a conceptual model of the potential antecedents and consequences of consumers' attitudes toward using AI chatbots. Specifically, three primary objectives of the study are: (1) to examine relationships between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*; (2) to investigate relationships between consumers' *attitudes toward using AI chatbots* and their behavioral intentions as measured in terms of *willingness to buy apparel with the help of AI chatbots* and *eWOM*; and (3) to examine the moderating role of *technology familiarity* on the relationship between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*.

Data were collected from 717 participants through a self-administered questionnaire distributed on Amazon Mechanical Turk (MTurk), an online panel. After careful screening, the final sample consisted of 632 usable responses for statistical analysis. Among participants, 35.1% were female, 64.9% were male. The majority (32.1%) were aged between 26 and 30. In

addition, the largest proportion of participants identified as White (90.2%). A total of 58 measurement items were adapted from previous studies and assessed using a 5-point Likert-type scale. The two-step approach, as outlined by Anderson and Gerbing (1988), was employed using Mplus version 8 to establish both measurement and structural models. The confirmatory factor analysis (CFA) was employed first. After the measurement model was established, the path analysis was performed to test all hypothesized relationships using the structural equation model (SEM).

Results showed that *reasons for* factors, such as *responsiveness*, *reliability*, and *assurance* positively influenced *attitudes toward using AI chatbots*. Conversely, there were no positive relationships between most *reasons against* factors, such as *usage barrier*, *risk barrier*, *value barrier*, *image barrier*, and *attitudes toward using AI chatbots*. While this study identified a significant positive relationship between *tradition barrier* and *attitudes toward using AI chatbots*, the result did not align with the proposed hypothesis. Therefore, this study highlighted the significance of *responsiveness*, *reliability*, and *assurance* as important factors influencing consumers' adoption of AI chatbots for apparel shopping. In contrast, this study suggested that all five barriers, namely *usage barrier, risk barrier, value barrier, image barrier*, and *tradition barrier*, may not be important factors in either rejecting or accepting AI chatbots for apparel shopping. Furthermore, the results revealed that *attitudes toward using AI chatbots* positively influenced both *willingness to buy apparel with the help of AI chatbots* and *eWOM*. Thus, the study suggested that consumers with positive attitudes toward AI chatbots are more likely to use them and share favorable reviews and comments about AI chatbots on social media and other online platforms. Subsequently, consumers' positive reviews may encourage other online shoppers to engage with AI chatbot services offered by apparel brands. The results also indicated

a positive moderating effect of *technology familiarity* on the relationship between *reliability* and *attitudes toward using AI chatbots.* In addition, the moderating effect of *technology familiarity* on the relationship between *tradition barrier* and *attitudes toward using AI chatbots* was negatively significant.

This dissertation provides significant contributions to the literature by developing and testing a research model that investigates the antecedents and consequences of *attitudes toward using AI chatbots* for apparel shopping. Moreover, the findings also provide empirical evidence for the moderating role of technology familiarity on attitudes toward using AI chatbots. Practical implications are also provided. Additionally, this dissertation addresses limitations and suggests future research directions.

EXPLORING THE BEHAVIORAL INTENTIONS
TO USE AI-BASED CHATBOTS
FOR APPAREL SHOPPING

by

Mon Thu A. Myin

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Approved by

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DEDICATION

I dedicate this dissertation to my daughter, Emily Oo, and my husband, Pyayt Oo.

APPROVAL PAGE

This dissertation written by Mon Thu A. Myin has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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CHAPTER I: INTRODUCTION

This chapter introduces the dissertation and includes the following sections: (1) Research Background, (2) Statement of the Problem, (3) Purpose and Objectives of the Study, (4) Significance of the Study, (5) Definition of Key Terms, and (6) Organization of the Study.

Research Background

The Impact of AI Chatbots on Apparel Retail Business

Technology has become an essential tool in our society today. Advanced technologies such as artificial intelligence (AI), machine learning, and augmented reality (AR) have not only changed people's everyday lifestyles but also rapidly transformed countless industries, including marketing and retailing (Smutny & Schreiberova, 2020). One of the latest technologies adopted by the retail industry is the artificial intelligence-driven chatbot (i.e., AI chatbot). AI chatbots have served as digital service assistants, mimicking human-to-human communication (Youn & Jin, 2021) through voice or text. Currently, text-based chatbots facilitate a wide range of retail business processes. AI chatbots have become increasingly essential in the retail industry due to their ability to provide 24/7 virtual customer services and generate sales (Ashfaq, Yun, Yu, & Loureiro, 2020). Before AI chatbots, human customer service agents were crucial as the primary method for providing customers with excellent customer service, such as answering customers' questions, helping them find products, providing product information, solving customer problems, providing suggestions to customers, and processing returns (Rita, Oliveira, & Farisa, 2019). Chatbots serve as virtual assistants, providing speedy and relevant product information, assisting customers with their inquiries, and proposing a variety of suggestions to help customers better understand and pinpoint their needs and wants (Przegalinska, Ciechanowski, Stroz, Gloor, & Mazurek, 2019; Rese, Ganster, & Baier, 2020). In addition, chatbots' responses can be faster than human service agents, which could result in a higher rate of successful sales compared to a human salesperson. Customer service today, however, is far more than just helping customers find what they are looking for: it is a critical factor for increasing retail customers’ loyalty, enhancing customers’ satisfaction, meeting customers’ expectations, and establishing a successful retail business (Paulins, 2005). Indeed, Ashfaq et al. (2020) assert that 41% of chatbot usage among retailers is related to sales, and 37% is related to customer service. Jyng and Rubasundram (2020) contend that although the initial cost of adopting chatbots as virtual agents may cause some retailers to hesitate, they are, in fact, relatively cheaper than human agents in the long run. Therefore, the introduction of AI chatbots and their subsequent adoption by retailers has rapidly revolutionized the ability of businesses to effectively assist and interact with their consumers (Olmez, 2018) and has dramatically changed the customer service profession by boosting company business and improving consumers’ satisfaction and overall shopping experience (Youn & Jin, 2021).

Furthermore, AI chatbot offers various unique benefits in the retail business setting (Przegalinska et al., 2019; Zumstein & Hundertmark, 2017). For example, the chatbot can facilitate a wide range of retail business processes, particularly in providing excellent customer service due to accessibility, ease of use, and low cost (Przegalinska et al., 2019). It also provides a personalized recommendation service for individualized customer needs and wants anytime and anywhere (Zumstein & Hundertmark, 2017). As a result, the use of AI chatbots in retail business makes retail companies more competitive and provides a deeper insight into consumers’ satisfaction, preferences, and behavior (Chung, Ko, Joung, & Kim, 2020; Grewal, Hulland, Kopalle, & Karahanna, 2020; Huang & Rust, 2021).

In the apparel retail industry, AI chatbots have been adopted by many well-known and leading apparel retail brands (Pizzi, Scarpi, & Pantano, 2020) because of their extreme usefulness; they help consumers interact with businesses in a wide variety of ways—through text messaging using mobile applications (e.g., Kik, Chatterbot), social media applications (e.g., Facebook Messenger, Twitter Messenger, Instagram, Telegram, WhatsApp), and websites. For example, in 2016, Burberry introduced Burberry's chatbot technology on Facebook Messenger to boost sales, promote new apparel products, and assist customers (Tran, Pallant, & Johnson, 2021). In early 2016, Tommy Hilfiger introduced retail chatbots on Facebook Messenger, and H&M launched AI chatbot technology on the Kik messaging application to establish a strong relationship with their customers and to assist their customers in browsing outfits, selecting fashion items, and creating their own clothing ensembles (Kokoszka, 2018).

In addition, the COVID-19 pandemic, which emerged as a global challenge in 2019, served as a catalyst to increase the speed at which technology changed the marketplace. Social distancing negatively impacted retail companies, making people hesitant to visit physical stores. Therefore, the pandemic encouraged retailers to adopt innovation to provide their online consumers with better customer service and a better online shopping experience. Consequently, promoting products, increasing sales, and providing automated customer service for the online shopping experience have become essential retail activities (McLean, Osei-Frimpong, & Barhorst, 2021). With the COVID-19 pandemic forcing the closure of many physical stores, the role of AI chatbots in the retail industry has risen sharply. Retailers had to move rapidly to digital technology-based solutions such as online ordering, assisting, and collecting consumers' information with the help of advanced technology tools like AI chatbots. Fortunately, AI chatbots met the COVID challenge magnificently: they handled over 85% of customer interactions in 2020 and increased sales by 67% (on average) the next year, accounting for 26% of all sales in 2021 (Sands, Ferraro, Campbell, & Tsao, 2021).

According to de Cicco, Silva, and Alparone (2020), the chatbot market size is expected to increase from USD 2.6 billion in 2019 to USD 9.4 billion in 2024. It is reported that 85% of customer interactions in the retail industry in 2020 were handled by AI chatbots (Sands et al., 2021); the trend is expected to continue, and chatbot customer service is expected to grow at a significant rate from 2019 to 2026 (Nguyen, 2017). For example, according to *MIT Technology Review*, 90% of businesses reported faster complaint resolution with chatbots (Bocian, 2024). Furthermore, Schuetzler, Grimes, and Giboney (2020) reported that the global market for AI chatbots is expected to reach USD 14.9 billion by 2027, with a growing compound annual growth rate (CAGR) of nearly 25% during the forecast period.

Statement of the Problem

Although the rapid growth of chatbots in the apparel retail sector has attracted more and more attention from apparel and retail scholars, few studies have been conducted on this new phenomenon, especially in the field of apparel retailing (e.g., Chung et al., 2020; Huang & Kao, 2021; Toader, Boca, Toader, Macelaru, Toader, Ighian, & Radulescu, 2020). Thus, this field merits further academic research to gain a deeper understanding of how consumers use AI chatbots for apparel shopping purposes. In addition, due to the newness of the phenomena, a number of empirical gaps exist between what we already understand and what we need to understand (i.e., what theory can systematically explain consumers' adoption and rejection of AI chatbot, what other antecedents and consequences of the use of AI chatbot in apparel retail still need to be explored, and what other moderators still need to be examined). As such, the current study focuses on consumers’ apparel shopping behavior using AI chatbots and attempts to answer the research questions described above to fill this critical gap.

According to the literature, the Technology Acceptance Model (TAM) (Davis, 1989) is one of the most popular models for explaining a person’s intention to adopt chatbots (e.g., Ashfaq et al., 2020; Kasilingam, 2020; Rese et al., 2020). For example, Kasilingam (2020) applied the TAM as a theoretical foundation and identified seven external factors, such as perceived ease of use, perceived usefulness, perceived enjoyment, and price consciousness, as influencing factors of consumers’ attitudes and intentions to use mobile phone chatbots for shopping purposes. Previous chatbot researchers have also applied other theories. For example, McLean et al. (2021) applied the social response theory, and de Cicco et al. (2020) applied the social presence theory to explore whether chatbot features, such as interaction and avatar presence and/or absence influence social presence and lead to trust, perceived enjoyment, and a positive attitude towards using chatbots. Another empirical study by Melian-Gonzalez, Gutierrez-Tano, and Bulchand-Gidumal (2021) applied the Unified Theory of Adoption and Use of Technology (UTAUT) to investigate consumers’ intentions to use chatbots. They found that consumers’ intentions to use chatbots are directly influenced by several factors, including performance expectancy, effort expectancy, the habit of using chatbots, hedonic motivations, and social influences in the travel and tourism context.

Furthermore, according to Pedersen (2007), theories are vital to identify, predict, and understand phenomena that extend the existing knowledge in the research. Research using well-established theories is essential to gain insight into AI chatbots, as they are a relatively new phenomenon in apparel, retail, and consumer behavior literature. Therefore, many future empirical studies are still needed to test different theories, such as the behavioral reasoning theory (BRT) (Westaby, 2005) to gain more profound knowledge about apparel consumer behavior associated with AI chatbot usage in apparel shopping. The BRT theory is an extension of the conventional belief-based framework, e.g., the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), the theory of planned behavior (TPB) (Ajzen, 1991), and the Technology Acceptance Model (TAM) (Davis, 1989) by taking into account the role of reason in determining behavior. According to Westaby (2005), BRT allows researchers to investigate context-specific reasons to better understand consumers' specific behaviors, including their adoption and/or rejection of innovation. Reasons are defined as "the specific subjective factors people use to explain their anticipated behavior" (Westaby, 2005, p. 100) and are theoretically different from beliefs in that reasons exist prior to attitudes being developed and can play a significant role in the decision-making process (Gupta & Arora, 2017). The BRT includes two reasons—reasons for (adoption) and reasons against (rejection)—that provide a deeper understanding of a person's decision-making process (Sahu, Padhy, & Dhir, 2020). The BRT also suggests the relationships between value, reasons for/against, attitude, and behavioral intention to use innovation (Westaby, 2005). According to the literature, BRT has been employed to understand consumer behaviors in contexts related to technology, such as e-waste recycling (Dhir, Koshta, Goyal, Sakashita, & Almotairi, 2021) and mobile banking (Gupta & Arora, 2017).

There has been little empirical research about AI chatbot usage in apparel shopping based on BRT. Furthermore, since the AI chatbot is a new technology in the apparel retail sector, this current study employs the BRT by integrating three factors of service quality and five barriers from the innovative resistance theory into the original BRT to develop a comprehensive research framework in order to provide a better understanding of consumers' attitudes and their reasons for adoption or rejection of this new technology. Thus, this study aims to add theoretical contributions to the AI chatbot literature by investigating which factors encourage and discourage consumers' attitudes toward using AI chatbots.

This study also discusses the research gaps related to antecedents and consequences of using AI chatbots in the apparel retail context. While several studies have recently identified important characteristics of AI chatbots (e.g., convenience, trustworthiness, entertainment, informativeness, gamification, interaction, trendiness, customization, and problem-solving ability), other studies have used the TAM's key dimensions, including perceived ease of use, usefulness, and enjoyment, to predict attitude and intention toward using chatbot (e.g., Ashfaq et al., 2020; Rese et al., 2020). Other researchers (e.g., Kasilingam, 2020; Rhee & Choi, 2020; Zarouali et al., 2018) have also explored the role of various perceptions, such as perceived helpfulness, perceived trust/distrust, perceived innovativeness, and perceived risk in determining consumers' adoption of AI chatbots. Additionally, other studies (e.g., Chi et al., 2022; Chopra, 2019; Melián-González et al., 2021; Rese et al., 2020) have examined how different types of motivation (e.g., utilitarian, hedonic, intrinsic, forced-choice, extrinsic) positively influenced attitude toward using chatbot and intention to use it. However, there are many factors that could positively influence consumers' attitudes and intentions to use AI chatbot (e.g., reliability, responsiveness, assurance, empathy, tangibility) that are the measures of service quality (SERVQUAL) (Parasuraman, Zeithaml, & Berry, 1985). According to Zeithaml (1988), perceived service quality is defined as "the judgement of the consumer on the excellence or superiority of a product/service" (p. 3) and is considered an important construct that can build a stronger relationship between companies and their consumers and positively influence consumers' word-of-mouth (WOM) behaviors about the companies and their products/services (Roy, Shekhar, Lassarc, & Chen, 2018). Chen, Hsu, and Lee (2020) also stated that these factors (reliability, responsiveness, assurance, empathy, and tangibility) have been used to measure service quality in the online environment. However, there is a lack of study using these factors as antecedents in the AI chatbot context. Parasuraman and Grewal (2000) suggested that “the definitions and relative important dimensions of service quality change when customers interact with technology rather than with service personnel" (p. 171). Therefore, this current study uses the revised service quality known as “perceived chatbot service quality” as reasons for factors including responsiveness, reliability, and assurance. Responsiveness refers to the ability to respond to consumers' requirements in a manner that is both timely and flexible (Iberahim, Taufik, Adzmir, & Saharuddin, 2016). Several studies have also indicated that the responsiveness of online stores includes services such as customer inquiries and information retrieval (Yang & Fang, 2004). Reliability is defined as the capacity to always deliver the expected standard of services the first time they are required (Iberahim et al., 2016). Technology-based service focuses on the importance of reliability (Lee & Lin, 2005). Assurance refers to an individual's confidence in the intentions, motives, and sincerity of others (Ribbink, Van Riel, Liljander, & Streukens, 2004). Assurance can encourage consumers to purchase products online and impact consumers' attitudes toward buying online (Lee & Lin, 2005). Given that AI chatbot is an innovative technology in the apparel retail industry, it can act as a virtual customer service agent that is immediately available and provides accurate information. Since an AI chatbot is not a human, and consumers cannot see a chatbot’s appearance or receive empathy from it, tangibility (which is defined as physical facilities and employee appearance) and empathy (which is defined as caring for and paying attention to customers by salespersons) are not relevant to the context of this current study. Thus, this study focuses on three factors (responsiveness, reliability, and assurance) that are relevant to chatbot quality and excludes two dimensions (tangibility and empathy) that are irrelevant to chatbot quality.

In addition, other studies have investigated factors that negatively influence consumers' intentions to use AI chatbots, including immature technology (Rese et al., 2020), privacy concerns, and privacy risks (Cheng & Jiang, 2020). However, other negative factors still need to be explored, such as the reasons why some consumers are not willing to use AI chatbots. Ram and Sheth (1989) contended that the innovation resistance theory (IRT) helps researchers understand consumers' resistance to using innovations. The theory provides five resistance factors: usage barrier, value barrier, risk barrier, image barrier, and tradition barrier. Usage, value, and risk barriers are functional barriers, while tradition and image barriers are psychological barriers. As Ram and Sheth (1989) stated, the usage barrier occurs when users perceive a new technology as incompatible with existing practices, habits, or work. The value barrier occurs when potential users evaluate the differences between existing and innovative products/services. The risk barrier occurs when potential users allow inadequate information, uncertainties, or unseen risks to influence their ability to understand and use innovation (Ram & Sheth, 1989). The image barrier occurs "when the user has an unfavorable impression of the originating country, brand, industry, or side effects of the innovation" (Lian & Yen, 2013, p. 666). The tradition barrier occurs when the innovation causes conflicts and disruptions between users and their traditional culture (Ram & Sheth, 1989). Lian and Yen (2014) found that these barriers prevent consumers from adopting online shopping. Furthermore, many previous studies have applied the IRT to investigate the barriers that prevent consumers' acceptance of innovations such as retail banking services (Iberahim et al., 2016), mobile banking (Laukkanen, 2016), e-banking (Borraz-Mora, Bordonaba-Juste, & Polo-Redondo, 2017), and online shopping

(Lian & Yen, 2014). However, no prior research was found examining the impact of these barriers in the AI chatbot context. Therefore, to fill this gap, this study applies all five barriers (usage barrier, value barrier, risk barrier, image barrier, and tradition barrier) as reasons against suggested by the IRT to investigate the negative impact of consumers' attitudes and behavioral intentions to use AI chatbots for apparel shopping purposes.

Besides the gap related to the antecedents of using AI chatbots, the literature also suggests identifying the consequences of using AI chatbots. Understanding the consequences could create not only scholarly knowledge but also practical implications for retailers. Most prior studies have focused on the consequences of attitudes, such as purchase intention, intention to use technology, and customer satisfaction. For instance, de Cosmo, Piper, and Di Vittorio (2021) examined the impact of attitudes toward mobile advertising on attitudes toward chatbots and intention to use them. They found that attitudes toward mobile advertising had a significant influence on the intention to use chatbot through attitudes toward chatbots. Kasilingam (2020) investigated the association of perceived usefulness, perceived ease of use, perceived enjoyment, price consciousness, perceived risk, trust, and personal innovativeness with consumers' attitudes and their intentions to use chatbots. He revealed that the variables (perceived usefulness, perceived ease of use, perceived enjoyment, price consciousness, perceived risk, and personal innovativeness) influenced attitude toward chatbots. Personal innovativeness and attitude had a direct effect on the intention to use chatbots. Zarouali et al. (2018) examined the impact of perceived usefulness, perceived ease of use, perceived helpfulness, pleasure, arousal, and dominance on attitude and purchase intention. They found that attitude had a significant impact on purchase intention. All variables also have a significant effect on purchase intention through attitude.

Indeed, there are other consequences of attitudes, including consumers' willingness to buy and electronic word-of-mouth (eWOM) intention, which remain to be explored in the AI chatbot context. The relationship between attitudes and behavioral intention, such as willingness to buy and eWOM, has been largely ignored. It is imperative to study how the use of chatbots changes consumers' behavioral outcomes (i.e., willingness to buy and eWOM). Moreover, Chan and Ngai (2010) stated that willingness to buy and eWOM constructs have been extensively studied in marketing and information system (IS) research. Huang and Hsu-Liu (2014) suggested that innovative technologies (i.e., augmented reality) that offer users a simulated experience with something could encourage them to buy a specific product. Thus, new technology like AI chatbots may provide accurate and reliable product information to consumers, which in turn may strengthen consumers' willingness to buy. Another study explored eWOM, which also plays an important part in increasing consumers' adoption of a product or service related to advanced technology (Kim, Jang, & Adler, 2015). Hennig-Thurau, Gwinner, Walsh, and Gremler (2004) stated that eWOM can be positive or negative online communication made by potential consumers about a product or service. Therefore, this study examines the relationship between reasons for (perceived chatbot service quality) factors, reasons against (perceived chatbot barriers) factors, attitudes, and the effect of attitudes toward using AI chatbot on willingness to buy with the help of AI chatbot and eWOM. The current study contributes to the apparel and consumer behavior literature by advancing the understanding of how AI chatbots can increase consumers' willingness to buy and eWOM behavior.

Finally, several previous studies have identified some moderators that affect the strength of the relationships between chatbot characteristics and behavioral intention. Moderators such as perceived ease of use, perceived usefulness, perceived enjoyment, perceived risk, involvement, need for human interaction, and time orientation have been examined in other chatbot studies (e.g., Ashfaq et al., 2020; Kasilingam, 2020; McLean et al., 2021; Rese et al., 2020; Rhee & Choi, 2020). For example, Sheehan, Jin, and Gottlieb (2020) found that consumers' need for human interaction makes the relationship between anthropomorphic perceptions and adoption intention stronger. Moreover, familiarity has already become an interesting factor in consumer behavior literature (Maenpaa, Kale, Kuusela, Mesiranta, 2008), as it can further explain consumers' decision-making behavior (Rao & Monroe, 1988). However, no extant research has used technology familiarity as a moderator. Zaichkowsky (1985) presented the concept of familiarity in terms of expertise in product and/or service use. Kanchan and Kumar (2015) found that users' technology familiarity is positively related to their past experience. It is important to know whether consumers' previous experience and their knowledge of using innovation leads to using AI chatbots for apparel shopping since AI chatbots are a relatively new technology in the apparel retail environment. Therefore, the current study incorporates a technology familiarity variable as a moderator in order to examine whether technology familiarity can affect the strength of the relationship between reasons for and against using AI chatbots and consumers' attitudes toward using them. A few studies have determined that familiarity with technology has a positive relationship with consumers' intentions and their behavior (Lee & Kwon, 2011). Obviously, an examination of the moderating effects on the relationship between perceived chatbot service quality, perceived chatbot barriers, and consumers' attitudes toward using AI chatbots is absolutely needed. To fill an important gap, this study uses "technology familiarity" as a moderator to investigate how technology familiarity affects the strength of the relationship between perceived chatbot service quality, perceived chatbot barriers, and attitudes toward using AI chatbots. Hence, this study makes an additional contribution to the literature.

Purpose and Objectives of the Study

Although the AI chatbot has become a powerful tool in the retail apparel industry, it is still in its infancy in the apparel and retail literature. Therefore, as described in the previous section, this study aims to fill several research gaps in the apparel and retail literature: (1) limited amount of knowledge about using BRT theory that can systematically explain consumers' adoption and rejection of AI chatbots within a single framework, (2) lack of knowledge about other consumers' antecedents (reasons for and reasons against) and consequences (willingness to buy and eWOM) of the attitudes toward using AI chatbots, and (3) lack of knowledge about the moderator (technology familiarity).

Because of the potential influence of consumers' attitudes toward using AI chatbots and behavioral intentions, research questions in this area must be developed from a broad and integrative framework. Therefore, the purpose of this study is to develop and test a conceptual model of the potential antecedents and consequences of consumers' attitudes toward using AI chatbots. Three primary objectives guide the study:

1. To examine relationships between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*;
2. To investigate relationships between consumers' *attitudes toward using AI chatbots* and their behavioral intentions as measured in terms of *willingness to buy apparel with the help of AI chatbots* and *eWOM*; and
3. To examine the moderating role of *technology familiarity* on the relationship between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*.

Significance of the Study

Given that AI chatbot technology is a growing trend in the apparel retail sector, this study expands the knowledge about consumers' behaviors toward AI chatbot usage in the apparel retail sector. In addition, the results of this current study contribute to the existing literature on AI chatbots. By addressing the above objectives, this study also examines the factors that influence consumers' attitudes toward using AI chatbots, which, in turn, influence their willingness to buy and eWOM.

According to the literature, several prior studies have focused on examining the factors influencing behavioral aspects, such as purchase intention and intention to use chatbots (e.g., Hsieh, Lee, & Tseng, 2021; Rese et al., 2020; Sands et al., 2021). However, no extant literature has examined the influencing factors of reasons for (perceived service quality), reasons against (perceived chatbot barriers), and attitudes toward using AI chatbots on behavioral intentions as measured in terms of consumers' willingness to buy and eWOM intentions. Although several studies (e.g., de Cicco et al., 2020; Hsieh et al., 2021; Rese et al., 2020) have already identified some influencing factors of consumers' attributes, such as convenience, trustworthiness, entertainment, informativeness, entertainment, gamification, interaction, trendiness, customization, and problem-solving ability, as well as some perceived characteristics of chatbots, such as perceived ease of use, perceived usefulness, perceived enjoyment, and perceived intelligence, many factors still need to be explored in future research, including responsiveness, reliability, assurance, usage barrier, risk barrier, and tradition barrier. Many previous studies have examined the impact of these factors on consumers' shopping behaviors in different contexts, such as retail banking (Ibrahim et al., 2016) and e-travel services (Ho & Lee, 2007). However, few studies have explored the relationship between these factors and consumers' attitudes toward using AI chatbots. Furthermore, although a few previous studies have used moderators (i.e., age, gender, and experience) to better understand an individual's behavioral intention and actual use of chatbot (Molinillo, Aguilar-Illescas, Anaya-Sánchez, & Liébana-Cabanillas, 2021), little is known as to how technology familiarity moderates the relationships between perceived chatbot service quality, perceived chatbot barriers, and attitudes toward using AI chatbots in the context of apparel retailing. Thus, this dissertation fills these gaps by providing knowledge about potential consumers' adoption of AI chatbots in the apparel retail sector. By doing so, this study also provides several new theoretical and practical implications to the existing literature.

In terms of theoretical implications, this is the first study to examine the antecedents of consumers' adoption of AI chatbots by integrating the dimensions of perceived service quality and barriers from the innovative resistance theory (IRT) into the BRT. Therefore, this study provides valuable insight into the literature by providing a more detailed understanding of how reasons for (perceived chatbot service quality, including responsiveness, reliability, and assurance) and reasons against (perceived chatbot barriers, including usage barrier, risk barrier, value barrier, image barrier, and tradition barrier) influence consumers' attitudes toward using AI chatbots and how their attitudes impact their willingness to buy and eWOM. This is important given that most prior studies focused on factors that influenced consumers' adoption of AI chatbots. In comparison, few have examined the factors that may cause consumers to refuse to use chatbots. Thus, the study's findings provide a comprehensive understanding of apparel consumers' adoption of AI chatbots.

This study contributes to the existing literature on AI chatbot usage by exploring the moderating role of technology familiarity. Thus, this study adds to the literature by providing important insight as to how technology familiarity moderates the relationship between perceived chatbot service quality (i.e., responsiveness, reliability, and assurance), perceived chatbot barriers (i.e., usage barrier, risk barrier, and tradition barrier), and attitudes toward using AI chatbots. In addition, the findings of this study contribute to an understanding of how consumers who are familiar with technology, in general, are more willing to use AI chatbots for apparel shopping.

In terms of practical implications, the findings of this study could also provide online retailers and marketers with a greater understanding of which factors encourage or discourage consumers from using AI chatbots for apparel shopping. Thus, the findings may assist online retailers and marketers in becoming more aware of the impact of perceived chatbot service quality on consumers' attitudes, willingness to buy, and eWOM. For instance, online retailers and marketers may use the three perceived chatbot service quality dimensions (i.e., responsiveness, reliability, and assurance) to offer a better and more acceptable quality of chatbot service to their consumers. They may also pay great attention to a better quality of chatbot that can deliver product information on time and present the products accurately. The findings of this study may further help online retailers and marketers understand the different effects of consumers' barriers (i.e., usage barrier, risk barrier, and value barrier) on attitudes, willingness to buy, and eWOM. Thus, they can focus on reducing consumers' perceptions of chatbot barriers. For example, they may (1) offer a better quality of chatbot (e.g., one that provides quick responses to help customers and continue the conversation, detailed product information, and appropriate and accurate website links to browse fashion products) to give a better chatbot experience to their consumers; (2) utilize the study's findings to develop and improve their marketing strategies to promote their chatbot services; and (3) provide appropriate information and guidance regarding how to use chatbot services.

Definition of Key Terms

Table 1 provides definitions for key terms that are applied throughout this dissertation.

Table 1. Definition of Key Terms

Terms	Definitions
AI Chatbot (or) Chatbot	AI chatbot is an artificial intelligence software that can understand what humans want by interpreting human conversation via text messaging or voice messaging (Smutny & Schreiberova, 2020).
Behavioral Reasoning Theory (BRT)	The behavioral reasoning theory is a popular behavioral theory to understand consumers' innovation adoption (Westaby, Probst, & Lee, 2010). According to the BRT, intentions predict actual behavior, global motives (attitudes, subjective norms, and perceived control) and reasons (for behavior and against behavior) predict intention, and beliefs and values predict reasons.
Perceived Chatbot Service Quality	Perceived service quality is defined as "the judgement of the consumer on the excellence or superiority of a product/service" (Zeithaml, 1988, p. 3). Originally, there were five characteristics (responsiveness, reliability, assurance, tangibility, and empathy) in perceived service quality. This current study chooses three of the five factors (responsiveness, reliability, and assurance) that are relevant to the study and revises the term "perceived service quality" to "perceived chatbot service quality."
Reasons For	Reasons for refers to the favorable factor that can encourage the adoption of a particular behavior (Westaby, 2005).

Terms	Definitions
Reasons Against	Reasons against refers to the negative factor that can persuade someone to reject a specific behavior (Westaby, 2005).
Responsiveness	Responsiveness refers to the willingness to help customers and provide prompt service (Parasuraman et al., 1985).
Reliability	Reliability refers to the ability to perform the promised service in a consistent and accurate manner (Parasuraman et al., 1985).
Assurance	Assurance is "the term given in the services world to describe the sensation that a supplier of customer services transmits in terms of security and credibility" (Parasuraman et al., 1985, p. 12).
Innovation Resistance Theory	The innovation resistance theory (IRT; Ram & Sheth, 1989) helps researchers understand consumers' resistance toward the adoption of innovations. The theory provides five resistance factors: usage barrier, value barrier, risk barrier, image barrier, and tradition barrier. Barriers include both functional (i.e., usage barrier, value barrier, and risk barrier) and psychological barriers (i.e., tradition barrier and image barrier) that prevent consumers from performing a specific behavior (Lian & Yen, 2014).
Usage Barrier	Usage barrier is defined as how consumers perceive the difficulty of using an innovation compared to their familiarity with an existing product (Ma & Lee, 2019).
Risk Barrier	Risk barrier is defined as "when the user does not adequately understand the innovative technology in the new product, the user cannot assess the associated risks and uncertainties that will arise after its use" (Lian & Yen, 2014, p. 135).
Value Barrier	Value barrier occurs when there is resistance to an innovation due to its inconsistency with an existing product or service (Morar, 2013).

