

Universidade do Minho
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The impact of chatbots on purchase intention

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The impact of chatbots on purchase intention

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Thank you all!

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not resorted to plagiarism or any form of misuse of information or falsification of results leading to the completion of this research.

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ABSTRACT

The implementation of chatbots can be seen as a way of saving money in the department of customer services, since these artificial intelligence powered mechanisms can do repetitive tasks without fatigue. However, it is important to analyse how much these innovations can affect the overall purchase intention since consumers react differently to technology.

This research aims to understand the use of chatbots as digital assistants in e-commerce sites. We investigate the impact of a number of chatbot attributes, specifically perceived usefulness, perceived ease of use, and trust, in purchase intention, mediated by attitudes and satisfaction with the chatbot. Data from a survey carried out with 300 respondents was analysed to test the proposed model.

Findings from the quantitative data analysis supported all the proposed hypotheses. In particular findings show that perceived usefulness has a higher impact on attitude and customer satisfaction towards chatbots than perceived ease of use. Moreover, attitude towards the chatbot had higher variance percentage to predict his/her intention to purchase from chatbots.

Our results are relevant for companies because we provide evidence that customers who have a positive attitude and are satisfied with the chatbot have a higher purchase intention. Thus, it is relevant to develop chatbots that are perceived as useful, easy to use and trustable.

Keywords: Chatbots, Purchase Intention, Trust, Perceived Usefulness; Perceived Ease of Use, Satisfaction.

RESUMO

A implementação de chatbots pode ser vista como uma forma de economizar dinheiro no departamento de atendimento ao cliente, uma vez que esses mecanismos de inteligência artificial podem realizar tarefas repetitivas sem fadiga. No entanto, importante analisar o quanto estas inovações podem afetar a intenção geral de compra, uma vez que os consumidores reagem de maneira diferente à tecnologia.

Esta pesquisa visa compreender a utilização de chatbots como assistentes digitais em sites de e-commerce. Investigamos o impacto de uma série de atributos do chatbot, especificamente utilidade percebida, facilidade de uso percebida e confiança na intenção de compra, mediados por atitudes e satisfação com o chatbot. Os dados de uma pesquisa realizada com 300 respondentes foram analisados para testar o modelo proposto.

Os resultados da análise de dados quantitativos suportam as 10 hipóteses testadas. Estas indicam que a utilidade percebida teve um impacto maior na atitude e na satisfação do cliente em relação aos chatbots em comparação com a facilidade de uso percebida. Além disso, a atitude em relação ao chatbot teve maior percentagem de variância para prever sua intenção de compra de chatbots.

Isto é relevante para as empresas, visto que os chatbots podem processar dezenas de perguntas dos consumidores instantaneamente e com isto poupar tempo não só à pessoa, mas também a empresa, dado que os chatbots podem trabalhar 24h por dia.

Palavras-chave: Chatbots, Intenção de Compra, Confiança, Utilidade Percebida; Facilidade de uso percebida, Satisfação.

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1. Introduction

This research aims to understand how artificial intelligence (AI) will affect the future of marketing, more precisely influence of AI marketing strategies and customer behaviour through the use of chatbots as digital assistants in e-commerce sites. Although AI has already had some impact on marketing, it is expected that it will have even more impact in the future (Davenport, Guha, Grewal, & Bressgott, 2019) with predictions of $5 billion to be invested in chatbots by 2021 (Jovic, 2020). Indeed, a Salesforce survey shows that AI will be the technology most adopted by marketers in the coming years (Columbus, 2019).

The focus on e-commerce sites was chosen due to customer service being the fastest growing industry using chatbots, accumulating an annual growth rate of 31,6% from 2019 to 2026 (Cheng & Jiang, 2020; Tran, Pallant, & Johnson, 2021).

Artificial intelligence often labelled simply as AI refers to programs, algorithms, systems and machines that demonstrate intelligence (Shankar, 2018) and is represented by machines that exhibit aspects of human intelligence (Huang & Rust, 2018). In addition, it involves machines that mimic "intelligent human behaviour" (Syam & Sharma, 2018) and provides a means to interpret external data correctly, learn from that data and exhibit flexible adaptation (Kaplan & Haenlein, 2019). These machines consistently adapt to the environment, much like a human, to complete tasks and as a result, people may be able to make better use of their time and use resources on other tasks (Kim, Merrill, & Collins, 2021).

Artificial intelligence in the field of marketing can be a valuable tool for the challenges of managing and personalizing customer service. One of the most visible facets of AI applications is the inclusion of bots and chatbots to assist consumers when navigating online to answer queries and assist with purchase. A bot is a program that automatically completes an action based on specific triggers and algorithms while a chatbot is a computer program that's designed to simulate human conversation. Moreover, chatbots interpret the words provided to them and provide a pre-set answer. With bots and chatbots, businesses can automate the process of answering repetitive questions from their customers, speeding the time of resolution for clients, and reducing the pressure on agents.

AI tools can be used to allow the best targeting and personalized communication to each customer (Kaplan & Haenlein, 2019), including recommendations to buy specific products based on previous choices. Consequently, the recommendations of the "next product to buy" aimed at individual customers, as companies like Amazon and Netflix have been doing, can lead to a double increase in the rate of desired sales (Chui, et al., 2018; Tran, Pallant, & Johnson, 2021). The case studies from Davenport, Guha, Grewal, & Bressgott, (2019) show that using customer data to personalize promotions, for example, including customised daily offers, can lead to an increase of one to two percent in incremental sales of traditional retailers only.

However, bots and chatbots are still relatively new concepts in the modern marketplace (Carter, 2019). For example, in what concerns younger consumers, despite the fact that millennials' predominant use of instant text messaging suggests that they are more likely to give chatbots a chance, little is still known about the factors that positively influence their attitude towards this technology (De Cicco, Costa, & Alparone, 2020). Compared to offline shopping, the online purchasing experience may be viewed as lacking human warmth and sociability as it is more impersonal, anonymous, and automated. For these reasons, understanding how to create a higher level of engagement in online environments with new technologies such as chatbots is a complex process (Cyr, Hassanein, Head, & Ivanov, 2007) and should be taken into consideration when trying to retain a consumer with an end goal of purchasing.

User satisfaction and intentions of continued use are crucial for long-term sustainability of chatbot services and corporate business communication (Cheng & Jiang, 2020). According to a 2018 survey, 46% of people mentioned they would prefer interacting with a human even if a chatbot saved them ten minutes (Garcia, 2018; Jovic, 2020). Although these AI-powered helpers can answer questions 24/7 and do not make users wait on hold (Tran, Pallant, & Johnson, 2021), not everyone sees the benefits of interacting with chatbots *in lieu* of other channels (Garcia, 2018). In fact, 41% of respondents stated chatbots do not provide enough detailed answers, while 37% said chatbots are not helpful generally. Six out of 10 respondents said they would give up on a chatbot if the issue is too complex, and 41% would do the same if the chatbot directs them to Frequently Asked Questions (Garcia, 2019).

It is important to understand the importance of the customer experience with the introduction of these innovations because consumers react differently to technology (Wang &

Emurian, 2005). In that sense, this study aims at analysing the attitudes towards the use of a chatbot. Specifically, we aim to answer the following research question:

What is the impact of chatbots on individuals' purchase intention?

Davenport, Guha, Grewal & Bressgott (2019) claim that customers consider the bot to be less pleasurable, they hold back when interacting with bots and therefore buy less. We need to have a better understanding of how likely consumers are to return to the website if they feel that the chatbot was helpful and contributed to finding what they were looking for. Hence this research intends to study which factors influence the use of AI-powered chatbots. This will be analysed through a quantitative study with seven hypotheses being tested regarding the impact of chatbot attributes in purchase intention through the mediation of attitude and satisfaction.

The aim of this research is to understand whether a chatbot can influence the purchase intention of a consumer and how different variables can affect the use of a website. In other words, if consumers rely on the website to come back to it again, therefore increasing sales.

This thesis is organised as follows: in the next chapter a literature review is presented, followed by the hypothesis of the research. The literature review firstly gives the definition of a chatbot and its limitations and secondly, the chatbot perceived attributes such as trust, perceived usefulness and perceived ease of use are discussed. Thirdly, we refer to customer satisfaction and how it influences the purchase intention of a product. The third chapter presents the methodology followed to answer the research questions, including the design process of the survey. The fourth chapter consists in the results analysis, that is followed by the fifth and last chapter, containing the conclusions, as well as the limitations of the dissertation and suggestions for future research on the topic.

2. Literature Review

The subsequent chapter builds a theoretical framework for the research question of the thesis. A comprehensive background of previous studies and the theories within the topic of interest are presented aiming at summarizing, contrasting, and criticizing the extant knowledge on relevant topics for understanding the context around the research purpose.

This chapter is subdivided into four main topics: chatbots technology attributes, customer satisfaction, attitude towards chatbot and purchase intention. In the first part of the literature review, we define the concept of chatbots. This is followed by the study of chatbot technology through a careful explanation of its various typologies and limitations. Further, the next part is dedicated to its technology attributes that impact customer satisfaction and attitude towards chatbots. Moreover, we will analyse the effect on purchase intention as purchases are the ultimate goal of any business. To conclude, a conceptual framework outlining the interdependencies between the variables and presenting the multiple hypotheses to be studied is proposed.

2.1. Chatbots – concept definition

Chatbots consist of software that can establish a sequential conversation looking for a certain result as a facilitating tool for humans with whom it interacts (Illescas-Manzano, Vicente, Afonso, & Cristofol, 2021). It is important to also clarify the difference between AI bots and chatbots. Miller (2016) describes the difference between an AI bot and a chatbot. In short, chatbots rely on "relatively" simple algorithms, while AI bots have more features, incorporating complex algorithms and neurolinguistic programming. As an example, in internet customer service, AI can be applied in the form of chatbots that can generate automatic responses to questions sent through social media channels or emails (Kaplan & Haenlein, 2019). To simplify, chatbots are programs that simulate human conversation, allowing humans to interact with digital devices as if they were communicating with a real person (Oracle, 2019; Shawar & Atwell, 2005).

