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Purchase intentions in a chatbot environment: An examination of the effects of customer experience

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Keywords: *artificial intelligence tools; chatbot; customer experience; purchase intention; uses and gratifications theory; usage frequency*

Abstract

Research background: Chatbots represent valuable technological tools that allow companies to improve customer experiences, meet their expectations in real time, and provide them with personalized assistance. They have contributed to the transformation of conventional customer service models into online solutions, offering accessibility and efficiency through their integration across various digital platforms. Nevertheless, the existing literature is limited in terms of exploring the potential of chatbots in business communication and studying their impact on the customer's response.
Purpose of the article: The main objective of this study is to examine how consumers perceive chatbots as customer service devices. In particular, the paper aims to analyze the influence of the dimensions of "Information", "Entertainment", "Media Appeal", "Social Presence" and "Risk for Privacy" on the "Customer Experience" and the latter on the "Purchase Intention", under the consideration of the Uses and Gratifications Theory. Moderations due to Chatbot Usage Frequency for some of the relationships proposed are also analyzed.
Methods: An empirical study was performed through a questionnaire to Spanish consumers. The statistical data analysis was conducted with R software through the lavaan package. To test the hypotheses from the conceptual model a structural equation modelling approach was adopted.
Findings & value added: The results obtained identify the main characteristics of chatbots that can support brands to effectively develop their virtual assistants in order to manage their relational communication strategies and enhance their value proposal through the online customer journey. Findings demonstrate the contribution that chatbot dimensions make to the online consumer experience and its impact on the purchase intention, with the consideration of the moderating effect exercised by the user's level of experience (novice vs. experienced) with the use of chatbots. Regarding managerial implications, this research offers recommendations for e-commerce professionals to manage chatbots more effectively. The "Entertainment" and "Social Presence" dimensions can be operationalized at a visual (e.g., appearance of the avatar and text box, use of designs aligned with the website) and textual level (e.g., style and tone of voice, use of expressions typical of the target audience) to generate a feeling of proximity with the chatbot and facilitate its adoption. "Media Appeal" requires that the chatbot be easy to use, effective, and accessible, to facilitate its usability. Finally, mitigation of "Privacy Risk" concerns should be achieved by presenting an appropriate privacy policy and requesting permission for the use of customers' private information.

Introduction

Companies make notable efforts to offer better experiences to their customers allowing them to build and consolidate solid relationships between consumers and brands. In this regard, technological advances play a fundamental role to help companies to improve their customers' experience (GS1, 2023).

Technology currently represents an essential tool for the expansion of the economy and e-commerce is gaining increasing importance in the context of business activity (Delloite, 2023). According to the Digital Market Outlook, the number of e-commerce users in Europe is expected to reach 564.4 million by 2026 (Statista, 2022). At the same time, consumers are increasingly demanding and expectant of their online experience (Emplifi, 2022). They demand a 24-hour service to receive assistance or advice in areas ranging from finances to leisure, health and well-being. To satisfy such requirements companies have opted for the development and implementation of virtual assistants.

In this context, chatbots have increased in popularity among businesses and consumers and have contributed to the transformation of conventional customer service models into digital solutions (Yuen, 2022). Chatbots transform the customers' experience by interacting with them through a natural dialogue. In addition to enabling immediate conversations on websites, social networks, or instant messaging applications anywhere (Hagberg *et al.*, 2016), chatbots also use a personalized language that mimics human speech, to improve the customer experience (Huang & Rust, 2018) and stimulate the purchase.

Thus, it is estimated that the total number of chatbot messaging applications worldwide will increase from 3.5 billion recorded in 2022 to 9.5 billion in 2026 (Juniper Research, 2022). This 169 per cent growth will be driven by the increasing adoption of omnichannel retail strategies by e-commerce agents and the growing integration of chatbots into messaging platforms. In addition, the number of revenues associated with these chatbots was estimated to be around 112bn in 2023 (Yuen, 2022).

Despite the significant boom in the use of chatbots and the increased interest of researchers in their study (e.g., Rese *et al.*, 2020; Jenneboer *et al.*, 2022; Chen *et al.*, 2022), the existing literature is mainly focused on the customer intention to use chatbots (De Keyser & Kunz, 2022; Ling *et al.*, 2021) and is limited in terms of exploring the potential of chatbots in business communication. Furthermore, there is scarce literature about the impact that chatbots have on the customer's relationship with the brand or company and the customer's response (Cheng & Jiang, 2020a) so additional research is needed to attain a better understanding about what factors customers look for when they use a chatbot service (De Keyser & Kunz, 2022; Illescas-Manzano *et al.*, 2021).

In this context, the present study aims to analyze consumer’s perception of chatbots as customer service devices. More specifically, it intends to verify the impact of dimensions of “Information”, “Entertainment”, “Media

Appeal", "Social Presence" and "Risk for Privacy" on the "Customer Experience" and the latter on the "Purchase Intention". The theoretical framework is built on the Uses and Gratifications Theory and encompasses usage-related factors, agent-related factors, and users-related factors (Ling *et al*., 2021).

To this end, a study of a quantitative nature was carried out using a questionnaire survey administered to a sample of consumers in the Spanish market, a territory in which this topic has hardly been studied. In this sense, the paper aims to contribute to the claims for the exploration of European contexts in order to investigate less developed and immature chatbot markets than those traditionally analyzed such as the North American market (De Keyser & Kunz, 2022).

At the academic level, this study aims to demonstrate how the chatbot can constitute an important component of the consumer experience and how this can have positive implications on purchase intention, a relationship that has been little explored in previous studies in the field of marketing (Trivedi, 2019; Yen & Chiang, 2021). In addition, this study applies the Uses and Gratifications model which, despite the importance it has been given in previous studies in the field of information and communication technologies, has received little attention in the study of chatbots users' perceptions (Ling *et al*., 2021). Complementarily, the present research includes dimensions such as "Customer Experience" (Alsharhan *et al*., 2023; De Keyser & Kunz, 2022) and "Purchase Intention" (De Keyser & Kunz, 2022) which have been less examined in previous studies and aims to contribute to the analysis of customer privacy issues related to the marketing strategies promoted by artificial intelligence (Rana *et al*., 2021).

Finally, our proposal aims to expand the analysis of moderating variables, a key aspect of understanding consumer behavior respecting chatbots. Previous research has found that the use of moderating variables in analysing the perception and process of using chatbots has been little explored and has therefore recommended their use in future research has been (De Cicco *et al*., 2020; Meyer-Waarden *et al*., 2020; Chen *et al*., 2021). To the best of our knowledge, the incorporation of moderators in the Uses and Gratifications Theory has not been previously considered in chatbot research under an e-commerce context. To fill this gap, our proposal incorporates the "chatbot usage frequency" as a moderator of some relationships proposed through the Uses and Gratifications Theory in order to elucidate if users' perceptions are different depending on their experience level. Despite the limited existing literature that incorporates moderators in chatbot research, previous studies have considered the user experience degree as a moderator (Alsharhan *et al*., 2023) because expectations can be linked to previous interactions with chatbots so experienced users could have different expectations than novice users (Gnewuch *et al*., 2022). Frequency of use is a behavioral variable that can be considered a moderator of customer-retailer relationships (Molinillo *et al*., 2021).

Along these lines, researchers have demonstrated the moderating role of frequency of use in customer behavior in different contexts, such as purchases made via the internet (Hernández *et al*., 2010), the use of restaurant services (Liang & Zhang, 2011), the use of electronic banking (Liébana-Cabanillas *et al*., 2016); the perception of tourist destinations (Tosun *et al*., 2015); and loyalty towards social commerce websites (Molinillo *et al*., 2021). However, the incorporation of this variable as a moderator is limited in existing chatbot research, and especially, in the Uses and Gratifications Theory research.

At the business level, this research intends to launch recommendations for e-commerce professionals to use chatbots more effectively to drive customer purchases, since businesses can design chatbots based on factors sought by the customer, in order to attain a gratifying customer experience (Ling *et al*., 2021).

The article is organized into three main parts. The first includes the theoretical background and the formulation of the research hypotheses. The second explains the methodology of the empirical work. Finally, the third part presents the conclusions and the main academic and management contributions that are intended to be made.

Theoretical background and research hypotheses

Uses and gratifications

Chatbots can provide positive experiences to customers and incorporate factors that motivate their use. In this context, one of the theoretical frameworks that allow us to understand the consumers' motivations to use chatbots is the Uses and Gratifications Theory. This theory seeks to explain the reasons why individuals use a particular media, or technological system, to satisfy specific communication needs (Cheung *et al*., 2011; Brandtzaeg &

Følstad, 2017). From this perspective, the use of these media, or technological systems, depends on the gratification they can provide to users and the goals they can satisfy (Luo & Remus, 2014; Rese *et al*., 2020).

The study of consumers' motivations to use new media and interactive technologies can be carried out from different theoretical approaches, many of which are widely used in the literature, such as the TAM Model (Davis, 1989), the Innovation Diffusion Model (Rogers, 1983), Relationship Marketing (Morgan & Hunt, 1994), among others. However, the Uses and Gratifications Theory deserves special attention, as it incorporates considerably more diverse motivations (Luo *et al*., 2011) and it turns out to be especially interesting for the study of the use and adoption of technologies and services (Rauschnabel, 2018). The Uses and Gratifications Theory has been applied in several studies related to the use of information and communication channels and technologies, such as the Internet (Song *et al*., 2004), social media (Gan & Wang, 2015; Elhadidi, 2018); email (Ku *et al*., 2013), mobile augmented reality games (Rauschnabel *et al*., 2017) and instant messaging services (Gan & Li, 2018).

Concept and importance of chatbot

Chatbots, also known as conversational agents (Kerly *et al*., 2007), can be described as an application or software that establishes a personalized dialogue and interaction with the user (Dale, 2016) by mimicking a human conversation (Yen & Chiang, 2021). In the context of e-commerce, chatbots allow users to ask questions related to the products or services they want to buy and receive faster, automated responses, without having to wait for a real salesperson, which could take longer (Rese *et al*., 2020). Chatbots have been on the rise in recent years and have already been widely adopted by companies that have online shops (Yen & Chiang, 2021). These conversational agents represent a channel that allows companies to reach their customers anytime and anywhere. Moreover, chatbots allow online shops to improve customer experience and meet customers' expectations through a real-time interaction system (Yen & Chiang, 2021).

Several authors have investigated the relationship between the use of chatbots and positive customer attitudes. Chung *et al*. (2020) studied the effect of chatbot services in the luxury retail context on customer satisfaction and demonstrated that these tools can help build positive relationships with customers. Jenneboer *et al*. (2022) found that there is a positive relationship between the use of chatbots and consumer loyalty, which in turn has implications for customer satisfaction and engagement.

However, despite the potential benefits associated with the use of chatbot, this tool also offers significant challenges for customer management. For example, users may feel uncomfortable interacting with artificial intelligence programs or taking their help into account in purchase decisions. The fact that chatbots lack feelings and empathy can cause them to be perceived as undesirable (Leung *et al.*, 2018), less trustworthy, or to generate dislike (Dietvorst *et al.*, 2018). Consumers also can fear the disclosure of their personal information and the disruption of their privacy (Cheng & Jiang, 2020a). In this sense, Huang and Rust (2018) point out that the future trend of these applications requires the development of algorithms to understand the emotional state of people and respond to it appropriately with care and feeling.

However, despite the relevance of the Uses and Gratifications model when applied to the use of chatbots, there has been little previous research.

Table 1 shows some examples of studies that have analysed users' perceptions of chatbots and that have used a conceptual model systematising the correlations between dimensions. Of the various studies analysed, only one uses the Uses and Gratifications model (Cheng & Jiang, 2020a, 2020b), and that one does not use "consumer experience" and "purchase intention" as dependent variables. By combining these dimensions as independent and dependent variables, the present study provides a new way of analysing this phenomenon.

All these studies used mediating dimensions, but few used moderating dimensions or multi-group analysis (Ischen *et al.*, 2020; Kasilingam, 2020; Kopplin, 2023; Li *et al.*, 2021; Rese *et al.*, 2020; Trivedi, 2019). Of the studies that used moderating variables, only one used the "experience of use" of mobile applications. Therefore, in this respect too, this study presents a different perspective of analysis compared to previous research, which reinforces the innovative nature of this study.

Research hypotheses

Following the perspective of previous research regarding the Uses and Gratifications model, we propose the conceptual model shown in Figure 1. Key concepts and relationships embedded in this model are detailed below.

Entertainment

The "Entertainment" dimension, in the context of using technology, refers to the search for hedonic gratification and the perception of value that can be provided by the feeling of emotional pleasure (Chung *et al*., 2020; Jansom *et al*., 2022). In the specific case of chatbots, it concerns the entertainment that can be provided by these devices and the pleasure that can be gained from using them (Fitria, *et al*., 2023).

Entertainment and fun seem to be at the root of users' attitudes towards technology. Thus, the use of digital tools is highly influenced by the level of entertainment that the individual associates with this type of activity, implying that the assumption of entertainment in a digital service positively influences the intention to use it (Misischia *et al*., 2022).