Terms	Definitions
Image Barrier	Image barrier is defined as how consumers feel about how difficult or easy it is to use innovations (Mani & Chouk, 2018).
Tradition Barrier	A tradition barrier arises when an innovation leads to conflicts and changes between users and their traditional culture (Ram & Sheth, 1989).
Technology Familiarity	Technology familiarity is defined as "the degree of experience and ability to use digital tools," including smartphones, tablets, etc. (Byungura, Hansson, Muparasi, & Ruhinda, 2018, p. 32).
Attitude	Attitude is defined as the assessment of a person who encourages or discourages the use of a particular behavior (Ajzen, 1991).
Willingness to Buy	Willingness to buy is defined as consumers' behavioral intention to buy a targeted product in the future (Donato & Raimondo, 2020; Morrison, 1979).
Electronic Word-of-Mouth (eWOM)	eWOM is defined as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institution[s] via the internet" (Hennig-Thurau et al., 2004, p. 39).

Organization of the Study

This current dissertation proposal consists of three chapters. Chapter I provides an introduction to the study, including the research background of relevant topics, the statement of the problem, the purpose and objectives of the study, the significance of the study, definitions of key terms, and the organization of the study. Chapter II reviews the literature that is relevant to the topic, providing previous studies related to AI chatbot usage in consumer behavior. This chapter also provides the conceptual framework and proposes a set of hypotheses. Chapter III explains the study's research methodology, which includes the development of the survey instrument, the selection of the sample, the data collection procedures, and the statistical analysis that will be used to test all proposed hypotheses. Chapter IV presents an overview of the sample characteristics, descriptive statistics of all variables, confirmatory factor analysis, and, finally, the results of the proposed hypotheses. Chapter V includes a discussion, conclusions, implications, limitations, and potential avenues to explore in future research.

CHAPTER II: LITERATURE REVIEW

This chapter consists of five sections. First, the general concepts related to artificial intelligence (AI) chatbots are introduced, including definitions of an AI chatbot, the history of chatbots, and the use of AI chatbots. Second, earlier empirical studies on the AI chatbot context are reviewed. Third, the theoretical foundation, including the concepts, major constructs, and former studies related to the theory, is discussed. Fourth, the conceptual framework is proposed. Finally, all hypothesized relationships specified in the conceptual framework are proposed.

What is an AI Chatbot?

The term *chatbot* is a combination of two words: *chat* and *bot* (Rese et al., 2020). A chatbot is an AI software that relies on natural language to understand and respond to human beings through voice or text messaging (Adamopoulou & Moussiades, 2020). The main purpose of chatbots is to provide interaction between people and services (Shawar & Atwell, 2007). Thus, making conversation with a chatbot is pretty simple, given that it was designed to answer users' questions and help users fulfill their needs and wants.

AI chatbots are already acting as digital assistants in various forms (e.g., animated pictures, interactive 3D avatars mimicking human-to-human communication, and human-like animated customer service agents) in retail (Youn & Jin, 2021) and across other industries, including education, marketing, and training (Smutny & Schreiberova, 2020). The latest chatbots can simulate human conversation through both text and voice messaging using mobile applications (e.g., Kik, Chatterbot), social media applications (e.g., Facebook Messenger, Twitter Messenger, WhatsApp), and websites. A text-messaging chatbot gives helpful virtual assistance by providing speedy and capable product information and helpful suggestions until customers are satisfied. Besides functioning as voice assistants (VAs), chatbots can comprehend what humans say and respond by synthesized voice (Chopra, 2018). A large variety of tasks that once required humans are now performed by VAs, including reading and sending text messages, searching for information, answering questions, making phone calls, playing music, and controlling users' home electronic devices (e.g., turning television, air conditioner, heater, lights, locks, alarms on/off (Chopra, 2018). Amazon's Alexa and Echo, Microsoft's Cortana, Apple's Siri, and Google Assistant are voice assistant applications (Poushneh, 2021) that have recently been integrated into many devices, such as computers, mobile phones, and smart speakers. Because chatbots are based on the principle behind the first chatbot, "ELIZA" (Rese et al., 2020), they are often related to text-based applications.

Defining an AI Chatbot

Different scholars have defined a chatbot in different ways. For example, Han (2021) explains, "Chatbots are programmed to use human-like dialogue with natural language processing so consumers will experience chatbots as human-like or anthropomorphic" (p. 46). Youn and Jin (2021) define a chatbot as a simulation of human language with the help of a text-based dialogue system. Similarly, Rese et al. (2020) define chatbots as conversational agents that communicate with humans using natural language. Chen, Tran-Thien-Y, and Florence (2021) further state that chatbots, also known as text-based automated conversational agents (ACAs), can be implemented on social media such as Twitter, Facebook, and other business websites. Kasilingam (2020) describes chatbots as conversational commerce (c-Commerce), which can be defined as a system application utilizing chat, text messaging, and voice messaging to interact with people, companies, and services. De Cicco et al. (2020) define chatbots as computer programs that simulate human conversation and assist human interaction with digital devices. Furthermore, Chung et al. (2020) define chatbots as technologically advanced applications that fulfill customers’ expectations and enhance customer experiences in real-time interactions. Overall, a common thread throughout these definitions is that chatbots are computerized programs that allow users to engage with them. Consequently, chatbots are known by a variety of names, including virtual agents (Przegalinska et al., 2019), virtual assistants, digital assistants (Smutny & Schreiberova, 2020), conversational agents (Han, 2021; Schuetzler et al., 2020), interactive agents, smart bots (Adamopoulou & Moussiades, 2020), e-service agents (Chung et al., 2020), and chatterbots (Buch, Ahmed, & Maruthappu, 2018). In this study, chatbot refers to *AI chatbot*, as it is closely related to artificial intelligence (AI).

History of Chatbots

In the 1960s, at the Massachusetts Institute of Technology (MIT), Professor Joseph Weizenbaum developed a chatbot called *Eliza*, which is considered one of the oldest chatbots (Zemcik, 2019). *Eliza* can ask questions as well as respond to answers in a human-like manner. Next, *Parry* became a well-known chatbot that was developed by a Stanford psychiatrist and computer scientist, Kenneth Mark Colby, in 1972 (Wei, Yu, & Fong, 2018). *Parry* was different from *Eliza* since it behaved like a paranoid schizophrenic patient. It helped young psychiatrists learn how to communicate with paranoid schizophrenic patients. *Racter* was also an artificial intelligence chatbot that was able to make conversation with humans. William Chamberlain and Thomas Etter developed it under the Inrac Corporation (Zemcik, 2019) in 1983. In 1991, *Dr. Sbaitso* was introduced by Creative Labs for MS-DOS to interact with users verbally (Wei et al., 2018). It behaved even more human-like than its predecessors (Zemcik, 2019). In 1995, *ALICE* (Artificial Linguistic Internet Computer Entity) was developed by Richard Wallace. It simulates speaking with an actual human through the internet (Adamopoulou & Mousiades, 2020). After *ALICE*, other AI chatbot programs appeared (e.g., *IBM Watson* in 2006, *Siri* in 2010, *Google*

Now in 2012, and *Alexa* in 2015). In 2016, Facebook launched a chatbot Messenger platform to interact with Facebook users. Additionally, other community chatbot applications, such as Kik, Chatterbot, and Fitmeal have been launched (Dredge, 2016). These chatbots allow users to connect with brands, either in groups or one-on-one chats, to buy and order goods—even via smartphones.

As their capabilities have increased, chatbots have become effective for use in many applications. For example, Facebook Messenger has more than 1.3 billion active users every month. It has user accounts with over 300,000 chatbots, with 8 billion messages a day sent between chatbot users and business companies (Nair, Johnson, & Sathya, 2018). In addition to Facebook Messenger, many other messaging applications such as Twitter, Skype, Instagram, and Telegram are used for a variety of purposes (e.g., chatting and ordering goods).

The Use of AI Chatbots in the Apparel Retail Industry

Chatbots facilitate various retail business processes, particularly in providing excellent customer service and personalized recommendations (Przegalinska et al., 2019). Since AI chatbots have the valuable capability to interact with humans, they are more likely to influence consumers' purchase decisions (Han, 2021; Lee & Park, 2022; Siripipatthanakul, Nurittamont, Phayaphrom, & Nuanchaona, 2021). Consequently, apparel brands are turning to chatbot technology and offering free personal stylist services online to help their customers find the desired fashion items that meet their needs. Notably, the apparel industry was the first to recognize the practicality and effectiveness that chatbot technology brings to its e-commerce (Moghis, 2020), so many leading fashion brands such as Burberry, Louis Vuitton, Ted Baker, Victoria Beckham, Tommy Hilfiger, and H&M have adopted text-based AI chatbots (Pizzi et al., 2021) to interact with their consumers. Chatbots used by these apparel companies can operate through mobile applications (e.g., Kik, Chatterbot), social media applications (e.g., Facebook Messenger, Twitter Messenger, Instagram, Telegram, WhatsApp), and websites.

Chatbots can serve as customer service agents to enhance consumers' entire shopping experiences (Copulsky, 2019). For example, a customer may need help from an AI chatbot service to look for a jacket. First, they need to let the chatbot know, through messaging, the style, design, color, and expected price of the jacket they are looking for. The chatbot then replies and suggests a personalized selection of jackets based on the consumers' preferences. If the customer is satisfied with the chatbot's suggestion, the chatbot provides a specific website link to buy such a jacket. If the customer needs more advice, they can keep chatting with the chatbot until they find the right jacket. To further explore chatbot usage in this type of context, this study focuses on how text-based AI chatbots influence consumers' apparel purchase behaviors.

Human Customer Service vs. Digital Service (AI chatbot)

According to Sparks (1992), customer service is "all about attracting, retaining and enhancing customer relationships" (p. 167). Human customer service in retailing provides suggestions and answers to customers' questions, helps customers find products, and processes return policies/handling during and after customers buy the stores' products/services (Rita et al., 2019). Customer service is and has always been key to providing excellent services and, consequently, to being a successful brand and company. Furthermore, it is a key factor to increase retail customer loyalty and generate a successful retail business (Paulins, 2005). The attraction to customers might include not only the price offer (Kusuma, Hadinoto, Ayucitra, Soetaredjo, & Ismadji, 2013) but also services such as gift wrapping, free parking, and delivery (Paulins, 2005). Additionally, warm greetings and personalized attention from human customer service agents can also enhance customer satisfaction and foster a sense of fulfilled expectations (Gagliano & Hathcote, 1994).

Like human customer service representatives, chatbots can also generate sales and provide services. However, However, there are a number of key differences--both advantages and disadvantages--between chatbots and human customer services. In terms of advantages, unlike human customer service, chatbots can provide 24/7 customer service. Since they employ artificial intelligence, they may be more responsive than human service agents. Although there is an initial cost for retailers to adopt chatbots as virtual agents, they are relatively cheaper than human agents in the long run (Jyng & Rubasundram, 2020). On the other hand, chatbots can also have some disadvantages. One of the biggest disadvantages is that, unlike human agents, chatbots have no empathy for customers. Due to the lack of a personal touch, consumers may not feel the same sense of warmth from a chatbot that they receive from a good human agent. Therefore, consumers may experience some degree of discomfort when interacting with chatbots. If the chatbot is not well programmed, there may be some difficulties in interaction, such as customers not getting answers to specific questions. Lastly, given that chatbots store all customers' conversations, some people could have concerns related to their privacy.

AI Chatbot Studies in Various Contexts

Recently, interacting with consumers through chatbots has become increasingly popular. Chatbots provide real-time services to customers in multiple business areas (Adam, Wessel, & Benlian, 2021), such as marketing, retail, banking, and travel/tourism. Many businesses deploy chatbots as leaders in customer service due to their unique innovations that significantly enhance the customer experience (Trivedi, 2019).

In the banking industry, where chatbots are still a relatively new technology platform, they are called digital assistants. They have become an essential tool for banks to build better customer relationships. In terms of empirical research on using AI chatbots in the banking context, chatbots have proven capable of providing fast and efficient customer information, improving customer service, and helping bankers increase revenue. They also help improve customer experiences (Froment, 2022). Trivedi (2019), for example, investigated the use of chatbots in banking and its impact on customer experience. As a new technology offered by banks to understand consumers' expectations, he specifically examined whether banking chatbots' information quality, system quality, and service quality can impact brand love through customer experience and how perceived risk can moderate the relationship between these qualities and customer experience. He found that information quality, system quality, and service quality were key to ensuring a seamless customer experience with the chatbot and that all three qualities had significant positive associations with perceived risk. Trivedi's study revealed that the adoption of chatbot digital assistants in the banking industry resulted in stronger customer and brand relationships.

Furthermore, Adam et al. (2021) examined whether anthropomorphic design cues affect user compliance when interacting with a bank AI chatbot in customer self-service. Anthropomorphism refers to the extent to which users perceive AI chatbots have human-like features and characteristics such as a name, the ability to talk, or an avatar (Ruijten, Haans, Ham, & Midden, 2019). These features help develop and enhance users' positive opinions on chatbot usage (Ho & Macdorman, 2017). In Adam et al.'s (2021) study, anthropomorphic design cues (e.g., identity, empathy, and small talk) were shown to increase the likelihood of user compliance with chatbot service requests (Adam et al., 2021). Adam et al. (2021) found that social presence mediated the effects of anthropomorphic design cues on user compliance but did not find a moderating effect of social presence on the same relationship. In further studies, Roy and Naidoo (2021) examined whether chatbots capable of projecting human qualities such as warmth and competence could enhance positive consumer experiences, attitudes toward a hotel brand, and purchase intention. They found that when consumers perceived chatbots to behave like real humans, the chatbots were more likely to influence positive opinions and purchase intention for specific products.

Recently, travel companies have adopted chatbots to create travel plans, book vacation packages, provide recommendations and suggestions to customers (Pillai & Sivathanu, 2020), answer customers' questions, and ask customers' needs/wants. Thus, chatbots are increasingly involved in travel and tourism fields; as a result, whether human-like chatbots can influence people's evaluation and behaviors in those settings has become a topic of interest. Pillai and Sivathanu (2020) examined consumers' behavioral intentions and actual usage of AI chatbots for hospitality and tourism in India. They reported that customers' behavioral intentions and actual usage of AI chatbots for hospitality and tourism organizations were influenced by perceived ease of use, perceived usefulness, perceived trust, perceived intelligence, and anthropomorphism. Chi et al (2022) investigated whether utilitarian or hedonic services influence tourists' attitudes toward AI chatbot usage. They found that anthropomorphism (emotions toward artificially intelligent devices), performance and effort expectancy, social influence, and hedonic motivation influenced the tourists' acceptance of using AI devices such as chatbots. Li, Lee, Emokpae, and Yang (2021) investigated the effects of chatbot quality on consumer confirmation, leading to the use of continuance in the chatbot-based online travel agent context. Additionally, they examined the moderating role of technology anxiety in the relationship between chatbot quality and consumers' confirmation and identified that chatbot quality positively influenced confirmation and intention to continue using a chatbot. They also found that technology anxiety positively moderated the relationship between chatbot quality and consumers' confirmation. Thus, they indicated that the higher the levels of technology anxiety, the stronger the relationship between chatbot quality and consumers' confirmation. Melián-González et al. (2021) examined the factors that impact consumers' intentions to use chatbots for travel and tourism. They found that consumers' intention to use chatbots was positively influenced by several factors, including expected performance, habit, hedonic motivation, attitudes toward chatbots, social influence, inconvenience, automation, and anthropomorphism.

An AI chatbot has also become a valuable and popular advanced technological tool in the restaurant industry. A few studies have investigated customers' perceptions and behaviors in the context of restaurant takeout orders. For example, Leung and Wen (2020) found that ordering through a chatbot was considered a good option for quick service since online orders generated the highest order amounts. De Cicco et al. (2020) examined whether avatar presence or absence and interaction styles (social-oriented and task-oriented interaction styles were measured by empathy, friendliness, fulfillment, and responsibilities) impact social presence, attitude, trust, and enjoyment in the online food delivery context. Social presence is a construct that "refers to the extent to which a medium is perceived as sociable, warm, sensitive and personal when it is used to interact with others" (De Cicco et al., 2020, p. 1216). They found that only the social-oriented interaction style increased users' perception of social presence, which, in turn, positively influenced attitude, trust, and enjoyment.

Additionally, most studies in the chatbot context have focused on marketing and retailing (Rese et al., 2020). AI chatbots have transformed the fashion industry by playing key roles, including chatbot assistance such as customer service, product recommendations, and friendly interaction with consumers (Landim, Pereira, Vieira, de Costa, Moura, Wanick, & Bazaki, 2022). According to the apparel retail literature, Rese et al. (2020) identified key factors influencing consumers' adoption intentions toward chatbots in an online shopping context. They found that utilitarian factors, such as the authenticity of conversation and perceived usefulness, and hedonic factors, such as perceived enjoyment, had a positive impact on the intention to use chatbots for shopping. However, privacy concerns and the nature of immature technology negatively influenced consumers' intentions to use chatbots. Chung and colleagues (2020) also considered whether chatbot service agents could affect customers' satisfaction in the context of luxury fashion brands. Their findings concluded that luxury brand marketers/retailers need to provide accurate and credible interactions so that customers can determine whether they should accept chatbot e-service. Youn and Jin (2021) further studied the importance of chatbots in customer service encounters and the impacts of a chatbot's relationship type (assistant vs. friend) on consumers' behavioral intentions, satisfaction, and trust. They reported that consumers who interacted with a chatbot as a virtual friend experienced a stronger parasocial interaction with the chatbot than those who interacted with a chatbot as a virtual assistant. Parasocial interaction (PSI) refers to an illusionary mediated experience such that users interact with media personas as if they are present and engaged in reciprocal relationships (Horton & Wohl, 1956). Hence, they are more likely to intend to visit the apparel brand's website recommended by the chatbot, satisfy their relationship with the chatbot, and trust the chatbot.

Chatbots can search for product information, complete purchases, and provide sales services through consumers' mobile devices and computers. Thus, consumers have become increasingly interested in issues regarding chatbot privacy concerns and personal security (e.g., de Cosmo et al., 2021; Lai, Leu, & Lin, 2018; Rese et al., 2020). In response to these concerns, de Cosmo et al. (2021) examined the role of consumers' attitudes toward chatbots and internet privacy concerns in the relationship between attitudes toward mobile advertising and behavioral intention to use chatbots. They found that attitude toward mobile advertising did not impact behavioral intention to use chatbots and that internet privacy concerns negatively moderated the relationship between consumers' attitudes toward chatbots and behavioral intentions.

Several studies focused on understanding consumers' motivations to use chatbots. For instance, McLean et al. (2021) examined what factors motivate consumers to use chatbot voice assistants for brand-related information. They found that social presence, perceived intelligence, and social attraction positively influenced consumer brand engagement through chatbot voice assistance. They also found no relationship between hedonic values and brand engagement. Lastly, they also asserted that trust negatively influenced consumer brand engagement. Chopra (2019) explored consumers' motivation to use AI tools such as chatbots and voice assistants. He found that consumers' motivation played a key role in the use of chatbots while shopping.

The majority of studies emphasized the exploration of the factors that influence behavioral outcomes, such as attitude, intention, and satisfaction. Ashfaq et al. (2020) identified the drivers that determine consumers' satisfaction and continuance intention toward chatbot e-service. They found that information quality (IQ) and service quality (SQ) had a positive impact on consumers' satisfaction and that continuance intentions are significantly predicted by perceived enjoyment, perceived usefulness, and perceived ease of use. They also found that the need for interaction with a service employee significantly moderated the effects of perceived ease of use and perceived usefulness on satisfaction. Zarouali et al. (2018) examined the impact of Facebook Messenger chatbots on consumers' choice of movie theatre locations. They examined whether perceived usefulness, perceived ease of use, and perceived helpfulness, pleasure, arousal, and dominance potentially influenced consumers' attitudes toward the chatbot brand and patronage intentions. They reported that perceived usefulness, perceived helpfulness, pleasure, arousal, and dominance had a positive effect on patronage intention through consumers' attitudes toward the chatbot brand. Toader and colleagues (2020) explored the impact of anthropomorphic design cues (e.g., gender) on social presence, trust, and perceived competence, which, in turn, influenced positive consumer responses; they also examined the moderating role of chatbot error between the anthropomorphic design cues and perceived competence. They found chatbot errors (e.g., no response to a user’s message) had no moderating effect on the anthropomorphic design cues and perceived competence. They also confirmed that gender cues (female/male) were important for positive consumer responses. Kasilingam (2020) investigated the impact of perceived usefulness, perceived ease of use, perceived enjoyment, price consciousness, perceived risk, trust, and personal innovativeness on attitudes and intentions to adopt chatbots for online shopping. Kasilingam’s findings suggested that personal innovativeness, price consciousness, perceived risk, perceived enjoyment, perceived usefulness, and perceived ease of use influenced the intention to use chatbots through attitudes.

Chatbots often act like humans in their interactions with users. Several studies, therefore, explored how chatbots’ human-like cues, such as language style, name, appearance, identity cues, and message interactivity cues, can influence consumers’ perceptions and experiences. For instance, Araujo (2018) explored whether anthropomorphic design cues (e.g., language style, name, greeting) and a chatbot’s framing influence consumers’ perceptions of conversational agent chatbots and how these perceptions, in turn, can influence company-related outcomes such as attitude, satisfaction, and the emotional connection that consumers feel when interacting with a chatbot. Araujo identified that a chatbot's human-like language style, name, and greeting resulted in significantly higher levels of mindful and mindless anthropomorphism. Moreover, he also suggested that given the increased awareness of artificial intelligence, the chatbot framework, in itself, might influence consumers' perceptions of the chatbot agent. Go and Sundar (2019) also examined the effect of humanizing chatbots' anthropomorphism, message interactivity, and identity cues (human vs. chatbot) on users' perceptions and how their perceptions influenced attitudes and behavioral intentions toward a website. They indicated that higher-level chatbots with human-like behavior influenced user perceptions and increased expectations for interactivity. Sheehan et al. (2020) studied the relationship between anthropomorphism and adoption intent for customer service chatbots and whether the need for human interaction moderated the relationship between anthropomorphism and adoption intent. They found that anthropomorphism had a higher level of adoption intention when a consumer's need for human interaction was high.

Sands and colleagues (2021) examined whether chatbot service interaction predicts emotion and rapport, which, in turn, influences customer satisfaction and purchase intention. They further examined the moderating role of service scripts (education-based or entertainment-based) in the relationship between service interaction, emotion, and rapport. A service script is a guideline for frontline service employees (FSE) to manage interactions between consumers and FSE (Kirsch, 1996). They also found that an education-based service script had a significant positive effect on chatbot service interaction compared to entertainment-based service scripts in terms of both satisfaction and purchase intention. Rhee and Choi (2020) explored whether the personalized message reflecting the consumers' preferences and the social role of a chatbot voice agent generate a more positive effect on attitudes toward product involvement in the context of voice shopping. Their results revealed that both personalized messages and the social role influenced attitudes toward the product. Pizzi et al. (2020) examined the effect of consumers' reactance as a function of assistants' appearance (human-like vs. not human-like) and activation (automatic vs. human-initiated) in the retail and consumer service contexts. They found that consumers' reactance had a positive impact on confidence, perceived performance, and choice satisfaction when interacting with a chatbot. Park, Jang, Cho, and Choi (2021) studied factors, including ethical ideology, social competence, and perceived human likeness, that influence chatbot users' use of profanity or offensive words, employing the concepts of ethical ideology, social competence, and perceived human likeness of the chatbot. They reported that users' idealistic orientation significantly influenced liking of chatbots' active intervention and reactive responses.

Finally, in a mass-shooting disaster context, Cheng and Jiang (2020) explored the effectiveness of a mental health chatbot and examined how a chatbot enhances uses and gratification (U&G) motivations (i.e., perceived enjoyment, social presence), protection motivations (i.e., self-efficacy, response efficacy), active communicative action, and online/offline engagement behavior. They found that U&G motivations and protection motivations had a positive impact on active communicative action and that active communicative action significantly influences users' online/offline engagement behavior. Table 2 summarizes major chatbot studies in various contexts.

Table 2. AI Chatbot Studies in Various Contexts

Authors/Years	Context	Method	Sample/Country	Data Analysis	Findings
Adam et al. (2021)	Banking	Survey	308 consumers/USA	CFA & regression analysis	Social presence mediated the effects of anthropomorphic design cues on user compliance but did not find a moderating effect of social presence on the same relationship.
Araujo (2018)	Customer service in marketing	Survey	175 consumers/ USA	ANCOVA	A chatbot's human-like language style, name, and greeting resulted in significantly higher mindful and mindless anthropomorphism levels. Given the increased awareness of artificial intelligence, the chatbot framework might influence consumers' perceptions about the chatbot agent.
Ashfaq et al. (2020)	Chatbot e-service	Survey	370 participants/ USA	PLS-SEM	Information quality (IQ) and service quality (SQ) had a positive impact on consumers' satisfaction, and their continuance intentions were significantly predicted by perceived enjoyment, perceived usefulness, and perceived ease of use.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Findings
Cheng & Jiang (2020)	Mental health	Survey	1,114 participants/ USA	CFA & SEM	Uses and gratification (U&G) motivations and protection motivations had a positive impact on active communicative action. Active communicative action significantly influenced users’ online/offline engagement behavior.
Chi et al. (2022)	Tourism	Survey	422 participants/ USA	CFA & SEM	Anthropomorphism, performance and effort expectancy, social influence, and hedonic motivation influenced the tourists’ acceptance of AI devices like chatbots.
Chopra (2019)	Artificial intelligence (AI) tools	Semi-structured interview	35 university students/ India	Opening coding	Motivation played a key role in the use of chatbots while shopping.
Chung et al. (2020)	Luxury brand shopping	Survey	161 university students/ South Korea	CFA & SEM	Chatbot service agents could affect customers’ satisfaction in the context of luxury fashion brands.
De Cicco et al. (2020)	Online food delivery	Survey	193 university students/ Italy	ANOVA	Chatbots’ social-oriented interaction style increased users’ perception of social presence, which in turn, positively influenced attitude, trust, and enjoyment.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Findings
de Cosmo et al. (2021)	Mobile advertising	Survey	900 university students/ Italy	MANOVA	Attitude toward mobile advertising did not directly influence behavioral intention to use chatbots. However, privacy concerns negatively moderated the relationship between attitude and behavioral intention to use chatbots.
Go & Sundar (2019)	Live chat	Survey	141 participants/ USA	ANOVA	Higher-level chatbots with human-like behavior impacted user perceptions and increased expectations for interactivity.
Kasilingam (2020)	Smartphone for shopping	Survey	305 smart phone users/ India	PLS-SEM	Personal innovativeness, price consciousness, perceived risk, enjoyment, usefulness, and ease of use impacted the intention to use chatbots through attitudes.
Leung & Wen (2020)	Restaurant takeout order	Survey	153 consumers/ USA	MANCOVA	Ordering through a chatbot was considered a good option for quick service since online orders generated the highest order amounts.
Li et al. (2021)	Tourism	Survey	331 participants/ China	CFA & SEM	Chatbot quality positively influenced confirmation and intention to continue using a chatbot. Technology anxiety moderated the relationship between chatbot quality and consumers' confirmation.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Findings
McLean et al. (2021)	Brand engagement in marketing	Mixed method/ survey & in-depth interview	724 consumers & 21 informants / USA	Thematic analysis & EFA, CFA & SEM	Social presence, perceived intelligence, and social attraction positively influenced consumer brand engagement through chatbot voice assistance.
Melián-González et al. (2021)	Tourism	Survey	476 university students/ Spain	PLS-SEM	Expected performance, habit, hedonic motivation, attitudes toward chatbots, social influence, inconvenience, automation, and anthropomorphism positively influenced consumers’ intention to use chatbots.
Park et al. (2021)	E-commerce	Survey	645 smartphone users/ South Korea	Multiple regression	Users’ idealistic orientation significantly influenced their liking of active intervention and reactive responses of chatbots.
Pillai & Sivathanu (2020)	Tourism	Mixed method (survey & in-depth interview)	1,480 travelers & 36 senior managers and executives/ India	PLS-SEM & two-step coding	Perceived trust, intelligence, ease of use, usefulness, and anthropomorphism were predictors of chatbot adoption intention.
Pizzi et al. (2020)	Car rental	Survey	400 participants/ NA	MANOVA	Consumers’ reactance as a function of assistants’ appearance positively impacted confidence, perceived performance, and choice satisfaction when interacting with a chatbot.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Findings
Rese et al. (2020)	Apparel shopping	Survey	205 university students/ Germany	PLS-SEM	Utilitarian factors, such as the authenticity of conversation and perceived usefulness, and hedonic factors, such as perceived enjoyment, positively impacted the intention to use chatbots for shopping.
Rhee & Choi (2020)	Voice shopping	Survey	124 university students/ USA	ANOVA	Both personalization and the social role had a positive impact on attitudes toward the product.
Roy & Naido (2021)	Banking	Survey	323 university students/ USA	ANOVA	When consumers perceived chatbots to behave like real humans, the chatbots were more likely to influence positive opinions and purchase intention for specific products.
Sands et al. (2021)	Education	Survey	262 consumers/ USA	ANOVA	An education-based service script had a significant positive effect on chatbot service interaction compared to entertainment-based service scripts in terms of both satisfaction and purchase intention.
Sheehan et al. (2020)	Customer service in marketing	Survey	200 participants/ USA	ANOVA	Anthropomorphism had a higher level of adoption intention when a consumer's need for human interaction was high.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Findings
Toader et al. (2020)	Digital marketing	Survey	240 participants/ USA	CFA & SEM	Chatbot errors (e.g., no response to a user’s message) did not moderate the relationship between anthropomorphic design cues and perceived competence. Gender cues (female/male) were important for positive consumer responses.
Trivedi (2019)	Banking	Survey	258 consumers/ India	Regression analysis	Information quality, system quality, and service quality are key to ensuring a seamless customer experience with the chatbot, and that all three qualities had significant positive associations with perceived risk. The adoption of chatbot digital assistants in the banking industry resulted in stronger customer and brand relationships.
Youn & Jin (2021)	Apparel shopping	Survey	607 consumers/ USA	t-test analysis/ MANCOVA	Consumers who interacted with a chatbot as a virtual friend experienced a stronger parasocial interaction with the chatbot than those who interacted with a chatbot as a virtual assistant.
Zarouali et al. (2018)	Cinema	Survey	245 consumers/ USA	CFA & SEM	Perceived usefulness, perceived helpfulness, pleasure, arousal, and dominance positively affected patronage intention through consumers' attitudes toward the chatbot brand.

Note. SEM = Structural Equation Modeling; CFA = Confirmatory Factor Analysis; EFA = Exploratory Factor Analysis; ANOVA = Analysis of Variance; ANCOVA = Analysis of Covariance; MANOVA = Multivariate Analysis of Variance; MANCOVA = Multivariate Analysis of Covariance.