With respect to how users respond to the chatbot's enquiries, Hill, Ford, & Farreras (2015) found that users communicate with chatbots using shorter messages and a less rich vocabulary compared to conversations with another human, while Corti & Gillespie (2016) found that people are less willing to repair misunderstandings with chatbots compared to humans. According to the

authors, this is probably due to the lower expectations people have of chatbots, as they are believed to be unable to engage in complex intersubjective processes.

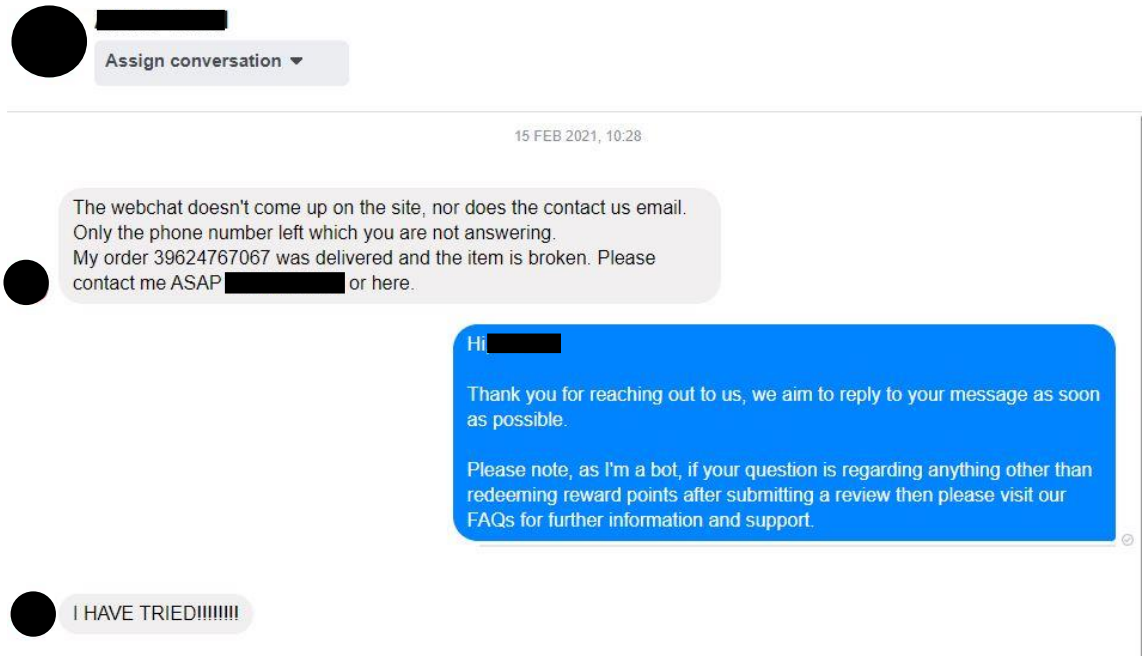
In the future, companies will be able to use mostly AI bots, which - in some cases - work just as well as human salespeople, to make initial contact with prospective consumers. However, there is a risk that if customers discover that they are interacting with a bot, they may feel uncomfortable, causing negative consequences (Davenport, Guha, Grewal, & Bressgott, 2019), as customers view AI negatively, it may become a barrier to adoption (Levin, 2017). Furthermore, as customers consider the bot to be less pleasurable, they are short when interacting with bots and therefore buy less (Davenport, Guha, Grewal, & Bressgott, 2019). In addition, interacting with a physical robot is interpreted as more pleasant than interacting with a simulated robot on a computer or interacting with a real robot presented by teleconference (Wainer, Feil-Seifer, Shell, & Mataric, 2006).

2.1.2. Typologies of Chatbots

Chatbots are implemented so that companies can answer questions and resolve doubts while users are placing orders over the Internet (Illescas-Manzano, Vicente, Afonso, & Cristofol, 2021). Retailers are increasingly using conversational AI (chatbots) for customer service due to the perceived benefits and reduced operational costs of this emerging technology (Tran, Pallant, & Johnson, 2021).

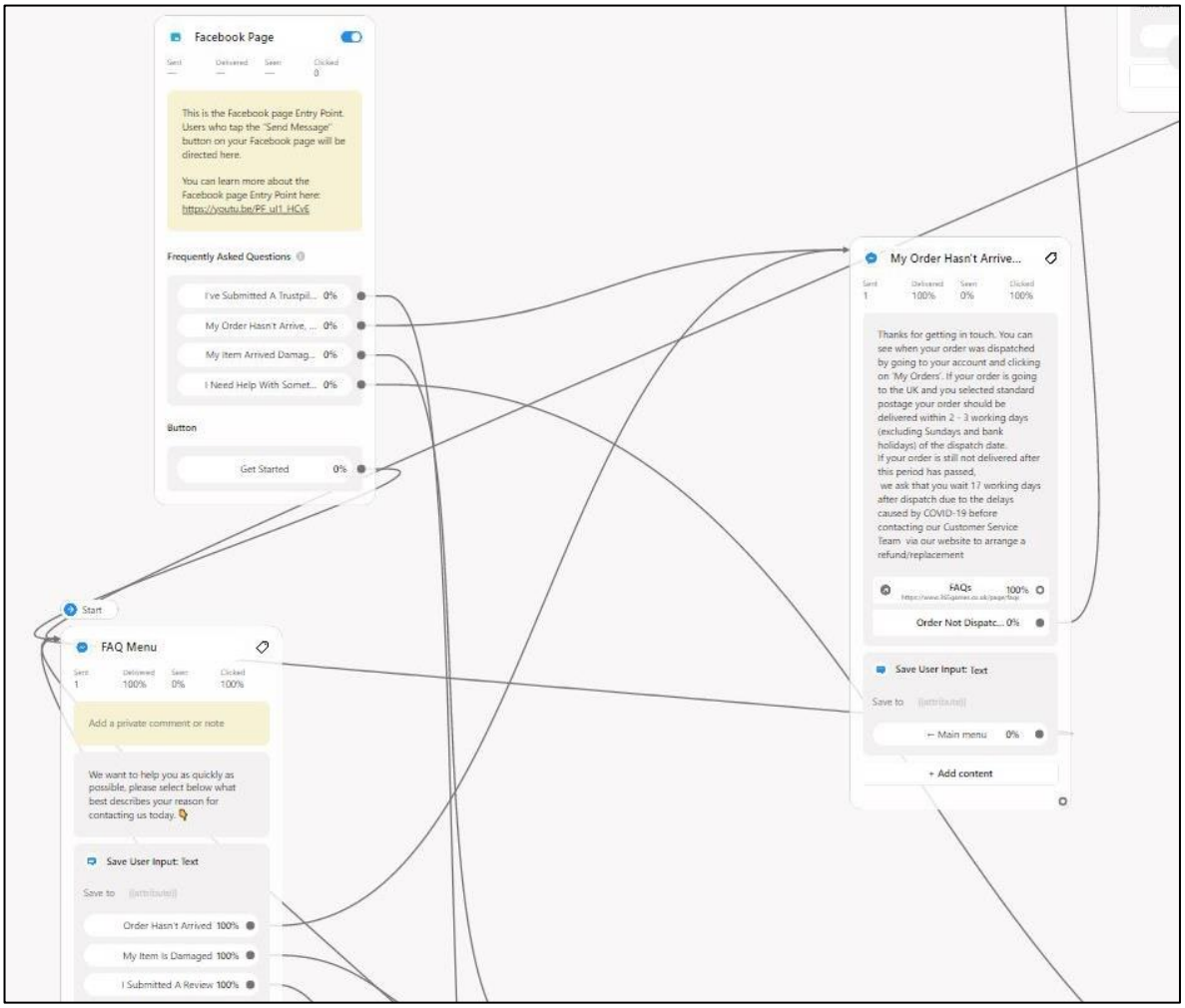
There are three different types of chatbots: (a) based on rules, (b) smart and (c) hybrid. The first type, commonly known as flow-oriented chatbots, work by setting triggering keywords, or the customer must choose from among the options (Illescas-Manzano, Vicente, Afonso, & Cristofol, 2021). This kind of chatbots lack in deep learning compared to artificial intelligence bots as they are not able to learn over time. This is the type of chatbot featured in figure 1 and 2 as they are fast to develop and low cost. Figures 1 and 2 illustrate an example of a flow-oriented chatbot and the backend of the company Xbite, an online retailer. To explain it further, the chatbot is connected to the user through an interface, which can be an application, a website, a chat pop-up window, or a social network such as Facebook Messenger – figure 1 – and these interactions are managed by a dialogue management system (Illescas-Manzano, Vicente, Afonso, & Cristofol, 2021).

Figure 1 - Example of a rule based chatbot



Source: Own screenshot of company Xbite

Figure 2 - The backend of a chatbot's flowchart



Source: Own screenshot of company Xbite

The second type of chatbots is labelled as smart and are artificially intelligent chatbots. As the name itself indicates, this type of chatbots is based on artificial intelligence, by which it collects information through conversations with customers (Illescas-Manzano, Vicente, Afonso, & Cristofol, 2021). This type of AI can be seen as functional AI. The primary role of this type of AI is focused on helping people complete tasks in a more efficient and effective manner (Kim, Merrill, & Collins, 2021). Thanks to this technology, the chatbot can learn and provide its own answers. We have the case of Siri for Apple, Cortana for Microsoft and Bixby for Samsung. As illustrated on figure 3, Siri has learned and adapted its answers to always provide different ones. This can also be seen through predictive algorithms, for instance social media recommendations for new potential friends to add, or music platforms that generate personalised playlists (Kim, Merrill, & Collins, 2021).