In the particular situation of chatbots, the perception of entertainment positively affects consumers' attitudes towards the performance of the service and, consequently, also their intention to buy with the support of this technology (Misischia *et al*., 2022). In other words, the more the user enjoys shopping using the chatbot as a fun interface, the more the chatbot will be considered in future purchases. In fact, several studies have concluded that "Entertainment" is positively related to user satisfaction when using chatbot services (Lee & Choi, 2017; Cheng & Jiang, 2020a). We have, therefore, established the following hypothesis:

H1: *"Entertainment" has a positive impact on "Customer Experience".*

Risk to privacy

This dimension refers to users' uncertainty about chatbots, fearing negative outcomes associated with the disclosure of personal information (Cheng & Jiang, 2020a).

The perception of risk to user privacy may negatively predict satisfaction with chatbot services (Cheng & Jiang, 2020a). Lack of security and privacy can lead to anxiety and a greater level of perceived risk among customers (Talwar *et al*., 2020) and a negative impact on customers' shopping and intentions (Collier & Bienstock, 2006). Customers are more likely to develop negative attitudes and eschew interaction with a company when they feel they have a lack of control over their data during the shopping experience (Kim, 2018). Therefore, concerns about unapproved access or use of consumer data are a critical component of customer experience (Piotrowicz & Cuthbertson, 2014). The decline or removal of these concerns about the risk for the consumer will increase customers' perceptions about the value in relation to the exchange experience (Rose *et al*., 2011). Thus, the privacy of the customers' personal information represents one of the crucial dimensions for the online customer experience (Anshu *et al*., 2022). Consequently, we suggest this hypothesis:

H2: *"Risk to Privacy" has a negative impact on "Customer Experience".*

Information

In the context of the Theory of Uses and Gratifications, "Information" corresponds to the search and obtaining of answers to certain questions posed by the user. This information can be transmitted by the company using text, images, or videos (Cheng & Jiang, 2020). Thus, the ability to transmit information refers to the aptitude of the medium to provide relevant data or information to users (Li & Mao, 2015).

When it comes to the use of chatbots, "Information Quality" has a positive impact on "Customer Experience" (Sfenrianto & Vivensius, 2020), and is positively related to user satisfaction (Cheng & Jiang, 2020). Thus, we postulate the following hypothesis:

H3a: *"Information Quality" has a positive impact on "Customer Experience".*

"Information Quality" encompasses the comprehensibility, sufficiency, and objectivity of information (Zhu *et al*., 2023). This aspect holds significance for chatbot services as the provision of accurate information to consumers is deemed vital in the utilization of chatbot-based services (Chung & Park, 2019).

Thus, the quality of the information provided by the chatbot influences "Customer Experience" and the intentions towards its use (Alagarsamy *et al*., 2023). Nevertheless, little research has explored the interactive role of frequency of use of chatbots and the relationship between "Information Quality" and "Customer Experience".

When a chatbot fails to provide the correct information at the right time, this can lead to bad user experiences that result in downtime (Trivedi, 2019). If the information quality is good, but not as per customer expectation, it creates a negative customer experience (Kushwaha *et al*., 2021). Then, users' expectations about a chatbot may depend on their prior experience with other chatbots (Gnewuch *et al*., 2022). Different studies suggest that users transfer expectations from their prior experience with other chatbots to their current interaction with a chatbot (Moussawi *et al*., 2020; Grimes *et al*., 2021).

Furthermore, the efficacy and capabilities of information systems can be more confidently assessed by users with prior experiences. In the consumer behavior discipline, the user's perceptions of efficacy and usefulness of a product or a service become more confident and solid as experience accumulates (Homburg *et al*., 2006). Thus, based on the above considerations, we postulate the following hypothesis:

H3b: *Chatbot Usage Frequency moderates the effect of "Information Quality" on "Customer Experience" so the effect is negative for experienced users.*

Media Appeal

"Media Appeal" refers to the ability of a technology to reach individuals quickly and easily. It describes the extent to which a medium can help users to communicate clearly and efficiently (Cheng & Jiang, 2020). In the case of social media, for example, this dimension represents the perception of using a technologically innovative platform (Wang & Oh, 2023).

In various studies, this dimension has been linked to positive attitudes or behaviors towards a particular technology. For example, Wibowo *et al*. (2018), in the context of the use of YouTube, found that technological gratification positively influenced the intention to continue using this platform. Gan and Li (2018) concluded that technological gratification was the dimension with the greatest impact on the intention to continue using instant messaging services (WeChat), followed by hedonic gratification (perceived pleasure) and utilitarian gratification (information). In his study, Jo (2022) found that media appeal, along with perceived enjoyment and information sharing, was a key factor in increasing the intention to continue using social networks. For his part, Gao (2023) found that technological gratification, incorporated into the notion of intelligence, was a determining factor in the intention to continue using smart mobile learning, and Cheng and Jiang (2020a) concluded that "Media Appeal" was positively related to user satisfaction with chatbot services. Thus, we propose the following hypothesis:

H4a: *"Media Appeal" has a positive impact on the "Customer Experience".*

Users may assess a chatbot's media capabilities differently based on their prior experience for several reasons. First, for more frequent users, the main motivation for using a chatbot is functionality and productivity, which is closely linked to the concept of usefulness, that is, expert users aim to receive a fast, reliable, and effective service that resolves their queries when interacting with chatbots (Brandtzaeg & Følstad, 2017) so a chatbot with strong media appeal can enhance their customer experience.

Second, self-confidence and anxiety levels of users depend on their prior experience when interacting with chatbots so more experienced users are likely to feel less anxiety and more self-confidence whereas novice users are likely to be less self-confident and experience a feeling of anxiety (Fernandes & Oliveira, 2021). On the one hand, previous studies support that technology anxiety reduces the intention to use self-service technologies (Li *et al*., 2021), and can provoke a feeling of creepiness that reduces trust and loyalty in chatbot technology (Rajaobelina *et al*., 2021), so novice users may assess its media ability inappropriately. On the other hand, when a user feels more self-confident, they seek a reliable and efficient chatbot that replies in a more appealing way to users' queries (Zhu *et al*., 2022). Additionally, based on their higher level of self-confidence to use self-service technologies, experienced users can better understand how to use them properly and so value their capabilities more highly. As a result, more frequent users can perceive specific self-service technologies, namely chatbots, as being easier to use and more useful than less experienced users (Blut *et al*., 2016) and experienced users can welcome their media appeal in a stronger way. Thus, previous literature supports a stronger impact of usefulness on purchase intention in online shopping (Gefen *et al*., 2003) and on the acceptance of chatbots (Fernandes & Oliveira, 2021) for more frequent users.

Considering the points mentioned above, the usage frequency of a technology can influence the level of technology anxiety and the perception of both the ease of use and usefulness, meaning that it can have an influence on the "Media Appeal" dimension. Therefore, we propose the following hypothesis.

H4b: *Chatbot Usage Frequency moderates the effect of "Media Appeal" on "Customer Experience" and the effect is stronger for experienced users than for novice users.*

Social presence

"Social Presence" can be referred to as the feeling of being with others and can be used to describe the relationships between users and brands or online shops (Ben Mimoun & Poncin, 2015). This dimension implies a psychological connection with the user because social presence represents "the extent to which machines (e.g., chatbots) make consumers feel that they are in the company of another social entity" (van Doorn *et al*., 2017, p. 44).

McLean and Osei-Frimpong (2019) emphasized the pivotal role of social presence in determining the technology's success. They underscored how the perception of being cared for influences the adoption of technology and consequently affects consumer behavior (Fernandes & Oliveira, 2021). Furthermore, the sense of belonging and social connection with others is fundamental to human functioning, serving to mitigate threats to identity, such as those encountered when interacting with humanoid robots (Mende *et al*., 2019; Kim *et al*., 2022). More specifically the social presence of chatbots influence consumer experience (Tsai *et al*., 2021), to the extent that it positively affects consumer engagement and consumers' behavioral intentions (Mariani *et al*., 2023; Jiang *et al*., 2022).

Like other factors related to Uses and Gratifications Theory, "Social Presence" is positively related to user satisfaction with chatbot services (Cheng & Jiang, 2020) and has a positive impact on loyalty (Jenneboer *et al*., 2022). Moreover, social interaction reduces the negative effects of a dehumanized technological environment (Wünderlich *et al*., 2013). In this way, social and emotional connections between the customer and the web-based service environment contribute to create a positive customer experience (Molinillo *et al*., 2021). Social presence does lead to more positive emotions (Konya-Baumbach *et al*., 2023) and generates a more positive experience (Rhim *et al*., 2022). Thus, we can posit the following hypothesis:

H5a: *"Social Presence" has a positive impact on "Customer Experience".*

Novice and experienced chatbot users show different expectations when interacting with a chatbot (Gnewuch *et al*., 2022). Novice users have high expectations about the human communication skills that chatbot can bring whereas experienced users are better aware of the limitations and instead of focusing on the level of social presence, they tend to consider other characteristics and functionalities (Brandtzaeg & Følstad, 2017). Based on the expectancy violations theory, which postulates that negative violated expectations have a stronger influence than negative confirmed expectations (Burgoon, 2015), the non-fulfilment of high expectations on human communication skills can cause a feeling of frustration (Gnewuch *et al*., 2022), which can lead to a worse customer experience among infrequent users. Therefore, a high level of social presence provided by a chatbot could represent for novice users a more appealing gratification than for experienced users. Furthermore, the impact of social presence on the intention to use chatbots is greater for novice users than for experienced users (Gnewuch *et al*., 2022) and some human communication characteristics implemented in chatbots such as response time (Gnewuch *et al*., 2022) or typing indicators (Gnewuch *et al*., 2018) foster a higher social presence level for novice users. Consequently, based on the above considerations, we establish the following hypothesis:

H5b: *Chatbot Usage Frequency moderates the effect of "Social Presence" on "Customer Experience" and the effect is stronger for novice users than for experienced users.*

Customer experience

"Customer Experience" (CX) can be considered as an aggregate of feelings, perceptions and attitudes formed during the decision-making process, involving an integrated series of interactions with people, objects, processes, and environments, leading to cognitive, emotional, sensory, and behavioral responses (Jain *et al*., 2017).

Thus, customer experience can be seen as a broad concept representing customers' subjective responses resulting from any contact with companies and brands (Gentile *et al*., 2007; Meyer & Schwager, 2007).

In the online environment, these interactions can be established with the website, platforms, and digital technologies, during service delivery (Trevinal & Stenger, 2014), which support customer purchase decisions (Kushwaha *et al*., 2021).

This subjective response is a multidimensional construct that can incorporate both cognitive and affective aspects (Rose *et al*., 2011). Therefore, online customer experience can be associated with functional factors, such as time saving and quality information, and with affective aspects, such as entertainment (Chen *et al*., 2021; Gümüş & Çark, 2021).

Customer experience has become a strategic goal for several companies (Bilgihan *et al*., 2016), and a central theme in market research due to its importance in competitive advantage and customer loyalty (Lemon & Verhoef, 2016).

Effectively, experience with brands plays a key role in determining consumer preferences and future decisions (Gentile *et al*., 2007). This experience can have implications for online consumer behavior (Rose *et al*., 2011), and brand loyalty (Pullman & Gross, 2004). There is, therefore, a positive and significant relationship between customer experience and behavioral intentions (Amenuvor *et al*., 2019). Several studies have found that customer experience is positively correlated with purchase intention (Yang & He, 2011; Nasermoadeli *et al*., 2013).

Purchase intention

"Purchase Intention" can then be considered as a probability expressed by customers to intend to purchase a particular product (Yeo *et al*., 2023). In the context of the Theory of Planned Behavior (TPB), proposed by Ajzen (1991), the individual's intention is the most appropriate predictor to explain his behavior (Haris *et al*., 2021). In fact, there is a significant relationship between purchase intention and actual purchase (Khan *et al*., 2023).

Information about consumer’s purchase intention can help companies make marketing decisions related to product demand, market segmentation, and promotional strategies (Dogra, & Kaushal, 2023), and it can positively influence the user experience (Stefko *et al*., 2022).

Consequently, online purchase intention is seen as an essential factor to predict the effectiveness of a series of digital strategies, such as the use of chatbots, for example (McLean *et al*., 2020). Thus, we postulate the following hypothesis:

H6: *"Customer Experience" has a positive impact on "Purchase Intention".*

Method

The empirical component of the present study was carried out in Spain, a country that has gained a significant number of e-commerce users in recent years (Statista, 2022) which, together with the spectacular rise in the use of chatbots (Forbes, 2017), has reinvigorated the percentage of Spanish companies that use them (Ontsi, 2021).

However, the adoption of artificial intelligence by Spanish companies is still incipient: 11.8% of Spanish companies with ten or more employees use artificial intelligence technologies. This percentage is 4.6% for microbusinesses with fewer than ten employees, and companies with fewer than 10 employees represent over 93% of the Spanish businesses (Ministry of Industry & Tourism, 2024). Regarding other types of technology, 31.8% of Spanish companies use cloud computing, 13.9% analyze big data, 7.8% use robots in their business processes and 30% offer online sales (Ontsi, 2023). In addition, around 40% of companies in the information and communication technology sectors have incorporated artificial intelligence. Nevertheless, the remaining Spanish industries offer much lower percentages (Ontsi, 2023).