Theoretical Foundations

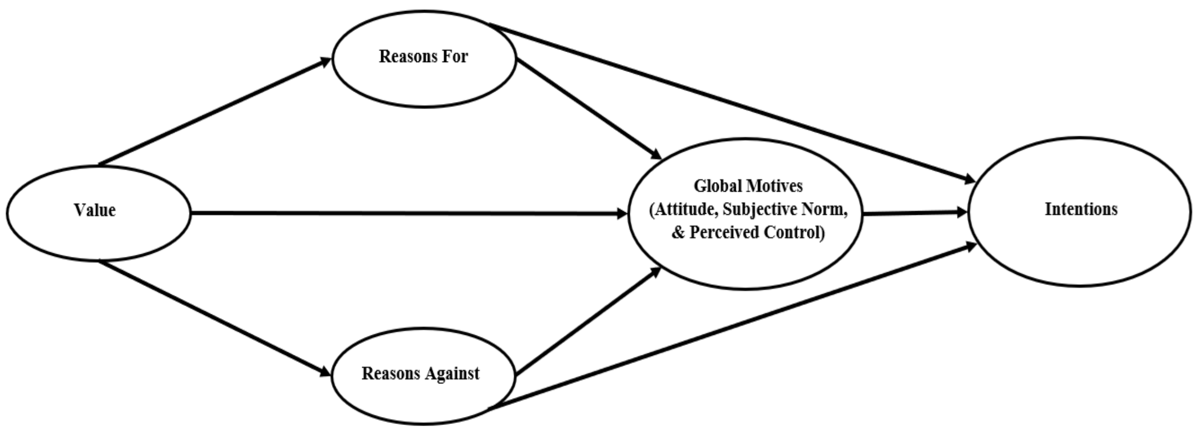
This section presents the theoretical foundation of this study, including (a) the behavioral reasoning theory (BRT), (b) previous studies related to BRT in different contexts, (c) the innovation resistance theory, and (d) perceived chatbot service quality.

Behavioral Reasoning Theory (BRT)

The behavioral reasoning theory (BRT) is a well-known behavioral theory developed by Westaby (2005), as it has been applied to understand consumers' adoption of innovation (Westaby et al., 2010). According to Gupta and Arora (2017), BRT can be seen as an extension of the theory of planned behavior (TPB; Ajzen, 1991). However, unlike other behavioral theories, such as the theory of reasoned action (TRA; Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB; Ajzen, 1991), BRT can indicate consumers' adoption or rejection of a particular behavior within a single existing theory (Dhir et al., 2021; Gupta & Arora, 2017; Westaby, 2005). It includes context-specific reasons as significant determinants of attitude formation and intention (Gupta & Arora, 2017). Therefore, it can be seen as a unique theory that considers what makes people have positive attitudes and intentions toward particular phenomena and what makes them have negative attitudes and intentions toward particular phenomena. Originally, BRT consisted of four components: beliefs and values, reasons, attitudes, and intentions/behavior (Westaby, 2005). According to BRT, intentions predict behavior; global motives (attitudes, subjective norms, and perceived control) and reasons (for and against behavior) predict intentions; and beliefs and values predict reasons. Figure 1 illustrates the BRT framework.

According to the literature, BRT has been applied to understand consumers' adoption of innovation in different contexts, such as innovative technology (Claudy, Garcia, & O'Driscoll, 2015), urban bicycle commuting (Claudy & Peterson, 2014), mobile banking (Gupta & Auraro, 2017), online shopping (Gupta & Arora, 2017), and e-waste recycling (Dhir et al., 2021). However, very few studies apply BRT in the context of apparel consumer behavior using AI chatbots. Applying BRT in the study's conceptual framework allows us to examine the reasons for and against the adoption of AI chatbots in apparel buying behavior. As such, BRT is employed as the theoretical foundation for this current study.

Figure 1. Behavioral Reasoning Theory (BRT)



Note. Adapted from Claudy & Peterson (2014)

BRT - Value

Value can be described as an individual's concept or belief and desirable behavior and can guide individuals' selection and/or evaluation of behavior (Sihombing, 2014). It plays an important role in individuals' decision-making in their personal and professional lives (Dhir et al., 2021). Kareklas, Carlson, and Muehling (2014) stated that consumers' personal values, beliefs, and norms could influence their reasons for/against and attitudes toward a particular behavior. According to BRT, value is an important construct influencing reasons for/against and attitudes toward a particular behavior (Claudy et al., 2015; Dhir et al., 2021; Westaby, 2005). In the consumer behavior literature, Gupta and Arora (2017) emphasized the importance of value in the consumer's decision-making process. For example, Gupta and Arora (2017) found that value was associated with reasons for mobile shopping and attitudes toward the adoption of mobile banking among Indian consumers.

BRT - Reasons

According to Westaby (2005), reasons are defined as “specific subjective factors people use to explain their anticipated behavior and can be conceptualized as anticipated reasons, concurrent reasons, and post hoc reasons” (p. 100). Ryan and Casidy (2018) define reasons as “the process used by an individual to determine his/her course of action” (p. 240). They also state that reasons represent powerful and important determinants of BRT, as they also serve as strong linkages between beliefs/values, reasons, attitudes, and intention/behavior (Westaby, 2005). Specifically, reasons are further categorized into two dimensions—reasons for and reasons against—that can determine the performance of a consumer’s behavior. The reasons for and reasons against have been conceptualized as “to subsume pro/com, benefit/cost, and facilitator/constraint” (Westaby, 2005, p. 570). Therefore, consumers will make decisions on whether to adopt or reject the use of an innovation based on the positive or negative impact of using it. Furthermore, both reasons for and reasons against are key elements that influence attitudes and intention toward a specific behavior (Ashfaq, Zhang, Ali, Waheed, & Nawaz, 2021). For this reason, prior empirical research has shown that reasons for were positively associated with attitudes and intentions, while reasons against were negatively related to attitudes and intentions (Pillai & Sivathanu, 2018).

BRT - Global Motives

Westaby (2005) defines global motives as "broad substantive factors that consistently influence intentions across diverse behavioral domains" (p. 98). According to BRT, there are three global motive constructs: attitude, subjective norms, and perceived behavioral control (Ajzen, 1991). Attitude is defined as the level of a person's judgment; the performance of the behavior is dependent on a positive or negative feeling (Ajzen, 1991). Subjective norms refer to the fact that consumers perceive social pressure from others to perform or not to perform a particular behavior (Ajzen, 1991). Perceived control refers to "the extent to which the person perceives he or she controls the execution of the behavior or finds the behavior easy or difficult to perform" (Westaby, 2005, p. 99). Westaby (2005) asserted that these three factors directly influence consumers' intentions; he also suggested that the stronger the global motives are, the greater the intention is to perform the behavior.

BRT – Intentions

Intentions are defined as "indicators of how hard individuals are willing to try to perform a behavior, of how much effort they are planning to exert, in order to perform the behavior" (Ajzen, 1991, p. 181). Intentions are considered strong and powerful predictors of consumers' actual behavior (Ajzen, 2001; Ajzen, 1991; Chatzidakis, Hibbert, & Winklhofer, 2016; Claudy et al., 2015; Claudy & Peterson, 2014; Groening, Sarkis, & Zhu, 2018; Gupta & Arora, 2017; Sheeran, 2002; Westaby, 2005). Intentions are "hypothesized to mediate the effect of other cognitive, affective, and contextual variables for the prediction of behavior in past behavioral intention models" (Westaby, 2005, p. 99), such as the theory of reasoned action (Fishbein & Ajzen, 1975) and theory of planned behavior (Ajzen, 1985). Furthermore, intentions are also positively and significantly influenced by attitudes. Hence, in BRT, intentions are also influenced by attitudes (Claudy et al., 2015; Claudy & Peterson, 2014; Dhir et al., 2021; Westaby, 2005).

Behavioral Reasoning Theory (BRT) Used in Prior Literature in Various Contexts

The behavioral reasoning theory (BRT) is a relatively new theory that determines the relationship between beliefs/values, reasons, global motives, intentions, and behavior in the marketing field. However, it has been widely used in different contexts across various technologies to understand consumer behaviors and their decision-making, including e-waste recycling (Dhir et al., 2021), mobile shopping (Gupta & Arora, 2017), mobile banking (Gupta & Arora, 2017), mobile learning apps (Pillai & Sivathanu, 2018), and online gaming (Ashfaq et al., 2021). Likewise, BRT has also been employed to understand consumer behaviors in other contexts unrelated to technology, including organic food consumption (Ryan & Casidy, 2018; Tandon, Dhir, Kaur, Kushwah, & Salo, 2020) and car sharing (Peterson & Simkins, 2019).

According to the literature, Ashfaq et al. (2021) examined whether value and reasons for/against impact users' attitudes toward the Ant Forest mobile game application and their intentions to continue using the Ant Forest mobile game application. They also investigated the moderating role of environmental knowledge on the relationship between attitudes and intentions. Value is measured using the "openness to change" component. Environmental benefits, social influence, hedonic motivation, and convenience were used to estimate reasons for using the Ant Forest mobile application. Privacy concerns, usage barrier, and green skepticism were used to measure reasons against using Ant Forest. Their results showed that value had a significant impact on reasons for, reasons against, and gamers' attitudes toward the Ant Forest mobile game application. Furthermore, reasons for and against both had a significant impact on gamers' attitudes and intentions to continue using Ant Forest, and, finally, environmental knowledge moderated the relationship between attitudes and the intention to continue using Ant Forest.

Dhir et al. (2021) examined the relationship between value, reasons for and reasons against using e-waste recycling, and attitudes and the relative influence of reasons for and against in predicting attitudes and intentions to recycle in the e-waste recycling context. They also examined the moderating role of environmental assessment and environmental concerns in influencing the relationship between reasons for, reasons against, attitudes, and intentions to use e-waste recycling. Environmental assessment refers to consumers' perceptions regarding the method of e-waste management in the last ten years (Echegaray & Hansstein, 2017). In the Dhir et al. (2021) study, value was measured using environmental concerns. Environmental benefits and personal benefits were used as components of reasons for using e-waste recycling, while risk, value, usage, and image barriers were used as components of reasons against using e-waste recycling. Dhir et al. (2021) reported that while value and reasons for using e-waste recycling had no significant relationship, value had a significant and negative association with reasons against using e-waste recycling. They found that reasons for using e-waste recycling had a significant impact on attitudes and intentions to use e-waste recycling. However, reasons against using e-waste recycling only had a significant impact on intentions to use e-waste recycling. They also found environmental assessment and environmental awareness played a moderating role in influencing the relationship between reasons for and against using e-waste recycling, attitudes, and intentions to use e-waste recycling.

Huang and Qian (2021) applied BRT as a theoretical framework to understand Chinese consumers' attitudes and intentions toward using autonomous vehicles. Autonomous vehicles, also known as self-driving cars, are one of the most innovative technologies to reduce road incidents, improve road efficiency, and enhance mobility for underserved populations (Huang & Qian, 2021). Additionally, they examined how psychological traits, including the need for uniqueness and risk aversion, moderated the associations between consumers' reasons for/against autonomous vehicles and their attitudes or adoption intentions toward autonomous vehicles. Risk aversion refers to consumers' decision-making, particularly when faced with uncertainty in an ambiguous situation. Huang and Qian (2021) employed face consciousness to measure the value component of BRT. According to their findings, both reasons for and against using autonomous vehicles significantly influenced attitudes. Reasons for had a significant impact on intentions, while reasons against had no significant relationship with intentions. Value had a direct influence on both reasons for and against using autonomous vehicles. The consumers' need for uniqueness moderated the association with consumers' reasons for and their adoption intentions toward using autonomous vehicles. Consumers' risk aversion significantly moderated the linkage between reasons against autonomous vehicles and attitudes.

In the AI chatbot context, only one study, Lalicic and Weismayer (2021), applied BRT as a theoretical framework to understand whether consumers use chatbot travel service agents. They used perceived value co-creation to assess attitudes. They measured reasons for using chatbot travel service agents through perceived personalization, convenience, super functionality, and ubiquity (availability). The tradition barrier, privacy concerns, technology anxiety, need for personal interaction, and perceived value co-creation (a desirable goal for businesses as they can identify consumers' needs and wants) were used to estimate reasons against using chatbot travel service agents. Their study revealed that while value had a significant relationship with reasons for using chatbot travel service agents, it had no significant relationship with reasons against using chatbot travel service agents. They also found that both reasons had a positive and negative relationship with perceived value co-creation and behavioral intention to use chatbot travel service agents.

Sreen, Dhir, Talwar, Tan, and Alharbi (2021) investigated the relationship between value and reasons for, reasons against, and attitudes, as well as the relationship between reasons for, reasons against, attitudes, and brand love toward natural products (e.g., food, apparel). They also investigated the moderating effect of environmental concerns and household size on the association of brand love with reasons for, reasons against, and attitudes. In Sreen et al.'s (2021) study, health consciousness is a measured component of value. Their study identified that value had a positive relationship with reasons for brand love for natural products and attitude. They also identified the positive relationship between reasons for, attitude, and brand love toward natural products. They further found that reasons against brand love for natural products had a negative association with attitude, while it had no association with brand love. In addition, they reported that only environmental concern moderated the association between attitude and brand love.

Delgosha and Hajiheydarib (2020) examined how consumers' reasons for/against using on-demand service platforms (ODSPs) impacted attitudes and intentions toward their use. They also examined the moderating role of inertia and perceived effectiveness on the relationship between reasons for/against and intentions to use ODSP. Inertia is defined as "attachment to, and persistence of, existing behavioral patterns (i.e., the status quo), even if there are better alternatives or incentives to change" (Polites & Karahanna, 2012, p. 24). Perceived effectiveness is defined as consumers' overall belief that it facilitates or encourages social interactions within markets (Delgosha & Hajiheydarib, 2020). In their study, the ODSP special services, ODSP superior functionality, flexibility, and financial benefits act as reasons for components engaging in the specific behavior. Perceived complexity, service provider trustworthiness issues, platform application security concerns, financial concerns, and service provider performance ambiguity are the measured components of reasons against. Delgosha and Hajiheydarib (2020) found that both reasons for and against using ODSP had a significant impact on attitudes and intentions toward adopting ODSPs. They showed that perceived effectiveness had a significant and negative moderating role in the relationship between reasons for using ODSP, attitudes, and intentions toward using ODSP, while inertia did not have a significant moderating role in the relationship between reasons for adoption of ODPS, attitudes, and intentions toward using ODSP. However, inertia positively moderated the relationship between reasons against adoption of ODSP, attitudes, and intentions toward using ODSP, while perceived effectiveness negatively moderated the relationship between reasons against using ODSP, attitudes, and intention toward using ODSP.

Tandon et al. (2020) studied the impact of value (health consciousness) on reasons for, reasons against, and attitudes and the relationships between reasons for, reasons against, attitudes, and purchase intention toward buying organic food. They also studied the moderating effect of food safety concerns and buying involvement on reasons for, reasons against, and attitudes. Reasons for are measured through components including nutritional content, natural content, and ecological welfare. Ecological welfare refers to consumers' concern for environmental well-being (Tandon et al., 2020). Reasons against are measured through two components: usage barrier and risk barrier. According to the results of Tandon et al.'s (2020) study, value significantly influenced reasons for, reasons against, and attitudes toward buying organic food. Both reasons for and against had a significant impact on attitudes, but only reasons for buying organic food had a significant impact on purchase intention toward buying organic food. Buying involvement moderated the relationship between reasons for and reasons against buying organic food.

Peterson and Simkins (2019) examined whether values influence subjective norms, as well as the relationships between reasons for, reasons against, attitudes toward car sharing, subjective norms, and car-sharing behavior. They found that values influenced subjective norms. Reasons for car sharing also influenced subjective norms and consumers' attitudes toward car sharing. Both attitudes and subjective norms had an influence on consumers' car-sharing behaviors.

Pillai and Sivathanu (2020) investigated whether value (openness to change) influences reasons for, reasons against, and attitudes toward the adoption of the Internet of Things (IoT) in the agriculture industry. The IoT is defined as "an open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data and resources, reacting and acting in case of situations and changes in the environment" (Madakam, Lake, Lake, & Lake, 2015, p. 165). The IoT technology is a useful internet-based dynamic global architecture that is rapidly and widely used worldwide (Pillai & Sivathanu, 2020). Pillai and Sivathanu (2020) further investigated the impact of reasons for and reasons against the adoption of IoT on attitudes and intentions toward its adoption in the agriculture industry. Reasons for adoption of IoT are measured in terms of relative advantage, social influence, perceived convenience, and perceived usefulness; reasons against adoption of IoT are measured in terms of image barrier, technological anxiety, perceived price, and perceived risk. Pillai and Sivathanu (2018) found that value did not have a significant association with reasons for, reasons against, and attitude. Reasons for and reasons against adoption of IoT significantly influenced attitudes and adoption intentions of IoT. Attitudes had a significant impact on IoT adoption intentions.

Ryan and Casidy (2018) examined the impact of consumers' values on reasons for/against consuming organic food and their attitude toward organic food. They also examined relationships between reasons for/against, attitude, and purchase intention toward organic food. They found that value had a significant relationship with reasons for/against consuming organic food and attitude toward organic food. Reasons for/against consuming organic foods had a significant impact on attitude, which led to purchase intention toward organic food.

Gupta and Arora (2017) investigated the relative influence of reasons for and reasons against adoption intention of mobile banking (m-banking) among Indian consumers. Openness to change is a measured component of value. Ubiquitousness, convenience, and relative advantage are the measured components of reasons for, and usage, risk, and tradition barriers are the measured components of reasons against. Gupta and Arora's (2017) findings indicated that both reasons for and reasons against adoption of m-banking had a significant influence on attitudes toward adoption and adoption intention of m-banking. Their findings also confirmed that the value of openness to change significantly influenced reasons for adoption of m-banking but had no influence on reasons against adoption of m-banking or attitude toward m-banking.

Claudy et al. (2015) examined the relationships between value, reasons for, reasons against, and attitudes and the relative influence of reasons for and against on attitudes and intentions toward innovation. Reasons for are measured through components such as financial, environmental, and independence benefits, while reasons against are measured through components such as value, risk, and usage barriers. Claudy et al. (2015) reported that value influenced the reasons for innovation adoption intention and both reasons for and reasons against impact attitudes. They further reported reasons for adoption innovation influenced adoption intention while reasons against adoption innovation did not impact adoption intention. They also found that adoption intention was influenced by attitudes.

This study's literature review on the contexts of prior BRT studies has shown that most studies used quantitative methodological approaches such as surveys (e.g., Dhir et al., 2021; Huang & Qian, 2021; Tandon et al., 2020). Only one study used a mixed-method (qualitative and quantitative) approach (Lalicic & Weismayer, 2021). A summary of prior studies that used BRT in different contexts is presented in Table 3 below.

Table 3. Behavioral Reasoning Theory in Prior Studies

Authors/Years	Context	Method	Sample/Country	Data Analysis	Finding
Ashfaq et al. (2021)	Ant-forest mobile gaming	Survey	293 actual Ant Forest users/ China	PLS-SEM	Value significantly impacted reasons for, reasons against, and gamers' attitudes toward the Ant Forest mobile game application. Furthermore, reasons for and against the Ant Forest mobile game application had a significant impact on gamers' attitudes and intentions to continue using the Ant Forest mobile gaming app. In addition, environmental knowledge moderated the relationship between attitudes and the intentions to continue using Ant Forest.
Claudy et al. (2015)	Resistance to innovation	Survey	254 house owners/ Republic of Ireland	CFA & SEM	Value influenced the reasons for adoption intention innovation and both reasons for and reasons against impact attitudes. Reasons for adoption innovation influenced adoption intention toward innovation, while reasons against adoption innovation did not impact adoption intention toward innovation. In addition, the adoption intention toward innovation was influenced by attitudes.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Finding
Delgosha & Hajiheydarib (2020)	On-demand service platforms	Survey	523 consumers/UK	EFA & PLS-SEM	Both reasons for and against using ODSP had a significant impact on attitudes and intentions toward adopting ODSPs. Perceived effectiveness had a significant and negative moderating role in the relationship between reasons for, attitudes, and intentions, while inertia did not have a significant moderating role in the relation between reasons for, attitudes, and intentions. However, inertia positively moderated the relationship between reasons against, attitudes, and intentions, while perceived effectiveness negatively moderated the relationship between reasons against, attitudes, and intention toward using ODSP.
Dhir et al. (2021)	E-waste recycling	Survey	774 consumers/ Japan	CFA & SEM	Value had a significant and negative association with reasons against using e-waste recycling. Reasons for using e-waste recycling had a significant impact on attitudes and intentions to use e-waste recycling while reasons against using e-waste recycling had a significant impact on only intentions to use e-waste recycling. Environmental assessment and environmental awareness moderated the relationship between both reasons for and against using e-waste recycling, attitudes, and intentions to use e-waste recycling.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Finding
Gupta & Arora (2017)	Mobile banking	Survey	379 banking consumers/ India	CFA & SEM	Both reasons for and reasons against the adoption of m-banking significantly influenced attitudes and adoption intentions. Value significantly influenced reasons for the adoption of m-banking but had no influence on reasons against the adoption of m-banking and attitudes toward using m-banking.
Gupta & Arora (2017)	Mobile shopping	Survey	237 consumers/ India	PLS-SEM	Both reasons for and reasons against mobile shopping significantly impacted attitudes and intentions to adopt mobile shopping. Value had a significant impact on reasons for the adoption of mobile shopping, while it had no significant effect on reasons against the adoption of mobile shopping.
Huang & Qian (2021)	Autonomous vehicles	Survey	849 consumers/ China	CFA & SEM	Both reasons for and against using autonomous vehicles significantly influenced attitudes. Reasons for had a significant impact on intentions, while reasons against had no significant relationship with intentions. Value directly influenced both reasons for and against using autonomous vehicles. Consumers' need for uniqueness moderated the relationship with consumers' reasons for and their adoption intentions toward using autonomous vehicles. Consumers' risk aversion significantly moderated the linkage between reasons against autonomous vehicles and attitudes.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Finding
Lalicic & Weismayer (2021)	AI-enabled travel service agents	Survey/ focus group interview	147 university students (survey) & 12 students (focus group interview)/ Australia	CFA & SEM / fuzzyset qualitative comparative analysis (FsQCA)	Value had a significant relationship with reasons for using chatbot travel service agents. It significantly influenced reasons against using chatbot travel service agents. Both reasons for/against had a positive and negative relationship with perceived value co-creation and behavioral intention to use chatbot travel service agents.
Peterson & Simkins (2019)	Car sharing	Survey	100 students/ Ireland	Path analysis	Value had partially impacted subjective norms and consumers' reasons for/against car sharing had also partially impacted attitudes and subjective norms. Both attitudes and subjective norms had a significant association with consumers' car sharing behavior. However, consumers' reasons for and against car sharing had no significant influence on their adoption of car sharing.
Pillai & Sivathanu (2020)	Internet of things (IoT) in the agriculture industry	Survey	680 IT employees/ India	PLS-SEM	Value had no significant association with reasons for, reasons against, and attitudes. Reasons for and reasons against the adoption intention of IoT significantly influenced attitudes and adoption intention of IoT. Attitudes also had a significant impact on the adoption intention of IoT.

Authors/Years	Context	Method	Sample/Country	Data Analysis	Finding
Ryan & Casidy (2018)	Organic food consumption	Survey	617 consumers/ USA	CFA/ SEM	Value had a significant relationship with reasons for/against and attitudes. Reasons for/against consuming organic foods significantly impacted attitudes, which led to purchase intention toward organic food.
Sreen et al. (2021)	Brand love	Survey	949 consumers/ India	CFA/ SEM	Value had a positive relationship with only reasons for the brand love for natural product and attitudes. Reasons for had a significant relationship with attitudes and brand love. Reasons against had a negative association with attitudes, while it had no association with brand love. In addition, environmental concern moderated the association between attitudes and brand love.
Tandon et al. (2020)	Organic food purchase	Survey	307 consumers/ India	CFA/ SEM	Value significantly influenced reasons for, reasons against, and attitudes. Both reasons for and against had a significant impact on attitudes but only reason for buying organic food had a significant impact on purchase intention toward buying organic food. Buying involvement moderated, the relationship between reasons for and reason against buying organic food.

Note. CFA= Confirmatory Factor Analysis; SEM= Structural Equation Modeling; EFA= Exploratory Factor Analysis

As mentioned previously, the original BRT consisted of value, reasons, three global motives (attitude, subjective norms, and perceived behavioral control), intentions, and actual behaviors (Westaby, 2005). According to the literature, most studies applied BRT to examine the influence of value, reasons for attitudes, and consumers' adoption intentions (e.g., Delgosha & Hajiheydarib, 2020; Huang & Qian, 2021; Lalicic & Weismayer, 2021; Peterson & Simkins, 2019; Pillai & Sivathanu, 2018; Ryan & Casidy, 2018; Tandon et al., 2020). Adoption intention, purchase intention, and entrepreneurial intention are the most common constructs examined in the BRT literature.

Innovation Resistance Theory (IRT)

Ram and Sheth (1989) introduced the IRT theory as a theoretical framework for customer resistance. IRT refers to "the resistance offered by consumers to innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure" (Leong, Hew, Ooi, & Wei, 2020, p. 3). IRT helps explain how consumer resistance plays a vital role in consumers' acceptance or rejection of new technologies (Ram & Sheth, 1989; Sadiq, Adil, & Paul, 2021). An individual's ability to accept or reject new technology is influenced by a variety of factors: many drivers can persuade users to accept new technology, while many barriers can cause users to resist it. Ram and Sheth (1989) proposed two types of barriers (i.e., functional barriers and psychological barriers) that can help us understand why potential users are unwilling to adopt new technology. Functional barriers include usage, value, and risk barriers, while psychological barriers include tradition and image barriers. According to IRT, these five barriers (usage, value, image, tradition, and risk) influence consumer response to new technology (Kaur, Dhir, Singh, Sahu, & Almotairi, 2020; Ram & Sheth, 1989; Sadiq et al., 2021).

Later, Yu and Chantatub (2016) suggested that customer resistance can be classified as active or passive. They further explained that active resistance is a resistive behavior that stems from intimidating characteristics of an innovation. Functional barriers, including usage, value, and risk barriers, are considered as active resistance. On the other hand, passive resistance emerges from an individual's conflict with their existing beliefs as a result of using innovation (Yu & Chantatub, 2016). Psychological barriers, including image and tradition barriers, are considered passive resistance (Yu & Chantatub, 2016). These five barriers are illustrated in detail below.

Usage Barrier

Usage barrier refers to consumers' feelings about the difficulty of using an innovation compared to the familiarity of using an existing product (Ma & Lee, 2019). It occurs when potential users think an innovation is incompatible with their existing practices, habits, or work (Ram & Sheth, 1989). Rogers (1983) further explained that consumers may refuse to use innovations when they find them complex and/or difficult to understand and use. Then, consumers facing a usage barrier need more time to embrace the innovation (Lian & Yen, 2014). The usage barrier is mostly related to the usability of a product/service and the necessary changes its use will require from the consumers' perspective (Laukkanen, Sinkkonen, Kivijärvi, & Laukkanen, 2007). This barrier is also linked to the concept of the complexity of the innovation (Davis et al., 1989; Laukkanen et al., 2007; Venkatesh, Morris, & Davis, 2003). Laukkanen and Lauronen (2005) reported that in an innovation-related context such as mobile banking services, consumers likely perceived that bill payment via mobile phone was too complex or tedious, as the device could process only a limited amount of information, so the usage barrier may emerge (Laukkanen & Lauronen, 2005). Similarly, the usage barrier can be a significant inhibitor in the context of using any type of unfamiliar products/services (Tandon et al., 2020) such as AI chatbots.

Risk Barrier

Risk barrier is defined as "when the user does not adequately understand the innovative technology in the new product, the user cannot assess the associated risks and uncertainties that will arise after its use" (Lian & Yen, 2014, p. 135). Uncertainty is inherent in innovation (Ram & Sheth, 1989); therefore, the likelihood of adoption of innovation becomes lower when such innovation involves higher levels of uncertainty. Risk is one of the functional barriers, as mentioned above. Functional risk barriers occur when consumers are concerned that a product/service may be dysfunctional (Talke & Heidenreich, 2014). The security and privacy of services are usually brought to the attention of consumers through online transactions (Laukkanen et al., 2007). For instance, consumers are worried about making mistakes when conducting their bank affairs via a computing device or mobile phone while they are looking for product information (Laukkanen & Laukkanen, 2005). This risk barrier can lead to users' refusal to accept innovation.

Value Barrier

Value barriers refer to resistance caused due to inconsistency with the existing product/service (Morar, 2013). They occur when potential users evaluate the differences between existing and innovative products/services, when users do not prefer to use innovation over an existing product/service, or when they believe that innovation has no higher value than an existing product/service (Ram & Sheth, 1989). This barrier is related to the performance of a product/service against its substitutes (Ram & Sheth, 1987). Prior research has shown that the value barrier is one of the strongest barriers hindering consumer motivation to adopt new products or innovations (Kushwah, Dhir, & Sagar, 2019; Seth, Talwar, Bhatia, Saxena, & Dhir, 2020; Talwar et al., 2020).

Image Barrier

Image barrier is defined as the consumers' perception of how difficult or easy it is to use innovations (Mani & Chouk, 2018). Image barrier is associated with a negative perception of innovations stemming from higher levels of complexity related to their origins (Lian & Yen, 2013). Prior research reported image as a barrier negatively influencing consumers' behavior regarding various digitization initiatives (Kaur et al., 2020). For example, the image barrier negatively influenced consumers' behavior in digital technology contexts such as mobile payments (Kaur et al., 2020), mobile banking (Laukkanen, 2016), and mobile services (Joachim, Spieth, & Heidenreich, 2018). Thus, it may be that when some consumers perceive innovations, such as AI chatbots, as too difficult to use, these innovations immediately engender a negative image.

Tradition Barrier

Tradition is deeply embedded in our society, strongly influencing people's daily lives and their view of the world (John & Klein, 2003). It has the ability to ensure the success of any product/service (Kaur et al., 2020). A tradition barrier occurs when an innovation causes conflicts and changes between users and their traditional culture (Ram & Sheth, 1989). This barrier exists when the innovation might be perceived as having a negative effect on consumers' daily lives. For example, in the mobile banking context, the tradition barrier may arise among consumers who prefer to use a traditional banking method and deal directly/in person with bank-related affairs instead of using applicable technologies (Heinonen, 2004). The strength of the tradition barrier is relative: the more intense the conflict, the stronger the resistance would be (Lian & Yen, 2013).

According to the literature, these barriers apply in some technology-related areas, such as online shopping, internet banking, and mobile banking. For example, Lian and Yen (2014) demonstrated that value, risk, and tradition barriers are major barriers that impact older people's intention to shop online. Laukkanen et al. (2007) found that usage, value, image, and tradition barriers may explain why non-adopters may resist Internet banking when they perceive it to be inconvenient, complicated, or slow. Furthermore, they identified the value barrier as the strongest factor that prohibits consumers' acceptance of mobile banking. In contrast, the image barrier makes consumers slow to accept mobile banking, and the tradition barrier can explain consumers' rejection of mobile banking. In similar contexts, Lian and Yen (2013) found that value and image barriers led users to refuse online shopping.

The literature also indicates IRT can explain consumer resistance in innovation contexts (Kaur et al., 2020). Most studies utilizing IRT's barriers focus on intangible variables like innovative technologies—for example, mobile banking, online shopping, etc. (Laukkanen et al., 2007; Lian, Liu, & Liu, 2012; Lian & Yen, 2014). Since AI chatbots are also innovative online platforms in the retail setting, applying IRT in the study may provide insights into the barriers influencing consumers' opposition to using AI chatbots for apparel shopping.