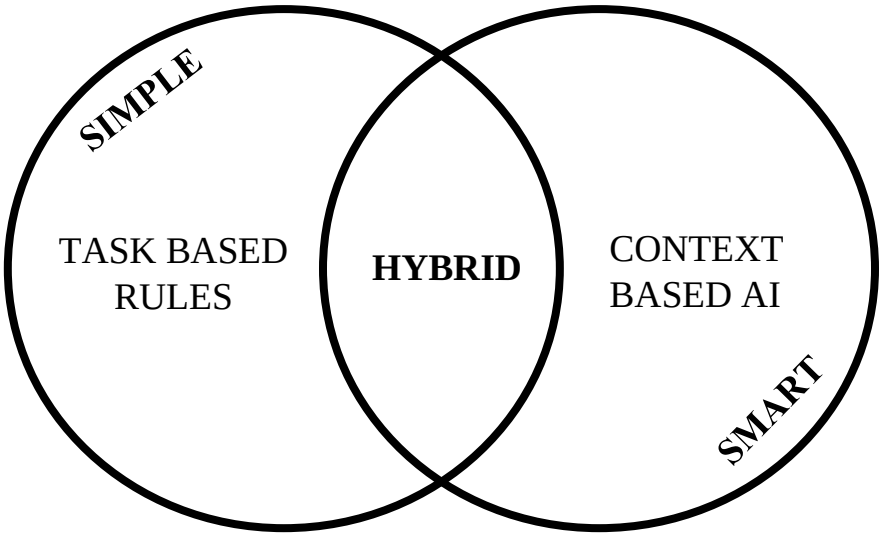
Figure 3 - Artificially intelligent chatbots (Siri)



Source: Own screenshot of a test on the author's phone

The third type of chatbot is known as hybrid and it is defined as a mix of the two previous types, combining rules and artificial intelligence (Illescas-Manzano, Vicente, Afonso, & Cristofol, 2021). It is a combination of both simple and smart chatbots, thus it has some rule-based tasks while simultaneously understanding context.

Figure 4 - Hybrid example



Source: Adapted from freshworks.com/live-chat-software/chatbots/threetypesofchatbots

2.1.3. Chatbot Limitations

Many academics and practitioners foresee that AI will change the execution of marketing strategies and customer behaviour. However, AI may not deliver on all its promises, due to the challenges it presents related to data privacy, algorithmic bias and ethics (Larson, 2019).

Interaction with chatbots poses specific challenges that personal interactions do not seem to suffer. There is no opportunity for personalized services in impersonal interaction between the consumer and an internet server, therefore several studies show that the introduction of these stimuli can increase the perceived confidence and credibility of online stores (Alves & Soares, 2013). Hence, it impacts the buying behaviour and loyalty towards a website.

Coined by computing pioneer Alan Turing in 1950, the Turing test was designed to be a rudimentary way of determining whether a computer counts as "intelligent". If a person cannot distinguish whether he/she is talking to a human or a machine, the machine exhibits intelligent behaviour (Turing, 1950).

If customers learn that an AI algorithm can predict their preferred choices, in such a way that they perceive a loss of autonomy, they may deliberately choose a nonpreferred option, to reaffirm their autonomy (Davenport, Guha, Grewal, & Bressgott, 2019; André, et al., 2018). In addition, if customers' ideal preferences really differ from their past behaviours (for example, customers trying to stop eating unhealthy foods), AI may make it difficult for a person to transition

from their preferred options to those previously ordered, only reflecting choices based on their past behaviour (Davenport, Guha, Grewal, & Bressgott, 2019).

There are some other limitations to take into account, for instance, in face-to-face human interactions, trustworthiness is usually manifested through trivial (yet considered important) social cues (Qiu & Benbasat, 2009). When it comes to human to non-human interaction, this process is no different, as consumers rely on a variety of sources to form their trusting beliefs, and perceived quality of the information provided by the agent is only one of the factors that contribute to the cognitive evaluation of the agent's trustworthiness (Qiu & Benbasat, 2009).

Moreover, consumer trust in a company's website was shown to positively impact attitude towards the company and willingness to buy from the online vendor (Gefen & Straub, 2003), in other words, higher levels of trust will have a positive effect on the attitude towards the chatbot (De Cicco, Costa, & Alparone, 2020). Therefore, it should be drawn attention to the need to consider the interaction style in human–chatbot communications as an antecedent of social presence, demonstrating that a social-oriented interaction style may work to compensate for the impersonal nature often associated with AI (De Cicco, Costa, & Alparone, 2020). As Cheng and Jiang (2020) stated, individuals might trust machines more than humans with personal information, with users providing more personal information even when they are concerned about privacy.

The obstacle for computers is not just understanding the meanings of words but understanding the endless variability of terms in how those words are expressed in language use to communicate meaning (Hill, Ford, & Farreras, 2015). Secondly, while chatbots are designed to sustain conversations, they are limited in their ability to have an extended goal-directed discussion and in their depth of information on a particular topic (Hill, Ford, & Farreras, 2015).

If a demand is made on a chatbot that extends beyond its capabilities or makes its task more complicated, the chatbot might struggle—and that has negative consequences for businesses and customers. There are questions and issues that chatbots simply may not be able to answer or resolve — for example, complex service issues that have a large number of variables (Oracle, 2019).

The main challenge with chatbots involves interpretational problems: in most cases, chatbots cannot address more specific or complex requests, or do not always understand what the customer is asking (Brandtzaeg & Følstad, 2017).

Developers can work around these limitations by adding a contingency to their chatbot application that routes the user to another resource (such as a live agent) or prompts a customer for a different question or issue. Some chatbots can move seamlessly through transitions between chatbot, live agent, and back again. As AI technology and implementation continue to evolve, chatbots and digital assistants will become more seamlessly integrated into our everyday experience (Oracle, 2019).

Sometimes chatbots still cannot address highly specific or complex requests (Brandtzaeg & Følstad, 2017), therefore businesses in which a relatively short number of options are required to fulfil online orders – so those which can use an easier algorithm – are more prone to the use of chatbots (De Cicco, Costa, & Alparone, Millennials' attitude toward chatbots: an experimental study in a social relationship perspective, 2020).

2.2. Chatbot Perceived Attributes

As previously discussed, studies focusing on virtual assistants and chatbots has uncovered a number of attributes that have an impact on how they are perceived and evaluated by consumer. Below we discuss trust, perceived ease of use and perceived usefulness.

2.2.1. Trust

Trust with all its connotations has been studied in numerous disciplinary fields, and it presents important research opportunities and applications in an online context. The importance of the relationship between the consumer and the seller in this new form of direct marketing is high because of the high degree of uncertainty and risk associated with most transactions (Pavlou, 2003). If online retailers can improve the perceived trust on their platforms, then e-commerce sales may increase substantially.

Trust is considered a vital aspect of the purchase intention from the early stages of e-commerce, as was stated twenty-one years ago by Jarcenpaa, Tractinsky, & Vitale (2000, p.45): “Trust is a critical factor in stimulating purchases over the Internet, especially at this early stage of commercial development” and it still resonates with the literature today.

Retailers find the need to represent themselves on the internet to get more brand awareness, in order to get more customers with the aim of selling more products (Grabner-Kraeeter, 2002). If websites increase the security of their e-commerce systems, then it is likely that both consumers and companies will engage more with online vendors.

Online sellers presently face a difficult challenge – to build consumer trust to make purchases on the Internet, especially when a user needs to provide financial and personal information on the internet (McKnight, Choudhury, & Kacmar, 2002). This is not an easy task because trust is a complex and abstract concept and online merchants are solely responsible to present their websites as trustworthy to potential customers (Wang & Emurian, 2005).

Pavlou (2003, p.102) argues that "the notion of trust is perhaps the most important component of consumer-marketer transactions" and this can be hindered by the risk of loss of privacy associated with providing (whether intentionally or involuntarily) personal information to Web retailers (Pavlou, 2003). Trust can be viewed as a significant antecedent belief that creates a positive attitude toward the transaction behaviour (Jarcenpaa, Tractinsky, & Vitale, 2000) which in turn leads to transaction intentions.

According to Wang & Emurian (2005), trust is the most crucial factor for the success of e-commerce. Since human interaction is viewed as a precondition of trust (Lu, Fan, & Zhou, 2016), the buyer-web interactions should also contribute to the building of trust online (Alves & Soares, 2014). Trust is needed to buy online and human interaction is needed to have trust on a website, therefore this is a cycle that requires a human to work efficiently.

Cheng and Jiang, (2020) claim that user satisfaction and intentions of continued use are crucial for the long-term sustainability of chatbot services. In addition, Lu, Fan, and Zhou (2016) argue that trust is the key feature for returning customers and it is a central factor for the success of an e-commerce platform. Customer trust is particularly important in the online context because customers increasingly rely on the Internet for information and purchases (Bart, Shankar, Sultan, & Urban, 2005).

A contrary opinion states that, avatars generate a greater satisfaction with the merchant's site, a better opinion about the product and increased purchase intention (Holzwarth, Janiszewski,

& Neumann, 2006). Such technology allows consumers to engage in a two-way conversation with the virtual character and get answers in a more intuitive and pleasant way (Alves & Soares, 2014).

Another aspect to consider is the amount of purchase – if a consumer spends a large amount of money on a flight, for instance, the outcome of it should be as favourable as expected (no delays, no cancelled flights, etc.) (Tran, Pallant, & Johnson, 2021). The need for trust on the merchant is higher in these cases, thus trust might be influenced by the amount of the purchase (Jarcenpaa, Tractinsky, & Vitale, 2000). Trust in both parties – seller and buyer – is needed to enable such transaction to be completed (Kartika, Firdhaus, & Najib, 2019), especially in sites where both information risk and involvement are high, such as travel sites (Bart, Shankar, Sultan, & Urban, 2005).