Considering the above, the choice of the Spanish context for this research is based on its economic relevance, e-commerce growth, distinctive features due to the predominance of SMEs, and the lack of marketing papers addressing the study of chatbots in this country (as can be seen in Table 1). Statistics reveal that in Spain, the number of e-commerce users has significantly increased in recent years, although the use of artificial intelligence tools and applications is still very limited for Spanish businesses. Additionally, Spain is characterized by a business network with a clear predominance of small and medium-sized enterprises (SMEs). Specifically, 93.18% of Spanish companies are SMEs (Ministry of Industry & Tourism, 2024), so Spanish SMEs are pivotal in the national economy. These companies play a significant role in worldwide economies, as they face significant challenges due to limited access to resources and financing.

The potential development and the future evolution of the Spanish context represent an opportunity for marketing research, as understanding the capitalization of its digital growth could lead to interesting conclusions (Santos-Jaén *et al*. 2023). In this sense, data collection in the Spanish market can facilitate the development of comparative studies with other European countries in terms of cultural, socioeconomic, or technological differences.

Selection of units for the described study

To develop the quantitative study, a convenience sample, a technique that is widely used in social science research (Winton & Sabol, 2022), was used in an online survey. The participants included in the sample were asked to fill in a structured questionnaire with 33 questions based on their own experience of using chatbot in e-retailing (Chen *et al*., 2021) but first they had to complete screening questions to ensure that their most recent experience with chatbots was in the year prior to the survey and that they were able to remember this last encounter. The remaining questions for the final participants covered demographic details and items to measure the dimensions incorporated in the conceptual model (Figure 1).

A questionnaire in the Spanish language was developed about the experience with chatbots in e-commerce using Google Forms. Given that Internet data collection methods through self-reporting questionnaires from self-selected samples, are comparable in terms of data quality to other traditional methods (Gosling *et al*., 2004), this questionnaire was disseminated through popular social networks, forums, and email. Although, convenience samples have been questioned in marketing research (Ashraf & Merunka, 2017) due to the lack of generalizability and the related issues of non-random selection (Bethlehem, 2010), several reasons can justify their use. First, a convenience sample is a representative and appropriate sample when the goal is the analysis of fundamental human behavior (Viglia & Dolnicar, 2020), especially in e-retailing research (Walczuch & Lundgren, 2004). Second, in addition to the convenience of recruitment, this kind of sample also provides greater homogeneity in the responses, which allows researchers to be more confident in disconfirming the theoretical model in the case of a negative result (Viglia & Dolnicar, 2020). Third, contrary to the belief of lack of generalizability and the bias associated with this type of sample, it has been verified that the source from which the convenience sample comes does not have an impact on either the measurement model or the structural model and there are no significant differences with the results from probabilistic samples, so unobserved heterogeneity related to the convenience sample is not present (Winton & Sabol, 2022). Finally, following Winton and Sabol (2022), to avoid bias and lack of generalizability issues, the convenience sample could be justified through a high demographic variability. Table 3 shows a high variability regarding gender, age, and education. Additionally, related to the study population (chatbot users in e-retailing), Table 4 also shows a high variability regarding online shopping frequency, chatbot use frequency and regarding the commercial sector featuring in the last time a chatbot was used. All the previous reasons suggest that the sample obtained is free of bias and generalizability issues.

The data collection instrument was structured based on measurement scales used in previous literature research, which were adapted, modified, and extended for this study (Table 2). A five-point Likert scale (Chen *et al*., 2021) was employed to measure all constructs included in the questionnaire. The survey length spanned three weeks (the final sample was received by the last week of December 2021) and after rejecting cases with missing data and invalid participants, 173 responses were obtained.

Statistical data

The statistical data analysis was conducted with R software through the lavaan package. Specifically, to validate the measurement scale, we carried out a confirmatory factor analysis (CFA) and considered the usual measures for reliability, convergent validity, and discriminant validity. Next, to test the hypotheses of the conceptual model (Figure 1), we adopted a structural equation modelling approach due to its advantages over other traditional methods, such as multiple regression (Bagozzi & Yi, 1989). The sample size (N=173) exceeds the minimum sample size required of five times the number of indicators included in the model for the application of SEM (Hair *et al*., 2006). Table 3 shows the demographic characteristics of the participants.

First, regarding gender, there was a slight predominance of women (63%) compared to men (37%). Regarding the educational level, almost half of the respondents had a university degree.

Regarding the frequency of online purchases, slightly fewer than half of the respondents (45.1%) made a purchase per month (Table 4). Approximately 20% made purchases every 3 months, and 20.8% made a weekly purchase. As for the sector in which the respondents last interacted with a chatbot, the fashion, technology and other sectors predominate with percentages of 24.3%, 21.4% and 20% respectively (the remaining sectors considered were restaurants and takeaway food, supermarkets and hypermarkets, sports, cosmetics, and travel, hotels, and tourism). Finally, 35.8% of respondents had interacted with chatbots once in the last 6 months, 20.8%

had interacted twice in the last 6 months, and 16.2% had interacted at least 5 times in the last 6 months.

To check non-response bias in the sample (Armstrong & Overton, 1977) we performed a t-test to compare the answers of the early and the late respondents, which did not reveal significant differences.

In the proposed model, we also considered three control variables, namely, gender, education level and sector of the most recent interaction with a chatbot. To incorporate the moderator variable chatbot usage frequency in the structural model, participants that had not used or had used a chatbot only once in the last six months were classified as less frequent users, whereas participants that had used chatbot two or more times in the last six months were classified as more frequent users. Furthermore, unlike previous studies on chatbot research, which either check the moderations through simple t-Student tests (Kasilingam, 2020), multiple regression models (Trivedi, 2019) or multigroup analysis (Chen *et al*., 2021; Rese *et al*., 2020), to test the moderation hypotheses H3b, H4b and H5b, we considered the double-mean-centering procedure (Kolbe & Jorgensen, 2019; Lin *et al*., 2010) that requires mean-centering the indicators of the latent variables involved in the moderations. Indicators for the latent interaction factor are obtained by mean-centering the product terms produced by multiplying the mean-centered indicators of the associated latent variable and by the different levels of the moderator (Kolbe & Jorgensen, 2019). Several reasons justified the use of this procedure. First, unlike multigroup analysis (Kolbe & Jorgensen, 2019), a large sample size is not required for each group. Second, neither a mean structure nor a multiple-step procedure is involved in the model estimation (Lin *et al*., 2010). Finally, since the proposed model did not meet the normality requirement (p-value of the Mardia asymmetry test=2.0E-32; p-value Mardia kurtosis test=5.3E-32), this procedure outperforms other methodologies under non-normality conditions (Kolbe & Jorgensen, 2019).

Results

To analyze the reliability and validity of the measurement scales, we used CFA with the maximum likelihood method. For reliability, we considered the factor loadings of each item, the average factor loadings for each dimension, Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE). The criteria considered were factor loadings above 0.7 and mean factor loading for each construct above 0.7 (Hair *et al*., 2006), and both Cronbach's alpha values (Nunnally, 1978) and CR values above 0.7 (Fornell & Larcker, 1981) whereas for AVE the threshold considered was 0.5 (Fornell & Larcker, 1981). For discriminant validity, we have considered the Fornell and Larcker (1981) criterion, so that we had to compare the root of AVE with the correlations between dimensions.

Since the risk to privacy construct showed low convergent validity (AVE below 0.5), the item RP1 was removed. Additionally, due to the lack of discriminant validity, since the correlation between the dimensions "Information" and "Entertainment" and the correlation between "Social Presence" and "Customer Experience" were higher than the square root of the AVE of "Information" and "Social Presence" respectively, it was necessary to delete some items. Specifically, for this reason items IN2, EN1, SP2 and CX4 were removed.

Finally, Table 5 provides the factor loadings of the individual items, the average factor loading for the dimensions, CR and AVE for the final model, where most factor loadings (86.97%) are greater than 0.7, as well as the average factor loading of all the dimensions included in the final model, that were also greater than 0.7. Cronbach's alpha values ranged between 0.746 and 0.971 and CR ranged between 0.753 and 0.971, while AVE varied between 0.525 and 0.892 values, confirming that the final model m*et al*l the reliability criteria considered.

Next, Table 6 provides the square roots of the average variance in the diagonal and the correlation coefficients between dimensions under the diagonal for the analysis of discriminant validity. All the correlation coefficients are below the diagonal values and therefore the dimensions included in the final model comply with discriminant validity.

Since our survey data collected the independent and dependent variables through a self-report questionnaire, there could be a risk of common method bias (CMB). To control CMB, some actions were taken in the survey such as participants' anonymity, participants' knowledge, and participants' honesty (MacKenzie & Podsakoff, 2012). Additionally, some tests were performed to analyze the CMB. First, under the correlation matrix procedure CMV is not a problem if the correlations among dimensions are under 0.9 (Bagozzi *et al*., 1991) and Table 5 shows that all correlations are less than 0.874. Second, a common method factor containing all the items of all the dimensions was included in the CFA (following Williams *et al*., 2003). The result of chi-square difference test between the model with and without the common method factor (Table 7) showed that the difference between the models is not significant, so it is unlikely that the CMB is a problem. Additionally, Table 7 includes the squared factor loadings of each item in the substantive latent variables (substantive variance) and the squared factor loadings of common method (method-based variance). The small magnitude of the average method-based variance (R22=0.106) compared to the average substantively variance (R12=0.642) shows that CMB is not a serious concern.

Once the measurement model had been evaluated, a SEM model was then adjusted to test the hypotheses included in the final model. Given the non-fulfilment of the normality condition, for the model fit we considered the Satorra-Bentler statistic (Satorra & Bentler, 1994), ($\chi 2$ =713.480; p-value=0.005, df=580) so that the ratio $\chi 2$/df = 1.230 was below cutoff 2 (Tabachnick *et al*., 2007). We also considered the non-normality correction (Brosseau-Liard *et al*., 2012) for the root mean square error of approximation (RMSEA) whose value 0.036 (with a CI= [0.028,0.044]) was below the required threshold of 0.06 (Hu & Bentler, 1999). Additionally, we considered the non-normality versions (Brosseau-Liard & Savalei, 2014) for the comparative fit index (CFI) with a value of 0.970 and the Tucker-Lewis index (TLI) with a value of 0.966 and, therefore, above the threshold of 0.95 (Hu & Bentler, 1999). In addition, we considered the non-normed fit index (NNFI) with a value of 0.966, the incremental fit index (IFI) with a value of 0.970 (both index greater than 0.95) and the SRMR value with a value of 0.061 (less than 0.08) (Hu & Bentler, 1999).

Table 8 and Figure 2 provide standardized coefficients for the hypothesized relationships in the final model and summarize the main model fit values. To test the set of hypotheses established in the conceptual model (Figure 1), we consider the Wald test (Wang & Rhemtulla, 2021). Concerning hypotheses related to "Customer Experience", the dimensions considered in the conceptual model explained 89.3% of the variance in "Customer Experience". Hypothesis H1 is accepted because there is a significant positive impact of "Entertainment" (0.393, $p<0.001$). Thus, the entertainment provided by the interaction with chatbots improves the experiences of customers. Regarding risk to privacy, this has a significantly negative impact on "Customer Experience" (-0.082, p-value=0.046) so hypothesis H2 is supported.

Regarding hypothesis related to “Information”, although the moderation hypothesis H3b (-0.264, p-value=0.032) is supported and hence this dimension has a negative impact on the “Customer experience” of users with a high chatbot usage frequency (-0.279), hypothesis H3a is rejected due to the negative insignificant impact of “Information” on “Customer experience” for novice users (-0.016, p-value=0.894).

Next, the dimension “Media Appeal” impacts directly and significantly on “Customer Experience” in a positive way (0.297, p-value=0.055), so through the skills associated to chatbots, novice customers can enjoy better experiences. This direct effect on “Customer experience” is significantly moderated by chatbot usage frequency (0.491, p-value=0.035) and for expertise customer the effect of “Media Appeal” is stronger (0.748). Consequently, hypothesis H4a and H4b are confirmed.

Regarding “Social Presence”, a significant positive relationship between “Social Presence” and “Customer Experience” is also supported (0.351, p-value=0.010), but moderated by chatbot usage frequency (-0.279, p-value=0.057) which confirms hypothesis H4b. Specifically, the resulting effect for experienced user is positive but not significant (0.073), so the effect is significant only for infrequent users and hence hypothesis H4a is partly confirmed.

Concerning hypothesis H6, a better customer experience can impact on “Purchase Intention” positively (0.735, p-value<0.001) supporting H6 with an overall R2=0.540.