Perceived Chatbot Service Quality

Service quality has been recognized as a critical factor in determining the success or failure of online businesses, including online shopping (Bauer, Belogurov, Chan, Descovich, Detwiler, Di Marco, & Tull, 2006; Lee & Lin, 2005) and e-banking (Loonam & D. O'Loughlin, 2008; Zhu & Lin, 2010). Combining internet marketing and traditional service quality studies, Parasuraman (2002) also proposed the concept of service quality in e-commerce (alternatively referred to as e-service quality). Initially, there were five dimensions of service quality: tangibility, reliability, responsiveness, assurance, and empathy. Parasuraman and Grewal (2000) suggested that "research study is needed on whether the definitions and relative important dimensions of service quality change when customers interact with technology rather than with service personnel" (p. 171). Related to other innovative technology in the apparel retail industry, an AI chatbot can act as a virtual customer service agent that is available immediately and provides accurate information. Thus, this present study uses a revised service quality that consists of only three dimensions—responsiveness, reliability, and assurance—to better capture chatbot e-service quality. Given that an AI chatbot is not a human and customers cannot see its appearance, tangibility (defined as physical faculties and employee appearance) and empathy (defined as caring for and paying attention to customers by a salesperson) are not relevant to the context of the current study. Therefore, this current study excludes two dimensions, tangibility, and empathy, that are irrelevant to the quality of AI chatbots.

Responsiveness

According to Parasuraman et al. (1985), responsiveness refers to a willingness to help customers and provide prompt service. This includes the capability to both respond and provide requirements to consumers in a manner that is both timely and flexible (Ayo, Oni, Adewoye, & Eweoya, 2016; Iberahim et al., 2016). Yang and Fang (2004) pointed out that the responsiveness of online stores includes services such as responding to customer inquiries and information retrieval. Therefore, given that AI chatbots can answer customers' questions and provide product information to them quickly, responsiveness is considered a relevant factor for new online services (Yang & Fang, 2004), including AI chatbots. Furthermore, Parasuraman, Zeithaml, and

Berry (1988) found that responsiveness had a significant and positive impact on customer satisfaction.

Reliability

Reliability refers to the ability to perform the promised service reliably and accurately (Parasuraman et al., 1985). It encompasses the capacity to consistently meet expected and accurate service standards (Iberahim et al., 2016), which has long been the central focus of technology-based services (Lee & Lin, 2005). Reliability is one of the most important factors for customers to evaluate service quality (Liao & Cheung, 2002; Parasuraman et al., 1985). For example, in the context of e-banking, Markovic and Jankovic (2013) found that reliability had a significant influence on customer satisfaction. Since many apparel companies already offer customer service chatbots to their customers 24/7, the reliability dimension of service quality can be one of the key factors in the chatbot context.

Assurance

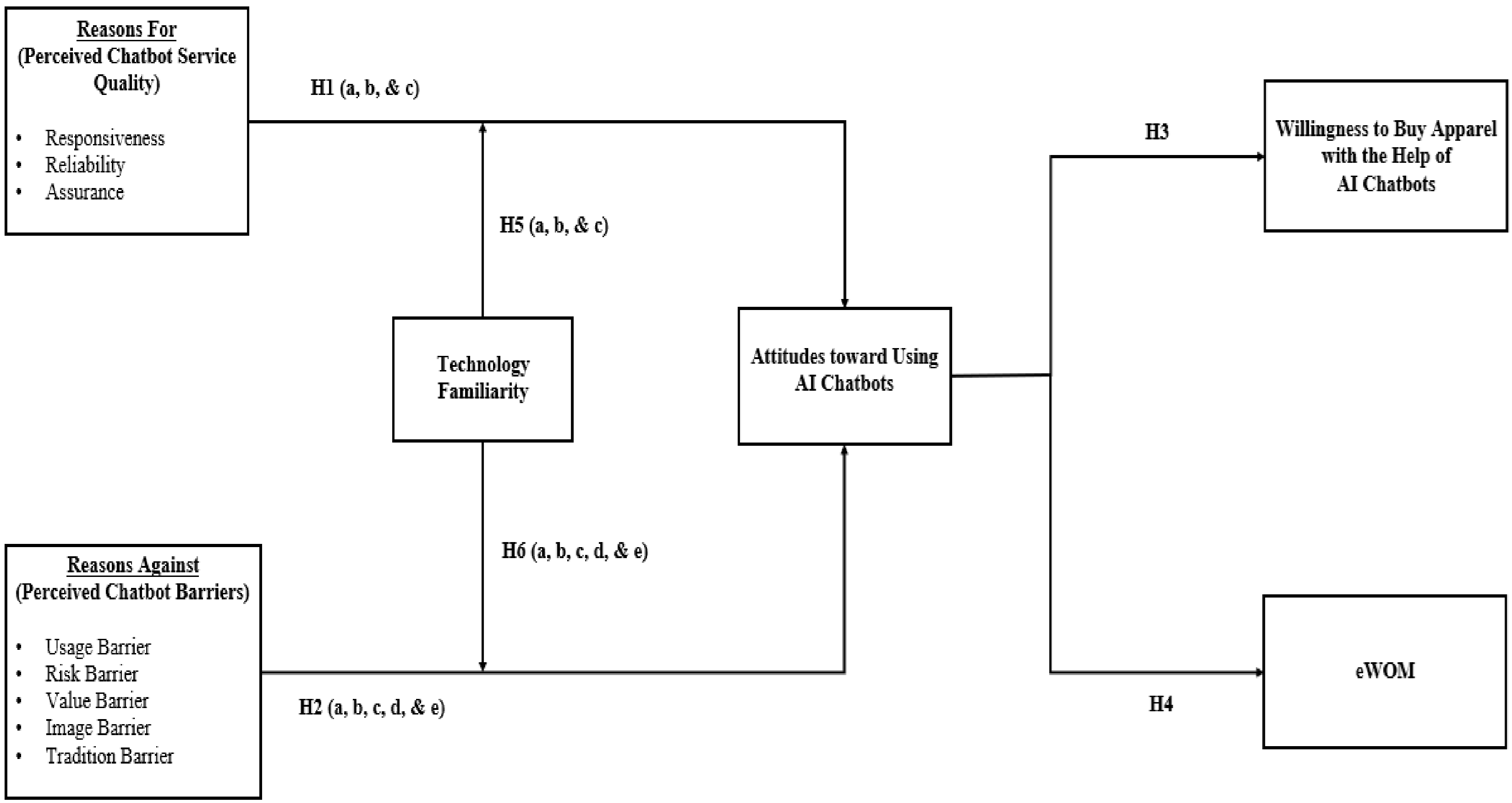
According to Parasuraman et al. (1985), assurance is “the term given in the services world to describe the sensation that a supplier of customer services transmits in terms of security and credibility” (p. 12). It also refers to the knowledge of an employee, which can strengthen consumer confidence and build trust (Cai & Jun, 2003; Meesalaa & Paul, 2018) to buy goods or to use services. Ribbink et al. (2004) determined that assurance can inspire higher confidence in individuals and impact consumers’ attitudes toward buying online, thus serving to encourage them to purchase products online (Lee & Lin, 2005). Building on this idea, Kitapci, Akdogan, and Dortyol (2014) identified that the assurance dimension had a positive relationship with customer satisfaction.

Conceptual Framework

This study integrates the behavioral reasoning theory (BRT) by adding three factors of service quality and five barriers from the innovative resistance theory (IRT) to develop a research framework to understand apparel consumers' AI chatbot usage behaviors. The BRT is a relatively new behavioral theory that helps one understand consumer innovation adoption and determines the link between beliefs, reasons, motives (i.e., attitude), intentions, and behavior (Westaby et al., 2010). The innovation resistance theory (IRT) helps researchers understand "why consumers choose to buy or not to buy (use or not to use)" a specific product or service, "why consumers choose one product type over another, and why consumers choose one brand over another" (Sheth et al., 1991, p. 159). The IRT helps researchers to understand consumer resistance to innovations (Ram & Sheth, 1989).

By doing so, this dissertation's adapted model (see Figure 2) suggests that consumers' reasons for (perceived chatbot service quality) and reasons against (perceived chatbot barriers) using AI chatbots are expected to subsequently influence their attitudes towards AI chatbot use. Their attitudes, in turn, are expected to affect their behavioral outcomes as measured in terms of their willingness to buy apparel with the help of AI chatbots and electronic word-of-mouth (eWOM). This current study also further examines how "technology familiarity" moderates the relationship between reasons for, reasons against, and attitudes toward using AI chatbots.

Figure 2. Conceptual Framework



Hypotheses Development

Development of Hypotheses 1 & 2: The Relationships between Reasons For, Reasons Against, and Consumers' Attitudes toward Using AI Chatbots

This study considers the *reasons for* the adoption of AI chatbots, including three factors: responsiveness, reliability, and assurance. Yang and Fang (2004) pointed out that the responsiveness of online stores included services such as customer inquiries and information retrieval. Responsiveness is defined as "speedy response to customers" (Ayo et al., 2016, p. 352). It is also considered a relevant factor for new online services (Yang & Fang, 2004). Reliability refers to the ability to consistently deliver expected and correct standards of services (Iberahim et al., 2016) and is a fundamental component of technology-based services (Lee & Lin, 2005). Assurance refers to an individual's confidence in the intentions, motives, and sincerity of others (Ribbink et al., 2004), as it can encourage consumers to purchase products online and impact their attitudes toward online shopping (Lee & Lin, 2005). Numerous studies have focused on the importance of these three factors (responsiveness, reliability, and assurance) in relation to consumers and online platforms such as online stores (Ayo et al., 2016), online banking (Cristobal, Flavian, & Guinaliu, 2007), and websites (Long & McMellon, 2004). Apparel retail companies have adopted new technologies, such as AI chatbots, to build strong customer relationships. Consumers can interact with AI chatbots as if they were real humans providing customer service since chatbots can respond quickly to customer questions, provide accurate product information and suggestions for product choices, and make the customers' interactions with chatbots enjoyable (Kim & Ko, 2010). As such, responsiveness, reliability, and assurance dimensions of perceived chatbot service quality may be important reasons for using AI chatbots and may have a strong impact on consumers' adoption intention toward AI chatbots.

Consumers' *reasons against* act as powerful prohibitors that can create negative opinions toward accepting a specific behavior (Sahu et al., 2020). Numerous studies examined the *reasons against* by using the IRT barriers (e.g., usage, value, image, and risk) in different contexts, such as e-waste recycling (Dhir et al., 2021), mobile banking (Gupta & Arora, 2017), social media-based local food distribution systems (Kaur et al., 2020), and organic food (Tandon et al., 2020). According to IRT, the usage barrier is one of the most common prohibitors that prevents consumers from using an innovation (Laukkanen et al., 2007; Mani & Chouk, 2018). The usage barrier mostly "implies the role of functional usability of an innovation" (Wu & Wang, 2005, p. 375). Dhir et al. (2021) confirmed that the perceived complexity of an innovation could be considered a usage barrier to consumers' adoption of innovation. Maximizing the complexity or inconvenience of the task decreases individuals' willingness to perform it (Dorner, 1980). On the other hand, some researchers (e.g., Kochan et al., 2016; Zhang et al., 2019) argued that decreasing the inconvenience increases individuals' intention to use innovations (e.g., in the e-waste recycling industry). According to the literature, the usage barrier had a negative association with the users' intention to adopt new innovations, such as online shopping (Gupta & Arora, 2017), mobile banking (Borraz-Mora et al., 2017), and mobile services (Joachim et al., 2018). However, other studies found that the usage barrier had a positive association with the users' intention to adopt new innovations, such as mobile banking (Yu & Chantatub, 2016), e-tourism (Jansukpum & Kettem, 2015), and food delivery applications (Kaur et al., 2021).

Risk barriers arise when potential users allow unseen risks or inadequate information to make them hesitant to understand and use innovations (Ram & Sheth, 1989). Therefore, if such innovations lead to a high level of uncertainty or pose a risk to consumers, they will refuse to use them or be slow to accept them (Ram & Sheth, 1989). In the online shopping setting, when consumers cannot access product information such as style, quality, and desired features, or they cannot pay online, they actively perceive the risks (Gerrard, Cunningham, & Devlin, 2006). In the context of mobile payments, perceived risk could stem from users' fear that their money may be lost due to circumstances such as poor internet connectivity or a dying smartphone battery (Kaur et al., 2020). In the case of shopping with chatbots, there are risks that consumers are likely to face in the buying process, such as privacy concerns or obtaining inaccurate product information (Kasilingam, 2020). According to the literature, risk barriers have a negative association with consumers' intentions and behavior in various contexts, including e-tourism (Jansukpum & Kettem, 2015), online shopping (Lian & Yen, 2014), mobile commerce (Moorthy, Ling, Fatt, Yee, Yin, Yee, & Wei 2017), mobile shopping (Gupta & Arora, 2017), payments (Kaur et al., 2020), and banking (Yu & Chantatub, 2016). However, risk barriers have a positive association with consumers' behavioral intentions in different contexts, such as mobile banking (Yu & Chantatub, 2016) and digital payments (Sivathanu, 2018).

Value barriers are also some of the strongest prohibitors that demotivate consumers to use innovation (Kushwah, Dhir, & Sager, 2019). Ram and Sheth (1989) contended that when innovation offers no higher value or service than the existing product or service, consumers are less likely to use such innovation. Lian and Yen (2014) later showed that "when the consumer tries to assess the value difference between the innovative product and an existing product, the user will not be willing to accept the change unless the innovative product provides a higher value than does the existing product" (p. 135). Kaur et al. (2021) stated that, in the context of innovation use, value barriers are associated with an individual's resistance to adopt the innovation. Previous studies suggested that value barriers negatively impact user intentions in diverse contexts, such as online shopping (Lian et al., 2012; Lian & Yen, 2013; Lian & Yen, 2014), mobile banking (Laukkanen, 2016), mobile commerce (Moorthy et al., 2017), and mobile payments (Kaur et al., 2020). However, the value barrier is not insurmountable; Ram and Sheth (1989) found that the value barrier will be lower when innovation can provide better performance and value than the existing product/service. Therefore, value barriers tend to have a positive impact on an individual's resistance toward e-tourism (Jansukpum & Kettem, 2015), mobile banking (Yu & Chantatub, 2016), and mobile payments (Sivathanu, 2018).

Image barriers arise when consumers compare a new product or innovation with an existing product or innovation (Lian & Yen, 2013; Ram & Sheth, 1989). Image barriers are "produced when the user has an unfavorable impression of the originating country, brand, industry, or side effects of the innovation" (Lian & Yen, 2014, p. 135). For instance, when consumers believe AI chatbots are not easy to use or inconvenient for their apparel shopping, this belief builds a negative image. Thus, image barriers can influence consumers' intentions toward a specific behavior (Kushwah et al., 2019) in various contexts, such as mobile banking (Laukkanen, 2016), mobile commerce (Moorthy et al., 2017), and mobile services (Joachim et al., 2018). In addition, Kaur et al. (2021) reported that image barriers had a positive association with behavioral intention as word-of-mouth intention when using food delivery applications.

Tradition is deeply rooted in an individual's personality and behavior (Ryan, 2016). Thus, the tradition barrier emerges when an innovation brings changes that can disrupt people's existing culture, traditions, or behavior or when consumers encounter conflict while using an innovation (Kushwaha et al., 2019). The greater the conflict or difference, the stronger the resistance to accept innovation (Ram & Sheth, 1989). For instance, chatbots act as customer service representatives in the retail industry. Unlike traditional customer service representatives, however—since chatbots are software with artificial intelligence—they cannot communicate verbally with customers, empathize with them, and lack a personal touch, so consumers may miss the warmth and face-to-face interaction of traditional human communication. Tradition barriers may also create inconvenient situations for consumers when they prefer a warm greeting from human customer service representatives or receive product information and personalized attention from expert agents (Gagliano & Hathcote, 1994; Haridasan & Fernando, 2018). According to previous studies, tradition barriers negatively influenced individuals' adoption intentions in various contexts, such as online shopping (Lian & Yen, 2014), mobile banking (Laukkanen, 2016), mobile commerce (Moorthy et al., 2017), and food delivery applications (Kaur et al., 2021). On the other hand, some studies have shown that tradition barriers positively influence individuals' behavioral intentions toward behavior in e-tourism (Jansukpum & Kettem, 2015) and mobile banking (Yu, Li, & Chantatub, 2015).

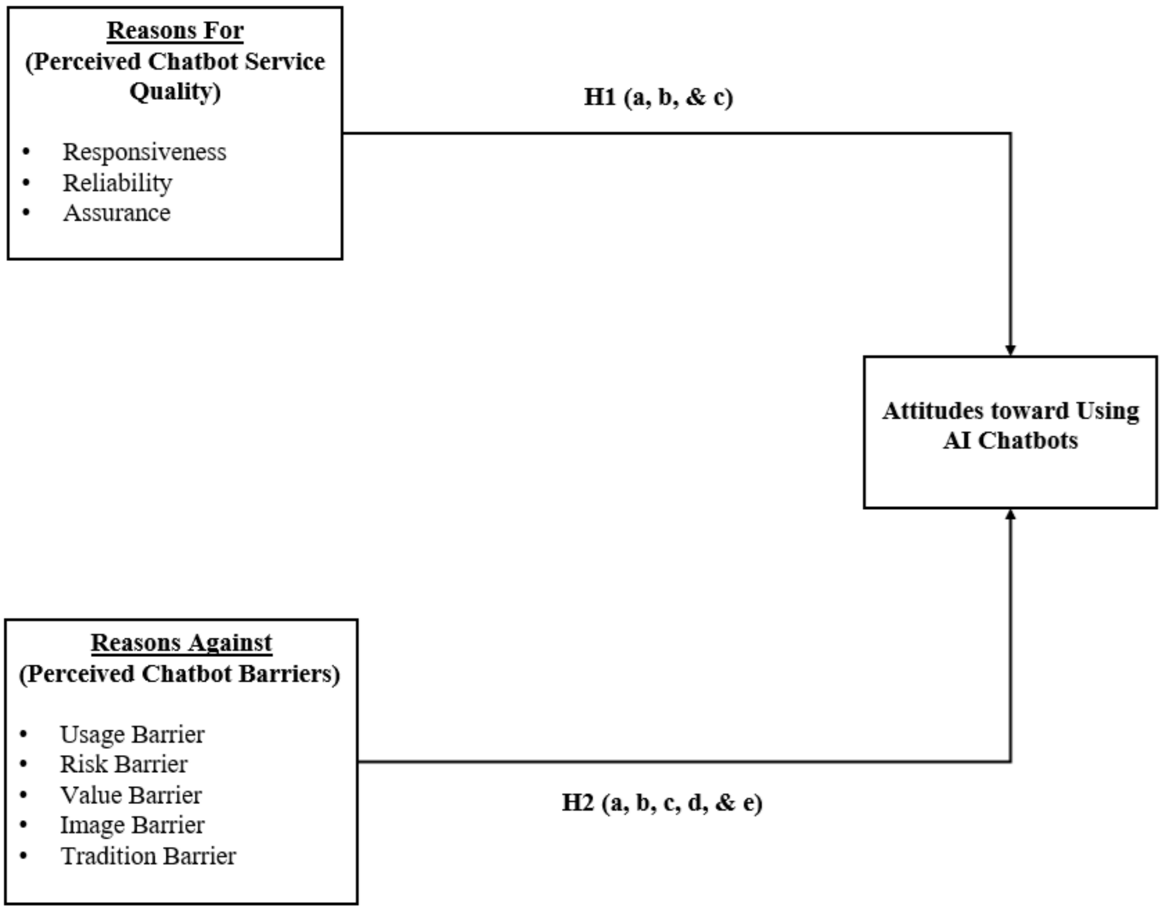
Based on the concepts and findings of the previous studies, when consumers perceive AI chatbots as potentially causing a technological shopping conflict (compared to traditional shopping methods like in-store shopping) or when consumers cannot understand how to use AI chatbots (resulting in perceived complexity and difficulty), tradition and image barriers may arise to prevent them from using chatbots. According to the literature, several previous studies have found that these five barriers (usage, risk, value, tradition, and image) have a negative impact on consumers' intention behaviors in various contexts related to innovation, including online shopping (Lian & Yen, 2014), mobile banking (Laukkanen, 2016), mobile commerce (Moorthy et al., 2017), and mobile payments (Kaur et al., 2020).

According to BRT, reasons are robust determinants of individuals' attitudes, which, in turn, lead to their intentions toward a specific behavior (Diddi, Yan, Bloodhart, Bajtelsmit, & McShane, 2019; Gupta & Arora, 2017). When a person has a good reason to engage in a specific behavior, that person has a positive view of performing that behavior (Delgosha & Hajiheydari, 2020). Several previous studies have explained that *reasons for* have a positive impact and *reasons against* have a negative impact on consumers' attitudes toward a behavior (Westaby, 2005; Westaby, 2010; Claudy et al., 2015). In Lalicic and Weismayer's (2021) study, they reported that travelers' *reasons for* and *reasons against* using AI service agents influenced their attitudes toward using them. However, in the consumer apparel and retail literature, no empirical study has explored the relationships between attitudes, reasons for, and reasons against using AI chatbots for apparel shopping. Hence, it is critical to know whether apparel consumers' attitudes toward using AI chatbots would be impacted by consumers' adoption (reasons for) or rejection (reasons against) of chatbot use. This study applies three drivers—responsiveness, reliability, and assurance—as the *reasons for* factors and five barriers—usage, value, risk, tradition, and image—as the *reasons against* factors to explore whether consumers' strong reasons for or reasons against using AI chatbots will have a positive or negative influence on attitudes toward using them. Furthermore, based on the concepts discussed in the above paragraphs, this study proposes the following hypotheses (see Figure 3):

H1: Consumers' *reasons for* factors (a) *responsiveness*, (b) *reliability*, and (c) *assurance* using AI chatbots will have a positive influence on their *attitudes toward using AI chatbots*.

H2: Consumers' *reasons against* factors (a) *usage barrier*, (b) *risk barrier*, (c) *value barrier*, (d) *image barrier*, and *tradition barrier* using AI chatbots will have a negative influence on their *attitudes toward using AI chatbots*.

Figure 3. The Relationships between Reasons For Factors, Reasons Against Factors, and Consumers' Attitudes toward Using AI Chatbots



Development of Hypotheses 3 & 4: The Relationships between Attitudes toward Using AI Chatbots, Willingness to Buy Apparel with the Help of AI Chatbots, and eWOM

Attitude refers to the degree to which a person favorably or unfavorably evaluates a behavior (Ajzen, 1991). It is all about the feelings of an individual about a particular product or service (Roy & Naidoo, 2021) and is a strong indicator of behavioral intention and actual behavior (Bagozzi, 1992; Biddle, Bank, & Slavings, 1987; Dodds, Monroe, & Grewal, 1991).

According to BRT, attitude is an important antecedent of consumers' adoption intention (Claudy et al., 2015), and it is a key component in the online shopping context (Mathwick, Malhotra, & Rigdon, 2001). As attitude represents consumers' positive or negative feelings toward the performance of a behavior (Westaby, 2005), consumers who have a positive attitude toward a specific behavior would be more likely to perform such behavior (Bagozzi, 1992).

Willingness to buy is defined as consumers' behavioral intention to buy a targeted product or service in the future (Donato & Raimondo, 2020; Morrison, 1979). Phau, Sequeira, and Dix (2009) found that willingness to buy can also be used as a reinforcement indicator to make actual purchases. The more positive consumers' opinions are about a specific product or service, the greater their willingness to buy that product or use that service (Krarup & Russell, 2005). Chang, Chih, Liou, and Yang (2016) asserted that consumers' willingness to buy via online depends on the extent of their positivity toward website services. Based on the above concepts, when consumers make positive comments about AI chatbots, they will be more willing to purchase apparel products through AI chatbots. Furthermore, attitude is also a good predictor of willingness to buy (Barber, Taylor, & Strick, 2009; Phau et al., 2009; Ryan & Bonfield, 1975). Notably, no study was found to explain the relative influence of consumers' attitudes toward using AI chatbots on their willingness to buy. Aoki, Obeng, Borders, and Lester (2019) stated that word-of-mouth (WOM) is historically an important communication method in marketing. Word-of-mouth is one of the oldest methods of information sharing with others concerning consumers' opinions about products/services (Ennew, Banerjee, & Li, 2000). Word-of-mouth has significantly influenced consumers' decision-making in marketing and advertising literature (Engel, Kegerreis, & Blackwell, 1969). In traditional WOM, people's messages about a product/service spread slowly and can disappear as soon as they speak or reach out to others.

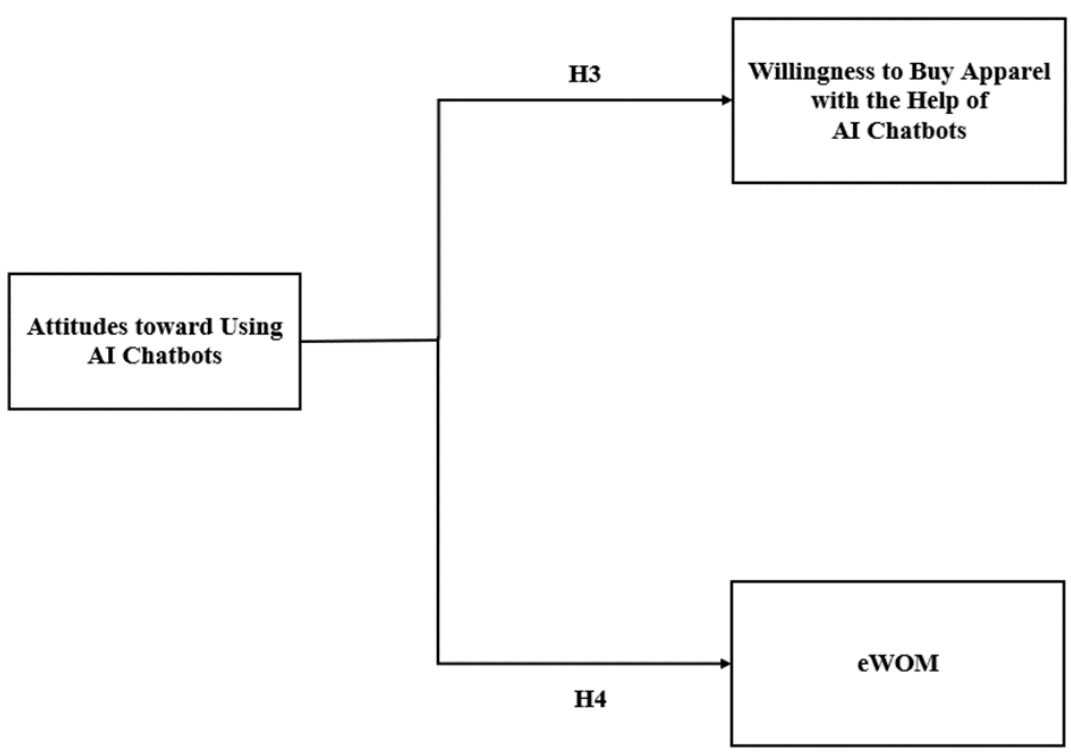
Today, however, rapid advancements in technology have dramatically changed the way consumers share product information and buy products. Consumers have widely used eWOM on various online platforms such as forums, blogs, social media, online reviews, and emails (Phelps, Lewis, Mobilio, Perry, & Raman, 2004) to obtain more in-depth product/service information (Baird & Parasnis, 2011). Litvin, Goldsmith, and Pan (2008) define eWOM as “all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers” (p. 461). Consumers clearly believe that eWOM is a credible source of information they can share with others regarding their experiences and opinions (Sotiriadis & Van Zyl, 2013). Since WOM can be a valuable source of information from peers, consumers may consider it as one of their most effective tools for product research (Brown, Burgess, & Braithwaite, 2007). When consumers want to buy a product or a service, they typically check other people’s reviews of the product/service through various online channels before making a decision. On the other hand, liking, posting, and commenting on a brand/service online shows how much people like that brand and/or service. In academia, many scholars have applied eWOM in different contexts, such as website reputation (Park & Lee, 2009), online purchasing (Bulut & Karabulut, 2018), and sharing consumption (Liu et al., 2021). For example, Chu and Kim (2011) found that consumers’ attitudes positively influenced their eWOM behavior on social networking sites. Chu, Chen, and Gan (2020) also stated that attitude is a key factor influencing consumers’ eWOM in social commerce services.

It is important to know whether consumers would share their positive or negative opinions about AI chatbot usage in apparel shopping through eWOM and whether positive reviews of AI chatbots lead to consumers’ willingness to buy apparel with the help of AI chatbots. No other study in the AI chatbot context has examined whether consumers’ willingness to buy and eWOM were influenced by attitudes. Thus, this study examines the relative influence of consumers' attitudes toward using AI chatbots on their willingness to buy apparel with the help of AI chatbots and eWOM. Examining these relationships may contribute to the literature by providing a better understanding of how consumers' feelings about AI chatbots positively or negatively impact willingness to buy and eWOM behavior. Therefore, this study proposes the following hypotheses (see Figure 4):

H3: *Attitudes toward using AI chatbots* will have a positive influence on consumers' *willingness to buy apparel with the help of AI chatbots*.