In conclusion, the future of e-commerce depends on trust. The lack of it has been identified as one of the barriers for consumers who engage in e-commerce from the moment they disclose personal information to online sellers (Lu, Fan, & Zhou, 2016).

2.2.2. Perceived Usefulness & Perceived Ease of Use

According to the technology acceptance model (TAM), perceived usefulness and perceived ease of use are two key variables that explain various mechanisms related to technology adoption (Davis, 1989; Kim, Merrill, & Collins, 2021).

The concept of perceived usefulness was first proposed by (Davis, 1989) who stated that "people tend to use or not use an application to the extent they believe it will help them perform their job better" (Davis, 1989, p.320).

Perceived usefulness is concerned with how practical the technology might be in everyday interactions (Davis, 1989) - a person only adopts a new technology once he/she thinks this will improve their quality of life in a significant manner. Thus, a customer may not accept an application that is hard to use (Maryanto & Kaihatu, 2021).

Previous research in studying the consequences of perceived usefulness and perceived ease of use finds that perceived usefulness and ease of use have a positive impact on user acceptance (Keni, 2020). Perceived usefulness, as compared to other technology-related

perceptions such as perceived ease of use, is found to have stronger links to the various mechanisms that influence technological adoption in diverse contexts (Kim, Merrill, & Collins, 2021; Davis, 1989).

According to Pavlou (2003), perceived ease of use is not a factor that has a direct impact on consumer perceptions to acceptance of e-commerce". Pavlou (2003, p.125) distinguishes and defines both terms as follows "perceived usefulness influences Website acceptance for both purchase and inquiry purposes, whereas perceived ease of use induces acceptance of the Website only for inquiries".

From multiple disciplinary vantage points, perceived usefulness and perceived ease of use have been shown to be fundamental and distinct constructs that are influential in decisions to use information technology. They have a significant effect on transaction intentions, suggesting that TAM is applicable to consumer online behaviour to explain acceptance of B2C e-commerce (Pavlou, 2003). These two concepts align in the sense that if a system is easy to interact with, the less effort is needed to operate it, and the more effort can be allocated to other activities (Xia & Bechwati, 2008).

Furthermore, both trust and customer satisfaction have also been deemed as two of the most studied variables in the field of marketing and had long been understood as two variables which play significant roles in affecting customer loyalty and repurchase behaviour across all industries (Keni, 2020; Kartika, Firdhaus, & Najib, 2019; Menidjel, Benhabib, & Bilgihan, 2017).

2.2.2.1. Comments & Reviews

People's daily habits have changed greatly due to the rapid development of the Internet and e-commerce. With the rapid development of e-commerce, online comments have become an important reference for consumers when choosing and purchasing products or services (Lin, Bu, He, & Liang, 2019).

Research shows that word-of-mouth (WOM) plays an important role in influencing consumer behaviour (Xia & Bechwati, 2008) because consumers find information coming from a person they know more trustworthy than market-generated information. What used to be known as

word-of-mouth has now changed into word-of-mouse or electronic worth of mouth (EWOM) due to this digital era we are living. Online reviews and comments have become key information sources to draw inference regarding trustworthiness and usefulness (Xia & Bechwati, 2008).

Online shopping has many risks and in order to reduce such risks, consumers compare the goods in multiple stores before placing an order (Lin, Bu, He, & Liang, 2019). This is where comments and reviews come to light due to the impact they can have on the intention to purchase, since they are viewed as impartial, honest opinions of someone who already bought a given item and not just promotional information from the merchant (Lin, Bu, He, & Liang, 2019). Research has shown that this relationship is mediated by consumer's perceived usefulness of the review (Kim, Merrill, & Collins, 2021).

2.2.3. Customer Satisfaction

Customer satisfaction is defined by Keni (2020, p.484) as "consumers' sense of delight in which the expectation that they had toward the company exceeded by the true quality of the product or service that the company offered". Customer satisfaction also affects people's intention to rebuy or revisit the same company in the future (Menidjel, Benhabib, & Bilgihan, 2017).

In other words, customer satisfaction is happiness or regret depending on whether consumer's expectations have been met according to what they expected (Maryanto & Kaihatu, 2021; Kartika, Firdhaus, & Najib, 2019). If products meet customers' expectations, they are pleased, and if their expectation is exceeded, they become very satisfied or happy (Kartika, Firdhaus, & Najib, 2019).

Businesses endeavour to offer better customer experience in order to develop strong consumer–brand relationships (Trivedi, 2019). The importance of a concept like customer satisfaction can only increase in modern-day marketing as the focus of marketeers shifts from promoting unique selling propositions to building an emotional relationship with the consumers (Trivedi, 2019).

Consumer satisfaction significantly influences trust (Menidjel, Benhabib, & Bilgihan, 2017) - and highly satisfied customers tend to demonstrate higher likelihood of repurchase (Bart, Shankar,

Sultan, & Urban, 2005; Cheng & Jiang, 2020). Therefore, the variable of satisfaction will be studied in the specific context of a chatbot. People use the technology if they feel that its use is beneficial, thus perceived usefulness combined with customer satisfaction may impact how people use chatbots.

Today's customers also expect faster communication from companies, but immediate responses tend to be difficult and expensive for firms to achieve through traditional channels (e.g., face-to-face, telephone) (Miao, Kozlenkova, Wang, Xie, & Palmatier, 2021) – that is why companies resort to chatbots to try and save time but it is not always the preferred means of communication.

In the U.S., 27% of adults have used chatbots for shopping at least once, and nearly 40% of them favour this kind of shopping experience (Jovic, 2020) because they can give immediate responses since they are always on and they are programmed to reply to most of the questions made by users (Cheng & Jiang, 2020).

2.3. Purchase Intention

Trust and perceived risk are shown to be direct antecedents of intention to transact, suggesting that uncertainty reduction is a key component in consumer acceptance of e-commerce which deserves particular attention (Pavlou, 2003; Jarcenpaa, Tractinsky, & Vitale, 2000). As online comments can help consumers understand the product information in the first place and are considered to be more honest than the merchant's promotional information, these have an indispensable role in consumer product attitudes and purchasing decisions (Lin, Bu, He, & Liang, 2019). Perceived usefulness has also been shown to be a strong predictor of intentions to transact in e-commerce (Pavlou, 2003), since it deals with the adoption of new technologies (Davis, 1989).

Avatars are meant to impersonate a human sales agent and help customers with their purchase intentions. The purpose of a sales agent is to increase customers' purchase intention; thus, avatars are created with the same goal. Adding an avatar to Web-based information increased the customer's satisfaction with the retailer, attitude toward the product, and purchase intention (Holzwarth, Janiszewski, & Neumann, 2006). On the other hand, there is a long history of evidence that personal communication is more effective than mass-media communication, since face-to-face interactions are perceived as more accurate and more likely to be believed (Holzwarth, Janiszewski, & Neumann, 2006).

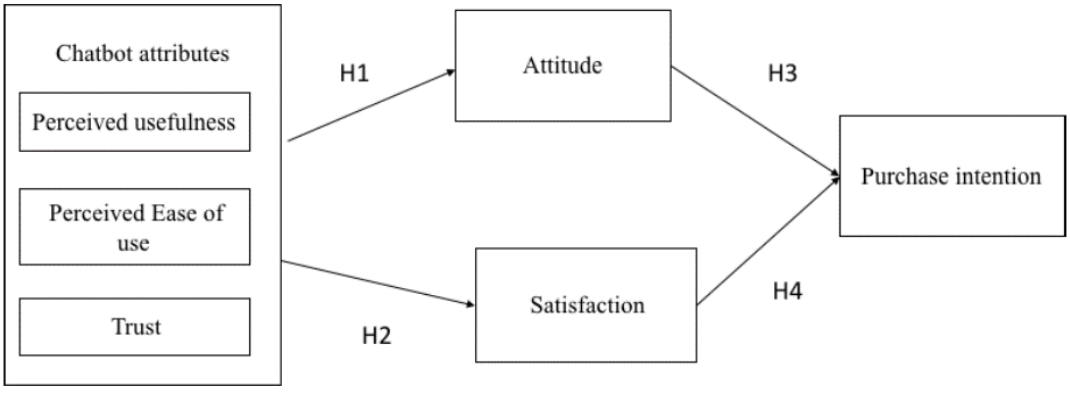
Companies use AI to analyse large amounts of numerical data (including less intuitive predictive variables) to set optimized prices and then change prices in real time (Davenport, Guha, Grewal, & Bressgott, 2019). In addition, the pricing guidelines must balance two competing concerns: that the price is low enough to attract customers; and high enough to allow the company to make sufficient profits. Herewith the company would target its advertising to undecided customers about a product, which would provide the highest returns and spend no effort on those most likely to buy or unlikely to buy (Davenport, Guha, Grewal, & Bressgott, 2019).

It is anticipated that the highest value potential of artificial intelligence will refer to domains related to marketing and sales (Chui, et al., 2018), through impacts on marketing campaigns, such as presenting the next best offers to customers (Davenport, Guha, Grewal, & Bressgott, 2019), in the purchase of scheduled digital ads (Parekh, 2018) and predictive lead scoring (Harding, 2017).

2.4. Research Model

Based on the previously reviewed literature, a research model is proposed entailing how chatbot attributes impact purchase intention.

Figure 5- Research Model



Source: Own creation

As chatbots are a new technology platform, consumers may find some risk in its use. Scholars believe that intentions of continued use are an important outcome of user satisfaction since people tend to use the website again, therefore purchase more depending on how satisfied they are with the website (Cheng & Jiang, 2020). Prior studies have shown that trusting beliefs in specific online

vendors are correlated with transaction intentions with those same vendors (McKnight & Chervany, 2001; Pavlou, 2003). This predictor is important across industries as highly satisfied customers tend to demonstrate higher likelihood of repurchase, therefore firms need to build long-term customer relationships (Bart, Shankar, Sultan, & Urban, 2005).