Finally, Table 8 also summarizes the total indirect effects both for less and more frequent users of chatbot to show the influence of “Information”, “Entertainment”, “Media Appeal”, “Social Presence” and Risk to Privacy on Purchase Intention. The results show for less frequent users that “Entertainment” is the greatest gratification with the strongest positive indirect impact being on “Purchase Intention” (0.289), followed by “Social Presence” (0.258), “Media Appeal” (0.218) whereas Risk to Privacy has a negative impact (-0.060) and “Information” has no significant effect. For most frequent users, “Social Presence” is an insignificant gratification to foster “Purchase Intention” and “Media Appeal” has the most positive indirect impact (0.550), followed by “Entertainment” (0.280). On the other hand, “Information” (-0.205) and Risk to Privacy (-0.063) significantly reduce their “Purchase Intention”.

Discussion

The main objective of this work was to develop and validate a model to extend the understanding of the customer's purchase intention in an e-commerce context, taking into account the customer's experience with the use of chatbots. Unlike previous studies, which have analyzed the antecedents of customer experience in interaction with chatbots (Cheng *et al*., 2021; Kushwaha *et al*., 2021; Trivedi, 2019), our model contemplates the Theory of Uses and Gratifications to achieve a better knowledge of purchase intention (Yen & Chiang, 2021), but instead of considering consumer trust (Yen & Chiang, 2021), satisfaction (Cheng & Jiang, 2020a) or intention to use (Cheng & Jiang, 2020a; Rese *et al*., 2020), in our case we combine several constructs along with customer experience. Some discussions and contributions can be established from the findings.

First, the study establishes that the purchase intention of a potential customer is encouraged by a satisfactory customer experience with chatbot usage. These results are consistent with previous studies which found that experience can be positively correlated with consumers' behavioral intentions, namely purchase intention (Bilal *et al*., 2024; Chen *et al*., 2023).

Second, a hedonic gratification, entertainment, has a direct positive impact on customer experience and consequently it indirectly drives "Purchase Intention", contrary to results from Yen and Chiang (2021). This finding is in accordance with previous studies that established positive consequences such as satisfaction with chatbots (Cheng & Jiang, 2020a; Chung *et al*., 2020), intention to use chatbots (Gan & Li, 2018; Rese *et al*., 2020), attitude toward chatbots (De Cicco *et al*., 2020; Kasilingam, 2020), customer loyalty (Cheng & Jiang, 2020a) or positive customer-brand relationship (Cheng & Jiang, 2022) from enjoyable interactions with chatbots.

Third, "Media Appeal", the ability of the medium to help users to communicate clearly and efficiently, has been shown to have a positive impact on customer experience and hence on the "Purchase Intention", unlike results from Yen and Chiang (2021). Previous researchers have found positive relationships between media appeal and positive consequences of using chatbots, such as satisfaction and customer loyalty (Cheng & Jiang, 2020a) or intention to continue using a medium (Gan & Li, 2018). Furthermore, the influence of this dimension to provide better customer experience is stronger among experienced chatbot users, so for this kind of customer it is essential that they feel the chatbot can solve their queries in an efficient and fast way in order to encourage purchases.

Fourth, in line with Gnewuch *et al*. (2022), social presence is a gratification whose impact on customer experience is moderated by the users' experience level. However, contrary to Gnewuch *et al*. (2022), our results show that this gratification only provides better experiences that encourage purchase intention for novice users, while it is not significant for expert users, who do not expect a specific level of social presence in their interaction with a chatbot. Thus, our study expands on previous results on the influence of "Social Presence" on "Purchase Intention" of chatbot users (Yen & Chiang, 2021) and links its impact to the degree of user expertise.

Additionally, in accordance with previous results (Trivedi, 2019), our study reveals that if customers perceive privacy risk while interacting with a chatbot from an e-commerce company, their customer experience will be limited, and purchase intention would be reduced. Previous literature on chatbot usage also confirms this negative effect of privacy risk on concepts such as satisfaction with chatbots (Cheng & Jiang, 2020a), intention to use chatbots (Rese *et al*., 2020), attitude toward chatbot (Kasilingam, 2020) or loyalty (Cheng & Jiang, 2020a; Rajaobelina *et al*., 2021).

Finally, in this study it was not possible to demonstrate that "Information" has a positive impact on customer experience for customers with less chatbot usage frequency in accordance with Kushwaha *et al*. (2021). In fact, for expertise chatbot users this dimension has a negative effect on customer experience. Consequently, regardless of the information quality provided by chatbots, experienced customers demand the correct information linked to their specific queries at the right time, and a failure in their queries can drive users to downtime and negative customer experiences (Trivedi, 2019). Thus, more experienced consumers may not have product information or current trends among their expectations, so an information overload may occur (Hsu *et al*., 2023; Chou & Hsu, 2021), and this can impair the customer experience of these consumers. Contrary to previous results (Yen & Chiang, 2021), our findings show that information does not indirectly influence the purchase intention of non-expert consumers and it may even reduce the purchase intention of expert consumers. Specifically, when consumers use chatbots to buy certain products or services, they conceive that the role of the chatbot is to resolve their problems and support them in their purchase process, and they do not need information about current trends or new products. In accordance with Hsu *et al*.

(2023), our results reinforce chatbots as touchpoints that are more suitable within a light-information context than under an information-intensive one. This result is not entirely consistent with previous studies that established positive consumer behaviors deriving from information provided by chatbot usage, such as satisfaction and loyalty (Cheng & Jiang, 2020a) or customer-brand relationship (Cheng & Jiang, 2022). Nevertheless, Spain occupies the fourteenth position in Europe in the adoption of artificial intelligence, at a considerable distance from leading countries in the implementation of this technology, such as Denmark or Finland (Ontsi, 2023). At the regional level, there is high heterogeneity, and the digitalization process of companies is lagging behind. In this sense, the lack of technology maturity in the Spanish online shopping market may explain the eventually insignificant or negative effect of information quality.

Conclusions

Theoretical implications

Some theoretical contributions can be derived from our study. First, our work aims to extend previous studies on how technological advances and the use of artificial intelligence allow brands and companies to strengthen their relationships with customers by supporting the business value of chatbots as a new touchpoint in the online customer journey.

Second, our work may provide new empirical evidence of how the Uses and Gratifications Theory explains users' perception of chatbots, an approach that has rarely been used so far in this area of study. The proposed model incorporates usage-related factors and agent-related factors as antecedents of customer experience and a user-related factor as a moderator in order to analyse if novice and experienced users seek different gratifications when interacting with chatbots. With this proposal, we intend to provide insights into the dimensions of chatbots that improve online customer experience across industries and to explore the role of moderating variables, something that has enjoyed scant consideration in e-service agent research. Additionally, the contextual frame of our research is Spain, so our study contributes to the exploration of chatbot interaction in European contexts to analyse less developed chatbot markets.

Third, from a methodological point of view, the moderator has been incorporated in the structural model by the double-mean-centering procedure, an approach considered less frequently in this research area, where interactions have been mainly analyzed by multiple regression models or multigroup analysis.

Fourth, to understand how customer privacy impacts on the marketing strategies promoted by artificial intelligence, this work, delves into the influence that privacy risk has on reducing purchase intention and provides a better understanding of the role that privacy issues play in customers' interactions with chatbots. However, the positive gratifications that a chatbot can provide to both novice and experienced users can overcome their privacy concerns and boost their purchase intentions.

Finally, the present study is a new contribution towards a better understanding of antecedents and outcomes of online customer experiences with chatbots. The investigation also underlines that customer experience with chatbots is a key factor in driving sales in e-commerce by fully mediating the effect of dimensions included in the model on the purchase intention, a relationship that has been given scant consideration the previous literature about chatbots. Consequently, the results of this study aim to capture the main characteristics of chatbots that can support brands to effectively develop their virtual assistants to promote their sales strategies.

Managerial implications

Since chatbots are a novel technology for Spanish consumers, our research can provide guidelines for companies' chatbot designers to help them in the development of chatbots that drive sales of their products through the customer experiences delivered by the chatbot service. Among the dimensions analysed, our results suggest that for all Spanish users, "Entertainment", "Media Appeal" and avoiding privacy risk are significant aspects of chatbot service to drive sales through the chatbot customer experience. Additionally, social presence is a relevant chatbot skill only for Spanish novice users, whereas for Spanish experienced users information overload significantly diminishes the customer experience. Companies should analyse the best way to incorporate these characteristics in their chatbots in order to satisfy novice and experienced consumer expectations and to promote sales.

The "Entertainment" and "Social Presence" components can be worked on in the chatbot at a visual level, through the appearance of the avatar and text box, the use of colors and design that should be in line with the style of the website and the profile of the target consumer. On a textual level, the choice of a suitable style and tone of voice and the use of expressions typical of the target audience can contribute to a feeling of proximity and entertainment using the chatbot. Through social presence, companies can help novice customers who are averse to the use of new technologies and prefer the service provided by a human agent to make the transition to chatbot agents. Since in Spain the use of chatbots is an emerging trend that has not yet reached the level of other countries such as the USA or China, by increasing the number of users who use chatbots instead of human assistants when making their purchases, companies can reduce their costs and increase their profits.

Media appeal requires an effort at the level of usability of the chatbot itself, which should be easy, effective, and accessible to use in meeting customer's expectations. Especially for experienced users, an efficient way to drive sales is to provide short and concise information related to the user's query rather than promoting new products or trends through chatbots.

Finally, to encourage purchases, companies, and brands must guarantee consumer security in their interactions with chatbots. Mitigation of privacy risk concerns could be achieved by presenting an appropriate privacy policy and requesting permission for the use of private information.

Limitations and directions for future research

This work is not without limitations. First, the small size of the sample makes it difficult to extrapolate the results. In addition, since the questionnaire has been answered by people who have had some experience with a chatbot, it would also be interesting to consider those who have never used this tool yet, to explore the inhibitors and motivations that act negatively on chatbots. Furthermore, respondents were asked to recall their own experiences with chatbots, but future research could root the study in real data from consumers that perform a real purchase with a chatbot service.

Second, the study is not limited to a specific sector, so the results obtained could be considerably different in the case of considering a specific product or service as a moderator. Other potential moderators, such as

Internet speed or the device used for the chatbot interaction, need additional research to elucidate whether the relationships proposed in the model may vary. Third, the study is limited to the Spanish context with results that are contradictory with studies based on other markets, so it would be worth expanding the study to consider other culturally similar countries, as part of an intercultural comparative approach. Finally, antecedents of some dimensions such as "Social Presence" or "Entertainment" can be analyzed, for example, gender of the chatbot or the use of emoticons, gifts, or avatars.

References

Adam, M., Wessel, M., & Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 1–20. https://doi.org/10.1007/s12525-020-00414-7.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Alagarsamy, S., & Mehrolia, S. (2023). Exploring chatbot trust: Antecedents and behavioural outcomes. *Heliyon*, *9*(5), e16074. https://doi.org/10.1016/j.heliyon.2023.e16074.

Alsharhan, A., Al-Emran, M., & Shaalan, K. (2023). Chatbot adoption: A multiperspective systematic review and future research agenda. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2023.3298360.

Amenuvor, F., Owusu-Antwi, K., & Basilisco, R. (2019). Customer experience and behavioral intentions: The mediation role of customer perceived value. *International Journal of Scientific Research and Management*, *7*(10), 1359–1374. https://doi.org/10.18535/ijsrm/v7i10.em02.

Anshu, K., Gaur, L., & Singh, G. (2022). Impact of customer experience on attitude and repurchase intention in online grocery retailing: A moderation mechanism of value co-creation. *Journal of Retailing and Consumer Services*, *64*, 102798. https://doi.org/10.1016/j.jretconser.2021.102798.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior, 85*, 183–189. https://doi.org/10.1016/j.chb.2018.03.051.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*(3), 396–402. https://doi.org/10.1177/0022 24377701400320.

Ashraf, R., & Merunka, D. (2017). The use and misuse of student samples: An empirical investigation of European marketing research. *Journal of Consumer Behaviour*, *16(4)*, 295–308. https://doi.org/10.1002/cb.1590.

Bagozzi, R. P., & Yi, Y. (1989). On the use of structural equation models in experimental designs. *Journal of Marketing Research*, *26*(3), 271–284. https://doi.org/10.2307/3172900.

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly*, *36*(6), 421–458. https://doi.org/10.2307/2393203.

Ben Mimoun, M. S., & Poncin. I. (2015). A valued agent: How ECAs affect website customers' satisfaction and behaviors. *Journal of Retailing and Consumer Services*, *26*, 70–82. https://doi.org/10.1016/j.jretconser.2015.05.008.

Bethlehem, J. (2010). Selection bias in web surveys. *International Statistical Review*, *78(2)*, 161–188. https://doi.org/10.1111/j.1751-5823.2010.00112.x

Bilal, M. Zhang, Y., Cai, S., Akram, U., & Halibas, A. (2024). Artificial intelligence is the magic wand making customer-centric a reality! An investigation into the relationship between consumer purchase intention and consumer engagement through affective attachment. *Journal of Retailing and Consumer Services, 77*, 103674. https://doi.org/10.1016/j.jretconser.2023.103674.

Bilgihan, A., Kandampully, J., & Zhang, T. C. (2016). Towards a unified customer experience in online shopping environments: Antecedents and outcomes. *International Journal of Quality and Service Sciences*, *8*(1), 102–119. https://doi.org/10.1108/IJQSS-07-2015-0054.