H4: *Attitudes toward using AI chatbot*s will have a positive influence on *eWOM.*

Figure 4. The Relationships between Consumers' Attitudes toward Using AI Chatbots, Willingness to Buy Apparel with the Help of AI Chatbots, and eWOM



Development of Hypotheses 5 & 6: The Moderating Effects of Technology Familiarity on Relationships between Reasons For, Reasons Against, and Consumers' Attitudes toward Using AI Chatbots

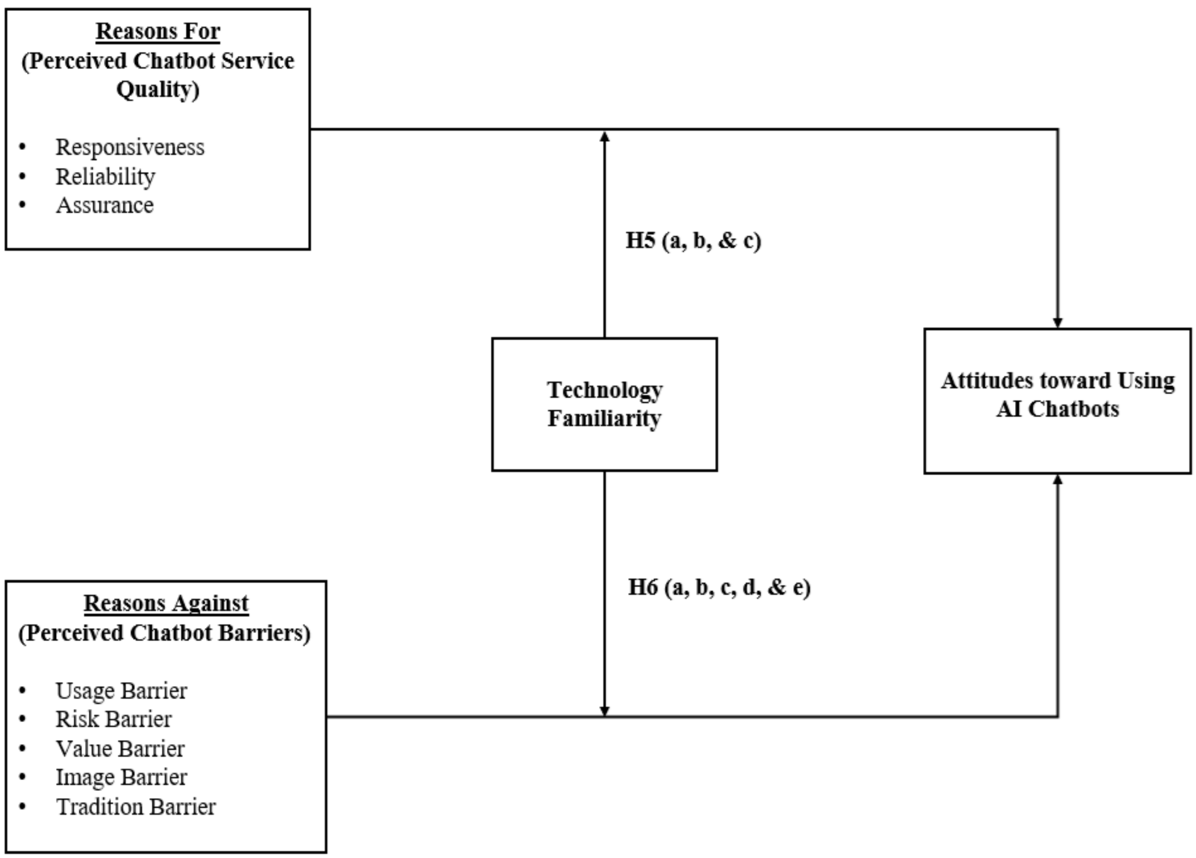
Familiarity is a critical component of consumers' knowledge (Philippe & Ngobo, 1999). Alba and Hutchinson (1987) define familiarity as "the number of product-related experiences that have been accumulated by the consumer" (p. 411). Some prior studies also explained that familiarity means that the familiarity of a product/service depends on advertising, word-of-mouth, or previous experiences with a particular product/service (Luhmann, 2000; O'Cass, 2004). In other words, familiarity means expertise in product/service use (Zaichkowsky, 1985). Kuhlmeier and Knight (2005) affirmed that people are generally comfortable using what they are already familiar with. In addition, familiarity with a specific product/service could reduce consumers' uncertainty in deciding to use it in the future (Dahl, Manchanda, & Argo, 2001). Familiarity has become an interesting component in consumer behavior literature (Maenpaa et al., 2008). Familiarity with a product/service can also impact consumers' decision-making and choice processes (Rao & Monroe, 1988; Shehryar & Hunt, 2005). Consequently, several studies have found a positive relationship between familiarity and consumers' intentions and behavior (e.g., Biswas & Roy, 2015; Lee & Kwon, 2011; Wang, Wang, Yang, Wang, & Li, 2018). For example, Lee and Kwon (2011) found that familiarity positively influenced consumers' intentions to continue using a web-based service. Zajonc (1968) explained that the more familiar consumers are with a particular product/service, the more positive their attitude toward using it. Gefen and Straub (2004) showed that familiarity had a positive impact on the process of formation of online trust.

Mitchell and Dacin (1996) also showed that people with more experience performing a particular behavior differ from those who have no experience or knowledge regarding that behavior. In the website context, when consumers' understanding of website use increases, they are, perhaps, more satisfied with the website services compared to those who are less familiar with them, which, in turn, leads to a stronger link between e-service quality and e-satisfaction (Kaya, Behravesh, Abubakar, Kaya & Orus, 2019). For instance, Casalo, Flavian, and Guinaliu (2008) reported that consumers' familiarity moderated the relationship between perceived usability and the website loyalty formation process. That is, consumers who have more prior knowledge and experience using technology/technological tools may be more likely to use AI chatbots for apparel shopping than those with less knowledge of or experience with technology. Furthermore, consumers who are highly familiar with technology usage could easily believe that AI chatbots would (a) be easy to use, (b) assist them 24/7, and (c) provide helpful and reliable product information whenever they use them for buying apparel products. Consequently, these consumers' beliefs would reduce the barriers (e.g., AI chatbot is incompatible and its product information is uncertain) that prohibit them from adopting AI chatbots and encourage positive attitudes toward using them. This study will examine whether *technology familiarity* may amplify the impact of *reasons for* and reduce the impact of *reasons against* on *attitudes toward using AI chatbots*. Therefore, this study proposes the following hypotheses (see Figure 5):

H5: *Technology familiarity* will have a moderating effect on the relationships between *reasons for* factors (a) *responsiveness*, (b) *reliability*, and (c) *assurance*, and consumers' *attitudes toward using AI chatbots.*

H6: *Technology familiarity* will have a moderating effect on the relationships between *reasons against* factors (a) *usage barrier*, (b) *risk barrier*, (c) *value barrier*, (d) *image barrier*, (e) *tradition barrier*, and consumers' *attitudes toward using AI chatbots.*

Figure 5. The Moderating Role of Technology Familiarity on Relationships between Reasons For, Reasons Against, and Attitudes toward Using AI Chatbots



Chapter Summary

The objective of this chapter is to discuss the major constructs examined in this study—reasons for (perceived chatbot service quality), reasons against (perceived chatbot barriers), attitudes toward using AI chatbots, willingness to buy apparel with the help of AI chatbots, electronic word-of-mouth (WOM), and technology familiarity—that are relevant to the context of the study. These constructs are included in the conceptual model, and the chapter then concludes with six testable hypotheses.

CHAPTER III: RESEARCH METHODOLOGY

This chapter presents the research methodology, including five major sections: (1) Research Purpose and Objectives, (2) Survey Instrument Development, (3) Sample and Data Collection Procedures, (4) Data Analysis, and (5) Chapter Summary.

Research Purpose and Objectives

This study aims to develop and test a conceptual model of the potential antecedents and consequences of consumers' attitudes toward using AI chatbots. Three specific objectives of the study are:

1. To examine relationships between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*;
2. To investigate relationships between consumers' *attitudes toward using AI chatbots* and their behavioral intentions as measured in terms of *willingness to buy apparel with the help of AI chatbots* and *eWOM*; and
3. To examine the moderating role of *technology familiarity* on the relationship between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*.

Survey Instrument Development

A review of extant literature provided conceptual and measurement information related to variables being investigated in the current study. The literature serves as the basis for developing a questionnaire used in the final data collection procedure. The resulting written questionnaire consisted of four major sections. In the first section, the participants were given an explanation of what a chatbot is. In the second section, the participants were asked to answer questions about whether they have previous experience using AI chatbots. In the third section, the participants evaluated all items based on the main constructs: (1) reasons for (perceived chatbot service quality), (2) reasons against (perceived chatbot barriers), (3) technology familiarity, (4) attitudes toward using AI chatbots, (5) willingness to buy apparel with the help of AI chatbots, and (6) eWOM. In the fourth section, participants were asked to complete questions pertaining to their demographic information, including age, gender, marital status, ethnicity, educational background, and annual income (see Appendix C: Survey Questionnaire).

Measures

The scales of measurement used for this survey were drawn from an extensive review of the previous literature (e.g., Baek & Oh, 2021; Chaoualia & Souiden, 2019; Teng, 2018). A five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to measure all scale items. Where possible, these measurement scales were selected for each construct for validation purposes. The summary of measurement items of the major constructs (factors of reasons for, factors of reasons against, attitudes toward using AI chatbots, technology familiarity, willingness to buy, and eWOM) for this study is shown in Table 4. All items on the questionnaire were adapted from previous studies.

Reasons For (Perceived Chatbot Service Quality)

Reasons for were assessed using perceived chatbot service quality and included three dimensions: responsiveness, reliability, and assurance. Responsiveness was measured with seven items adapted from Chen et al. (2021) and Lee and Lin (2005), e.g., “AI chatbots give prompt service to consumers” and “AI chatbots are never too busy to respond to users’ requests.” Reliability was measured with four items adapted from two studies: Mei, Dean, and White (1999) and Suh, Ahn, and Pedersen (2013). Examples include “AI chatbots are dependable” and

"I am able to access AI chatbots when I need to." Assurance was measured with five items adapted from Lee and Lin (2005) and Meesala and Paul (2018), e.g., "I believe product information provided by AI chatbots is trustworthy" and "AI chatbots are knowledgeable to answer my questions." The psychometric properties of these scales have been examined and evidence supports both reliability and validity (Lee & Lin, 2005; Mei et al., 1999; Meesala & Paul, 2018; Suh et al., 2013).

Reasons Against (Perceived Chatbot Barriers)

Reasons against were assessed using perceived chatbot barriers. It included five dimensions of perceived chatbot barriers, i.e., usage, risk, value, image, and tradition barriers. The usage barrier was measured with four items adapted from Chaoualia and Souiden (2019), e.g., "AI chatbots are not easy to use" and "I heard that the use of AI chatbots is not convenient." The risk barrier was measured with five items adapted from Laukkanen et al. (2007) and Sivathanu (2018), e.g., "I fear that while I am searching for apparel through AI chatbots, the connection will be lost" and "I fear that while I am using AI chatbots through my phone, the battery of the mobile phone will run out." The value barrier was measured with four items adapted from Chaoualia and Souiden (2019) and Leong et al. (2020), e.g., "I am quite skeptical about the benefits of using AI chatbots" and "In my opinion, AI chatbots do not offer any advantage compared to other shopping techniques, such as visiting physical stores and getting assistance from human customer services for searching apparel products." The image barrier was measured with three items adapted from Chaoualia and Souiden (2019), e.g., "I have a very negative image of AI chatbots" and "In my opinion, AI chatbots are often too complicated to be useful." The tradition barrier was measured with five items adapted from Chaoualia and Souiden (2019), e.g., "I find AI chatbots less pleasant than those offered personally to customers" and "I prefer to search for fashion products through physical stores rather than using AI chatbots." The psychometric properties of these scales have been examined, and evidence supports both reliability and validity (Chaoualia & Souiden, 2019; Laukkanen et al., 2017; Sivathanu, 2018).

Technology Familiarity

Technology familiarity was measured with eight items adapted from Lee and Wan (2010), Oday, Ozturen, Ilkan, and Abubakar (2021), and Olya, Altinay, Farmaki, Kenebayeva, and Gursoy (2021). Sample items include "I am familiar with new technology and technological practices," "Compared to the general public, I am familiar with new technology and technological practices," and "I am familiar with searching for apparel product information online." The psychometric properties of these scales have been examined, and evidence supports both reliability and validity (Lee & Wan, 2010; Oday et al., 2021; Olya et al., 2021).

Attitudes toward Using AI Chatbots

Consumers' attitudes toward using AI chatbots were measured with four items adapted from Kasilingam (2020) and Kim, Han, and Ariza-Montes (2021). Samples of items are "Using AI chatbots for shopping is a good idea," "The idea of using AI chatbots for apparel shopping is appealing," and "I like the idea of searching and buying a product from AI chatbot services." The psychometric properties of these scales have been examined, and evidence supports both reliability and validity (Kasilingam, 2020; Kim et al., 2021).

Willingness to Buy Apparel with the Help of AI Chatbots and eWOM

Willingness to buy was measured with four items adapted from Poushneh and Vasquez-Parraga (2017) and Zielke and Dobbelstein (2007). Samples of items are "I intend to buy apparel products via AI chatbots" and "I would be willing to buy apparel products via AI chatbots." Electronic word-of-mouth, or eWOM, was assessed with six items adapted from Augusto and

Torres (2018), Liu, Jayawardhena, Dibb, and Ranaweera (2019), and Feng, Zhang, van Klinken, and Cui (2021). Sample items include "I will recommend lots of people to use AI chatbots in the future" and "I will give lots of positive word-of-mouth via the internet in the future." The psychometric properties of these scales have been examined, and evidence supports both reliability and validity (Augusto & Torres, 2018; Feng et al., 2021; Liu et al., 2019; Poushneh & Vasquez-Parraga, 2017; Zielke & Dobbelstein, 2007).

Table 4. A Summary of Constructs and Measurement Items

Constructs	Definition	Number of Items	Description Items	Literature Source(s)
Reasons for				
Responsiveness	Refers to the capability to respond to consumers and provide consumers' requirements in a manner that is both timely and flexible	7	• AI chatbots give prompt service to consumers. • AI chatbots are always willing to help consumers. • AI chatbots are never too busy to respond to users' requests. • Getting in contact with an AI chatbot is easy. • AI chatbots are always available when I need them. • AI chatbots reply quickly. • AI chatbots provide credible advice.	Chen et al. (2021); Lee & Lin (2005)
Reliability	Refers to the ability to perform the promised service dependably and accurately	4	• AI chatbots are dependable. • AI chatbots provide the service right the first time. • AI chatbots are always working well. • I am able to access AI chatbots when I need to.	Mei et al. (1999); Suh et al. (2013)

Constructs	Definition	Number of Items	Description Items	Literature Source(s)
Assurance	Refers to the sensation that a supplier of customer services transmits in terms of security and credibility	5	• I believe product information provided by AI chatbots is trustworthy. • AI chatbots instill confidence in customers. • I would feel safe in the interaction with AI chatbots. • AI chatbots are knowledgeable to answer my questions. • AI chatbots are polite.	Lee & Lin (2005); Meesala & Paul (2018)
Reasons against				
Usage barrier	Occurs when potential users think innovation is incompatible with existing practices, habits, or work	4	• AI chatbots are not easy to use. • I heard that the use of AI chatbots is not convenient. • I think that AI chatbots are not fast to use. • In my opinion, the use of AI chatbots is not clear.	Chaoualia & Souiden (2019)
Risk barrier	Occurs when the user does not adequately understand the innovative technology in the new product, the user cannot assess the associated risks and	5	• I fear that while I am searching for apparel through AI chatbots, the connection will be lost. • I fear that while I am using AI chatbots through my phone, the battery of the mobile phone will run out.	Laukkanen et al. (2007); Sivathanu (2018)

Constructs	Definition	Number of Items	Description Items	Literature Source(s)
	uncertainties that will arise after its use		• I fear that while I am searching for apparel products through AI chatbots, I might make mistakes providing wrong information about what type of clothes I am looking for. • I feel that AI chatbot is not safe and secure to use for apparel shopping. • I fear that while using AI chatbot information will be misused.	
Value barrier	Occurs when potential users evaluate the differences between existing and innovative products/services	4	• I am quite skeptical about the benefits of using AI chatbots. • In my opinion, AI chatbots do not offer any advantage compared to other shopping techniques such as visiting physical stores and getting assistant from human customer services for searching apparel products. • In my opinion, the use of AI chatbots will not increase my ability to search for the right apparel products I want.	Chaoualia & Souiden (2019); Leonga et al. (2020)

Constructs	Definition	Number of Items	Description Items	Literature Source(s)
			• Using AI chatbots is not a good substitute for traditional shopping (i.e., in-store shopping).	
Image barrier	Occurs when the user has an unfavorable impression of the originating country, brand, industry, or side effects of the innovation	3	• I have a very negative image of AI chatbots. • In my opinion, AI chatbots are often too complicated to be useful. • I have such an image that AI chatbots are difficult to use.	Chaoualia & Souiden (2019)
Tradition barrier	Occurs when the innovation causes conflicts and changes between users and their traditional culture	4	• Patronizing in the fashion retail stores and chatting with the salespersons is a nice occasion on a weekday. • I find AI chatbots less pleasant than those offered personally to customers. • I prefer to search for fashion products through physical stores rather than using AI chatbots. • I am so used to traditional stores to do shopping that I find it difficult to use AI chatbots.	Chaoualia & Souiden (2019)

Constructs	Definition	Number of Items	Description Items	Literature Source(s)
Technology familiarity	Refers to the degree of experience and ability to use digital tools, including the internet, websites, social media, smartphones, and tablets.	8	• I am familiar with new technology and technological practices. • Compared to the general public, I am familiar with new technology and technological practices. • Compared to my friends and acquaintances, I am familiar with new technology and technological practices. • I am familiar with searching for apparel product information online. • I am familiar with social media platforms. • I am familiar with the process of searching and getting information about apparel products. • I am familiar with the procedures of buying apparel online. • I am familiar with online apparel shopping.	Lee & Wan, (2010); Oday et al. (2021); Olya et al. (2021)
Attitudes	Refer to the assessment of a person who encourages or	4	• Using AI chatbots for shopping is a good idea. • Using AI chatbots for shopping would be pleasant.	Kasilingam (2020); Kim et al. (2021)

Constructs	Definition	Number of Items	Description Items	Literature Source(s)
	discourages the use of a particular behavior.		• The idea of using AI chatbots for apparel shopping is appealing. • I like the idea of searching and buying a product from AI chatbot services.	
Willingness to buy apparel with the help of AI chatbots	Refers to consumers' behavioral intention to buy a targeted product in the future.	4	• I intend to buy apparel products via AI chatbots. • I would be willing to buy apparel products via AI chatbots. • In the future, I would buy apparel products via AI chatbots. • I would definitely try AI chatbots to buy apparel products.	Poushneh & Vasquez-Parraga (2017); Zielke & Dobbelstein (2007)
eWOM	Refers to any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institution(s) via the internet.	6	• I will recommend lots of people to use AI chatbots in the future. • I will frequently use AI chatbots and share my experience with my friends in the future. • I will give lots of positive word-of-mouth via the internet in the future. • This eWOM information will crucially affect my apparel purchase decision. • I will refer to this eWOM information in a purchase decision. • Overall, I think this eWOM information is credible.	Augusto & Torres (2018); Liu et al. (2019); Feng et al. (2021)

General Questions Regarding Participants' Prior Experiences with Using AI Chatbots

There were two general questions regarding participants' prior experiences using AI chatbots for shopping. The first question was, "Have you used an AI chatbot before?" and it is assessed with a "yes" or "no" dichotomous response. The second question was, "If yes, which business sector(s) and for what purpose(s) did you use it? (Please check all that apply)." The third question was, "On average, how often do you use AI chatbots for your specific purposes?" Response options were adapted from Linde et al. (2005), e.g., "Never," "Once a year or less," "Several times a year," "Once a month," "A few times a month," "Once a week," "A few times a week," and "Daily."

Demographic Information

Demographic information was obtained in terms of (1) age, (2) gender, (3) marital status, (4) ethnicity, (5) educational background, and (6) annual income. All items were assessed through categorical scales (see Appendix C: Survey Questionnaire).

Pretest

The survey instrument was refined through two main pretests before collecting the actual data. The pretest focuses on clarity, readability, and comprehension of items. For the first pretest, four research experts (e.g., faculty) from an academic setting reviewed the survey instrument. Based on their suggestions and feedback, the instrument was modified. Pretesting a questionnaire can help to ensure clarity of content and wording. Therefore, for the second pretest, the Qualtrics online survey was used to create and distribute the survey. Before launching the survey to the target population for the main study, a pretest was conducted with approximately 60 MTurkers (Amazon Mechanical Turk online panel members) who were 18 years and older and who had prior experience using AI chatbots. Participants were also asked to provide comments or suggestions on the survey flow to help ensure that the questions were clear, readable, and relevant to the research objectives.

Sample and Data Collection Procedures for the Main Study

The respondents were consumers aged 18 and older living in the United States. In this study, consumers who had prior experience using AI chatbots for apparel shopping participated. Before starting the main survey, participants were given a brief explanation about what an AI chatbot is and shown a YouTube video to demonstrate how it works. They were then asked a question to indicate whether they had prior experience using AI chatbots. If participants had no prior experience using an AI chatbot, they were instructed not to continue with the remaining questionnaire and to exit the survey. However, participants with prior experience using chatbots were asked two general questions about the frequency of their AI chatbot use, which business sector(s) they used, and for what purpose(s) they used AI chatbots.

In the study, an online crowdsourcing website called Amazon Mechanical Turk (MTurk) was utilized to recruit participants. MTurk online crowdsourcing service by Amazon.com is a popular online survey employed in social science research (Huff & Tingley, 2015). The demographic composition of MTurkers is much more diverse than student samples and can represent larger populations (Sheehan, 2018). MTurk provides the cheapest and fastest recruitment for academic researchers (Boas, Christenson, & Glick, 2020). Using the MTurk platform, Boas et al. (2020) obtained 500 samples in only 15 minutes and almost 1,000 samples in four hours. Though MTurk is often used for research surveys to meet federal regulations, this study was formally approved by the Institutional Review Board (IRB) to use MTurkers as human participants prior to data collection.

The Qualtrics survey platform was used to administer questionnaires to approximately 700 subjects through MTurk; the questionnaire was available through MTurk. The survey took approximately 10-15 minutes to complete. MTurkers who successfully completed the survey were presented with a code provided by Qualtrics on the last screen of the survey. Each respondent who submitted their user identification code received $1 for their participation.

Statistical Analysis

The data obtained from the pretest was analyzed to determine the content validity—whether the study's survey was appropriate for measuring issues related to reasons for (perceived chatbot service quality), reasons against (perceived chatbot barriers), technology familiarity, attitudes toward using AI chatbots, willingness to buy, and eWOM. The final survey data were collected through MTurk, recorded in Qualtrics, and then saved in the Statistical Package for the Social Sciences (SPSS) file format. The researcher further evaluated the survey's consistency and ensured that respondents had completed all questions. Incomplete responses were not included in the final data analysis. Descriptive analysis (e.g., frequency, means, standard deviation) was performed on key variables and demographic information using SPSS Statistics version 28. For a reliability test, composite reliability (CR) was used to assess the internal consistency of all measures for variables.

In order to test all hypothesized relationships, the two-step approach was performed to establish measurement and structural models via Mplus version 8 (Anderson & Gerbing, 1984). A confirmatory factor analysis (CFA) using weighted least squares mean and variance adjusted (WLSMV) estimation and the sample covariance matrix as input was performed first to establish the measurement model (Joreskog & Sordom, 1993). CFA was driven by the theoretical relationship between the observed and unobserved variables (Schreiber, Nora, Stage, Barlow, &

King, 2006). CFA was performed to confirm unidimensionality, discriminant, and convergent validity and to examine the goodness-of-fit of the measurement model. According to Malhotra (2010), convergent validity is demonstrated when the scale correlates positively with other measures of the same construct and shares a high proportion variance in common (Hair, Black, Babin, & Anderson, 2010). Convergent validity was assessed using the strengths of the factor loadings of each observed variable on its respective construct. To demonstrate evidence of convergent validity, factor loadings of the observed variables for the underlying constructs should be high and statistically significant (Bagozzi, Yi, & Phillips, 1991). Discriminant validity is "the extent to which a measure does not correlate with other constructs from which it is supposed to differ. It involves demonstrating a lack of correlation among differing constructs" (Malhotra, 2010, p. 307).

After confirming the measurement model, path analysis was performed to test the conceptual model and all hypothesized relationships, including reasons for (perceived chatbot service quality), reasons against (perceived chatbot barriers), attitudes toward using AI chatbot, willingness to buy, and eWOM. Given that the moderating effect of technology familiarity was assessed using a Likert-type scale, the moderating effect was also tested through interactions between variables.

To evaluate the model fit, various fit indices were utilized: chi-square ($\chi2$), normed chi-square ($\chi2/df$), root mean square error of approximation (RMSEA), normed-fit index (NFI), comparative fit index (CFI), and non-normed fit index (NNFI or Tucker-Lewis Index, TLI) (Kline, 1998). Structural Equation Modeling (SEM) relies heavily on the chi-square ($\chi2$) goodness of fit test to determine the adequacy of the hypothesized model (Bryant & Satorra, 2012). The chi-square statistic is sensitive to sample size. For the chi-square test to be valid, the sample size should be large (Shi, Lee, & Maydeu-Olivares, 2019). However, Hooper, Coughlan, and Mullen (2008) argued that when larger sample sizes are used, the chi-square statistic always almost rejects the model. On the other hand, when smaller sample sizes are used, the chi-square statistic lacks robustness and cannot reliably differentiate between a good-fit model and a poor-fit model (Kenny & McCoach, 2003). Therefore, Hu and Bentler (1999) suggested using the relative or normed chi-square ($\chi 2/df$), given that this index is less sensitive to sample size. In addition, Xia and Yang (2019) explained that "RMSEA is an absolute fit index, in that it assesses how far a hypothesized model is from a perfect model" (p. 409). Values of RMSEA between 0.05 and 0.08 indicate an acceptable fit, while values between 0.08 and 0.10 indicate a mediocre fit (Hoe, 2008). RMSEA values less than 0.05 are considered a good fit (Joreskog & Sorbom, 1993). Bentler (1992) recommended that values for the NFI at 0.90 or above indicate a good fit. Bentler (1990) introduced the CFI, an improved form of the NFI. Values for the CFI at or greater than 0.90 indicate an acceptable fit (Hoe, 2008). The CFI index is relatively independent of sample size and provides better performance when a small sample size is performed (Hu & Bentler, 1998). TLI is also used to indicate the model fit because this index seems to prefer a simpler model (Joreskog & Sorbom, 1993). For the TLI, values at 0.90 or above indicate a reasonably good fit (Hair, Black, Babin, Anderson, & Tatham, 2006).

Chapter Summary

Chapter III provides detailed information regarding the research methodology of this study. This chapter discussed the study's research purpose and objectives, survey instrument development, sample and data collection procedures, pretest of the instrument, and statistical analysis.

CHAPTER IV: RESULTS

This chapter includes the following sections: (1) Data Collection Procedure; (2) Participants' Demographic Information; (3) Measurement Model Analysis; (4) Structural Model Analysis and Hypotheses Testing; and (5) Chapter Summary.

Data Collection Procedure

Pretest

As discussed in Chapter III, the questionnaire was refined through two main pretests before collecting the actual data. The pretest focused on clarity, readability, and comprehension of a questionnaire. For the first pretest, four research experts from an academic setting reviewed the survey instrument. Minor changes were made; for example, revising the question "In the past six months, how often have you used the AI chatbot for apparel shopping?" to "On average, how often do you use AI chatbots for your specific purposes?" and modifying the frequency of AI chatbots use options from "About once a year or less, Every couple of months, Every month, Every week, and Every day " to "Once a year or less, Several times a year, Once a month, A few times a month, Once a week, A few times a week, and Daily." Additionally, the question, "If yes, which business sector(s) and for what purpose(s) did you use it (Please check all that apply)?" was added to the survey based on the experts' suggestion.

After addressing all minor changes, the second pretest was conducted. That is, the survey was distributed in Qualtrics to approximately 60 MTurkers (Amazon Mechanical Turk online panel members) who were 18 years and older and had prior experience using AI chatbots. In addition, participants were asked to provide feedback on the survey flow to ensure that the questions were clear, readable, and relevant to the research objectives. Most responses described the survey as “Good,” “Very well laid out,” “No issues,” and “The survey seems ok” in their comments. No changes were made to the survey instrument before the final data collection.

Final Data Collection

Final data were collected through MTurk, using Qualtric to develop the survey and distribute the survey link to participants in March 2023. A total of 717 MTurkers who were 18 years or above and resided in the United States responded to the survey. Out of the total number of participants, 85 responses were excluded from the analysis because some did not meet the criteria, including specifically indicating no prior experience of using AI chatbots (n = 34), selecting incorrect attention-check questions (n = 39), and providing inconsistent responses (n = 12) by choosing “Never” when asked about their frequency of chatbots usage for specific purposes, despite having prior experience. As a result, the final sample consisted of 632 usable responses, which were subjected to subsequent analysis.

Participants’ Demographic Information

Table 5 presents a summary of the demographic characteristics of the participants. The descriptive statistics report indicates that 35.1% (n = 222) of participants were female, while 64.9% (n = 410) were male. The results revealed that the majority of participants, 32.1% (n = 203), were between the ages of 26 and 30. Regarding participants’ marital status, an overwhelming majority (87.7%, n = 554) reported being married. In terms of ethnicity, the majority of participants identified as White (90.2%, n = 570), followed by Asian (4.4%, n = 28), African American (3.8%, n = 24), American Indian or Alaska Native (0.8%, n = 5), Hispanic (0.5%, n = 3), Native Hawaiian or Pacific Islander (0.2%, n = 1), and other ethnicities (0.2%, n = 1).

Moreover, the results revealed that the majority of participants (69.8%, n = 441) held a Bachelor’s degree, while 22.8% (n = 144) of participants earned a Master’s degree. 4.4% (n = 28) of participants were High School Graduates. In addition, in terms of annual income, 34.2% (n = 216) of participants earned between USD 35,001 and 50,000, followed by 23.1% (n = 146) earning between USD 50,001 and 65,000, and 16.8% (n = 106) earning between USD 20,001 and 35,000.

Table 5. Participants’ Demographic Information (N = 632)

Characteristics		Frequency	Percentage
Gender	Male	410	64.9%
	Female	222	35.1%
Age	18-25	83	13.2%
	26-30	203	32.1%
	31-35	109	17.2%
	36-40	68	10.8%
	41-45	58	9.1%
	46-50	38	5.9%
	51-55	24	3.7%
	56-60	22	3.4%
	> 60	27	4.3%
Marital Status	Single, Never Married	71	11.2%
	Married	554	87.7%
	Separated	1	0.2%
	Divorced	5	0.8%
	Windowed	1	0.2%
Ethnicity	White	570	90.2%
	African American	24	3.8%
	American Indian or Alaska Native	5	0.8%
	Hispanic	3	0.5%
	Asian	28	4.4%
	Native Hawaiian or Pacific Islander	1	0.2%
	Others	1	0.2%
Education	Less than High School	1	0.2%
	High School Graduate	28	4.4%
	Trade/Technical/Vocational Training	1	0.2%
	Associate Degree	11	1.7%

Characteristics		Frequency	Percentage
	Bachelor's Degree	441	69.8%
	Master's Degree	144	22.8%
	Professional Degree	6	0.9%
Annual Income	Less than $20,000	19	3.0%
	$20,001 - $35,000	106	16.8%
	$35,001 - $50,000	216	34.2%
	$50,001 - $65,000	146	23.1%
	$65,000 - $80,000	97	15.3%
	$80,001 - $95,000	32	5.1%
	Over $95,000	16	2.5%
	Total	632	100%

Participants' Experience of Using AI Chatbots

In the questionnaire, participants were asked to answer questions, including "Have you used an AI chatbot before?," "If yes, which business sector(s) and for what purpose(s) did you use it (Please check all that apply)?," and "On average, how often do you use AI chatbots for your specific purposes?"

Table 6 illustrates that all participants had prior experience using AI chatbots, as those without any prior experience were not allowed to complete the questionnaire. Among those with experience (n=632), the majority of participants (68.8%, n = 420) reported using AI chatbots for fashion-related purposes, including buying and/or searching for clothing, shoes, and accessories. Additionally, 42.2% (n = 280) of participants reported using AI chatbots for buying/searching beauty products, and so on. Approximately 37.6% (n = 238) of participants reported using chatbots for traveling purposes, such as booking/buying travel tickets or inquiring about hotel rooms. In terms of frequency of usage, the majority of participants (24.7%, n = 156) indicated that they had used AI chatbots a few times a month, followed by 20.3% (n = 128) who had used them once a month, and 16.6% (n = 105) who had used once a week.