Building consumer trust is a strategic imperative for web-based vendors because trust strongly influences consumer intentions to transact with unfamiliar vendors via the web. This allows for consumer to share personal information with the vendor hence it is critical, to promote trust in order to transform a potential consumer from curious observer to one who is willing to transact over the site (McKnight, Choudhury, & Kacmar, 2002).

Consumers like to get the information they're asking for immediately, hence they recognize the usefulness of chatbot. Bots are the best at providing fast and reliable service; they're always on and they're programmed to answer the most common questions immediately, which gives them an advantage over email or social media (Jovic, 2020). The following hypotheses were proposed:

H1: Perceived attributes of a chatbot have a positive impact on the attitude towards chatbots.

H1a: Perceived usefulness has a positive impact on the attitude towards chatbots.

H1b: Perceived ease of use has a positive impact on the attitude towards chatbots.

H1c: Trust has a positive impact on the attitude towards chatbots.

H2: Perceived attributes have a positive impact on the customer satisfaction with the chatbot.

H2a: Perceived usefulness has a positive impact on the customer satisfaction with the chatbot.

H2b: Perceived ease of use has a positive impact on the customer satisfaction with the chatbot.

H2c: Trust has a positive impact on the customer satisfaction with the chatbot.

The theory of planned behaviour (TPB) suggests that attitudes are predictive of the intention to perform a behaviour (Ajzen, 1991). Attitude toward the behaviour is what a person thinks or feels about that particular behaviour (Ajzen, 1991). An individual tends to possess a favourable attitude when the outcomes are positively evaluated and therefore, he is likely to engage in that behaviour, i.e., an individual's positive attitude toward a particular behaviour increases his intention to perform that behaviour (Ajzen, 1991). Hence, the following is proposed:

H3: Attitude towards chatbots has a positive impact on purchase intention.

H4: Customer satisfaction with chatbots have a positive impact on purchase intention.

3. Methodology

The research question of this investigation is “What is the impact of chatbots on individuals' purchase intention?”. This research question aims to understand which attributes of AI mechanisms often known in the literature as avatars, virtual assistants or chatbots have an impact in online purchase intention. This dissertation will analyse the beliefs and attitudes towards the use of a chatbot and if they impact consumers’ purchase intention, contributing to a higher bounce rate.

3.1 Population and sampling

The target population for this research was the population between 18-65 years old and they could either be resident in Portugal or abroad, with data being collected online through survey. The sample was generated through snowball sampling, as the questionnaire was disseminated on online platforms with the possibility to be shared for other individuals. Participants did not receive any compensation for participating in the study; they were free to choose whether to participate in the study and share it with their acquaintances. The results were analysed through SPSS- version 27 using the license provided by the University of Minho.

Moreover, it should be noted that all data was obtained in digital format and it is not possible to identify respondents, as their confidentiality was guaranteed.

Participants were informed about the overall storage and processing of data according to Regulation (EU) 2016/GDPR. After participants gave their explicit consent to answer the questionnaire, they read a brief explanation about chatbots so that they could answer whether they have used this AI mechanism or not.

3.2 Questionnaire development

In order to test the proposed model, a quantitative approach using a survey was followed. The questionnaire included seven main sections referring to different concepts used in the model: trust, perceived usefulness, perceived ease of use, customer satisfaction, attitude towards chatbots, purchase intention and demographics. Previously developed scales were used to operationalize the studied constructs: Perceived Usefulness (PU) (Zarmpou, Saprikis, Markos, & Vlachopoulou, 2012; Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004), Perceived Ease of

Use (PEOU) (Wu & Wang, 2005), Trust (Bart, Shankar, Sultan, & Urban, 2005) (Alves & Soares, Evaluating the use of avatars in e-commerce, 2013), Attitude towards chatbots (Venkatesh, Morris, Davis, & Davis, 2003), Customer Satisfaction (Chung, Ko, Joung, & Kim, 2020), and Purchase Intention (Lu, Fan, & Zhou, 2016) (table 2).

Table 1 - Table of constructs and references

Construct	Items	Reference
Perceived Usefulness	I think using chatbots makes it easier for me to shop for products. I think using chatbots makes it easier for me to follow up on my orders. I think using chatbots enables me to shop for products online more quickly. I think using chatbots enables me to shop for products online more effectively. I find chatbots very useful in shopping for a product.	(Pikkarainen, et al., 2004; Zarmpou, et al., 2012)
Perceived Ease of Use	I think learning to use a chatbot is easy. I think becoming skilful at using a chatbot is easy. I think using a chatbot is easy.	(Wu & Wang, 2005)
Trust	The websites that use chatbots appear to be more trustworthy than other similar websites I have visited. The websites that use chatbots represent a company that will deliver on promises made. The websites that use chatbots provide information that deserves my trust. I trust the recommendations given to me by a chatbot on a website.	(Bart, Shankar, Sultan, & Urban, 2005; Alves & Soares, 2013)

Attitude towards chatbots	Using chatbots is a good idea. Chatbots make online shopping more interesting. Using a chatbot is fun. I would like online shopping with chatbots.	(Venkatesh, Morris, Davis, & Davis, 2003)
Customer Satisfaction	I am satisfied with the chatbot. I am content with the chatbot. The chatbot did a good job. The chatbot did what I expected. I am happy with the chatbot. I was satisfied with the experience of talking with the chatbot.	(Chung, Ko, Joung, & Kim, 2020)
Purchase intention	I am very likely to buy the product from a seller that uses a chatbot. I would consider buying the product from a seller that uses a chatbot in the future. I intend to buy the product from a seller that uses a chatbot.	(Lu, Fan, & Zhou, 2016)

All of the items were tested using a Likert measurement scale that was converted into a numerical scale, where "1" refers to "strongly disagree" and "7" refers to "strongly agree" (see table 1 below). Question number six had an additional numerical scale "8" which refers to "not applicable" since we can only test whether a user is satisfied with a chatbot if they previously interacted with one.

Table 2 - Likert scale

Likert scale	Number
Strongly disagree	1
Disagree	2
Somewhat disagree	3

Neither agree nor disagree	4
Somewhat agree	5
Agree	6
Strongly agree	7
Not applicable	8

The questionnaire was developed in English. The questionnaire was pre-tested with five respondents in order to rule out interpretation problems of the questions. A survey was applied online to a snowball sample of consumers. A total of 415 answers were obtained and 300 of which were valid.

3.3 Data collection

The survey was made available on November 4th via Instagram, Facebook, WhatsApp and Email and was online during a timeframe of eleven days. At the end of the submission on November 15th, the answers were collected and we started the data analysis. A total of 300 questionnaires were filled in total and an additional 115 which were left incomplete and therefore were not eligible for this study. In addition, four other respondents were removed due to not belonging to the target audience. Afterwards, all the data gathered has been filtered and cleaned using SPSS and we proceeded with the data analysis.

4. Results

This chapter aims at presenting the results from the data analysis of the quantitative data collected through the online survey questionnaire.

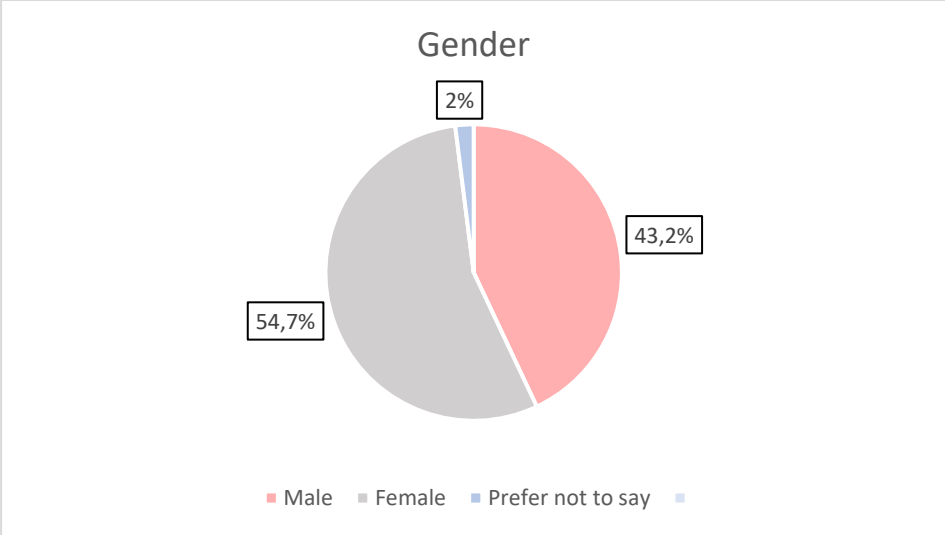
This chapter is organised as follows: we start by the sample characterization, followed by the descriptive analysis, reliability measurement, normality test, correlation finally regression analysis. Lastly, a description and analysis of the statistical tests of the proposed hypotheses are presented, resulting in their acceptance or rejection.

4.1. Sample Characterization

4.1.1. Gender

According to figure 6, most respondents are female. Although, the number is really balanced between the two genders, there is a majority of 162 female respondents (54,7%). There were 128 male respondents (43,2%) and 6 respondents who preferred not to reveal their gender (2%).