Blut, M., Wang, C., & Schoefer, K. (2016). Factors influencing the acceptance of self-service technologies: A meta-analysis. *Journal of Service Research*, *19*(4), 396–416. https://doi.org/10.1177/1094670516662352.

Brandtzaeg, P., & Følstad, A. (2017). Why people use chatbots. In *Proceedings of the 4th international conference on internet science, Thessaloniki, Greece, 22-24 November 2017*, (pp. 377–392) Springer. https://doi.org/10.1007/978-3-319-70284-1_30.

Brosseau-Liard, P. E., & Savalei, V. (2014). Adjusting incremental fit indices for nonnormality. *Multivariate Behavioral Research*, *49*(5), 460–470. https://doi.org/10.1080/00273171.2014.933697.

Brosseau-Liard, P. E., Savalei, V., & Li, L. (2012). An investigation of the sample performance of two nonnormality corrections for RMSEA. *Multivariate Behavioral Research, 47*(6), 904–930. https://doi.org/10.1080/00273171.2012.715252.

Burgoon, J. K. (2015). Expectancy violations theory. In C. R. Berger & M. E. Roloff (Eds). *The international encyclopedia of interpersonal communication* (pp 1–9). New York: Wiley Blackwell.

Chen, J. S., Tran-Thien-Y, L., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, *49*(11), 1512–1531. https://doi.org/10.1108/IJRDM-08-2020-0312.

Chen, Q., Gong, Y., Lu, Y., & Tang, J. (2022). Classifying and measuring the service quality of AI chatbot in frontline service. *Journal of Business Research*, *145*, 552–568. https://doi.org/10.1016/j.jbusres.2022.02.088.

Chen, S., Li, X., Liu, K., & Wang, X. (2023). Chatbot or human? The impact of online customer service on consumers' purchase intentions. *Psychology & Marketing, 40*, 2186–2200. https://doi.org/10.1002/mar.21862.

Cheng, Y., & Jiang, H. (2020a). How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. *Journal of Broadcasting & Electronic Media*, *64*(4), 592–614. https://doi.org/10.1080/08838151.2020.1834296.

Cheng, Y., & Jiang, H. (2020b). AI-Powered mental health chatbots: Examining users' motivations, active communicative action and engagement after mass-shooting disasters. *Journal of Contingencies and Crisis Management*, *28*, 339–354. https://doi.org/10.1111/1468-5973.12319.

Cheng, Y., & Jiang, H. (2022). Customer–brand relationship in the era of artificial intelligence: Understanding the role of chatbot marketing efforts. *Journal of Product & Brand Management*, *31*(2), 252–264. https://doi.org/10.1108/JPBM-05-2020-2907.

Cheung, C., Chiu, P.-Y., & Lee. M. (2011). Online social networks: Why do students use Facebook? *Computers in Human Behavior*, *27*, 1337–1343. https://doi.org/10.1016/j.chb.2010.07.028.

Chou, E-Y., & Hsu, W-C. (2021). Conversational service experiences in chatbots: A perspective on cognitive load. *Management Review, 40*, 111–130. https://doi.org/10.6656/MR.202101_40(1).ENG111.

Chung, K., & Park, R.C. (2019). Chatbot-based healthcare service with a knowledge base for cloud computing. *Cluster Computing*, *22*(S1), 1925–1937. https://doi.org/10.1007/s10586-018-2334-5.

Chung, M. J., Ko, E. J., Joung, H. R., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587–595. https://doi.org/10.1016/j.jbusres.2018.10.004.

Chung, S., Kramer, T., & Wong, E. M. (2018). Do touch interface users feel more engaged? The impact of input device type on online shoppers' engagement, affect, and purchase decisions. *Psychology & Marketing, 35*(11), 795–806. https://doi.org/10.1002/mar.21135.

Collier, J. E., & Bienstock, C. C. (2006). How do customers judge quality in an e-tailer? *MIT Sloan Management Review, 48*(1), 35–40.

Dale, R. (2016). The return of the chatbots. *Natural Language Engineering*, *22*(5), 811–817. https://doi.org/10.1017/S1351324916000243.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008.

De Cicco, R., Silva, S. C., & Alparone, F. R. (2020). Millennials' attitude toward chatbots: an experimental study in a social relationship perspective. *International Journal of Retail & Distribution Management*, *48*(11), 1213–1233. https://doi.org/10.1108/IJRDM-12-2019-0406.

De Keyser, A., & Kunz, W. H. (2022). Living and working with service robots: A TCCM analysis and considerations for future research. *Journal of Service Management*. https://doi.org/10.1108/JOSM-12-2021-0488.

Delloitte (2023). Unlock the full potential of your e-commerce transformation. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/de/Documents/customer-marketing/Deloitte_Unlock-eCommerce-Transformation-2023.pdf

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, *64*(3), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643.

Dogra, P., & Kaushal, A. (2023). The impact of digital marketing and promotional strategies on attitude and purchase intention towards financial products and service: A Case of emerging economy. *Journal of Marketing Communications*, *29*(4), 403–430. https://doi.org/10.1080/13527266.2022.2032798.

Elhadidi, A. (2018). Beyond access to social media: A comparison of gratifications, interactivity, and content usage among Egyptian adults. *Global Media Journal*, *16*(30), 1–13.

Emplifi (2022). Top 35+ customer experience statistics to know in 2022. Emplifi Retrieved from https://emplifi.io/resources/blog/customer-experience-statistics (5.08.2022).

Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, *122*, 180–191. https://doi.org/1016/j.jbusres.2020.08.058.

Fitria, T., Simbolon, N., & Afdaleni (2023). Chatbots as online chat conversation in the education sector. *International Journal of Computer and Information System*, *4*(3), 93–104.

Forbes (2017). How chatbots improve customer experience in every industry: An infograph. Forbes Inc. Retrieved from https://www.forbes.com/sites/blakemorgan/2017/06/08/how-chatbots-improve-customer-experience-in-every-industry-an-infograph/?sh=377115d067df (5.08.2022).

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312.

Gan, C., & Li, H. (2018). Understanding the effects of gratifications on the continuance intention to use WeChat in China: A perspective on uses and gratifications. *Computers in Human Behavior*, *78*, 306–315. https://doi.org/10.1016/j.chb.2017.10.003.

Gan, C., & Wang, W. (2015). Uses and gratifications of social media: A comparison of microblog and WeChat. *Journal of Systems and Information Technology*, *17*(4), 1–12. https://doi.org/10.1108/JSIT-06-2015-0052.

Gao, B. (2023). A uses and gratifications approach to examining users' continuance intention towards smart mobile learning. *Humanities & Social Sciences Communications, 10*(726), 1–13. https://doi.org/10.1057/s41599-023-02239-z.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Inexperience and experience with online stores: The importance of TAM and trust. *IEEE Transactions on Engineering Management*, *50*(3), 307–321. https://doi.org/10.1109/TEM.2003.817277.

Gentile, C., Spiller, N., & Noci, G. (2007). How to sustain the customer experience: An overview of experience components that co-create value with the customer. *European Management Journal*, *25*(5), 395–410. https://doi.org/10.1016/j.emj.2007.08.005.

Gnewuch, U., Morana, S., Adam, M. T., & Maedche, A. (2018). "The chatbot is typing..." – the role of typing indicators in human-chatbot interaction. In *SIGHCI 2018 proceedings*. AIS e-Library. Retrieved from https://aisel.aisnet.org/sighci2018/14.

Gnewuch, U., Morana, S., Adam, M. T., & Maedche, A. (2022). Opposing effects of response time in human–chatbot interaction: The moderating role of prior experience. *Business & Information Systems Engineering, 64*(6), 773–791. https://doi.org/10.1007/s12599-022-00755-x.

Gosling, S. D., Vazire, S., Srivastava, S., & John, O. P. (2004). Should we trust web-based studies? A comparative analysis of six preconceptions about internet questionnaires. *American Psychologist*, *59*(2), 93. https://doi.org/10.1037/0003-066X.59.2.93.

Grimes, G. M., Schuetzler, R. M., & Giboney, J. S. (2021). Mental models and expectation violations in conversational AI interactions. *Decision Support System*, *144*, 113515. https://doi.org/10.1016/j.dss.2021.113515.

GS1 (2023). Trend research 2023-2024: Innovation in a world of continuous disruption. Retrieved from https://www.gs1.org/docs/innovation/gs1-trend-research-3rd-edition-090823.pdf

Gümüş, N., & Çark, Ö. (2021). The effect of customers' attitudes towards chatbots on their experience and behavioural intention in Turkey. *Interdisciplinary Description of Complex Systems: INDECS*, *19*(3), 420–436. https://doi.org/10.7906/indecs.19.3.6.

Gupta, A., & Sharma, D. (2019). Customers' attitude towards chatbots in banking industry of India. *International Journal of Innovative Technology and Exploring Engineering*, *8*(11), 1222–1225. https://doi.org/10.35940/ijitee.J9366.0981119.

Hagberg, J., Sundstrom, M., & Egels-Zandén, N. (2016). The digitalization of retailing: An exploratory framework. *International Journal of Retail & Distribution Management*, *44*(7), 694–712. https://doi.org/10.1108/IJRDM-09-2015-0140.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis*. *Vol. 6*. Upper Saddle River, NJ: Prentice Hall.

Haris, J., Rahim, S. A., Haris, M., & Zahari, M. S. (2021). Using the theory of planned behaviour to predict purchase intention towards using Taobao. *International Journal of Academic Research in Business and Social Sciences*, *11*(2), 952–959. https://doi.org/10.6007/IJARBSS/v11-i2/9191.

Hernández, B., Jiménez, J., & Martín, M.J. (2010). Customer behavior in electronic commerce: The moderating effect of e-purchasing experience. *Journal of Business Research*, 63(9–10), 964–971. https://doi.org/10.1016/j.jbusres.2009.01.019.

Homburg, C., Koschate, N., & Hoyer, W. D. (2006). The role of cognition and affect in the formation of customer satisfaction: A dynamic perspective. *Journal of Marketing*, 70(3), 21–31. https://doi.org/10.1509/jmkg.70.3.021.

Hsu, P. F., Nguyen, T., Wang, C. Y., & Huang, P. J. (2023). Chatbot commerce—How contextual factors affect Chatbot effectiveness. *Electronic Markets*, *33*(14), 1–22. https://doi.org/10.1007/s12525-023-00629-4.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459.

Illescas-Manzano, M. D., Vicente-López, N., Afonso-González, N., & Cristofol-Rodríguez, C. (2021). Implementation of chatbot in online commerce, and open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(2), 1–20. https://doi.org/10.3390/joitmc7020125.

Ischen, C., Araujo, T., Noort, G. van, Voorveld, H., & Smit, E. (2020). I am here to assist you today: The role of entity, interactivity and experiential perceptions in chatbot persuasion. *Journal of Broadcasting & Electronic Media, 64*(4), 615–639. https://doi.org/10.1080/08838151.2020.1834297.

Jain, R., Aagja, J., & Bagdare, S. (2017). Customer experience – A review and research agenda. *Journal of Service Theory and Practice*, *27*(3), 642–662. https://doi.org/10.1108/JSTP-03-2015-0064.

Jansom, A., Srisangkhajorn, T., & Limarunothai, W. (2022). How chatbot e-services motivate communication credibility and lead to customer satisfaction: The perspective of Thai consumers in the apparel retailing context. *Innovative Marketing*, *18*(3), 13–25. https://doi.org/10.21511/im.18(3).2022.02.

Jenneboer, L., Herrando, C., & Constantinides, E. (2022). The impact of chatbots on customer loyalty: A systematic literature review. *Journal of Theoretical and Applied Electronic Commerce Research*, *17*(1), 212–229. https://doi.org/10.3390/jtaer17010011.

Jiang, K., Qin, M., & Li, S. (2022). Chatbots in retail: How do they affect the continued use and purchase intentions of Chinese consumers? *Journal of Consumer Behavior, 21*, 756–772. https://doi.org/10.1002/cb.2034.

Jo, H. (2022). Antecedents of continuance intention of social networking services (SNS): Utilitarian, hedonic, and social contexts. *Mobile Information Systems, 2022*, 7904124. https://doi.org/10.1155/2022/7904124.

Juniper Research (2022). Chatbot messaging app accesses to reach 9.5 billion globally by 2026: Driven by online retail growth. Juniper Research. Retrieved from https://www.juniperresearch.com/press/chatbot-messaging-app-accesses-reach-9-bn?ch=chatbot (5.08.2022).

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*, 101280. https://doi.org/10.1016/j.techsoc.2020.101280.

Kerly, A., Hall, P., & Bull, S. (2007). Bringing chatbots into education: Towards natural language negotiation of open learner models. *Knowledge-based Systems*, *20*(2), 177–185. https://doi.org/10.1016/j.knosys.2006.11.014.

Khan, Y., Hameed, I., & Akram, U. (2023). What drives attitude, purchase intention and consumer buying behavior toward organic food? A self-determination theory and theory of planned behavior perspective. *British Food Journal*, *125*(7), 2572–2587. https://doi.org/10.1108/BFJ-07-2022-0564.