Table 6. Participants' AI Chatbot Usage Behavior

		Frequency	Percentage
AI Chatbot Experience	Prior Experience	632	100.0%
	No Experience	0	0.0%
Business sector(s) and purpose(s) of AI chatbots usage (Participants checked all that apply)	Fashion (e.g., for buying/searching clothing, shoes, accessories)	420	68.8%
	Beauty (e.g., for buying/searching beauty products)	280	42.2%
	Travel (e.g., for booking/buying travel tickets, inquiry hotel rooms)	238	37.6%
	Banking (e.g., for getting financial information and advice, getting alerts on potential issues or upcoming payments)	188	28.8%
	Medical (e.g., for scheduling Dr. Appointments, asking for medical records, prescription refills)	139	22.5%
	Personal Services (e.g., for fitness, diet plan, health, day-to-day activities)	167	26.7%
	Customer Services (e.g., for asking questions about product(s)/service(s)	180	28.8%
	Others	6	1.1%
AI Chatbot Usage Frequency	Once a year or less	44	7.0%
	Several times a year	98	15.5%
	Once a month	128	20.3%
	A few times a month	156	24.7%
	Once a week	105	16.6%
	A few times a week	80	12.7%
	Daily	21	3.3%
	Total	632	100%

Measurement Model Analysis

Using Mplus version 8, the two-step approach was performed to establish measurement and structural models (Anderson & Gerbing, 1988). Confirmatory factor analysis (CFA) was performed first to establish the measurement model (Joreskog & Sordom, 1993). Hurley and colleagues (1997) suggested that CFA is suitable for validating measurement models that are based on theoretical reasoning, while exploratory factor analysis (EFA) is appropriate for scale development purposes. Given that all measurement items for all constructs used in this study have been previously validated and no new scale was developed; therefore, this study primarily employed CFA to check factor loadings of variables and the overall measurement model before examining the hypothesized relationships (Joreskog & Sordom, 1993). In addition to confirming the unidimensionality of the constructs, the results of factor loadings from CFA were checked, and each construct's internal reliability was assessed using composite reliability (CR). In this study, all constructs, including *reasons for*, *reasons against*, *technology familiarity*, *attitudes toward using AI chatbots*, *willingness to buy apparel with the help of AI chatbots*, and *eWOM*, were measured using a five-point Likert-type scale (1 = "strongly disagree" to 5 = "strongly agree"). *Reasons for* included three factors: *responsiveness*, *reliability*, and *assurance*. *Reasons against* consisted of five factors: *usage barrier*, *risk barrier*, *value barrier*, *image barrier*, and *tradition barrier*.

Before conducting a factor analysis, Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of Sphericity were employed to assess the adequacy of the data for factor analysis (Orel & Kara, 2014; Wu, 2021; Yang, 2012).

KMO Test and Bartlett's Test of Sphericity

The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were implemented using SPSS version 28. According to Pallant (2016), the minimum acceptable value for KMO is 0.60, and Bartlett's test of sphericity should yield a significant result. The KMO measure for each construct of this study ranged from 0.68 to 0.87, and Bartlett's test of sphericity for all constructs was significant ($p < 0.001$). Therefore, these values indicated that the data met the adequacy criteria for factor analysis. Table 7 shows the results of the KMO Test and Bartlett's Test of Sphericity.

Table 7. Results of the KMO Test and Bartlett's Test of Sphericity

Construct	Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)	Bartlett's Test of Sphericity Approx. Chi-Square (df)	Significance
Reasons For (Perceived Chatbot Service Quality)			
Responsiveness	0.81	670.59	p<0.001
Reliability	0.68	192.62	p<0.001
Assurance	0.72	296.27	p<0.001
Reasons Against (Perceived Chatbot Barrier)			
Usage Barrier	0.83	1222.97	p<0.001
Risk Barrier	0.87	1418.9	p<0.001
Value Barrier	0.77	617.43	p<0.001
Image Barrier	0.71	763.39	p<0.001
Tradition Barrier	0.76	495.77	p<0.001
Technology Familiarity	0.82	929.95	p<0.001
Attitudes toward Using AI Chatbots	0.69	248.74	p<0.001
Willingness to Buy Apparel with the Help of AI Chatbots	0.69	268.61	p<0.001
eWOM	0.80	632.91	p<0.001

Note. N = 632

Confirmatory Factor Analysis (CFA)

To validate the measurement model, CFA was conducted using a weighted least square mean and variance adjusted (WLSMV) estimation for categorical variables (Muthén, 1984). Beauducel and Herzberg (2006) asserted that the performance of WLSMV estimation is superior to the performance of maximum likelihood (ML) estimation, especially when dealing with the categorical nature of data from Likert scales. They further emphasized the superiority of WLSMV, particularly in estimating factor loadings (Li, 2016). Consequently, in this study, we employed the WLSMV estimator to evaluate goodness-of-fit indexes, including the normed chi-square ($\chi 2$/df), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis fit index (TLI).

Hu and Bentler's (1999) suggested that using the normed chi-square ($\chi 2$/df) is more appropriate, as this index is less sensitive to sample size compared to other indices. According to Wheaton, Muthen, Alwin, and Summers (1977), the normed chi-square ($\chi 2$/df) value should fall between 1 and 5. The CFA result showed that the chi-square ($\chi 2$) statistic was 4100.041 with 1529 degrees of freedom at $p < .05$, indicating significance. That means the data did not fit the model (Hu & Bentler, 1999). The normed chi-square test of model fit ($\chi 2$/df) yielded a value of 2.68. The RMSEA values of 0.05 was considered an acceptable fit (Hoe, 2008). The CFI value was 0.93, and the TLI value was 0.92. Hair et al. (2006) suggested that values of CFI and TLI at 0.90 or above indicate a reasonably good fit. Overall, the model fit indices indicated an acceptable fit for the 58 items of each construct in the measurement model (see Table 8).

Table 8. Summary of Measurement Model Fit

Model Fit Indices	Recommended Fit Value Criteria	Value	Accepted
$\chi 2$	p>0.05	p<0.001	No
$\chi 2$/df	<5	2.68	Yes
RMSEA	<0.08	0.05	Yes
CFI	>0.90	0.93	Yes
TLI	>0.90	0.92	Yes

Note. $\chi 2$ = Chi-square; $\chi 2$/df = Normed Chi-square; df = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Fit Index

The CFA results were utilized to identify all 58 items loaded on each factor, confirm the unidimensionality of the constructs, and assess the validity and reliability of the measures. The results of the CFA model indicated that standardized factor loadings, ranging from 0.45 (ASS4) to 0.82 (U3), were all significant (see Table 9).

Table 9. Measurement Validity and Reliability

Construct/Factor Measure	Items	z-value	Unstandardized Factor Loading	Standardized Factor Loading	CR	AVE
Reasons For (Perceived Chatbot Service Quality)						
Responsiveness	RES1	27.42	1.00	0.69***	0.78	0.33
	RES2	22.96	0.90	0.61***		
	RES3	16.18	0.72	0.50***		
	RES4	20.77	0.85	0.58***		
	RES5	16.99	0.72	0.49***		
	RES6	19.14	0.80	0.55***		
	RES7	21.00	0.88	0.60***		
Reliability	REL1	18.19	1.00	0.56***	0.62	0.30
	REL2	19.43	0.96	0.53***		
	REL3	19.64	1.01	0.56***		
	REL4	17.34	0.91	0.51***		
Assurance	ASS1	21.60	1.00	0.60***	0.68	0.30
	ASS2	21.99	0.97	0.58***		
	ASS3	21.12	0.96	0.57***		
	ASS4	14.57	0.75	0.45***		
	ASS5	18.65	0.86	0.52***		
Reasons Against (Perceived Chatbot Barrier)						
Usage Barrier	U1	44.74	1.00	0.79***	0.88	0.64
	U2	46.21	1.01	0.80***		
	U3	52.18	1.04	0.82***		
	U4	49.18	1.03	0.81***		

Construct/Factor Measure	Items	z-value	Unstandardized Factor Loading	Standardized Factor Loading	CR	AVE
Risk Barrier	R1	52.50	1.00	0.81***	0.88	0.59
	R2	43.91	0.95	0.77***		
	R3	40.82	0.93	0.76***		
	R4	37.68	0.91	0.74***		
	R5	37.59	0.91	0.74***		
Value Barrier	V1	34.76	1.00	0.73***	0.78	0.47
	V2	28.66	0.91	0.67***		
	V3	32.32	0.94	0.69***		
	V4	28.87	0.89	0.66***		
Image Barrier	I1	47.99	1.00	0.80***	0.90	0.32
	I2	42.80	1.00	0.80***		
	I3	50.59	1.01	0.81***		
Tradition Barrier	T1	28.14	1.00	0.69***	0.83	0.32
	T2	27.93	0.95	0.66***		
	T3	21.70	0.85	0.59***		
	T4	28.81	1.00	0.69***		
Technology Familiarity					0.81	0.35
	TF1	22.66	1.00	0.62***		
	TF2	25.18	1.07	0.67***		
	TF3	23.12	1.01	0.63***		
	TF4	19.56	0.90	0.56***		
	TF5	21.03	0.94	0.59***		
	TF6	17.79	0.91	0.56***		
	TF7	19.17	0.91	0.56***		
	TF8	19.00	0.93	0.57***		
Attitudes toward Using AI Chatbots					0.66	0.33
	A1	20.03	1.00	0.58***		
	A2	20.25	1.00	0.58***		
	A3	20.54	1.00	0.58***		
	A4	18.93	0.93	0.54***		

Construct/Factor Measure	Items	z-value	Unstandardized Factor Loading	Standardized Factor Loading	CR	AVE
Willingness to Buy Apparel with the Help of AI Chatbots					0.67	0.34
	W1	23.92	1.00	0.65***		
	W2	19.16	0.83	0.54***		
	W3	18.62	0.85	0.55***		
	W4	21.84	0.91	0.59***		
eWOM					0.77	0.36
	EW1	26.28	1.00	0.66***		
	EW2	21.70	0.92	0.61***		
	EW3	21.53	0.88	0.58***		
	EW4	20.68	0.90	0.59***		
	EW5	18.87	0.85	0.56***		
	EW6	20.76	0.91	0.61***		

Note. *** p< 0.001.

Composite Reliability (CR) = $\frac{(\sum \lambda)2}{[(\sum \lambda)2 + (\sum \theta)]}$

Average Variance Extracted (AVE) = $\frac{(\sum \lambda 2)}{[(\sum \lambda 2) + (\sum \theta)]}$

Twelve constructs, namely three *reasons for* (perceived chatbot service quality), including *responsiveness*, *reliability*, and *assurance*, *reasons against* (perceived chatbot barriers), including *usage barrier*, *risk barrier*, *value barrier*, *image barrier*, and *tradition barrier*, *technology familiarity*, *attitudes toward using AI chatbots*, *willingness to buy apparel with the help of AI chatbots*, and *eWOM*, were used to measure consumers' use of AI chatbots for apparel shopping. Table 9 presents items, z-value, unstandardized factor loadings, standardized factor loadings, composite reliability (CR), and average variance extracted (AVE) values. Sixteen items were used to measure *reasons for* factors, including seven items for *responsiveness* with standardized factor loadings ranging from 0.49 to 0.69, four items for *reliability* with standardized factor loadings ranging from 0.51 to 0.56, and five items for *assurance* with standardized factor loadings ranging from 0.45 to 0.60. Twenty items were used to measure *reasons against* factors, including four items for *usage barrier* with standardized factor loadings ranging from 0.79 to 0.82, five items for *risk barrier* with standardized factor loadings ranging from 0.74 to 0.81, four items for *value barrier* with standardized factor loadings ranging from 0.66 to 0.73, three items for *image barrier* with standardized factor loadings ranging from 0.80 to 0.81, and four items for *tradition barrier* with standardized factor loadings ranging from 0.59 to 0.69. Eight items were used to measure *technology familiarity* with standardized factor loadings ranging from 0.56 to 0.67. Four items were used to measure consumers' *attitudes toward using AI chatbots* with standardized factor loadings ranging from 0.54 to 0.58. The *willingness to buy apparel with the help of AI chatbots* included four items with factor loadings ranging from 0.54 to 0.65. *eWOM* included six items with factor loadings ranging from 0.56 to 0.66. Tabancali, Simsek, and Korumaz (2017) reported that according to Comrey and Lee (1992), factor loadings as 0.32 are considered weak, factor loadings as 0.45 are considered reasonable, loadings as 0.55 are considered good, factor loadings as 0.63 are considered very good, and loadings as 0.71 are considered excellent. Table 9 indicated that the majority of factor loadings fell within the range of 0.55 to 0.82, suggesting good to excellent levels. However, only a few measurement items, such as RES3, RES5, REL2, REL4, ASS4, ASS5, and W2, were less than 0.55, which were still considered acceptable. Notably, all factor loadings were significant at $p < 0.001$.

Psychometric Properties

To assess the psychometric properties, composite reliability (CR) and average variance extracted (AVE) values were used to measure the reliability and validity of measurement items. Reliability, measured by composite reliability (CR), is considered acceptable when values are above 0.70 (Kline, 2012). In addition, Bagozzi, Yi, and Nassen (1988) suggested that a composite reliability of 0.60 meets the criteria. The CR value of all constructs exceeded the cutoff criterion of 0.60, ranging from 0.62 (reliability) to 0.90 (image barrier).

Convergent validity and discriminant validity were examined based on the results of the measurement model. Convergent validity refers to the degree to which two instruments of the same constructs are correlated (Ursachi, Horodnic, & Zait, 2015). Convergent validity was tested by using AVE. Convergent validity is acceptable if AVE is greater than 0.50 (Fornell & Larcker, 1981). The results indicated that the values of AVE of most constructs, such as responsiveness (0.33), reliability (0.30), assurance (0.30), technology familiarity (0.35), and eWOM (0.36), were below the threshold of 0.50. However, the AVE value for the usage barrier (0.64) and risk barrier (0.59) exceeded 0.50. The AVE value of the value barrier (0.47) was marginally below the cutoff point of 0.50. Fornell and Larcker (1981) suggested that a CR value higher than 0.60 is generally considered acceptable for convergent validity, even if the AVE value is less than 0.50. In this study, the composite reliability of all constructs exceeded 0.60, indicating a satisfactory level of reliability. The factor loading values ranged from 0.45 to 0.82, with most factor loadings above 0.5, which is considered acceptable (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). Table 9 shows the reliability and validity of the measurement model.

Discriminant validity refers to the extent to which a construct is truly distinct from other constructs (Hair et al., 2006; Orel & Kara, 2014). This study assessed discriminant validity by comparing the square root of the average variance extracted (AVE) with the correlation between the construct and other constructs in the model (Fornell & Larcker, 1981). According to Fornell and Larcker (1981), discriminant validity is established when the square roots of the average variance extracted (AVE) for each construct are larger than their correlation with other constructs. Table 10 presents the mean, standard deviations (SD), correlations of all constructs, and the bold diagonal values representing the square root of the AVE. However, upon evaluation, it was found that the correlation coefficients of some constructs, ranging from 0.56 to 0.75, were greater than their corresponding square root of AVE values, ranging from 0.54 to 0.69. Despite this, it is important to note that discriminant validity was still established between some constructs. However, as depicted in Table 10, the square root of the average variance extracted (AVE) values for most constructs were larger than their correlations with other constructs. Therefore, both convergent and discriminant validity can be considered satisfactory in this study.

Table 10. Correlation Matrix for All Constructs

			Correlations											
Construct	Mean	SD	RES	REL	ASS	U	R	V	I	T	TF	A	W	EW
RES	3.95	0.61	**0.58**											
REL	4.12	0.64	0.54**	**0.54**										
ASS	3.98	0.58	0.63**	0.57**	**0.55**									
U	3.59	1.12	0.01	0.25**	0.06	**0.80**								
R	3.59	0.94	0.06	0.25**	0.14**	0.76**	**0.77**							
V	3.81	0.87	0.15**	0.38**	0.22**	0.66**	0.71**	**0.69**						
I	3.54	1.09	0.02	0.25**	0.10*	0.71**	0.77**	0.68**	**0.57**					
T	3.90	0.81	0.19**	0.37**	0.25**	0.61**	0.69**	0.75**	0.69**	**0.56**				
TF	4.09	0.62	0.58**	0.48**	0.52**	0.11**	0.19**	0.30**	0.12**	0.33**	**0.60**			
A	4.13	0.64	0.52**	0.62**	0.53**	0.22**	0.25**	0.35**	0.23**	0.38**	0.63**	**0.57**		
W	4.13	0.65	0.48**	0.56**	0.51**	0.19**	0.25**	0.32**	0.19**	0.34**	0.56**	0.69**	**0.59**	
EW	4.02	0.64	0.43**	0.51**	0.48**	0.31**	0.36**	0.41**	0.33**	0.40**	0.51**	0.61**	0.59**	**0.60**

Note. The bold diagonal values are the square root of AVE for each construct. RES = responsiveness; REL = reliability; ASS = assurance; U = usage barrier; R = risk barrier; V = value barrier; I = image barrier; T = tradition barrier; TF = technology familiarity; A = attitudes toward using AI chatbots; W = willingness to buy apparel with the help of AI chatbots; EW = electronic word-of-mouth. **p < 0.01; *p < 0.05 (2 tailed).

Structural Model and Hypotheses Testing

Given that the measurement model demonstrated a satisfactory model fit, observed variables were created by averaging measurement items on their perspective variables in the structural equation modeling analysis (Tran, Sen, & Steenburg, 2023; Zeugner-Roth, Zabkar, & Diamantopoulos, 2015), thereby utilizing the path analysis to test hypotheses. Hypothesis testing involved two distinct analyses: one focused on the model of main effects, and the other examined the moderating effects of technology familiarity using Mplus version 8. Specifically, the model of main effects was tested in the first analysis, while the second analysis tested the moderating effect of *technology familiarity* on the relationship between *reasons for* (i.e., *responsibility*, *reliability,* and *assurance*) and *reasons against* factors (i.e., *usage barrier*, *risk barrier*, and *value barrier*) and *attitudes toward using AI chatbots*.

Testing Main Effects

Using the weighted least squares mean, and variance adjusted (WLSMV), the main effects of hypothesized relationships were tested first. The model result revealed a significant chi-square ($\chi2$) statistic of 26.508 (df = 16; p <0.047), indicating that the model did not fit the data well. However, the normed chi-square value ($\chi2$/df) was 1.66, which fell below the recommended threshold of 5, suggesting acceptability according to Hair, Anderson, Tatham, and Black (1998). Other fit indices, CFI (0.98) and TLI (0.97) were greater than 0.90, indicating a favorable fit to the research model. Moreover, the value of RMSEA (0.03) was less than 0.08, indicating a good fit. Therefore, it can be concluded that the measurement model fit is acceptable. Table 11 shows the results of the structural model of main effects.

Table 11. Summary of Main Effects

Model Fit Indices	Recommended Fit Value Criteria	Value	Accepted
$\chi 2$	p>0.05	p<0.05	No
$\chi 2$/df	<5	1.66	Yes
RMSEA	<0.08	0.03	Yes
CFI	>0.90	0.98	Yes
TLI	>0.90	0.97	Yes

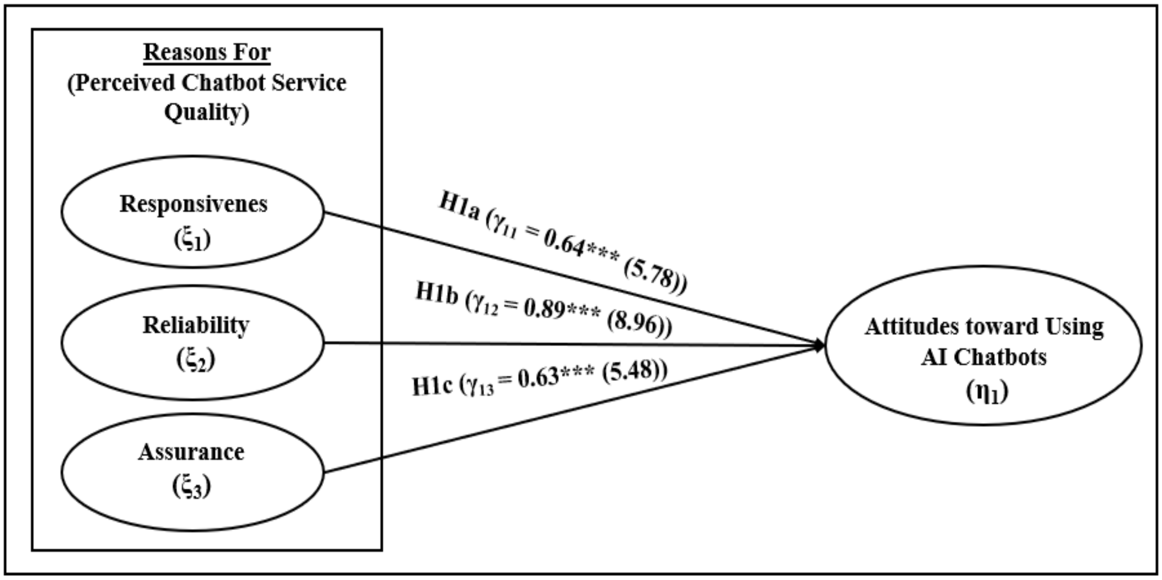
Note. $\chi 2$ = Chi-square; $\chi 2$/df = Normed Chi-square; df = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Fit Index

Hypotheses Testing Results for Main Effects

Hypothesis 1: The Relationship between *Reasons For* Factors (a) *Responsiveness*, (b) *Reliability*, and (c) *Assurance* and A*ttitudes toward Using AI Chatbots*

H1a proposed a positive relationship between *responsiveness* and *attitudes toward using AI chatbots*. The results revealed that *responsiveness* positively influenced *attitudes toward using AI chatbots* (γ_{11} = 0.64, z-value = 5.78, $p < 0.001$). Thus, H1a was supported. Similarly, H1b predicted a positive relationship between *reliability* and *attitudes toward using AI chatbots*. The findings showed that *reliability* positively influenced *attitudes toward using AI chatbots* (γ_{12} = 0.89, z-value = 8.96, $p < 0.001$). Thus, H1b was also supported. Furthermore, H1c proposed a positive influence of *assurance* on *attitudes toward using AI chatbots.* The results revealed that *assurance* positively influenced *attitudes toward using AI chatbots* (γ_{13} = 0.63, z-value = 5.48, $p < 0.001$). Thus, H1c was also supported (see Figure 6).

Figure 6. The Relationship between R*easons For* Factors (*Responsiveness*, *Reliability*, and *Assurance*) and *Attitudes toward Using AI Chatbots.*

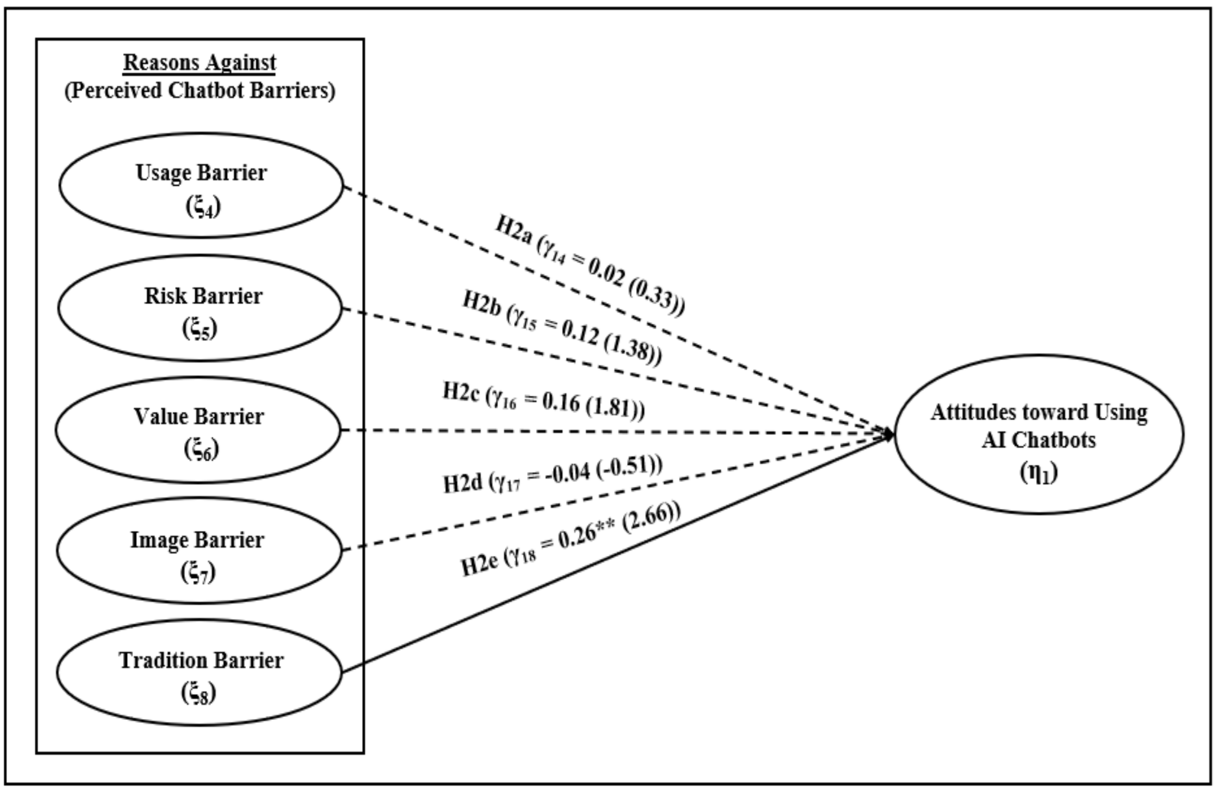


Note. *** $p < 0.001$.
The solid lines represent significant relationships. Values in paratheses represent the standardized coefficients in the outer parentheses and standard errors in the inner parentheses.

<u>Hypothesis 2: The Relationship between *Reasons Against* Factors and *Attitudes toward Using AI Chatbots*</u>

Hypotheses H2a, H2b, and H2c proposed a negative influence of *usage barrier*, *risk barrier*, and *value barrier* on *attitudes toward using AI chatbots*. However, the results revealed that the *usage barrier* (γ_{14} = 0.02, z-value = 0.33, $p > 0.05$), *risk barrier* (γ_{15} = 0.12, z-value = 1.38, $p > 0.05$), and *value barrier* (γ_{16} = 0.16, z-value = 1.81, $p > 0.05$) did not have a negative impact on *attitudes toward using AI chatbots*. Thus, H2a, 2b, and 2c were not supported. H2d also proposed a negative influence of *image barrier* on *attitudes toward using AI chatbots*. Results showed that the *image barrier* did not significantly influence *attitudes toward using AI chatbots* (γ_{17} = -0.04, z-value = -0.51, $p > 0.05$). Thus, H2d was not supported. Additionally, H2e proposed a negative relationship between *tradition barrier* and *attitudes toward using AI chatbots*. Although the result indicated a significant and positive relationship between *tradition barrier* and *attitudes towards using AI chatbots* (γ_{18} = 0.26, z-value = 2.66, $p < 0.05$), this relationship did not align with the proposed hypothesis. Thus, H2e was not supported (see Figure 7).

Figure 7. The Relationship between *Reasons Against* Factors (*Usage Barrier*, *Risk Barrier*, *Value Barrier*, *Image Barrier*, and *Tradition Barrier*) and *Attitudes toward Using AI Chatbots.*

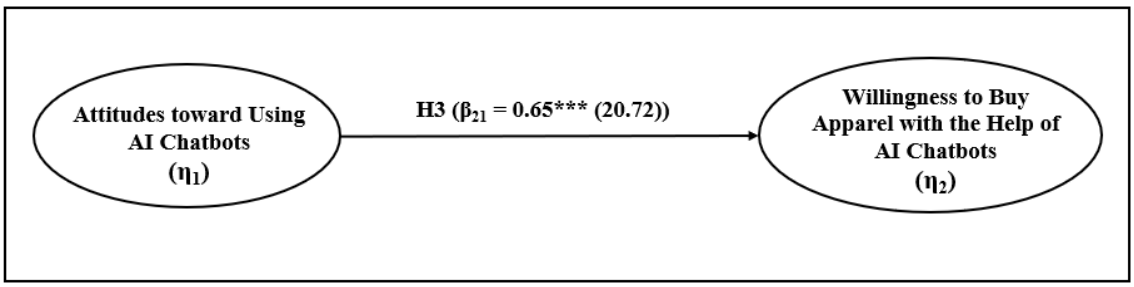


Note. ** $p < 0.01$.
The solid line represents a significant relationship, and the dashed lines represent non-significant relationships. Values in paratheses represent the standardized coefficients in the outer parentheses and standard errors in the inner parentheses.

Hypothesis 3: The Relationship between *Attitudes toward Using AI Chatbots* and *Willingness to Buy Apparel with the Help of AI Chatbots.*

H3 proposed a positive relationship between *attitudes* toward using AI chatbots and *willingness to buy apparel with the help of AI chatbots*. The result showed that *attitudes toward using AI chatbots* positively influenced *willingness to buy* (β_{21} = 0.65, z-value = 20.72, $p < .001$). Thus, H3 was supported (see Figure 8).

Figure 8. The Relationship between *Attitudes toward Using AI Chatbots* and *Willingness to Buy Apparel with the Help of AI Chatbots.*

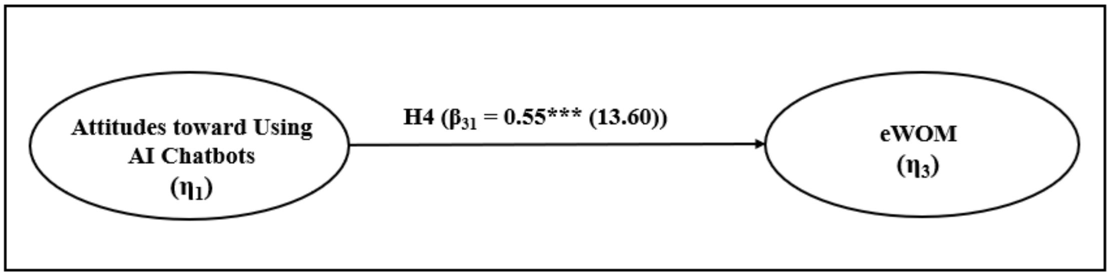


Note. *** $p < 0.001$.
The solid line represents a significant relationship. Values in paratheses represent the standardized coefficient in the outer parentheses and standard error in the inner parentheses.

Hypothesis 4: The Relationship between *Attitudes toward Using AI Chatbots* and *eWOM*

H4 proposed a positive relationship between *attitudes toward using AI chatbots* and *eWOM*. Results revealed that *attitudes toward using AI chatbots* positively influenced *eWOM* (β_{31} = 0.55, z-value = 13.60, $p < .001$). Therefore, H4 was supported (see Figure 9).

Figure 9. The Relationship between *Attitudes toward Using AI Chatbots* and *eWOM*



Note. *** $p < 0.001$.
The solid line represents a significant relationship. Values in paratheses represent the standardized coefficient in the outer parentheses and standard error in the inner parentheses.