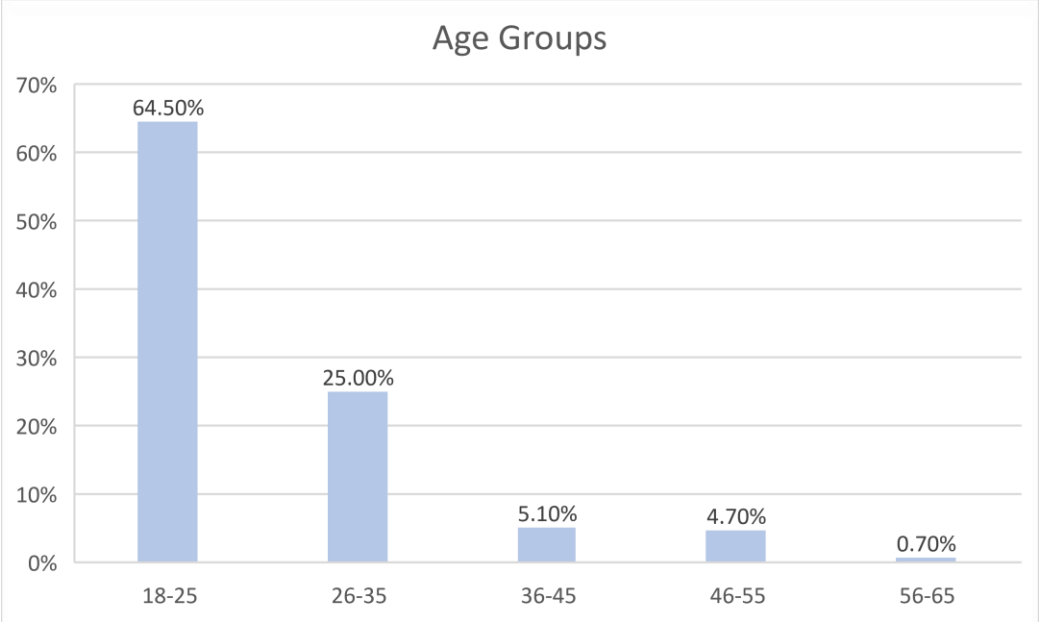
Figure 6 – Gender



4.1.2. Age

Regarding the ages of respondents, they are between 18 and 60 years old. To facilitate the analysis and make it more objective and clearer, the ages were divided into six different age groups: [18-25], [26-35], [36-45], [46-55], [56- 65]. According to the bar graph below, most respondents are aged between 18 and 25 (64,5%), with the age of 24 having the highest frequency of 40 respondents – this may be explained by the convenience and snowball sampling method used. This is followed by ages between 26 and 35, with a percentage of 25%. We can also verify that the average age of the collected sample is 26.29, suggesting that the population is adult, but quite young.

Figure 7 - Age

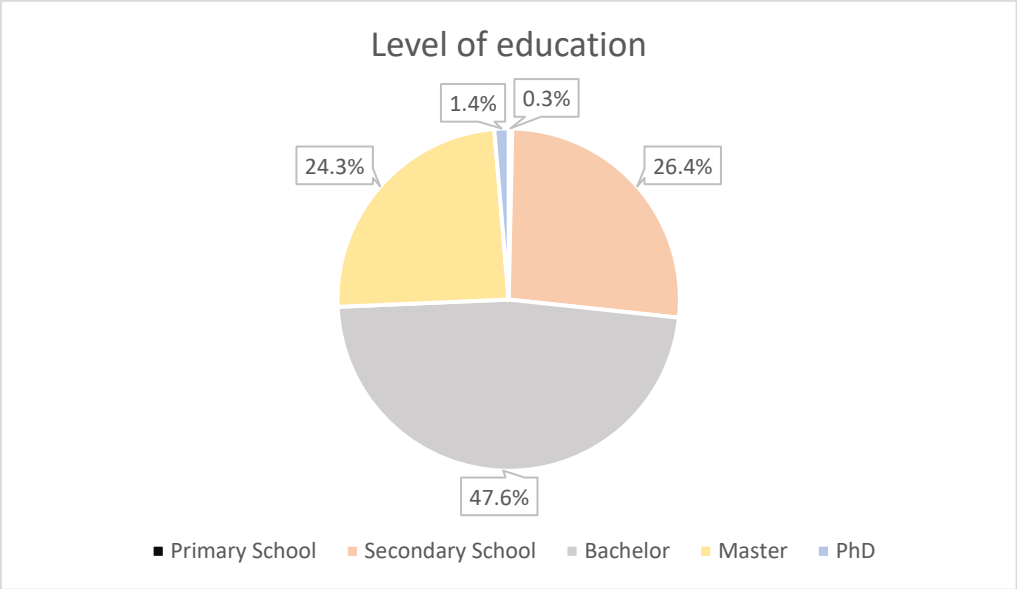


4.1.3. Level of education

Regarding the level of education of the participants, 217 of them are highly educated (i.e. finished bachelor's degree or higher), which represents 73,3% of the total sample. On the other hand, 79 of the participants have not yet completed any type of higher education, representing

26,7% people of the study. As we can see below, respondents doing a bachelor's degree represent half of the people who filled in the survey.

Figure 8 - Level of education



4.1.4. Nationality

In what concerns the nationality of respondents, we can see a big diversity of respondents from 24 different nationalities (table 3). The ones that stand out the most are Portuguese (211), Ecuadorian (33) and British (9). We can clearly understand a predominancy of Portuguese participants, given the nationality of the author and the dissemination of the survey.

Table 3 - Nationality

	Frequency	Percent	Valid Percent	Cumulative Percent
American	1	.3	.3	.3
Argentinian	1	.3	.3	.7
Armenian	1	.3	.3	1.0
Brazilian	4	1.4	1.4	2.4
British	9	3.0	3.0	5.4

Chilean	4	1.4	1.4	6.8
Croatian	1	.3	.3	7.1
Ecuadorian	33	11.1	11.1	18.2
French	1	.3	.3	18.6
German	4	1.4	1.4	19.9
Greek	1	.3	.3	20.3
Irish	1	.3	.3	20.6
Italian	4	1.4	1.4	22.0
Latvian	1	.3	.3	22.3
Lebanese	2	.7	.7	23.0
Mexican	1	.3	.3	23.3
Mozambique	1	.3	.3	23.6
Paraguay	1	.3	.3	24.0
Polish	3	1.0	1.0	25.0
Portuguese	211	71.3	71.3	96.3
Serbian	1	.3	.3	96.6
Spanish	4	1.4	1.4	98.0
Sri Lanka	1	.3	.3	98.3
Venezuelan	5	1.7	1.7	100.0

4.2. Descriptive analysis of the variables

In this section, the descriptive analysis of the variables is presented, in particular mean and standard deviation.

4.2.1. Perceived Usefulness

In what concerns perceived usefulness, the mean is between 4.01 and 4.34, which means that the majority of participants are neutral as to whether they think using chatbots can improve the performance of their work. When people believe that the technology is useful, they are more inclined to use the technology. We can also verify that the standard deviation in all items is close to 1.6, which means that the data are dispersed over a wider range of values.

Table 4 - Descriptive analysis (Perceived Usefulness)

	N	Mean	Std. Deviation
I think using chatbots makes it easier for me to shop for products.	296	4.27	1.563
I think using chatbots makes it easier for me to follow up on my orders.	296	4.34	1.557
I think using chatbots enables me to shop for products online quicker.	296	4.01	1.586
I think using chatbots enables me to shop for products online more effectively.	296	4.01	1.573
I find chatbots very useful in shopping for a product.	296	4.16	1.594

4.2.2. Perceived Ease of Use

For perceived ease of use, the mean varies between 5.12 and 5.49. Therefore, participants are more confident and competent in adopting chatbots, given the fact that they are more eager to agree with the statements. All three items have a standard deviation close to 1.3, thus data are dispersed over a wider range of values.

Table 5 - Descriptive analysis (Perceived Ease of Use)

	N	Mean	Std. Deviation
I think learning to use a chatbot is easy.	296	5.49	1.291
I think becoming skilful at using a chatbot is easy.	296	5.12	1.308
I think using a chatbot is easy.	296	5.46	1.285

4.2.3. Trust

Regarding trust on a brand, we can see that the mean of items varies, with the item "I trust the recommendations given to me by a chatbot on a website" having the highest mean (4.24). Most of the answers were neither agreeing nor disagreeing, so the level of trust that the respondents have in chatbots to perform expected activities without taking advantage is neutral.

Table 6 - Descriptive analysis (trust)

	N	Mean	Std. Deviation
The websites that use chatbots appear to be more trustworthy than other similar websites I have visited.	296	3.89	1.550
The websites that use chatbots represent a company that will deliver on promises made.	296	3.77	1.465
The websites that use chatbots provide information that deserves my trust.	296	3.89	1.422
I trust the recommendations given to me by a chatbot on a website.	296	4.24	1.451

4.2.4. Attitude towards chatbots

Respondents agree more with “using chatbots is a good idea” rather than “liking online shopping with chatbots”, given that the first statement presents a mean of 4.83. These results may indicate that although, a person might be willing to use a chatbot, they do not consider the experience to purchase through one as pleasurable.

Table 7 - Descriptive analysis (Attitude towards chatbots)

	N	Mean	Std. Deviation
Using chatbots is a good idea.	296	4.83	1.436
Chatbots make online shopping more interesting.	296	4.17	1.585

Using a chatbot is fun.	296	4.03	1.636
I would like online shopping with chatbots.	296	3.93	1.593

4.2.5. Customer Satisfaction

Regarding customer satisfaction, it should be taken into consideration if a person has interacted before with a chatbot to be able to be satisfied (or not) with it. Although, 63 respondents replied "no" as in never interacted with one, it is surprising how on average only 15 respondents inserted "not applicable" to all statements in this section. Even separating people who have interacted with a chatbot before and people who haven't, the mean is between 4.49 (lowest) and 5.09 (highest). (See attachment 8)

Table 8 - Descriptive analysis (Customer Satisfaction)

	N	Mean	Std. Deviation
In general I am satisfied with using a chatbot.	296	4.73	1.710
In general I am content with using a chatbot.	296	4.72	1.687
The chatbot does a good job.	296	4.81	1.643
The chatbot does what I expect.	296	4.77	1.651
In general I am happy with using a chatbot.	296	4.61	1.719
In general I am satisfied with the experience of talking with the chatbot.	296	4.56	1.795

We have the statement "In general I am satisfied with the experience of talking with the chatbot" as our lowest mean (be it for the whole sample of separated by the parameter mentioned above), thus suggesting that respondents are not satisfied with using chatbots. On the other hand, "The chatbot does a good job" has the highest mean. We can conclude from this section that,

overall people think that chatbots do a good job but they are not satisfied with using one if they have to.