Kim, H., So, K. K. F., & Wirtz, J. (2022). Service robots: Applying social exchange theory to better understand human–robot interactions. *Tourism Management, 92*, 104537. https://doi.org/10.1016/j.tourman.2022.104537.

Kim, M. S. (2018). Factors influencing willingness to provide personal information for personalized recommendations. *Computers in Human Behavior*, *88*, 143–152. https://doi.org/10.1016/j.chb.2018.06.031.

Kim, M., & Chang, B. (2020). The effect of service quality on the reuse intention of a chatbot: Focusing on user satisfaction, reliability, and immersion. *International Journal of Contents, 16*(4), 1–15. https://doi.org/10.5392/IJoC.2020.16.4.001.

Kolbe, L., & Jorgensen, T. D. (2019). Using restricted factor analysis to select anchor items and detect differential item functioning. *Behavior Research Methods, 51*, 138–151. https://doi.org/10.3758/s13428-018-1151-3.

Konya-Baumbach, E., Biller, M., & von Janda, S. (2023). Someone out there? A study on the social presence of anthropomorphized chatbots. *Computers in Human Behavior*, *139*, 107513. https://doi.org/10.1016/j.chb.2022.107513.

Kopplin, C. (2023). Chatbots in the workplace: A technology acceptance study applying uses and gratifications in coworking spaces. *Journal of Organizational Computing and Electronic Commerce, 32*(3-4), 232–257. https://doi.org/10.1080/10919392.2023.2215666.

Ku, Y., Chu, T., & Tseng, C. (2013). Gratifications for using CMC technologies: A comparison among SNS, IM, and e-mail. *Computers in Human Behavior, 29*(1), 226–234. https://doi.org/10.1016/j.chb.2012.08.009.

Kushwaha, A. K., Kumar, P., & Kar, A. K. (2021). What impacts customer experience for B2B enterprises on using AI-enabled chatbots? Insights from big data analytics. *Industrial Marketing Management*, *98*, 207–221. https://doi.org/10.1016/j.indmarman.2021.08.011.

Lee, S., & Choi, J. (2017). Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity. *International Journal of Human-Computer Studies*, *103*, 95–105. https://doi.org/10.1016/j.ijhcs.2017.02.005.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), 69–96. https://doi.org/10.1509/jm.15.0420.

Leung, E., Paolacci, G., & Puntoni, S. (2018). Man versus machine: Resisting automation in identity-based consumer behavior. *Journal of Marketing Research*, *55*(6), 818–831. https://doi.org/10.1177/0022243718818423.

Li, L., Lee, K. Y., Emokpae, E., & Yang, S. B. (2021). What makes you continuously use chatbot services? Evidence from Chinese online travel agencies. *Electronic Markets*, *31*, 575–599. https://doi.org/10.1007/s12525-020-00454-z.

Li, M., & Mao, J. (2015). Hedonic or utilitarian? Exploring the impact of communication style alignment on user's perception of virtual health advisory services. *International Journal of Information Management, 35*(2), 229–243. https://doi.org/10.1016/j.ijinfomgt.2014.12.004.

Liang, R. D., & Zhang, J. S. (2011). The effect of service interaction orientation on customer satisfaction and behavioral intention: The moderating effect of dining frequency. *Procedia-Social and Behavioral Sciences*, *24*, 1026–1035. https://doi.org/10.1016/j.sbspro.2011.09.082.

Liébana-Cabanillas, F., Muñoz-Leiva, F., Sánchez-Fernández, J., & Viedma-del Jesús, M.I. (2016). The moderating effect of user experience on satisfaction with electronic banking: Empirical evidence from the Spanish case. *Information Systems and E-Business Management, 14*(1), 141–165. https://doi.org/10.1007/s10257-015-0277-4.

Lin, G. C., Wen, Z., Marsh, H. W., & Lin, H. S. (2010). Structural equation models of latent interactions: Clarification of orthogonalizing and double-mean-centering strategies. *Structural Equation Modeling, 17*(3), 374–391. https://doi.org/10.1080/10705511.2010.488999.

Ling, E. C., Tussyadiah, I., Tuomi, A., Stienmetz, J., & Ioannou, A. (2021). Factors influencing users' adoption and use of conversational agents: A systematic review. *Psychology & Marketing*, *38*(7), 1031–1051. https://doi.org/10.1002/mar.21491.

Lubbe, I., & Ngoma, N. (2021). Useful chatbot experience provides technological satisfaction: An emerging market perspective. *South African Journal of Information Management, 23*(1), a1299, 1–8. https://doi.org/10.4102/sajim.v23i1.1299.

Luo, M., & Remus, W. (2014). Uses and gratifications and acceptance of Web-based information services: An integrated model. *Computers in Human Behavior*, *38*, 281–295. https://doi.org/10.1016/j.chb.2014.05.042.

Luo, M., Chea, S., & Chen, J. (2011). Web-based information service adoption: A comparison of the motivational model and the uses and gratifications theory. *Decision Support Systems*, *51*(1), 21–30. https://doi.org/10.1016/j.dss.2010.11.015.

MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing, 88*(4), 542–555. https://doi.org/10.1016/j.jretai.2012.08.001.

Mariani, M. M., Hashemi, N., & Wirtz, J. (2023). Artificial intelligence empowered conversational agents: A systematic literature review and research agenda. *Journal of Business Research, 161*, 113838. https://doi.org/10.1016/j.jbusres.2023.113838.

McLean, G., Osei-Frimpong, K., Wilson, A., & Pitardi, V. (2020). How live chat assistants drive travel consumers' attitudes, trust and purchase intentions: The role of human touch. *International Journal of Contemporary Hospitality Management*, *32*(5), 1795–1812. https://doi.org/10.1108/IJCHM-07-2019-0605.

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa… examine the variables influencing the use of artificial intelligence in-home voice assistants. *Computers in Human Behavior, 99*, 28–37. https://doi.org/10.1016/j.chb.2019.05.009.

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research, 56*(4), 535–556. https://doi.org/10.1177/0022243718822827.

Meyer-Waarden, L., Pavone, G., Poocharoentou, T., Prayatsup, P., Ratinaud, M., Tison, A., & Tomé, S. (2020). How service quality influences customer acceptance and usage of chatbots? *Journal of Service Management Research, 4*(1), 35–51. https://doi.org/10.15358/2511-8676-2020-1-35.

Meyer, C., & Schwager, A. (2007). Understanding customer experience. *Harvard Business Review*, *85*(2), 116–126.

Ministry of Industry and Tourism (2024). PYME 2024 figures. Ministry of Industry and Tourism. Retrieved from https://industria.gob.es/es-es/estadisticas/paginas/estadisticas-y-publicaciones-sobre-pyme.aspx (18.02.2024).

Misischia, C. V., Poecze, F., & Strauss, C. (2022). Chatbots in customer service: Their relevance and impact on service quality. *Procedia Computer Science*, *201*, 421–428. https://doi.org/10.1016/j.procs.2022.03.055.

Molinillo, S., Aguilar-Illescas, R., Anaya-Sánchez, R., & Liébana-Cabanillas, F. (2021). Social commerce website design, perceived value and loyalty behavior intentions: The moderating roles of gender, age and frequency of use. *Journal of Retailing and Consumer Services, 63*, 102404. https://doi.org/10.1016/j.jretconser.2020.102404.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, *58*(3), 20–38. https://doi.org/10.2307/1252308.

Moriuchi, E., Landers, V. M., Colton, D., & Hair, N. (2021). Engagement with chatbots versus augmented reality interactive technology in e-commerce. *Journal of Strategic Marketing, 29*(5), 375–389. https://doi.org/10.1080/0965254X.2020.1740766.

Moussawi, S., Koufaris, M., Benbunan-Fich, R. (2020). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. *Electronic Markets, 31*, 343–364. https://doi.org/10.1007/s12525-020-00411-w.

Nasermoadeli, A., Ling, K., & Maghnati, F. (2013). Evaluating the impacts of customer experience on purchase intention. *International Journal of Business and Management*, *8*(6), 128–138. https://doi.org/10.5539/ijbm.v8n6p128.

Nunnally, J. C. (1978). *Psychometric theory.* New York: McGraw Hill.

Ontsi (2023). Use of artificial intelligence and big data in Spanish companies. National Observatory of Technology and Society. Retrieved from https://www.ontsi.es/sites/ontsi/files/2023-02/Br%C3%BAjula_IA_Big_data_2023.pdf (27.09.2023).

Piotrowicz, W., & Cuthbertson, R. (2014). Introduction to the special issue information technology in retail: Toward omnichannel retailing. *International Journal of Electronic Commerce*, *18*(4), 5–16. https://doi.org/10.2753/JEC1086-4415180400.

Pullman, M. E., & Gross, M. A. (2004). Ability of experience design elements to elicit emotions and loyalty behaviors. *Decision Sciences, 35*(3), 551–578. https://doi.org/10.1111/j.0011-7315.2004.02611.x.

Rajaobelina, L., Prom, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology & Marketing, 38*, 2339–2356. https://doi.org/10.1002/mar.21548.

Rana, J., Gaur, L., Singh, G., Awan, U., & Rasheed, M. I. (2021). Reinforcing customer journey through artificial intelligence: A review and research agenda. *International Journal of Emerging Markets*, *17*(7), 1738–1758. https://doi.org/10.1108/IJOEM-08-2021-1214.

Rauschnabel, P. A. (2018). Virtually enhancing the real world with holograms: An exploration of expected gratifications of using augmented reality smart glasses. *Psychology and Marketing*, *35*, 557–572. https://doi.org/10.1002/mar.21106.

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, *56*, 1–14. https://doi.org/10.1016/j.jretconser.2020.102176.

Rhim, J., Kwak, M., Gong, Y., & Gweon, G. (2022). Application of humanization to survey chatbots: Change in chatbot perception, interaction experience, and survey data quality. *Computers in Human Behavior*, *126*, 107034. https://doi.org/10.1016/j.chb.2021.107034.

Rogers, E. M. (1983). *Diffusion of innovations*. New York: Free Press.

Rose, S., Hair, N., & Clark, M. (2011). Online customer experience: A review of the Business-to-Consumer online purchase context. *International Journal of Management Reviews*, *13*(1), 24–39. https://doi.org/10.1111/j.1468-2370.2010.00280.x.

Santos-Jaén, J. M., Gimeno-Arias, F., León-Gómez, A., & Palacios-Manzano, M. (2023). The Business digitalization process in SMEs from the implementation of e-commerce: An empirical analysis. *Journal of Theorical and Applied Electronic Commerce Research*, 18, 1700–1720. https://doi.org/10.3390/ jtaer18040086.

Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.). *Latent variable analysis: Applications to developmental research* (pp. 399–419). Thousand Oaks, CA: Sage.

Song, I., Larose, R., Eastin, M., & Lin, C. (2004). Internet gratifications and Internet addiction: On the uses and abuses of new media. *Cyberpsychology & Behavior*, *7*(4), 384–394. https://doi.org/10.1089/cpb.2004.7.384

Stefko, R., Bacik, R., Fedorko, R., & Olearova, M. (2022). Gender-generation characteristic in relation to the customer behavior and purchasing process in terms of mobile marketing. *Oeconomia Copernicana*, *13*(1), 181–223. https://doi.org/10.24136/oc.2022.006.

Sfenrianto, S., & Vivensius, G. (2020). Analysis on factors influencing customer experience of e-commerce users in Indonesia through the application of chatbot technology*. Journal of Theoretical and Applied Information Technology*, *98*(7), 953–962.

Statista (2022). Number of e-commerce users in Europe from 2017 to 2025. Statista. Retrieved from https://www.statista.com/forecasts/715683/e-commerce-users-in-europe#statisticContainer (5.08.2022).

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2013). *Using multivariate statistics. Vol. 6*. Boston, MA: Pearson.

Talwar, S., Dhir, A., Kaur, P., & Mäntymäki, M. (2020). Barriers toward purchasing from online travel agencies. *International Journal of Hospitality Management*, *89*, 102593. https://doi.org/10.1016/j.ijhm.2020.102593.

Tosun, C., Dedeoglu, B. B., & Fyall, A. (2015). Destination service quality, affective image and revisit intention: The moderating role of past experience. *Journal of Destination Marketing & Management*, *4*(4), 222–234. https://doi.org/10.1016/j.jdmm.2015.08.002.

Trevinal, A. M., & Stenger, T. (2014). Toward a conceptualization of the online shopping experience. *Journal of Retailing and Consumer Services*, *21*(3), 314–326. https://doi.org/10.1016/j.jretconser.2014.02.009.

Trivedi, J. (2019). Examining the customer experience of using banking chatbots and its impact on brand love: The moderating role of perceived risk. *Journal of Internet Commerce*, *18*(1), 1–21. https://doi.org/10.1080/15332861.2019.1567188.

Tsai, W. H. S., Liu, Y., & Chuan, C. H. (2021). How chatbots' social presence communication enhances consumer engagement: The mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing*, *15*(3), 460–482. https://doi.org/10.1108/JRIM-12-2019-0200.

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers’ service experiences. *Journal of Service Research*, *20*(1), 43–58. https://doi.org/10.1177/1094670516679272.