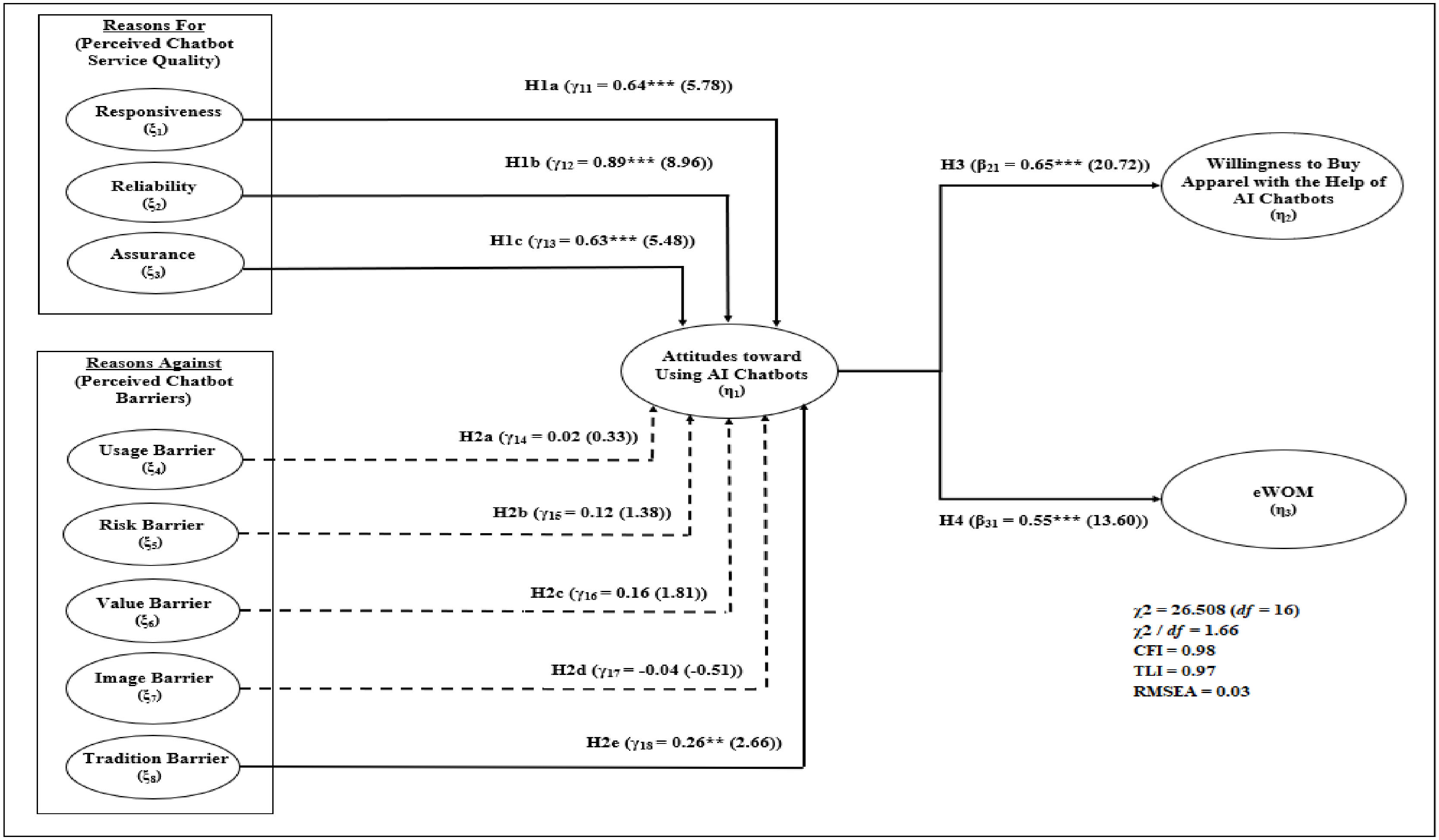
Table 12 and Figure 10 present the results of hypothesis testing related to the main effect of the structural model.

Table 12. Hypothesis Testing Results for Main Effects

	Hypothesis	Supported?
H1a:	Responsiveness will have a positive influence on attitudes toward using AI chatbots.	Yes
H1b:	Reliability will have a positive influence on attitudes toward using AI chatbots.	Yes
H1c:	Assurance will have a positive influence on attitudes toward using AI chatbots.	Yes
H2a:	Usage barrier will have a negative influence on attitudes toward using AI chatbots.	No
H2b:	Risk barrier will have a negative influence on attitudes toward using AI chatbots.	No
H2c:	Value barrier will have a negative influence on attitudes toward using AI chatbots.	No

	Hypothesis	Supported?
H2d:	Image barrier will have a negative influence on attitudes toward using AI chatbots.	No
H2e:	Tradition barrier will have a negative influence on attitudes toward using AI chatbots.	No
H3:	Attitudes toward using AI chatbots. will have a positive influence on willingness to buy apparel with the help of AI chatbots.	Yes
H4:	Attitudes toward using AI chatbots will have a positive influence on eWOM.	Yes

Figure 10. Results of Structural Model for Main Effects



Note. *** p<0.001; ** p< 0.01.

The solid lines represent significant relationships, and the dashed lines represent non-significant relationships. Values in paratheses represent the standardized coefficients in the outer parentheses and standard errors in the inner parentheses.

Testing Moderating Effects

To test the moderating effect of *technology familiarity* on the relationships between *reasons for* factors and *reasons against* factors and *attitudes toward using AI chatbots,* a separate path analysis was performed using the weighted least square mean and variance adjusted (WLSMV) estimation. The overall model demonstrated acceptable fit ($\chi 2$ = 37.874, df = 34, $\chi 2$ /df = 1.11, p > 0.05, RMSEA = 0.01, CFI = 0.98, and TLI = 0.97) (see Table 13).

Table 13. Summary of Moderating Effects

Model Fit Indices	Recommended Fit Value Criteria	Value	Accepted
$\chi 2$	p>0.05	p>0.05	Yes
$\chi 2$/df	<5	1.11	Yes
RMSEA	<0.08	0.01	Yes
CFI	>0.90	0.98	Yes
TLI	>0.90	0.97	Yes

Note. $\chi 2$ = Chi-square; $\chi 2$/df = Normed Chi-square; df = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Fit Index

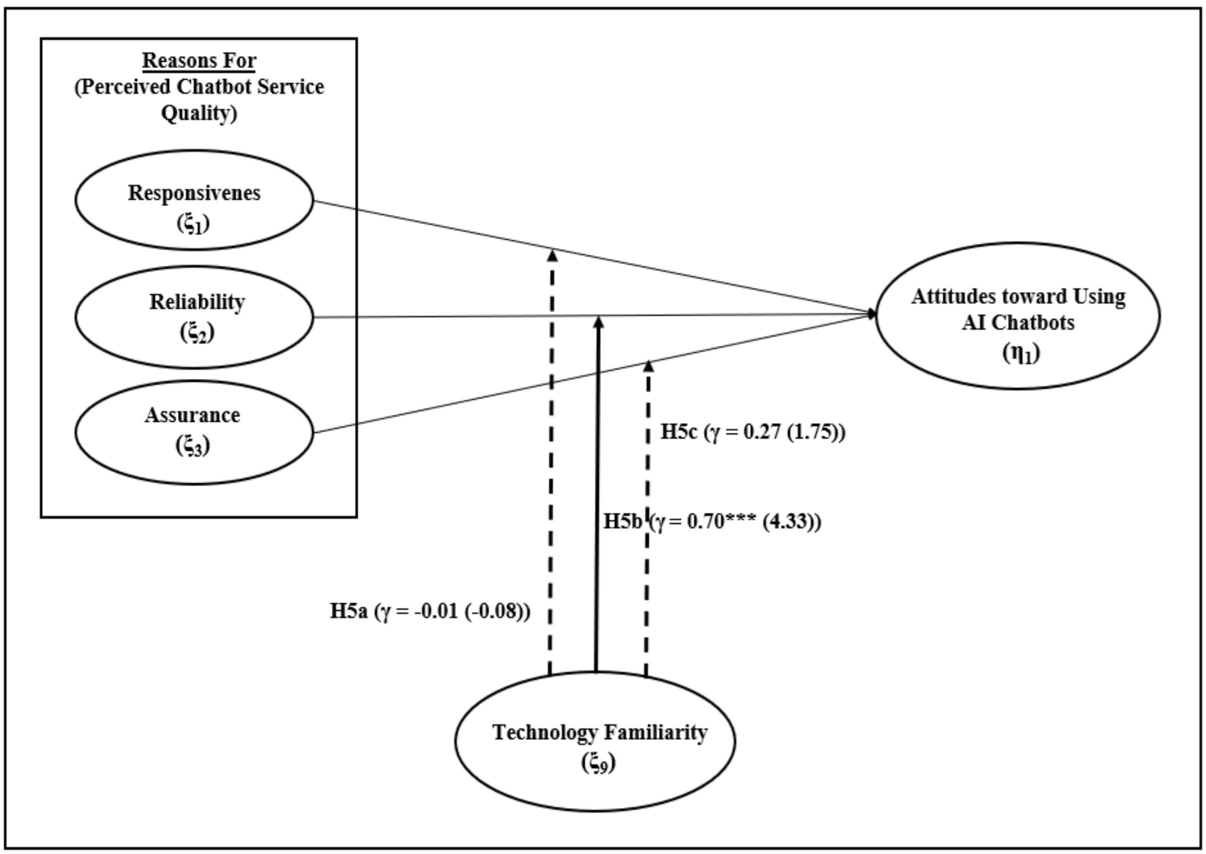
Hypotheses Testing Results for Moderating Effects

Hypothesis 5: The Moderating Effects of *Technology Familiarity* on Relationships between *Reasons For* Factors and *Attitudes toward Using AI Chatbots*

Hypothesis 5a proposed that *technology familiarity* would moderate the relationship between *responsiveness* and *attitudes toward using AI chatbots*. However, the findings revealed that the moderating effect of *technology familiarity* on the relationship between *responsiveness* and *attitudes toward using AI chatbots* was not significant (γ = -0.01, z-value = -0.08, p > 0.05). Thus, H5a was not supported. On the other hand, H5b proposed that technology familiarity would moderate the relationship between reliability and attitudes toward using AI chatbots. The results showed a significant positive relationship for the moderating effect of technology familiarity on the relationship between reliability and attitudes toward using AI chatbots (γ =

0.70, z-value = 4.33, p < 0 .001). Therefore, H5b was supported. In addition, H5c proposed moderating effects of *technology familiarity* on the relationship between *assurance* and *attitudes toward using AI chatbots*. However, the results indicated no significant moderating effect of *technology familiarity* on the relationship between *assurance* and *attitudes toward using AI chatbots* ($\gamma = 0.27$, z-value = 1.75, $p > 0.05$). Thus, H5c was not supported (see Figure 11).

Figure 11. The Moderating Effects of *Technology Familiarity* on Relationships between R*easons For* Factors and *Attitudes toward Using AI Chatbots*



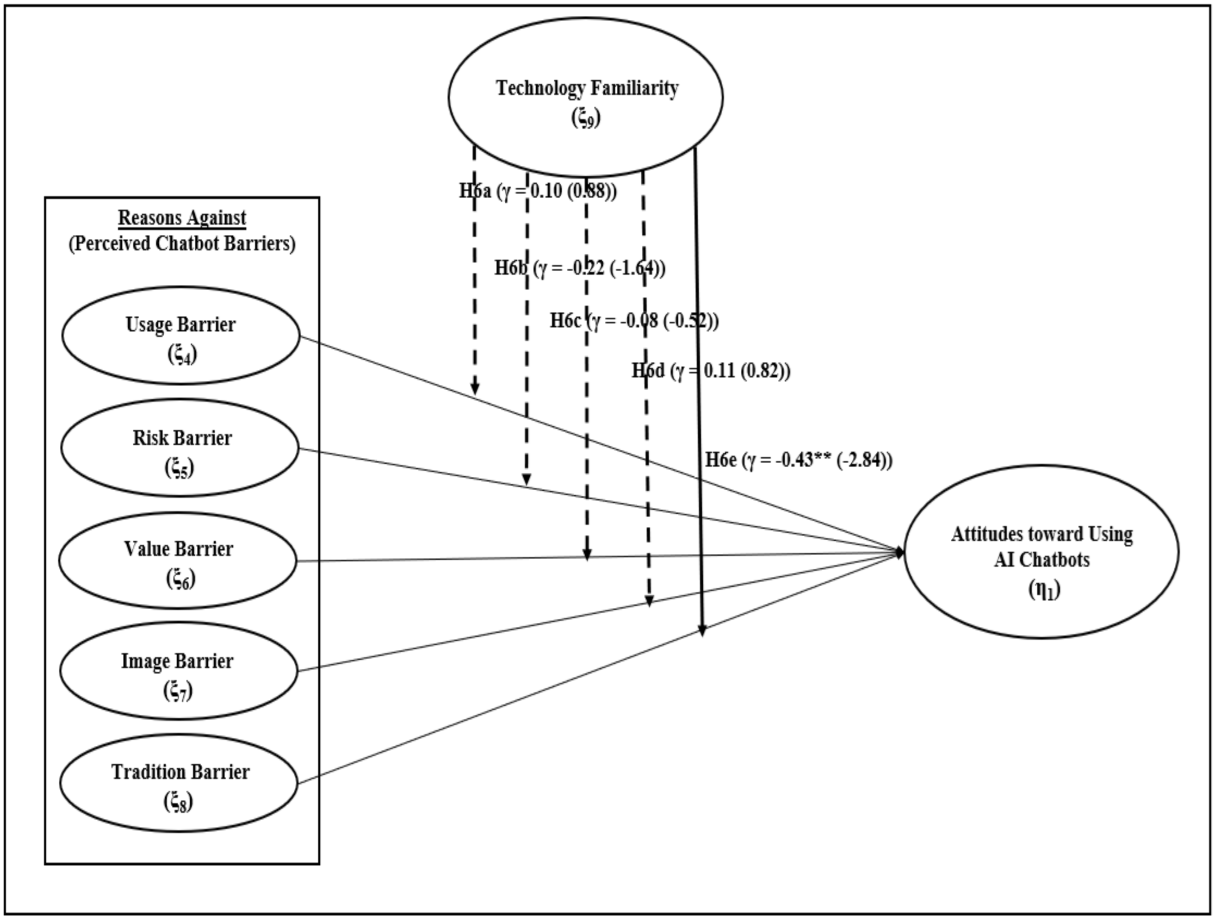
Note. *** $p < 0.001$.

The dashed lines represent non-significant relationships. Values in paratheses represent the standardized coefficients in the outer parentheses and standard errors in the inner parentheses.

Hypothesis 6: The Moderating Effects of *Technology Familiarity* on Relationships between R*easons Against* Factors and *Attitudes toward Using AI Chatbots*

Hypothesis 6a, 6b, 6c, and 6d proposed moderating effects of *technology familiarity* on the relationships between *usage barrier, risk barrier*, *value barrier, image barrier*, and *attitudes toward using AI chatbots*. The findings revealed no significant moderating effect of *technology familiarity* on the relationships between *usage barrier* (γ = 0.10, z-value = 0.88, $p > 0$ .05), *risk barrier* (γ = -0.22, z-value = -1.64, $p > 0$ .05), *value barrier* (γ = -0.08, z-value = -0.52, $p > 0$ .05), *image barrier* (γ = 0.11, z-value = 0.82, $p > 0$ .05), and *attitudes toward using AI chatbots*. Consequently, H6a, H6b, H6c, and H6d were not supported. However, Hypothesis 6e proposed that *technology familiarity* would moderate the relationship between *tradition barrier* and *attitudes toward using AI chatbots.* The results revealed a significant negative relationship (γ = -0.43, z-value = -2.84, $p < 0.05$), indicating that technology familiarity had a moderating effect on the relationship between tradition barrier and attitudes toward using AI chatbots (γ = -0.43, z-value = -2.84, $p < 0.05$). Thus, H6e was supported (see Figure 12).

Figure 12. The Moderating Effects of *Technology Familiarity* on Relationships between R*easons Against* Factors (*Usage Barrier*, *Risk Barrier*, *Value Barrier*, *Image Barrier*, and *Tradition Barrier*) and *Attitudes toward Using AI Chatbots.*



Note. ** $p < 0.01$.

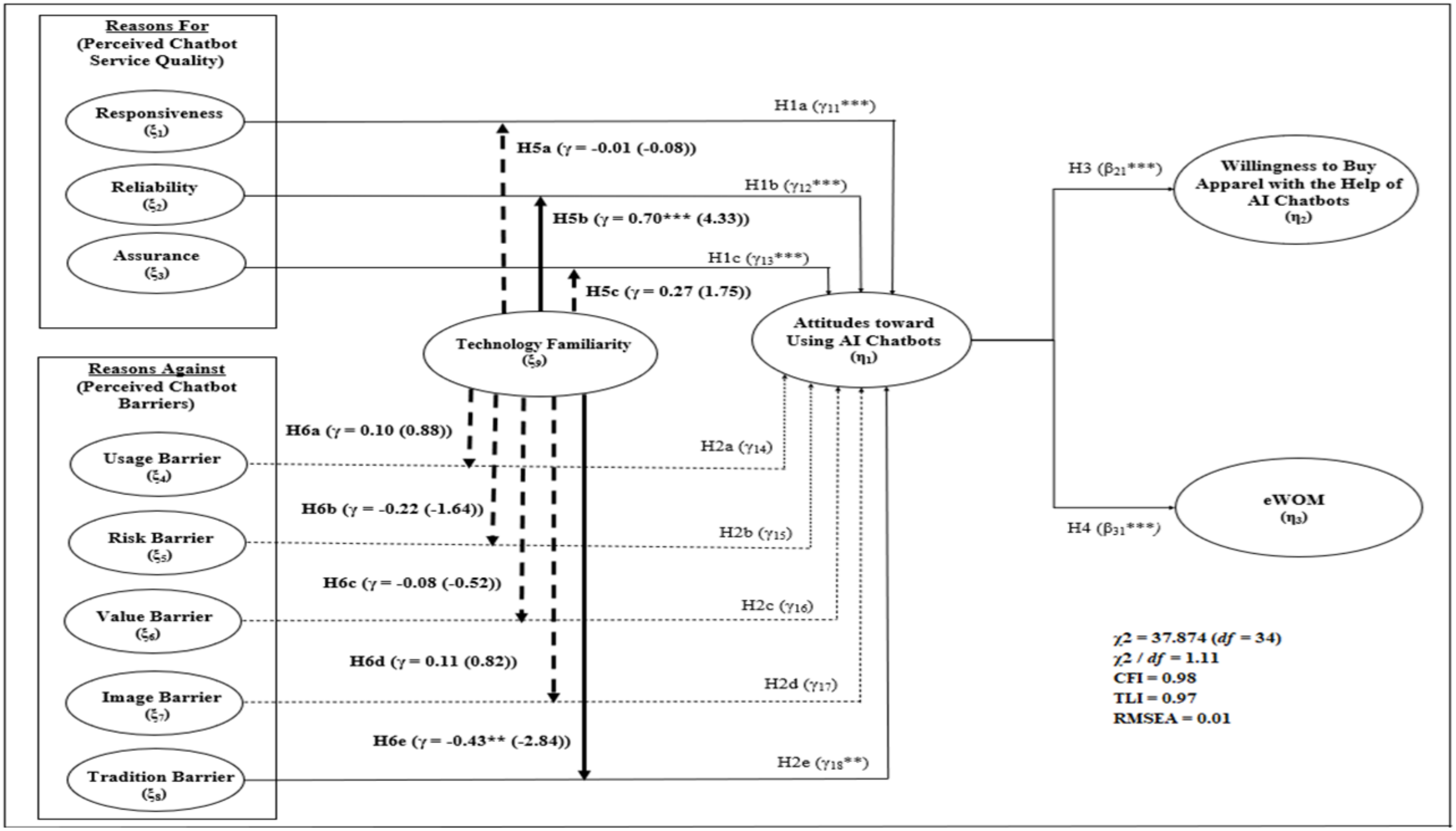
The dashed lines represent non-significant relationships. Values in paratheses represent the standardized coefficients in the outer parentheses and standard errors in the inner parentheses.

Table 14 and Figure 13 present the results of the moderating effects of *technology familiarity* on the model.

Table 14. Hypothesis Testing Results for Moderating Effects of Technology Familiarity

Hypothesis	Supported?
H5a: Technology familiarity will moderate the relationship between responsiveness and attitudes toward using AI chatbots.	No
H5b: Technology familiarity will moderate the relationship between reliability and attitudes toward using AI chatbots.	Yes
H5c: Technology familiarity will moderate the relationship between assurance and attitudes toward using AI chatbots.	No
H6a: Technology familiarity will moderate the relationship between usage barrier and attitudes toward using AI chatbots.	No
H6b: Technology familiarity will moderate the relationship between risk barrier and attitudes toward using AI chatbots.	No
H6c: Technology familiarity will moderate the relationship between value barrier and attitudes toward using AI chatbots.	No
H6d: Technology familiarity will moderate the relationship between image barrier and attitudes toward using AI chatbots.	No
H6e: Technology familiarity will moderate the relationship between tradition barrier and attitudes toward using AI chatbots.	Yes

Figure 13. Moderating Effects of Technology Familiarity



Note. *** p < 0.001; ** p < 0.01.

The dashed lines represent non-significant relationships. Values in paratheses represent the standardized coefficients in the outer parentheses and standard errors in the inner parentheses.

Chapter Summary

Chapter IV presented the data analysis, including descriptive statistics and confirmatory factor analysis. In addition, the hypothesized relationships were tested based on the two separate structural models, one on the main effects and the other one on the moderating effects. The next chapter will include a discussion, conclusions, implications, limitations, and future research directions.

CHAPTER V: DISCUSSION AND CONCLUSIONS

This chapter includes the following sections: (1) Discussion, (2) Conclusions, (3) Implications, (4) Limitations, and (5) Suggestions Recommendations for Future Research. Specifically, the first section discusses a summary of the study's findings. The second section presents conclusions from the study. The third section presents the practical and theoretical implications that arise from the study. Additionally, the third section highlights the weaknesses and limitations of the study. Finally, the fourth section provides suggestions and recommendations for future research.

Discussion

The purpose of this study was to develop and test a conceptual model of the antecedents and consequences of *attitudes toward using AI chatbots*. Specifically, the study examined the moderating effect of *technology familiarity* on the relationship between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots.*

To investigate the relationships between the antecedents and consequences of consumers' *attitudes toward using AI chatbots*, the study was guided by three primary objectives: (1) examining relationships between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*; (2) investigating relationships between consumers' *attitudes toward using AI chatbots* and their behavioral intentions as measured in terms of *willingness to buy apparel with the help of AI chatbots* and *eWOM*; and (3) examining the moderating role of *technology familiarity* on the relationships between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*. The findings of this study are discussed in the following sections.

Objective 1: Examining Relationships between *Reasons For* Factors (Perceived Chatbot Service Quality), *Reasons Against* Factors (Perceived Chatbot Barriers), and *Attitudes toward Using AI Chatbots*

Hypothesis 1: The Relationships between *Reasons For* Factors (a) *Responsiveness*, (b) R*eliability*, and (c) *Assurance* and *Attitudes toward Using AI Chatbots*

Reasons for is defined as the favorable factors that can encourage the adoption of a particular behavior (Westaby, 2005). Specifically, in this study, *reasons for* encompasses three dimensions of perceived chatbot service quality: *responsiveness*, *reliability*, and *assurance*. Responsiveness is defined as a chatbot's willingness to assist customers and provide them with timely and efficient service (Parasuraman et al., 1985). Reliability refers to the ability to perform the promised service in a consistent and accurate manner (Parasuraman et al., 1985). Assurance is "the term given in the services world to describe the sensation that a supplier of customer services transmits in terms of security and credibility" (Parasuraman et al., 1985, p. 12). Attitude refers to a person's feelings about a particular object (e.g., AI chatbots) that can encourage or discourage the performance of a specific behavior (Ajzen, 1991).

In this study, Hypothesis 1 proposed the relationship between *reasons for* (perceived chatbot service quality) factors (i.e., *responsiveness* (H1a), *reliability* (H1b), *assurance* (H1c)) and *attitudes toward using AI chatbots*. Prior research has shown that responsiveness is an important dimension of service quality (Parasuraman et al., 1988). Chang, Wang, and Yang (2009) found that responsiveness is positively associated with a user's overall perceived service quality. That is, a high level of responsiveness can enhance customer satisfaction and loyalty

(Parasuraman et al., 1988). Also, responsiveness has a positive influence on users' satisfaction in the context of online platform services (Kim, 2021). It also has a direct positive impact on customer engagement and loyalty in the context of service (Prentice & Nguyen, 2020). Some prior studies reported that different dimensions of e-service quality positively influenced consumer attitudes toward using a website in the context of online shopping (Wolfinbarger & Gilly, 2003; Yoo & Donthu, 2001). As responsiveness is one of the key dimensions of service quality, this study considered H1a, which predicted a relationship between *responsiveness* and *attitudes toward using AI chatbots*. The result indicates that *responsiveness* positively influences *attitudes toward using AI chatbots*. That is, consumers with favorable attitudes toward using AI chatbots are likely to perceive AI chatbots to be accessible, convenient for shopping, and highly responsive to customers' inquiries about product information (Chung et al., 2020). In other words, the higher consumers perceive an AI chatbot's level of responsiveness to be, the more likely consumers are to have a positive attitude toward using AI chatbots. The findings align with previous studies that responsiveness is positively related to attitudes in the context of video teller machine services (Nguyen, Vu, Nguyen, Nguyen, Do, & Nguyen, 2022) and online shopping (Wolfinbarger & Gilly, 2003; Yoo & Donthu, 2001).

According to Parasuraman et al. (1985), reliability is the ability of service providers to offer consistent services and fulfill their commitments to customers. In the context of AI chatbots, reliability can be viewed as the degree of how accuracy and consistency of the chatbots when providing information to customers' questions or inquiries. In this study, H1b predicted a relationship between *reliability* and *attitudes toward using AI chatbots*. The result indicates that *reliability* positively impacts *attitudes toward using AI chatbots*. Therefore, the findings are consistent with prior studies that identified the importance of reliability and proposed its impact on customers' satisfaction and their favorable attitudes toward services such as human interaction services (HIS) and self-service technology (SST) (Barua, Aimin, & Hongyi, 2018; Park et al., 2022). When consumers perceive AI chatbots to be reliable (i.e., they provide accurate product information and are effective in delivering request information), they are more likely to have a positive attitude toward using AI chatbots.

Assurance indicates service providers’ competency, knowledge, and capacity to establish trust with customers (Parasuraman et al., 1985). Assurance is an essential dimension of service quality and has a positive impact on customer satisfaction and engagement in different contexts, including on-demand home services (Sivathanu, 2019), restaurant businesses in South Korea (Kim & Shim, 2019), and the banking industry (Janahi & Al Mubarak, 2017; Selvakumar, 2016; Setiawan & Sayuti, 2017). Therefore, this study hypothesized *assurance* positively influences *attitudes toward using AI chatbots* (H1c). This result indicates a positive relationship between *assurance* and *attitudes toward using AI chatbots*. In other words, consumers are more likely to have positive attitudes toward AI chatbots when chatbots can provide trustworthy information and high-quality services and meet consumers' needs and wants. Moreover, consumers' perception of AI chatbots’ knowledge and competency could create a sense of confidence and reliability. This, in turn, can lead to a positive perception of the quality of service provided by AI chatbots. In addition, the study’s finding on H1c is consistent with Lee and Lin (2005), who also found a significant association between the assurance dimension of service quality and attitude in the context of online shopping.

The results indicate that there is a significant relationship between *reasons for* (perceived chatbot service quality) factors and *attitudes toward using AI chatbots*. Specifically, the findings confirm that r*esponsiveness*, *reliability*, and *assurance* dimensions of perceived chatbot service quality are key *reasons for* factors influencing consumers to develop favorable *attitudes toward using AI chatbots*. The results also confirm the behavioral reasoning theory (BRT), which states that reasons for particular behaviors are important and positive determinants of attitudes (Gupta & Arora, 2017; Pillai & Sivathanu, 2018).

Hypothesis 2: The Relationships between *Reasons Against* Factors (a) *Usage Barrier*, (b) *Risk Barrier*, (c) *Value Barrier*, (d) *Image Barrier*, and (e) *Tradition Barrier* and Consumers' *Attitudes toward Using AI Chatbots*

Reasons against is defined as the negative factors that can persuade a consumer to reject a specific behavior (Westaby, 2005). In this study, the *reasons against* construct includes five dimensions from the Innovative Resistance Theory (IRT) (Ram & Sheth, 1989): *usage barrier*, *value barrier*, *risk barrier*, *image barrier*, and *tradition barrier*. Usage barrier is defined as how consumers perceive the difficulty of using an innovation compared to their familiarity with an existing product (Ma & Lee, 2019). A value barrier occurs when there is resistance to an innovation due to its inconsistency with an existing product or service (Morar, 2013). Risk barrier is defined as "when the user does not adequately understand the innovative technology in the new product, the user cannot assess the associated risks and uncertainties that will arise after its use" (Lian & Yen, 2014, p. 135). Image barrier is defined as consumers' perceptions of the ease or difficulty of using an innovation (Mani & Chouk, 2018). A tradition barrier arises when an innovation leads to conflicts and changes between users and their traditional cultures (Ram & Sheth, 1989).

In this study, Hypothesis 2 investigated whether *reasons against* (perceived chatbot barriers) factors (i.e., *usage barrier* (H2a), *risk barrier* (H2b), *value barrier* (H2c), *image barrier* (H2d), and *tradition barrier* (H2e)) have negative relationships with *attitudes toward using AI* *chatbots.* According to Ram and Sheth (1989), all five barriers (usage barrier, image barrier, risk barrier, value barrier, and tradition barrier) can contribute to the acceptance or non-acceptance of new technologies.

H2a, H2b, H2c, and H2d were not supported by the results of the study that investigated negative relationships between *usage barrier*, *risk barrier*, *value barrier*, *image barrier*, and *attitudes toward using AI chatbots*. Since the usage barrier did not have a significant relationship with attitudes, other factors (risk barrier, value barrier, and image barrier) included in the *reasons for* also did not have significant relationships with attitudes. Therefore, the findings differ from what was expected, which could be that consumers may not perceive chatbot barriers (e.g., difficulty in use, offering lower-quality performance, and providing inaccurate product information) as important issues. Instead, if they are inclined to use chatbots for apparel shopping, they may simply use them. Furthermore, these consumers may also believe that they can overcome any challenges/difficulties that may arise when using AI chatbots for apparel shopping. Findings also suggest that in the specific context of AI chatbots for apparel shopping, these barriers may not be important factors influencing consumers' attitudes toward using AI chatbots. Interestingly, these results are not consistent with prior literature in various contexts, such as mobile gaming (Oktavianus, Oviedo, Gonzalez, Putri, & Lin, 2017), mobile commerce (Moorthy et al., 2017), mobile banking (Laukkanen, 2016), and e-tourism (Jansukpum & Kettem, 2015). However, the study findings align with a recent study conducted by Dhir et al. (2021) who found non-significant relationships between reasons against engaging in these barriers (usage, risk, value, and image barriers) and consumers' attitudes in the context of e-waste recycling. Hence, this study highlights that the connections between these barriers and attitudes may vary based on the context.

On the other hand, although only the tradition barrier (H2e) positively impacts attitudes toward using AI chatbots, the results do not support the proposed hypothesis. The term “positive association” implies that the tradition barrier increases, so do positive attitudes toward using AI chatbots. Consumers who prefer traditional shopping methods may be more inclined to use AI chatbots to fulfill their clothing shopping needs. In other words, consumers who value traditional in-store shopping experiences may approach new shopping methods, such as using AI chatbots, with caution. Consequently, they may harbor more positive feelings toward AI chatbots. Moreover, as they feel comfortable communicating with human customer service representatives, they may also have confidence when interacting with new technology like AI chatbots, even though it is a non-human customer service. Also, these consumers may perceive that AI chatbots can assist them in finding apparel products just as effectively as human customer service representatives. Consequently, their beliefs and appreciation of the capabilities of AI chatbots can significantly influence their attitudes toward using them for apparel shopping. Surprisingly, the study findings contradict previous studies; for example, the tradition barrier negatively influenced individuals’ adoption intentions in various contexts such as online shopping (Lian & Yen, 2014), mobile banking (Laukkanen, 2016), mobile commerce (Moorthy et al., 2017), and food delivery applications (Kaur et al., 2021). However, the results are consistent with some prior research, as the tradition barrier positively influences consumers’ resistance toward using online travel websites (Jansukpum & Kettem, 2015) and mobile banking (Yu et al., 2015).