4.2.6. Purchase Intention

Given the descriptive analysis of the variable purchase intention, we can confirm that the statement "I would consider buying from a seller that uses a chatbot in the future" has the highest mean of 4.23 - this represents a small leap from the statement with the lowest mean "I intend to buy from a seller that uses a chatbot" (3.90). The word choice makes all the difference since people might consider buying a product but not necessarily intend to buy it right after interacting with a chatbot.

Table 9 - Descriptive analysis (Purchase Intention)

	N	Mean	Std. Deviation
I am very likely to buy from a seller that uses a chatbot.	296	3.93	1.378
I would consider buying from a seller that uses a chatbot in the future.	296	4.23	1.383
I intend to buy from a seller that uses a chatbot.	296	3.90	1.347

4.3. Reliability

Even though all items used in the survey were adapted from previously literature, a Cronbach's Alpha was conducted to assess the internal consistency of the constructs with more than one item, providing a measure of the used scales' reliability.

The Alpha value must be evaluated according to its result, when the value is less than .6 the consistency is "Poor", when the value is between .6 and .7 the consistency is considered "Moderate ", when the value is between .7 and .8 the consistency is considered "Good", when the value is between .8 and .9 the consistency is "Very Good". Finally, when the value is greater than .9 the consistency is "Excellent" (Hair, et al., 2015) (table 10).

The results indicate a Cronbach's Alpha reliability coefficient of more than .88 for all constructs, in most cases the value is above .9, meaning the items are very reliable to predict the variables (Pallant, 2016). In addition, it was not necessary to recode any variable since there was no reverse items that required that, nor delete an item since alpha for the study was considered excellent.

According to Chung, Ko, Joung, & Kim (2020), the Customer Satisfaction scale has good internal consistency, with a Cronbach alpha coefficient reported of .884. In the current study, the Cronbach alpha coefficient is .92, suggesting very good internal consistency reliability for the scale with this sample, being it the highest value of all variables.

Next, we can verify the Cronbach's alpha calculations for all variables studied during this research.

Table 10 - Interpretation of Cronbach's Alpha

	Number of Items	Item Means	Cronbach's Alpha	Category
Perceived Usefulness	5	4.159	.921	Excellent
Perceived Ease of Use	3	5.356	.901	Excellent
Trust	4	3.947	.888	Very Good
Attitude towards chatbots	4	4.238	.909	Excellent
Customer Satisfaction	6	4.702	.961	Excellent
Purchase Intention	3	4.018	.927	Excellent

4.4. Normality Test

We assessed the normality of data through Kolmogorov-Smirnov and Shapiro-Wilk tests (Table 11). This test allows us to decide whether to do a parametric or a non-parametric study by testing our H_0 (null hypothesis). Parametric tests can only be used if the normal distribution for the

variables under study is guaranteed, therefore, non-parametric tests will be used when the distribution of variables is not considered normal (Field, 2005).

Results show that all variables have a significance value lower than 0,05, which means that the null hypothesis was rejected in all of them. We can then conclude that none of the variables have a normal distribution. Thus, taking into account the results obtained, given that the distribution is not normal, it is necessary to use non-parametric tests.

Table 11 - Normality test Kolmogorov-Smirnov and Shapiro-Wilk

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Perceived Usefulness	.103	296	.000	.982	296	.001
Perceived Ease of Use	.139	296	.000	.916	296	.000
Trust	.111	296	.000	.981	296	.001
Attitude Towards Chatbots	.108	296	.000	.969	296	.000
Customer Satisfaction	.096	296	.000	.975	296	.000
Purchase Intention	.214	296	.000	.934	296	.000

a. Lilliefors Significance Correction

4.5. Correlation

A perfect correlation of 1 or –1 indicates that the value of one variable can be determined exactly by knowing the value on the other variable (Pallant, 2016). A positive correlation indicates that as one variable increases, so does the other. A negative correlation indicates that as one variable increases, the other decreases. The statistical test used was Pearson Correlation to measure the strength and direction of linear relationship between pairs of metric variables.

Spearman's correlations were run to examine the relationships shown in the research model including chatbots attributes, customer satisfaction, attitude towards chatbots and purchase intention. There were positive and significant correlations between all the variables, having the same number of participants (n = 296) in all of them as follows (see table 12):

Table 12 - Spearman's correlation

		PU	PEOU	TRUST	Attitude Towards Chatbots	Customer Satisfaction	Purchase Intention
PU	Correlation Coefficient	1.000	.274**	.580**	.730**	.617**	.609**
	Sig. (2-tailed)	.	.000	.000	.000	.000	.000
	N	296	296	296	296	296	296
PEOU	Correlation Coefficient	.274**	1.000	.266**	.269**	.285**	.237**
	Sig. (2-tailed)	.000	.	.000	.000	.000	.000
	N	296	296	296	296	296	296
TRUST	Correlation Coefficient	.580**	.266**	1.000	.676**	.551**	.716**
	Sig. (2-tailed)	.000	.000	.	.000	.000	.000
	N	296	296	296	296	296	296
Attitude Towards Chatbots	Correlation Coefficient	.730**	.269**	.676**	1.000	.671**	.648**
	Sig. (2-tailed)	.000	.000	.000	.	.000	.000
	N	296	296	296	296	296	296
Customer Satisfaction	Correlation Coefficient	.617**	.285**	.551**	.671**	1.000	.517**
	Sig. (2-tailed)	.000	.000	.000	.000	.	.000
	N	296	296	296	296	296	296
Purchase Intention	Correlation Coefficient	.609**	.237**	.716**	.648**	.517**	1.000
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.
	N	296	296	296	296	296	296

**. Correlation is significant at the 0.01 level (2-tailed).

Chatbots attribute (PU) and attitude towards chatbots – $r_s = .730$, $p < .001$.

Chatbots attribute (PEOU) and attitude towards chatbots – $r_s = .269$, $p < .001$.

Chatbots attribute (Trust) and attitude towards chatbots – $r_s = .676$, $p < .001$.

Chatbots attribute (PU) and customer satisfaction – $r_s = .617$, $p < .001$.

Chatbots attribute (PEOU) and customer satisfaction – $r_s = .285$, $p < .001$.

Chatbots attribute (Trust) and customer satisfaction – $r_s = .551$, $p < .001$.

Attitude towards chatbots and purchase intention – $r_s = .648$, $p < .001$.

Customer satisfaction and purchase intention – $r_s = .517$, $p < .001$.

These results show that perceived ease of use, although having a positive correlation, has the weakest relationship with the other variables. While perceived usefulness and attitude towards chatbots show a strong positive correlation.

4.6. Regression

Using a regression model allows predicting future evaluations, since the purpose of regression analysis is to predict a dependent variable, taking into account the independent variable (Hair, et al., 2015).

However, the Kolmogorov-Smirnov test showed us that the distribution is not normal and, therefore, it is not appropriate to use the linear regression model since this model assumes that the distribution is, in fact, normal (Field, 2005). For this reason and to avoid inaccurate results, linear regression using bootstrapping was used. Non-parametric regression using bootstrapping is already widely studied in the non-parametric statistics literature (Ferraty, Laksaci, Tadj, & Vieu, 2010).

Bootstrapping is a statistical procedure that resamples a dataset and creates numerous simulated samples. In this way, this simulated sampling, which previously had a non-normal distribution, can be used to make statistical inferences (Ferraty, Laksaci, Tadj, & Vieu, 2010).

In this study, in order to test and validate our hypotheses, 2000 bootstrap samples were used with a confidence level of 95% and calculated using the bias-corrected and accelerated bootstrap method (BCa).

4.6.1. PU & Attitude towards chatbots

Table 13 - Linear regression using bootstrapping

	Attitude Towards Chatbots					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.593	4.003	.658		6.079	.000
Perceived Usefulness (PU)		.623	.030	.770	20.709	.000

According to the table above, we can see that, considering the value of R^2, 59.3% of the variability of attitude towards chatbots is explained by PU. Furthermore, the value of Sig. is less than 0.01, which means that attitude towards chatbots variable contributed significantly to explain the variable perceived usefulness. Finally, looking at the non-standardized coefficient, it appears that for each unit of PU, there is an increase of .623 units of attitude towards chatbots.

4.6.2. PEOU & Attitude towards chatbots

According to table 14, R^2 value represents 8,9% of the attitude towards chatbots variability regarding PEOU. Furthermore, the significance registers a value of .000, meaning that it is less than 0.05, which indicates that PEOU contributed statistically and significantly to explain the attitude towards chatbots variable. We can also analyse through the table that, for each unit of PEOU, attitude towards chatbots increase by.467 units.

Table 14 - Linear regression using bootstrapping

	Attitude Towards Chatbots					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.089	9.449	1.432		6.596	.000
Perceived Ease of Use (PEOU)		.467	.087	.299	5.364	.000

4.6.3. Trust & Attitude towards chatbots

After analysing table 15, we can see that the value of R^2 is .536, which shows that 53.6% of the variability of attitude towards chatbots is explained by trust. Furthermore, we can verify that the value of Sig. is less than .001, which proves that trust contributes significantly to explain the variable of attitude towards chatbots. Finally, we can highlight, in the non-standardized coefficient, that for each unit of trust, there is an increase of .673 units of attitude towards chatbots.

Table 15 - Linear regression using bootstrapping

	Attitude Towards Chatbots					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.536	4.378	.651		6.728	.000
Trust		.673	.036	.732	18.444	.000

4.6.4. PU & Customer Satisfaction

Subsequently, we will perform similar tests to evaluate the relationship of chatbot attributes with customer satisfaction.