Viglia, G., & Dolnicar, S. (2020). A review of experiments in tourism and hospitality. *Annals of Tourism Research*, *80*, 102858. https://doi.org/10.1016/j.annals.2020.102858.

Walczuch, R., & Lundgren, H. (2004). Psychological antecedents of institution-based consumer trust in e-retailing. *Information & Management, 42*(1), 159–177. https://doi.org/10.1016/j.im.2003.12.009.

Wang, J., & Oh, J. I. (2023). Factors influencing consumers' continuous purchase intentions on TikTok: An examination from the uses and gratifications (U&G) theory perspective. *Sustainability*, *15*, 1–19. https://doi.org/10.3390/su151310028.

Wang, Y. A., & Rhemtulla, M. (2021). Power analysis for parameter estimation in structural equation modeling: A discussion and tutorial. *Advances in Methods and Practices in Psychological Science*, *4*(1), 1–17. https://doi.org/10.1177/2515245920918253.

Wibowo, N., Suryanto, T., Faroqi, A., & Hadiwiyanti, R. (2018). Understanding the dominant factors towards the intention to use Youtube continuously in Indonesia. *Atlantis Highlights in Engineering, 1*, 465–470. https://doi.org/10.2991/icst-18.2018.97.

Williams, L. J., Edwards, J. R., & Vandenberg, R. J. (2003). Recent advances in causal modeling methods for organizational and management research. *Journal of Management*, *29*(6), 903–936. https://doi.org/10.1016/S0149-2063(03)00084-9.

Winton, B. G., & Sabol, M. A. (2022). A multi-group analysis of convenience samples: Free, cheap, friendly, and fancy sources. *International Journal of Social Research Methodology*, *25*(6), 861–876. https://doi.org/10.1080/13645579.2021.1961187.

Wünderlich, N. V., Wangenheim, F. V., & Bitner, M. J. (2013). High tech and high touch: A framework for understanding user attitudes and behaviors related to smart interactive services. *Journal of Service Research*, *16*(1), 3–20. https://doi.org/10.1177/1094670512448413.

Yang, Z., & He, L. (2011). Goal, customer experience and purchase intention in a retail context in China: An empirical study. *African Journal of Business Management*, *5*(16), 6738–6746. https://doi.org/10.5897/AJBM10.1287.

Yen, C., & Chiang, M. (2021). Trust me, if you can: A study on the factors that influence consumers' purchase intention triggered by chatbots based on brain image evidence and self-reported assessments. *Behaviour & Information Technology*, *40*(11), 1177–1194. https://doi.org/10.1080/0144929X.2020.1743362.

Yeo, S. F., Tan, C. L., Leong, I. Y. C., Palmucci, D. N., & Then, Y. J. (2023). Supplements purchase intention: Young consumer's perspective. *British Food Journal*, *125*(7), 2610–2627. https://doi.org/10.1108/BFJ-09-2022-0818

Yuen, M. (2022). Chatbot market in 2022: Stats, trends, and companies in the growing AI chatbot industry. Insider intelligence. Retrieved from https://www.insiderintelligence.com/insights/chatbot-market-stats-trends/ (15.04.2022).

Zhu, Y., Zhang, J., Wu, J., & Liu, Y. (2022). AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots. *Journal of Business Research*, *150*, 642–652. https://doi.org/10.1016/j.jbusres.2022.06.044.

Zhu, Y., Zhang, R. R., Zou, Y., & Jin, D. (2023). Investigating customers' responses to artificial intelligence chatbots in online travel agencies: The moderating role of product familiarity. *Journal of Hospitality and Tourism Technology*, *14*(2), 208–224. https://doi.org/10.1108/JHTT-02-2022-0041.

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Annex

Table 1. Examples of studies on user's perception of chatbots

Author	Sample	Context	Dimensions				Main results
			Independent	Mediator	Moderator / Multigroup analysis	Dependent	
Adam *et al*. (2020)	153 German participants	Online banking	Anthropomorphic design cues; foot-in-the-door technique	Social presence	The study hypothesizes that social presence moderates positively the effect of foot-in-the-door technique on user compliance.	User compliance	Social presence mediates the effect of anthropomorphic design cues on user compliance.
Chen *et al*. (2021)	425 users from USA, Europe, Asia and other countries	e-retailing	Chatbot adoption: usability; responsiveness	Extrinsic values; intrinsic values.	Personality moderates positively the effects of usability of a chatbot on extrinsic values of customer experience in e-retailing. Personality moderates positively the effects of the responsiveness of a chatbot on intrinsic values.	Customer satisfaction	The usability of the chatbot had a positive influence on the extrinsic values of the customer experience, while the responsiveness of the chatbot had a positive impact on the intrinsic values of the customer experience. In addition, customer experience had a positive influence on satisfaction. Personality influenced the relationship between chatbot usability and extrinsic customer experience values. The two moderating effects were supported.
Cheng & Jiang (2020a)	1,064 USA participants	e-retailing	Uses and gratification motivations: information; entertainment; media appeal; social presence; privacy risk	User satisfaction	Does not use moderating variables or multi-group analysis.	Continued use; customer loyalty	Perceived information, entertainment, media appeal, and social presence, resulting from the use of the chatbot had a positive influence on users' satisfaction with chatbot. On the other hand, perceived privacy risk had a negative influence on user satisfaction. In turn, user satisfaction had a positive influence on continued use intention and customer loyalty.
Cheng & Jiang (2020b)	1,114 USA participants	Mental health problems after disasters	Uses and gratification motivations: perceived enjoyment; social presence; browse information; media appeal. protection motivations: perceived severity; perceived susceptibility; self-efficacy; response efficacy	Active communication action: information seeking; information forefending; information forwarding	Does not use moderating variables or multi-group analysis.	Online engagement behavior; offline engagement behavior	Gratification motivations and protection motivations were positively associated with active communication action. For its part active communication action was positively linked to users' online engagement behavior and offline engagement behavior.

Table 1. Continued

Author	Sample	Context	Dimensions				Main results
			Independent	Mediator	Moderator / Multigroup analysis	Dependent	
Cheng & Jiang (2022)	1,072 customers in the USA	Several industries	Chatbot Marketing Efforts - CMEs: interaction, information, accessibility, entertainment, and customization	Credibility; accuracy; competence; customer–brand relationships – cbr: control mutuality, satisfaction, trust, commitment	Does not use moderating variables or multi-group analysis.	Customer response: brand loyalty, brand preferences, purchase intention	CMEs had a positive and direct influence on accuracy, competence, and credibility of communication with chatbot agents. In turn, these three dimensions had a positive and direct influence on CBR. For its part CBR had a direct and positive impact on customer response.
Chung *et al*. (2020)	161 Korean university students	Luxury fashion brands	Service agent marketing efforts: interaction; entertainment; trendiness; customization; problem solving	Accuracy; credibility; communication competence	Does not use moderating variables or multi-group analysis.	Satisfaction	Marketing efforts positively impacted accuracy and credibility, but not competence. Accuracy and credibility positively affected satisfaction. Competence had no impact on satisfaction.
Gümüş & Çark (2021)	211 Turkish chatbot users	Interaction with a chatbot in general	Perceived usefulness; perceived ease of use; perceived enjoyment; perceived risk	Customer experience	Does not use moderating variables or multi-group analysis.	Customer experience; behavioral intention	Perceived usefulness, perceived ease of use, and perceived enjoyment influenced; customer experience. Perceived usefulness, and perceived ease of use influenced behavioral intention. Customer experience also influenced behavioral intention.
Ischen *et al*. (2020)	242 participants in Netherlands	Website chatbot	Source of communication	Entity perceptions: anthropomorphism, social presence; perceived interactivity: two-way communication, active control; experiential perceptions: enjoyment, intrusiveness	Source of recommendation (human expert vs chatbot) moderates the effect of source of communication (chatbot, website) on entity perceptions, interactivity perceptions and experiential perceptions.	Recommendation adherence; attitudes towards the medium and the organization	Enjoyment is essential to explain the positive effect of chatbots (vs. web sites) on recommendation adherence and attitudes. Perceived anthropomorphism doesn't have a particular relevance in this comparison. The two moderating effects were not supported.
Kasilingam (2020)	350 responses	Facebook	Perceived usefulness; perceived ease of use; perceived enjoyment; price consciousness; perceived risk; trust; personal innovativeness	Attitude toward chatbots	Gender, age and experience in using mobile shopping applications, moderate all relationships. These three variables present significant difference in all independent variables.	Intention to use chatbots	Attitude towards chatbots was considerably influenced by all independent variables except trust. However, intention to use chatbots was directly influenced only by trust, personal innovativeness, and attitude toward chatbots. Gender, age, and experience in using mobile shopping apps moderate some of the relationships between independent and dependent variables. There were also significant differences in some dimensions taking these three variables into account.

Table 1. Continued

Author	Sample	Context	Dimensions				Main results
			Independent	Mediator	Moderator / Multigroup analysis	Dependent	
Kim & Chang (2020)	218 Korean users	Experience using chatbot services	Service quality: process quality; outcome quality; service scape quality	User satisfaction; reliability; immersion	Does not use moderating variables or multi-group analysis.	Reuse intention	Service quality had no influence on user satisfaction and reliability, while user satisfaction, reliability, and immersion had a positive influence on reuse intention.
Kopplin (2023)	101 German coworkers	Coworking spaces	Productivity; information quality; social norm; enjoyment; personal innovativeness	Instrumental gratifications; non-instrumental gratifications	Age, privacy concerns, and gender moderate all relationships between instrumental gratifications and non-instrumental gratifications and intention to use.	Intention to use	Instrumental and non-instrumental gratifications, as well as social norm, influence intention to use. Age, privacy concerns, and gender do not affect individuals' intention to use a chatbot.
Li *et al*. (2021)	295 Chinese users	Online Travel Agencies (OTAs)	Understandability; reliability; responsiveness; assurance; interactivity (chatbot quality dimensions)	Confirmation; satisfaction	Moderation of technology anxiety on the effect of understandability, reliability, responsiveness, assurance, and interactivity on confirmation.	Use continuance	All moderating effects were supported except for responsiveness. Thus, the higher levels of users' technology anxiety, the stronger the relationships between chatbot quality dimensions and their post-use confirmation of chatbot-based of online travel agencies.
Lubbe & Ngoma (2021)	333 South African millennials	Interaction with a chatbot in general	Perceived ease of use; perceived playfulness; perceived usefulness	Self-service; technology; experience	Does not use moderating variables or multi-group analysis.	Self-service technology satisfaction	Perceived ease of use, perceived playfulness, and perceived usefulness had a positive influence on self-service technology experience. In turn, self-service technology experience had a positive influence on service technology satisfaction.
Meyer-Waarden *et al*. (2020)	146 French participants	A travel chatbot in France (Flybot)	(SERVQUAL) Tangibles; competence; reliability; responsiveness; empathy; credibility	Perceived usefulness; perceived ease of use; trust	Does not use moderating variables or multi-group analysis.	Intention to reuse	Tangibles and reliability had positive influence on perceived usefulness. Tangibles had a positive influence on perceived ease of use and credibility had a positive influence on trust. In turn, perceived usefulness had a positive influence on intention to reuse.
Moriuchi *et al*. (2021)	68 undergraduate students, USA	E-commerce	Attitude toward AR/chatbot	Technology engagement; attitude toward firm; satisfaction	Does not use moderating variables or multi-group analysis.	Shopping intention; Revisit	Attitude toward technology had a positive influence on technology engagement (*), and this one had a positive on attitude toward firm. In turn, attitude toward firm had a positive influence on satisfaction which, in turn, had a positive influence on shopping intention and revisit intention (*). All these relations where partially supported, with the exception of those marked with*, which were effectively supported.

Table 1. Continued

Author	Sample	Context	Dimensions				Main results
			Independent	Mediator	Moderator / Multigroup analysis	Dependent	
Rajaobelina *et al*. (2021)	430 Canadian consumers	Car insurance online	Privacy concerns; usability; technology anxiety; need for human interaction	Creepiness; trust; negative emotions	Does not use moderating variables or multi-group analysis.	Loyalty	Privacy concerns, technology anxiety and need for human interaction had a positive relation with creepiness, and usability had a negative relation with creepiness, In turn, creepiness had a positive relation with negative emotions and a negative relation with trust and loyalty.
Rese *et al*. (2020)	205 students at a German university	Chatbot "Emma" on Zalando's website	Convenience; authenticity of conversation; enjoyment; pass time; privacy concerns; immature technology; modified tam model: perceived usefulness; perceived ease of use		Given the apparent differences in the acceptance of text-based chatbots between females and males, the authors utilized mean comparison and multigroup analysis.	Behavioral intention; intended usage frequency	Perceived ease of use had a positive relation with usefulness and with enjoyment. In turn, usefulness and enjoyment had a positive influence on behavioural intention and intended usage frequency. Females rated all constructs higher than males.
Sfenrianto & Vivensius (2020)	385 respondents in Indonesia	e-commerce	Information quality; system quality; service quality; e-trust; e-satisfaction; e-loyalty		Does not use moderating variables or multi-group analysis.	Customer experience	Information quality, system quality, service quality, e-trust, e-satisfaction, and e-loyalty had a positive influence on customer experience.
Trivedi (2019)	258 respondents from India's top four metro cities	Online banking	Information quality (INFQ); system quality (SYSQ); service quality (SERQ)	Customer experience	Moderation of perceived risk on the effect of INFQ, SYSQ, and SERQ on customer experience.	Brand love	Information quality, system quality, and service quality had a positive influence on customer experience. In turn, customer experience had a positive influence on brand love. Perceived risk moderates the relationship between INFQ, SYSQ, and SERQ and customer experience.
Gupta & Sharma (2019)	72 Indian participants	Banking industry	Observed utility; observed accessibility; observed threat		Does not use moderating variables or multi-group analysis.	Intention to use	Utility, accessibility and threat had a positive influence on the intention to use chatbots.
Yen & Chiang (2021)	204 participants in Taiwan	Several industries	Machine communication quality; competence; credibility; human-computer interaction; anthropomorphism; social presence; media richness; human use and gratification; informativeness; playfulness	Trust in chatbot; trust in seller	Does not use moderating variables or multi-group analysis.	Purchase intention	Credibility, competence, anthropomorphism, social presence, and informativeness have an influence on consumer trust in chatbots. In turn, trust in chatbots has an influence on purchase intention.