In addition, AI chatbots have recently emerged as a novel and distinctive technology in the context of apparel shopping; as such, consumers may have different perceptions, positive or negative, toward their usage. Surprisingly, the findings of this study revealed no significant relationships between *usage, risk, value, or image barriers* and *attitudes toward using AI chatbots*, except for a positive relationship between *tradition barrier* and *attitudes toward using AI chatbots*. The results suggest that, for consumers, these barriers are not perceived as deterrents to using AI chatbots. Overall, it can be stated that this study's results are not consistent with the behavioral reasoning theory (BRT) in that the reasons against are not robust predictors of attitudes (Westaby, 2005).

Objective 2: Investigating Relationships between Consumers' *Attitudes toward Using AI Chatbots* and Their Behavioral Intentions as Measured in Terms of *Willingness to Buy Apparel with the Help of AI Chatbots* and *eWOM*

Hypotheses 3 and 4: The Relationships between *Attitudes toward Using AI Chatbots*, *Willingness to Buy Apparel with the Help of AI Chatbots*, and *eWOM*

Willingness to buy is characterized as consumers' behavioral intention to purchase a specific product in the future (Donato & Raimondo, 2020; Morrison, 1979). The term eWOM is defined as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institution(s) via the internet" (Hennig-Thurau et al., 2004, p. 39).

In this study, Hypotheses 3 and 4 examined the relationships between *attitudes toward using AI chatbots* and *willingness to buy apparel with the help of AI chatbots* and *eWOM*. These hypotheses were supported, indicating that *attitudes toward using AI chatbots* exhibit a positive relationship with the *willingness to buy apparel with the help of AI chatbots* and *eWOM*. These findings contradict previous studies' findings in that attitudes impact willingness to buy in various contexts (e.g., website services) (Barber et al., 2009; Phau et al., 2009; Ryan & Bonfield, 1975). In addition, consumers' attitudes positively influence their eWOM behavior on social networking sites (Chu & Kim, 2011) and in social commerce (Chu et al., 2020). According to the results, when consumers hold a favorable view of using AI chatbots, they are more willing to purchase apparel with the help of AI chatbots. Furthermore, consumers with positive feelings toward AI chatbots are more inclined to share positive reviews and comments about their experience with AI chatbots in apparel shopping on social media and other online platforms. Consequently, positive reviews from consumers may encourage other shoppers to utilize chatbot services offered by apparel companies.

Objective 3: Examining the Moderating Role of *Technology Familiarity* on the Relationship between *Reasons For* Factors (Perceived Chatbot Service Quality), *Reasons Against* Factors (Perceived Chatbot Barriers), and *Attitudes toward Using AI Chatbots*

Hypothesis 5: The Moderating Effect of *Technology Familiarity* on the Relationship between R*easons For* Factors (a) *Responsiveness*, (b) *Reliability*, and (c) *Assurance* and *Attitudes toward Using AI Chatbots*

Technology familiarity is defined as “the degree of experience and ability to use digital tools,” including smartphones, tablets, etc. (Byungura et al., 2018, p. 32). In this study, Hypothesis 5 proposed the moderating effects of technology familiarity on relationships between reasons for (perceived chatbot service quality) factors (i.e., *responsiveness* (H5a), *reliability* (H5b), and *assurance* (H5c)) and attitudes toward using AI chatbots. H5a and H5c were not supported, suggesting that technology familiarity does not moderate the effect of responsiveness and assurance on attitudes toward using AI chatbots. The non-significant interaction term indicates that the level of technology familiarity does not influence the relationships between responsiveness, assurance, and attitudes toward using AI chatbots. In other words, consumers’ attitudes toward using AI chatbots and their perception of the promptness and assurance of chatbot technology may or may not depend on their level of technology familiarity. For instance, although consumers are familiar with technology, they may be less optimistic about the capabilities of AI chatbots (e.g., AI chatbots provide quick and accurate assistance, efficient and effective product information, and clear and concise answers to consumers' questions), especially when compared to the human customer services.

On the other hand, H5b was supported. This result shows that technology familiarity moderates the effect of reliability on attitudes toward using AI chatbots, with the significant positive interaction term indicating that the more familiar consumers are with technology, the greater the influence of reliability on attitudes toward using AI chatbots. In other words, when consumers possess prior knowledge and experience with technology, they are more likely to trust in the ability of AI chatbots that consistently provide accurate and timely responses to their queries or requests.

Hypothesis 6: The Moderating Effect of *Technology Familiarity* on the Relationship between *Reasons Against* Factors and *Attitudes toward Using AI Chatbots*

Hypothesis 6 proposed the moderating effects of technology familiarity on relationships between *reasons against* (perceived chatbot barriers) factors (*usage barrier* (H6a), *risk barrier* (H6b), *value barrier* (H6c), *image barrier* (H6d), and *tradition barrier* (H6e)) and *attitudes toward using AI chatbots*.

The results indicate that H6a, H6b, H6c, and H6d were not supported, which means that there are no moderating effects of *technology familiarity* on relationships between *usage barrier*, *risk barrier*, *value barrier*, *image barrier*, and *attitudes toward using AI chatbots*. The results suggest that consumers' familiarity with technology may not necessarily be an important factor that can strengthen or weaken the relationships between these barriers (usage, risk, value, and image barriers) and consumers' attitudes toward using AI chatbots. In other words, whether consumers are highly familiar or less familiar with technology, it might not significantly affect how these barriers influence their attitudes toward using AI chatbots in the context of apparel shopping. For example, consumers with technological knowledge and experience might choose not to engage with AI chatbots for their apparel shopping. Conversely, consumers without technological familiarity may utilize AI chatbots for apparel shopping out of curiosity about how they function, whether they provide responses like human customer services, and whether they possess the ability to answer specific questions from consumers.

On the contrary, H6e was supported, indicating a negative moderating effect of technology familiarity, specifically on the relationship between the tradition barrier, among the five reasons against AI chatbot use factors (usage, risk, value, image, tradition barriers) and attitudes toward using AI chatbots. The findings suggest that the negative influence of the tradition barrier on attitudes toward using AI chatbots would be strengthened among those who exhibit a high degree of technology familiarity than those who exhibit a low degree of technology familiarity. In other words, higher levels of technology familiarity contribute to increasing negative perceptions (such as concerns about usability, miscommunication, and the nonhuman aspect of chatbots), ultimately reducing attitudes toward adopting AI chatbots for apparel shopping.

Conclusions

The current study developed and tested a conceptual framework examining the antecedents and consequences of attitudes toward using AI chatbots. The behavioral reasoning theory (BRT) was utilized as a theoretical framework that helps understand, predict, and evaluate consumers' adoption of AI chatbots. The BRT was extended by integrating the dimensions of service quality and barriers of innovation resistance theory into the study's conceptual framework. Three primary objectives guided the study: (1) to examine relationships between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*; (2) to investigate relationships between consumers' *attitudes toward using AI chatbots* and their behavioral intentions as measured in terms of *willingness to buy apparel with the help of AI chatbots* and *eWOM*; and (3) to examine the moderating role of technology familiarity on the relationship between *reasons for* (perceived chatbot service quality) factors, *reasons against* (perceived chatbot barriers) factors, and *attitudes toward using AI chatbots*.

The results of this study indicated that there were significant relationships between *reasons for* factors ((a) *responsiveness*, (b) *reliability*, (c) *assurance*) and attitudes towards using AI chatbots. The results also indicated significant relationships between *attitudes toward using AI chatbots*, *willingness to apparel with the help of AI chatbots*, and *eWOM*. Regarding the moderation effect of technology familiarity, the study found that there was a negative moderating effect of technology familiarity on the relationships between tradition barrier and *attitudes toward using AI chatbots*.

Specifically, this study highlights that *responsiveness*, *reliability*, and *assurance* are important reasons for using AI chatbots and suggests that apparel retailers should focus on improving these aspects to increase consumers' adoption of AI chatbots. On the other hand, this study found that contrary to the proposed hypothesis, the tradition barrier had a positive relationship with attitudes toward using AI chatbots. Thus, all five barriers (usage barrier, risk barrier, value barrier, image barrier, and tradition barrier) used to measure *reasons against* did not show a negative relationship with consumers' attitudes toward using AI chatbots. This implies that academics and retailers should recognize that these barriers may not be important reasons against AI chatbots use for apparel shopping. Instead, they should focus on other important factors (e.g., privacy concerns, miscommunication, and emotional understanding) that could prevent consumers' adoption of AI chatbots.

Overall, this current study contributes to the existing literature by investigating consumers' adoption of AI chatbots for apparel shopping purposes. The findings highlight the importance of various chatbot characteristics that can enhance consumers' AI chatbot usage. Additionally, the results provide valuable insights for academics and apparel retailers, indicating that consumers' level of technology familiarity may not play a significant role, as technology familiarity did not affect the relationships between several *reasons for* and *reasons against* factors and attitudes. This study also provides implications for both academics and apparel retailers seeking to better understand AI chatbot usage.

Implications

The findings of this current study contribute to the existing literature on the use of AI chatbots in apparel shopping. By addressing specific objectives, this study examines the antecedents that influence consumers' attitudes toward using AI chatbots and the consequences of attitudes toward using AI chatbots that affect consumers' willingness to buy apparel with the help of AI chatbots and eWOM.

Theoretical Implications

This study provides three major theoretical implications. First, by integrating the dimensions of perceived service quality and perceived barriers from the IRT into the BRT, this study provides a fresh perspective for gaining a deeper understanding of consumers' acceptance and nonacceptance of AI chatbots. It thus contributes to the literature by emphasizing the importance of consumers' perceptions of barriers and chatbot service quality.

Second, the study offers valuable insights into the literature by providing a detailed understanding of whether *reasons for* (perceived chatbot service quality dimensions, including *responsiveness*, *reliability*, and *assurance*) and *reasons against* (perceived chatbot barrier dimensions, including *usage barrier, risk barrier*, *value barrier*, *image barrier*, and *tradition barrier*) influence consumers' attitudes toward using AI chatbots, which, in turn, affects consumers' *willingness to buy apparel with the help of AI chatbots* and engage in *eWOM*. This is significant, considering that most prior studies focused on factors (social influence, social presence, perceived intelligence, hedonic motivation, inconvenience, etc.) that influenced consumers' adoption of AI chatbots. However, no studies have investigated whether responsiveness, reliability, and assurance serve as measures of the *reasons for* construct in the AI chatbot context. The findings of this study support the importance of factors, such as responsiveness, reliability, and assurance in influencing consumers' attitudes toward using AI chatbots. In addition, the findings highlight that these *reasons for* factors not only enhance consumers' favorable perceptions but also encourage them to use AI chatbots. Specifically, the study demonstrates that these reasons for factors (responsiveness, reliability, and assurance) are crucial determinants of attitudes as well as strong reasons for consumers' adoption of AI chatbots for apparel shopping.

On the other hand, while few studies have investigated the factors that may cause consumers to refuse the use of AI chatbots, no study has yet examined whether the five barriers (usage, risk, value, image, and tradition barriers) of the innovation resistance theory serve as measures of the *reasons against* construct and prohibitors to AI chatbot use for apparel shopping.

Therefore, this study used these five barriers as measures of the *reasons against* construct and examined the influence of *reasons against* on attitudes toward using AI chatbots. This study identifies that four of the five barriers (excluding the tradition barrier) were not significant reasons for adopting or rejecting AI chatbots. Only the tradition barrier, out of the five barriers tested, demonstrated a positive relationship with *attitudes toward using AI chatbots*-contrary to the initially proposed hypothesis of a negative relationship. This suggests that the tradition barrier may play a critical role in determining consumers' adoption of AI chatbots. The study suggests that when the tradition barrier has a positive relationship with attitudes toward using AI chatbots, consumers who hold stronger traditional values and prefer traditional shopping methods are more likely to use AI chatbots in the context of shopping for apparel. They might perceive AI chatbots as useful and effective substitutes for human customer service, leading to a positive attitude and an increased willingness to adopt this technology for apparel shopping.

Third, this study investigated the moderating role of *technology familiarity* on the relationships between *reasons for* and *reasons against* factors and *attitudes toward using AI chatbots*. The use of technology familiarity as a moderator has not received much attention in previous research on AI chatbot usage in the apparel retail industry. The findings of this study highlight the moderating role of *technology familiarity* on a positive relationship between *reliability* (one of the *reasons for* factors) and *attitudes toward using AI chatbots,* as well as a negative relationship between *tradition barrier* (one of the *reasons against* factors) and *attitudes toward using AI chatbots*. The study suggests that consumers with a higher level of technology familiarity are more likely to trust that chatbots are helpful and provide reliable and accurate product information. The findings highlight the importance of improving consumers' technology skills and familiarity with technology to increase the adoption of AI chatbots. By identifying this factor, this study filled a gap in the existing literature and added new knowledge to the AI chatbot context.

Practical Implications

The findings of this study are useful for apparel retailers and marketers seeking a deeper understanding of consumers' adoption of AI chatbots. The study offers three major practical implications. First, this study suggests apparel retailers and marketers offering AI chatbots should focus on factors that encourage or discourage consumers from using AI chatbots for apparel shopping. For example, the findings demonstrate that all three *reasons for* factors (responsiveness, reliability, and assurance) have positive relationships with attitudes toward using AI chatbots. The study highlights that consumers are more willing to use AI chatbots when they believe these technologies are responsive to their needs, reliable in their performance, and provide a sense of assurance in their interactions. Therefore, apparel retailers and marketers should pay great attention to using high-quality chatbots capable of clearly understanding consumers' questions and promptly providing relevant apparel product information. Additionally, they should ensure that their chatbots are reliable, providing accurate and relevant product information, and offering clear and concise responses to consumers' inquiries. By focusing on these dimensions, retailers and marketers can enhance the likelihood of consumers' adoption of AI chatbots for apparel shopping.

Second, the study findings indicate that four out of five *reasons against* factors (usage, risk, value, image, and tradition barriers) have no significant relationship with attitudes toward using AI chatbots. Only the tradition barrier has a positive impact on consumers' attitudes toward using AI chatbots, contrary to the initially proposed negative impact on attitudes. Therefore, apparel retailers and marketers should acknowledge that consumers who value traditional in-store shopping experiences and interact with human customer service may still be willing to use AI chatbots. In other words, consumers who are more inclined to traditional practices may actually be more likely to facilitate the adoption of AI chatbots for apparel shopping. Such consumers may perceive that AI chatbots can replace human customer service representatives in terms of effectiveness. To ensure a seamless experience when using AI chatbots, retailers and marketers should focus on educating consumers, especially those with little experience with chatbot usage for apparel shopping, about the capabilities and benefits of using chatbots and how chatbots can help them in place of a human customer service representative. By doing so, retailers and marketers can increase consumers' confidence and enhance their experience of using AI technology. On the other hand, this study identifies that most barriers (i.e., usage barrier, risk barrier, and value barrier) may not be critical factors, as they did not have a negative or positive influence on consumers' adoption of AI chatbots for apparel shopping. Consequently, retailers should understand that these barriers may not be significant obstacles to consumers' adoption of AI chatbots for apparel shopping. They should, therefore, focus on other factors that could influence consumers' adoption of this technology, such as privacy concerns, miscommunication, and the quality of their chatbot's customer service.

Finally, apparel retailers and marketers need to understand that some consumers with prior knowledge and experience with advanced technology are more likely to adopt AI chatbots. However, these consumers may encounter some barriers associated with the characteristics of chatbots, such as a higher level of usage barrier, including concerns or fears about facing any challenges or difficulties in their dealings with chatbots. That is why apparel retailers and marketers should ensure their chatbots are reliable and provide accurate product information to help their consumers find products they are looking for. This study suggests that apparel retailers and marketers should encourage their customers to try to use chatbots. For example, they should educate their consumers about how chatbots are efficient and convenient for apparel shopping (e.g., 24/7 availability and quick response times) and how they are helpful, just like human customer service representatives (e.g., providing personalized recommendations and assistance). This study also suggests that by offering step-by-step instructions or demonstration videos on how to use chatbots directly on their apparel company websites, apparel retailers and marketers can reduce consumers' concerns and hesitation regarding the adoption of these new innovations.

Limitations and Future Research Directions

This study has some limitations that may be addressed in future research. First, the generalizability of this study would be limited, as it examined AI chatbot usage only among U.S. consumers. Future research should focus on validating the current study's findings with consumers from other countries/cultures (e.g., Asian and/or European countries). For example, Landim et al. (2022) stated that according to the Statista online platform, in 2019, 77% of retail businesses in the United Kingdom were using AI chatbots to help their customers. In addition, according to a recent report by iResearch (2021), the chatbot market size in China (one of the Asian countries) is expected to reach 9.85 billion Yuan in 2025 (Jiang, Qin, & Li, 2022). Therefore, for future research, collecting data from other countries, such as the United Kingdom and China, where chatbot usage rates are higher, may result in interesting findings.

Second, this study focused on consumers with prior experience using AI chatbots. Consequently, it is important to know that the characteristics and perceptions of consumers with prior experience and without prior experience using AI chatbots may be significantly different. It would be more interesting if future research could explore the contrast by comparing different samples, specifically consumers who have used AI chatbots, with those consumers who have never used them. Such a comparison could provide valuable insights into different consumers' perceptions and behaviors in the AI chatbot context. In addition, future research could contribute to the existing literature by providing a deeper understanding of how consumers' different experiences using AI chatbots can influence their attitudes toward using them.

Third, this study found that most barriers (i.e., usage, risk, and value barriers) of the innovation resistance theory (IRT) were not associated with *attitudes toward using AI chatbots*. Therefore, these barriers may not be important factors that influence consumers' adoption of AI chatbots for apparel shopping. However, it is important to note that the study participants' demographic information may have impacted the results: the majority of the participants were male, which raises the question of whether men are as strongly influenced by barrier considerations as women or if they might be more confident in using new innovation than women. To better understand these barriers that shape consumers' attitudes toward using AI chatbots, future research should be conducted with other populations with different demographic characteristics.

Fourth, this study used technology familiarity as a moderator. According to the results, it is important to acknowledge that participants' prior technology knowledge and experience using technology may not influence their perceptions and attitudes toward using chatbots for shopping. Therefore, in future research, the conceptual model of this study can be revised by adding another interesting factor, such as perceived control or social influence. Perceived control refers to consumers' perception of their own ability to control a specific behavior (Langer & Saegert, 1977; Pearlin & Schooler, 1978; Wallston, Smith, & Dobbins, 1987). Social influence refers to the influence of other people's perception of a person's decision to perform a specific behavior (Wang, 2014). As AI chatbot technology is a relatively new innovation in the apparel retail industry, it is necessary to explore whether factors such as perceived control or social influence can affect the strength of the relationships between *reasons for*, *reasons against*, and *attitudes toward using AI chatbots*.

Finally, according to several studies, the assumptions of the original behavioral reasoning theory (BRT) include: (a) reasons (for/against) play an important role in determining attitude and behavioral intention; (b) attitude is a significant predictor of intentions and behavior; and (c) both reasons and attitude act as mediating variables in the overall model (Dhir et al., 2021; Sreen et al., 2021; Tandon et al., 2020; Westaby, 2005). This study focused on the relationships between *reasons for*/*against*, attitudes, and behavioral intentions, such as willingness to buy and eWOM. Future research could add value/belief to the conceptual model of this study and examine the influence of values on *reasons for*, *reasons against*, and attitudes. Value/belief is one of the strong components of BRT and predicts attitude and reasons in the BRT (Westaby, 2005). Understanding how values influence the reasons for and against using AI chatbots, as well as attitudes, may provide valuable insights into apparel consumers' adoption of AI chatbots. In summary, this study offers not only limitations but also potential avenues for future research on consumers' adoption of AI chatbots in the apparel retail industry.

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APPENDIX A: INSTITUTIONAL REVIEW BOARD APPROVAL

UNC GREENSBORO

February 28, 2023

Mon Thu Myin
Kittichai Watchravesringkan
Consumer Apparel-Retail Stds

Re: Modification Approval - 20-0134 - Drivers and barriers of AI chatbot usage in apparel retail shopping: Integrating behavioral reasoning theory and technology acceptance model

Dear Mon Thu Myin:

UNCG Institutional Review Board has rendered the decision below for Drivers and barriers of AI chatbot usage in apparel retail shopping: Integrating behavioral reasoning theory and technology acceptance model. This modification is now approved.

Decision: Exempt

Modification Information

1. I intend to expand my study by including new variables. So, I uploaded the updated questionnaire, which includes items for those variables.
2. The number of participants decreased from 1000 to 700.
3. Hypotheses were revised.
4. The questionnaire will not include any questions that can identify the participants.

If this modification involved changes to the consent form/IRB Information Sheet, please utilize the consent form/information sheet with the most recent version date when enrolling participants.

Sincerely,

UNCG Institutional Review Board

APPENDIX B: CONSENT FORM

Dear Participants,

You are invited to participate in this study. You must be 18 or older to participate and have previous experience using AI chatbots. We are conducting a survey about consumers' attitudes and behavioral intentions toward using AI chatbots for apparel shopping.

Please read the Consent Form below for your understanding of your rights. By clicking the next button to continue, you agree that you have read and fully understand the contents that appear in the Consent Form, and you are 18 years or older and are agreeing to participate in this study.

Your input is very important to continue the study. Please take about approximately 10 to 15 minutes to complete the survey. There are no right or wrong answers to the questions. Your privacy will be protected as the survey is anonymous, and all responses from participants will be kept strictly confidential. There are no anticipated risks from participating in this study and no benefit to you from participating in this study. By completing this survey, you are agreeing to participate in this study. There will be a $1 payment through Amazon Mechanical Turk to you for participating in this survey.

Thank you in advance for your participation. If you have any questions, please feel free to ask the researchers. We would be glad to assist you. In addition, if you have questions concerning your rights as a research subject, you may contact the University of North Carolina at Greensboro Institutional Review Board at 1-855-251-2351.

Sincerely,

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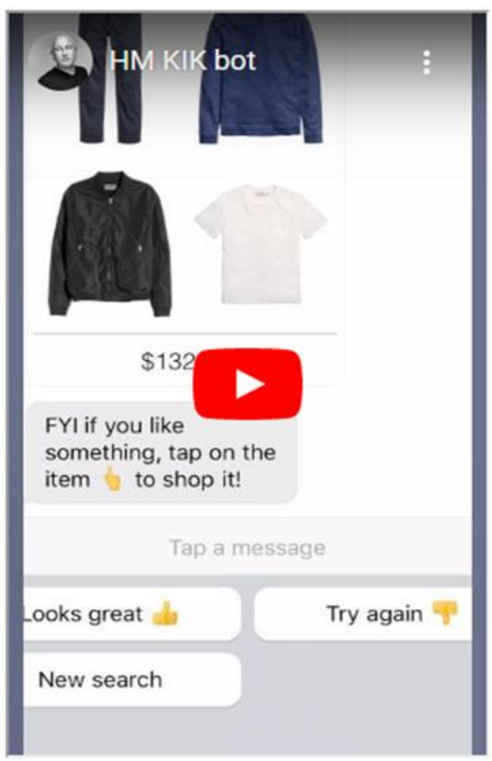
APPENDIX C: SURVEY QUESTIONNAIRE

Section – 1: What is AI chatbot?

Please read the brief description of the AI chatbot to answer questions in the following sections.

"AI chatbot or chatbot is an Artificial Intelligence software which can interact and chat with the users as human with the help of natural language processing (NLP). NLP is also the branch of AI, and it interprets human's language to the computer. AI chatbot can assist customers virtually as a stylist in searching for satisfied products in apparel shopping. The apparel brands Burberry, Tommy Hilfiger, Victoria's Secret, and H&M have adopted AI chatbots. Customers can use the chatbot application from a number of messaging platforms, including Facebook Messenger, Kik, and so on. If you want to use a chatbot for searching clothing items in Tommy Hilfiger, you can use it from the Facebook Messenger chatbot. However, if you want to use a chatbot for searching clothing items in H&M, you need to install the Kik application first and invite H&M, and then you can start your chatbot conversation."

H&M KIK bot YouTube video uploaded by Alex Picha also explains how the AI Chabot works below.



<u>Section – 2: Your experience of using AI chatbots</u>

Have you used AI chatbots before?

- ○ Yes
- ○ No

If yes, which business sector(s) and for what purpose(s) did you use it (Please check all that apply)?

- ☐ Fashion (e.g., for buying/searching clothing, shoes, accessories)
- ☐ Beauty (e.g., for buying/searching beauty products)
- ☐ Travel (e.g., for booking/buying travel tickets, booking and/or inquiry hotel rooms)
- ☐ Banking (e.g., for getting financial information and advice, getting alerts on potential issues or upcoming payments)
- ☐ Medical (e.g., for scheduling Dr. appointments, asking for medical records, prescription refills)
- ☐ Personal Services (e.g., for fitness, diet, health, day to day activities)
- ☐ Customer Services (e.g., for asking questions about a product or service, tracking shipping)
- ☐ Other (please specify it in the following box)

____

On average, how often do you use AI chatbots for your specific purposes?

- ○ Never
- ○ Once a year or less
- ○ Several times a year
- ○ Once a month
- ○ A few times a month
- ○ Once a week
- ○ A few times a week
- ○ Daily

Section – 3: Reasons for adoption of AI chatbots (Perceived chatbot service quality)

Please indicate **your agreement or disagreement** with the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
AI chatbots give prompt service to consumers.	○	○	○	○	○
AI chatbots are always willing to help consumers.	○	○	○	○	○
AI chatbots are never too busy to respond to users' requests.	○	○	○	○	○
Getting in contact with an AI chatbot is easy.	○	○	○	○	○
AI chatbots are always available when I need them.	○	○	○	○	○
AI chatbots reply quickly.	○	○	○	○	○
AI chatbots provide credible advice.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
AI chatbots are dependable.	○	○	○	○	○
AI chatbots provide the service right the first time.	○	○	○	○	○
AI chatbots are always working well.	○	○	○	○	○
I am able to access AI chatbots when I need to.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I believe product information provided by AI chatbots is trustworthy.	○	○	○	○	○
AI chatbots instill confidence in customers.	○	○	○	○	○
I would feel safe in the interaction with AI chatbots.	○	○	○	○	○
AI chatbots are knowledgeable to answer my questions.	○	○	○	○	○
AI chatbots are polite.	○	○	○	○	○

<u>Reasons against adoption AI chatbots (Perceived chatbot barriers)</u>

Please indicate **your agreement or disagreement** with the following statements about **the usage barrier that prevents using AI chatbots.**

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
AI chatbots are not easy to use.	○	○	○	○	○
I heard that the use of AI chatbots are not convenient.	○	○	○	○	○
I think that AI chatbots are not fast to use.	○	○	○	○	○
In my opinion, the use of AI chatbots is not clear.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements regarding **the risk barrier that prevents using AI chatbots**.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I fear that while I am searching for apparel through AI chatbots, the connection will be lost.	○	○	○	○	○
I fear that while I am using AI chatbots through my phone, the battery of the mobile phone will run out.	○	○	○	○	○
I fear that while I am searching for apparel products through AI chatbots, I might make mistakes providing wrong information about what type of clothes I am looking for.	○	○	○	○	○
Please choose "Neither agree nor disagree".	○	○	○	○	○
I feel that AI chatbot is not safe and secure to use for apparel shopping.	○	○	○	○	○
I fear that while using AI chatbot information will be misused.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements regarding **the value barrier that prevents using AI chatbots.**

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I am quite skeptical about the benefits of using AI chatbots.	○	○	○	○	○
In my opinion, AI chatbots do not offer any advantage compared to other shopping techniques such as visiting physical stores and getting assistant from human customer services for searching apparel products.	○	○	○	○	○
In my opinion, the use of AI chatbots will not increase my ability to search for the right apparel products I want.	○	○	○	○	○
Using AI chatbots is not a good substitute for traditional shopping (i.e., in-store shopping).	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements regarding **the image barrier that prevents using AI chatbots.**

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I have a very negative image of AI chatbots.	○	○	○	○	○
In my opinion, AI chatbots are often too complicated to be useful.	○	○	○	○	○
I have such an image that AI chatbots are difficult to use.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements regarding **the tradition barrier that prevents using AI chatbots.**

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Patronizing in the fashion retail stores and chatting with the salespersons is a nice occasion on a weekday.	○	○	○	○	○
I find AI chatbots less pleasant than those offered personally to customers.	○	○	○	○	○
I prefer to search for fashion products through physical stores rather than using AI chatbots.	○	○	○	○	○
I am so used to traditional stores to do shopping that I find it difficult to use AI chatbots.	○	○	○	○	○

<u>Technology familiarity, attitudes, willingness to buy, and eWOM.</u>

Please indicate **your agreement or disagreement** with the following statements about **your familiarity with using technology.**

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I am familiar with new technology and technological practices.	○	○	○	○	○
Compared to the general public, I am familiar with new technology and technological practices.	○	○	○	○	○
Compared to my friends and acquaintances, I am familiar with new technology and technological practices.	○	○	○	○	○
I am familiar with searching for apparel product information online.	○	○	○	○	○
Please choose "Neither agree nor disagree".	○	○	○	○	○
I am familiar with social media platforms.	○	○	○	○	○
I am familiar with the process of searching and getting information about apparel products.	○	○	○	○	○
I am familiar with the procedures of buying apparel online.	○	○	○	○	○
I am familiar with online apparel shopping.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements regarding **your attitudes toward using AI chatbots.**

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Using AI chatbots for shopping is a good idea.	○	○	○	○	○
Using AI chatbots for shopping would be pleasant.	○	○	○	○	○
The idea of using AI chatbots for apparel shopping is appealing.	○	○	○	○	○
I like the idea of searching and buying a product from AI chatbot services.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements regarding **your willingness to buy apparel with the help of AI chatbots.**

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I intend to buy apparel products via AI chatbots.	○	○	○	○	○
I would be willing to buy apparel products via AI chatbots.	○	○	○	○	○
In the future, I would buy apparel products via AI chatbots.	○	○	○	○	○
I would definitely try AI chatbots to buy apparel products.	○	○	○	○	○

Please indicate **your agreement or disagreement** with the following statements regarding **electronic word-of-mouth (eWOM)** intention to use AI chatbots.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I will recommend lots of people to use AI chatbots in the future.	○	○	○	○	○
I will frequently use AI chatbots and share my experience with my friends in the future.	○	○	○	○	○
I will give lots of positive word-of-mouth via the internet in the future.	○	○	○	○	○
Please choose "Neither agree nor disagree".	○	○	○	○	○
This eWOM information will crucially affect my apparel purchase decision.	○	○	○	○	○
I will refer to this eWOM information in a purchase decision.	○	○	○	○	○
Overall, I think this eWOM information is credible.	○	○	○	○	○

Section – 4: Your demographic information

Please indicate the following questions regarding your demographic information.

What is your age?

____

What is your gender?

○ Male

○ Female

What is your marital status?

○ Single, never married

○ Married

○ Separated

○ Divorced

○ Windowed

What is your ethnicity?

○ White

○ Black or African American

○ American Indian or Alaska Native

○ Hispanic

○ Asian

○ Native Hawaiian or Pacific Islander

○ Other

What is your educational background?

- ◯ Less than High School
- ◯ High School Graduate
- ◯ Trade/Technical/Vocational Training
- ◯ Associate Degree
- ◯ Bachelor's Degree
- ◯ Master's Degree
- ◯ Professional Degree
- ◯ Doctoral Degree

What is your annual income?

- ◯ Less than $20,000
- ◯ $20,001 - $35,000
- ◯ $35,001 - $50,000
- ◯ $50,001 - $65,000
- ◯ $65,000 - $80,000
- ◯ $80,001 - $95,000
- ◯ Over $95,000

Thank you for taking the time to complete this survey!