Table 1. Continued

Author	Sample	Context	Dimensions				Main results
			Independent	Mediator	Moderator / Multigroup analysis	Dependent	
Present study	173 Spanish participants	Experience with chatbots in e-commerce	Information, entertainment, media appeal, social presence and risk for privacy	Customer experience	This study presents the hypothesis that chatbot usage frequency moderates the effect of information, media appeal, social presence on customer experience.	Purchase intention	

Table 2. Measurement scales and items descriptions

Constructs	Bibliographical source	Items description
Information (IN)	Cheng & Jiang (2020a)	IN1. The chatbot helped me to obtain information about the company. IN2. The chatbot provided me recommendations on the company's products/services. IN3. The chatbot provided information that helped my purchasing decisions. IN4. The chatbot assisted me in making my final decision.
Entertainment (EN)	Chung *et al.* (2018)	EN1. It was fun and enjoyable to have a conversation with the chatbot. EN2. I was absorbed in the conversation with the chatbot. EN3. I enjoyed choosing products more if they were recommended by the chatbot than if I chose them myself. EN4. The conversation with the chatbot was exciting.
Media Appeal (MA)	Gan & Li (2018)	MA1. The chatbot saved me a lot of time. MA2. Using the chatbot saved me more time than if I had made a call to a company employee. MA3. Using the chatbot was more effective than other forms of communication. MA4. The chatbot provided an easy way to communicate with the company.
Social Presence (SP)	Araujo (2018)	SP1. When I was using the chatbot, I felt like I was interacting with a company employee. SP2. When I was using the chatbot, I felt that I was not alone. SP3. When I was using the chatbot, I felt like I was in the store with an employee. SP4. When I was using the chatbot, I felt like an employee was answering my questions.
Risk to Privacy (RP)	Cheng & Jiang (2020a)	RP1. When using the chatbot, my information could be used in a way that I am unable to foresee. RP2. The information I provided through the chatbot could be misused. RP3. There is too much uncertainty associated with the use of the chatbot. RP4. I am concerned about exchanging information through the chatbot because of what the company might do with it.
Customer Experience (CX)	Trivedi (2019); Chen *et al.* (2021)	CX1. I enjoyed my experience using the chatbot. CX2. The experience of using chatbots was interesting. CX3. I was happy with the experience of having used the chatbot. CX4. I enjoyed the customized experience received through the chatbot.
Purchase Intention (PI)	Yen & Chiang (2021)	PI1. There is a high likelihood that I will purchase this brand due to the experience with the chatbot. PI2. The probability of purchasing this brand is high because of the experience with the chatbot. PI3. I will purchase this brand next time because of the experience with the chatbot. PI4. I will consider purchasing this brand based on the experience with the chatbot.

Table 3. Respondents' demographic characteristics

Characteristic	N	(%)
Gender		
Male	64	37
Female	109	63
Education Level		
Primary School	2	1.2
High School	40	23.1
University degree	86	49.7
Master's degree	34	19.7
Doctorate	8	4.6
Age (in years)		
Under 20	27	15.61
20-40	112	64.74
41-55	30	17.3
56+	4	2.3

Table 4. Online shopping habits and use of chatbots

Habits and use of chatbots	n	(%)
Online Shopping Frequency		
Less than 1 time per 6 months or less	20	11.6
1 time per 3 months	35	20.2
1 time per month	78	45.1
1 time per week	36	20.8
Every day	4	2.3
Last time chatbot usage		
Restaurants and takeaways	7	4
Supermarkets and hypermarkets	7	4
Fashion	42	24.3
Sport	10	5.8
Cosmetic	4	2.3
Technology	37	21.4
Tourism, travel, and lodging	14	8.1
Financial entity	13	7.5
Insurance	4	2.3
Others	35	20.2
Chatbot use frequency (last 6 months)		
0 times	28	16.2
1 time	62	35.8
2 times	36	20.8
3 times	18	10.4
4 times	5	2.9
5 times or more	24	16.2

Table 5. Reliability analysis

Constructs and items	Standardized factor loading	Average Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Information (IN)		0.792	0.827	0.837	0.638
IN1	0.694				
IN3	0.839				
IN4	0.843				
Entertainment (EN)		0.842	0.880	0.880	0.710
EN2	0.877				
EN3	0.795				
EN4	0.840				
Media Appeal (MA)		0.886	0.934	0.936	0.789
MA1	0.859				
MA2	0.917				
MA3	0.914				
MA4	0.854				
Social Presence (SP)		0.8808	0.912	0.912	0.776
SP1	0.886				
SP3	0.859				
SP4	0.897				
Risk to Privacy (RP)		0.7070	0.746	0.753	0.525
RP2	0.641				
RP3	0.641				
RP4	0.839				
Customer Experience (CX)		0.929	0.949	0.950	0.861
CX1	0.946				
CX2	0.898				
CX3	0.941				
Purchase Intention (PI)		0.945	0.971	0.971	0.892
PI1	0.933				
PI2	0.957				
PI3	0.944				
PI4	0.944				

Table 6. Discriminant validity analysis

	IN	EN	MA	SP	RP	CX	PI
IN	**0.799**						
EN	0.701	**0.843**					
MA	0.780	0.677	**0.888**				
SP	0.666	0.751	0.850	**0.881**			
RP	-0.045	0.043	-0.085	-0.056	**0.725**		
CX	0.709	0.790	0.842	0.873	-0.107	**0.928**	
PI	0.558	0.681	0.633	0.727	0.002	0.716	**0.944**

Notes: Elements on the diagonal in bold indicate ($\sqrt{AVE}$). Correlation coefficients are below the diagonal.

Table 7. Common Method Bias Analysis

Chi-square difference test	**DF**	**P value**		
0.53566	1	0.464		
Constructs and items	**Substantive factor loading (R1)**	**$R1^2$**	**Common method factor loadings (R2)**	**$R2^2$**
Information (IN)				
IN1	0.622	0.387	0.330	0.109
IN3	0.760	0.577	0.330	0.109
IN4	0.794	0.630	0.308	0.095
Entertainment (EN)				
EN2	0.803	0.645	0.346	0.120
EN3	0.711	0.506	0.342	0.117
EN4	0.779	0.607	0.353	0.124
Media Appeal (MA)				
MA1	0.797	0.635	0.313	0.098
MA2	0.881	0.777	0.275	0.076
MA3	0.862	0.743	0.308	0.095
MA4	0.794	0.630	0.311	0.097
Social Presence (SP)				
SP1	0.832	0.693	0.309	0.096
SP3	0.798	0.637	0.312	0.098
SP4	0.841	0.707	0.314	0.099
Risk to Privacy (RP)				
RP2	0.550	0.302	0.379	0.144
RP3	0.557	0.311	0.346	0.120
RP4	0.755	0.570	0.326	0.106
Customer Experience (CX)				
CX1	0.886	0.785	0.327	0.107
CX2	0.842	0.709	0.310	0.096
CX3	0.887	0.786	0.317	0.100
Purchase Intention (PI)				
PI1	0.875	0.765	0.322	0.104
PI2	0.898	0.807	0.329	0.108
PI3	0.886	0.785	0.324	0.105
PI4	0.882	0.779	0.335	0.112
Average	0.795	0.642	0.325	0.106

Table 8. Standardized parameter estimates and hypotheses tests

Hypothesis	**Path Coefficient**	**Z value (Wald test)**	**P value**	**R^2**
H1 EN->CX	0.393^{***}	3.838	1.2E-4	0.893
H2 RP->CX	-0.082^{**}	-1.993	0.046	
H3a IN->CX	-0.016	-0.133	0.894	
H3b IN×CUF->CX	-0.264^{**}	-2.144	0.032	
H4a MA->CX	0.297^{*}	1.919	0.055	
H4b MA×CUF->CX	0.451^{**}	2.109	0.035	
H5a SP->CX	0.351^{***}	2.569	0.010	
H5b SP×CUF->CX	-0.279^{*}	-1.906	0.057	
H6 CX->PI	0.735^{***}	17.029	0.000	0.540

Table 8. Continued

Direct effects on Customer Experience		
	Path Coefficient	
Direct Path	**Novice users**	**Experienced users**
IN->PI	-0.016	-0.279*
MA->PI	0.297*	0.748***
SP->PI	0.351***	0.073
Indirect effects on Purchase Intention		
Indirect Path	**Path Coefficient**	
EN-> PI	0.289	
RP->PI	-0.060	
	Novice users	**Experienced users**
IN-> PI	-0.011	-0.205*
MA->PI	0.218*	0.550***
SP->PI	0.258**	0.054

Notes: ***Significant at 0.01 level. **Significant at 0.05 level. *Significant at 0.10 level.

Figure 1. Conceptual model

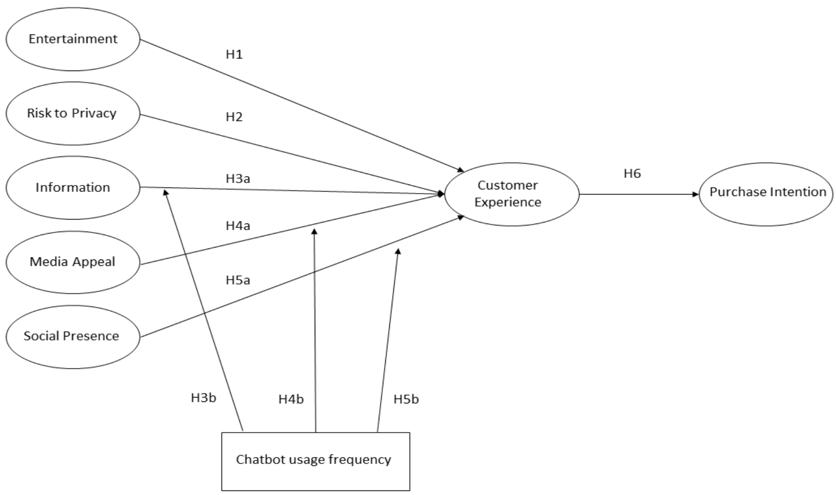
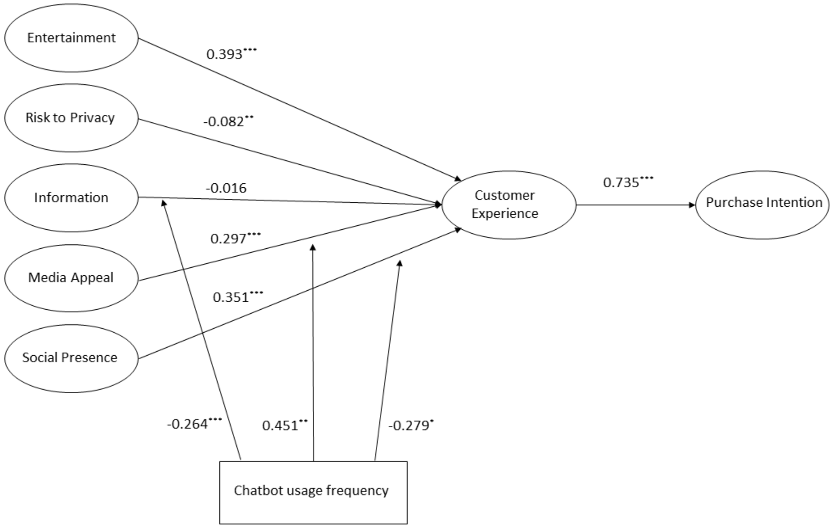


Figure 2. Standardized solutions of estimated model



Notes: *** Significant at 0.01 level. ** Significant at 0.05 level. * Significant at 0.10 level.
Model fit values: Satorra-Bentler statistic $\chi 2$ = 532.502, 452 df, p=0.005; RMSEA = 0.032; CI = [0.021, 0.041]; CFI = 0.981; TLI = 0.978; NNFI = 0.978; IFI = 0.981; SRMR = 0.049