The results of the regression model shows that the perceived usefulness predictor explains 38,6% of the variance that exists in our dependent variable – customer satisfaction (Table 16). We also observe that the regression coefficient of the perceived usefulness variable was significantly different from .000, which implies that the statistical significance of the regression model that was run is less than 0.05, so overall, the regression model statistically significantly predicts the outcome variable (i.e., it is a good fit for the data).

Table 16 - Linear regression using bootstrapping

	Customer Satisfaction					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.386	10.636	1.361		7.817	.000

Perceived Usefulness (PU)		.845	.062	.621	13.599	.000

4.6.5. PEOU & Customer Satisfaction

The regression model shows that the PEOU predictor explains 10,6% of the variance that exists in our dependent variable – customer satisfaction. We also observe that the regression coefficient of the perceived ease of use variable was significantly different from .000, which implies that the statistical significance of the regression model that was run is less than 0.05, so overall, the regression model statistically significantly predicts the outcome variable.

Table 17 - Linear regression using bootstrapping

	Customer Satisfaction					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.106	14.431	2.387		6.046	.000
Perceived Ease of Use (PEOU)		.858	.145	.326	5.911	.000

4.6.6. Trust & Customer Satisfaction

The regression model shows that the Trust predictor explains 31,3% of the variance that exists in our dependent variable – customer satisfaction. We also observe that the regression coefficient of the trust variable was significantly different from .000, which implies that the statistical significance of the regression model that was run is less than 0.05, so overall, the regression model statistically significantly predicts the outcome variable.

Table 18 - Linear regression using bootstrapping

	Customer Satisfaction					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.313	12.048	1.468		8.207	.000
Trust		1.024	.089	.559	11.566	.000

4.6.7. Customer Satisfaction & Purchase Intention

R^2 value indicates that 29,3% of the variance in customer satisfaction scores can be predicted from the variable purchase intention. This is an overall measure of the strength of association and does not reflect the extent to which any independent variable is associated with the dependent variable (Field, 2005). R-Square is also called the coefficient of determination (Pallant, 2016). For every increase of one unit in purchase intention, our customer satisfaction is predicted to be higher by .223 units.

Table 19 - Linear regression using bootstrapping

	Purchase Intention					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.293	5.775	.599		9.647	.000
Customer Satisfaction		.223	.020	.542	11.047	.000

4.6.8. Attitude Towards Chatbots & Purchase Intention

R^2 value indicates that 49,4% of the variance in purchase intention scores can be predicted from the variable attitude towards chatbots. For every increase of one unit in purchase intention, our attitude towards chatbots is predicted to be higher by .486 units. Furthermore, we can verify that the value of Sig. is less than 0.01, which means that purchase intention contributed significantly and statistically to explain the variable attitude towards chatbots.

Table 20 - Linear regression using bootstrapping

	Purchase Intention					
	R^2	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
(Constant)	.494	3.816	.511		7.462	.000
Attitude Towards Chatbots		.486	.029	.703	16.943	.000

4.7. Hypotheses validation

In sum, our results show support for all the proposed hypotheses (table 21).

Table 21 - Summary of hypotheses tests

H1: Perceived attributes of a chatbot have a positive impact on the attitude towards chatbots.	Validated
H1a: Perceived usefulness has a positive impact on the attitude towards chatbots.	Validated
H1b: Perceived ease of use has a positive impact on the attitude towards chatbots.	Validated
H1c: Trust has a positive impact on the attitude towards chatbots.	Validated
H2: Perceived attributes have a positive impact on the customer satisfaction with the chatbot.	Validated

H2a: Perceived usefulness has a positive impact on the customer satisfaction with the chatbot	Validated
H2b: Perceived ease of use has a positive impact on the customer satisfaction with the chatbot.	Validated
H2c: Trust has a positive impact on the customer satisfaction with the chatbot.	Validated
H3: Attitude towards chatbots has a positive impact on purchase intention.	Validated
H4: Customer satisfaction with chatbots have a positive impact on purchase intention.	Validated

5. Conclusion

The main goal of this dissertation was to understand the chatbot effect on customer satisfaction and ultimately on purchase intention, through the analysis of some perceived technology attributes, and investigating other factors that could impact this relationship in e-commerce platforms. This is particularly important for two reasons: since chatbots are quite a new feature on websites – more studies are needed to understand how they impact the buying behaviour of consumers; will they return to the website after a past bad experience with a chatbot? The second reason is related to the trend of using chatbots in the customer service areas, not always achieving the quality standards that customers are expecting, resulting in disappointment. Thus, the complex relationship between the customer experience and chatbot attributes was investigated.

Hence, this study investigates the impact of TAM factors (Perceived usefulness and perceived ease of use) and trust in purchase intention in sites displaying a chatbot feature, mediated by consumers' attitude and satisfaction with the chatbot. The results from our study, based on an online survey are expected to shed light on whether utilitarian-related factors and trust have a positive impact on attitudes and satisfaction with this technological tool and, ultimately, on the intention to purchase from e-commerce websites displaying this feature.

This chapter presents and discusses the main findings of the study and draws final conclusions. Lastly, academic and managerial implications will be presented, followed by the research limitations and recommendations for future research on the topic.

5.1. Main Findings

Using chatbots should not require too much effort for consumers. For instance, the technology should be easy to understand since the beginning. Our results show that PU has a higher positive correlation to consumers' attitude towards chatbots (r_s = .730) than to customer satisfaction (r_s = .617). Contrarily, the correlation of PEOU with customer satisfaction (r_s = .285) is higher than with the attitude towards chatbots (r_s = .269). According to the TAM model, perceived usefulness has a stronger relationship with attitude than perceived ease of use (Davis, 1989). Our results are in line with this finding. In other words, chatbots using artificial intelligence may be

perceived as bringing benefits to the future, in that it will contribute to the consumer's well-being, making their choices easier more practical, and more efficient, therefore our H1 is supported.

The future of e-commerce depends on trust. The lack of it, has been identified as one of the barriers for consumers who engage in e-commerce from the moment they disclosure personal information to online merchants (Wang & Emurian, 2005). Therefore, when people trust the seller, then there's a high probability that they will place their trust to the e-commerce company, which will ultimately motivate them to make or engage in further transactional activities with the company (Keni, 2020). Trust plays a more significant role in relation to the attitude towards chatbots (53.6%), rather than customer satisfaction (31.3%), therefore we can conclude that higher levels of trust will have a positive effect on attitude towards chatbots as it was seen in previous literature (De Cicco, Costa, & Alparone, 2020; McKnight & Chervany, 2001; Pavlou, 2003).

The second hypothesis is focused on the relationship between the perceived technology attributes of a chatbot and the customer satisfaction. The results indicate a positive and significant relationship between these variables. One of the most significant findings is the relative strength of the usefulness-satisfaction relationship compared to the ease of use-satisfaction relationship. The usefulness has a stronger positive impact in satisfaction (38,6%) than the ease of use (10,6%). This conclusion is in line with previous research about technology acceptance and usage (Davis, 1989), which has found that usefulness was significantly more strongly linked to technology usage than was ease of use. Answering the research question, the chatbot perceived technology attributes have a positive impact on customer satisfaction, even though the provided benefits, when performing a task with the chatbot, contribute more for a better experience than the extent of effort to conclude it. Our findings go in line with present literature that avatars generate a greater satisfaction with the merchant's site (Holzwarth, Janiszewski, & Neumann, 2006)

The third and fourth hypothesis predicted that attitude towards chatbots and satisfaction would positively influence intentions to purchase online. Attitude was found to be significantly associated with intentions to purchase online given that the coefficient of determination ($R^2 = .494$, $p < .000$) explained the variance predicted from the independent variable. Furthermore, it should be highlighted that attitude was the construct with the most significant impact on intentions to purchase online, with satisfaction variable representing ($R^2 = .293$, $p < .000$), which represents a good value for behavioural research. Thus, our study agree with (Holzwarth, Janiszewski, &

Neumann, 2006) which stated that adding an avatar to a website increased the customer's satisfaction with the retailer, attitude toward the product, and purchase intention.

5.2. Academic and Managerial Implications

As retailers increase their use of chatbots as a form of customer service, there is an increasing need to gain more knowledge and insights about consumers' perceptions and attitudes towards this technology. Particularly, it is vital for retailers and scholars to understand the effects of this technology on service interactions (Tran, Pallant, & Johnson, 2021).

Regarding who would benefit from the new findings of our research, the first beneficiaries would be companies that do not market their products online, as this research could encourage them to operate on the Internet. In particular, our results suggest that online marketers need to pay close attention to the factors that contribute to a favourable attitude. This study has evidenced that perceived usefulness, perceived ease of use and trust have a positive impact in attitude.

Secondly, this study has implications for companies that operate online but are not familiar with chatbots, as this research could open their eyes to the benefits of this new way of attracting and keeping customers, since, nowadays, chatbots can serve as a new way for customers to acquire purchases and solve their doubts rapidly. Chatbots are often introduced as an additional customer service program to coexist with frontline employees, rather than replacing human agents completely (Tran, Pallant, & Johnson, 2021).

Our results provide strong evidence that highly satisfied customers with the chatbot have a higher purchase intention, thus it is relevant to understand what leads to satisfaction for these customers. There is a clear importance of perceived technology attributes as a determinant of satisfaction supported by this research, therefore both usefulness and ease of use should be considered when designing a chatbot regardless of its function. However, usefulness has a higher impact on customer satisfaction than ease of use. This result suggests that users may be willing to cope with some difficulty of use in a system that provides critically needed functionality (Davis, 1989). As a result, e-commerce managers should focus in the chatbot functionality and make sure customers understand it and subsequently convey simplicity for customers to interact and solve a specific problem.

Despite the importance of the customer experience, it is known that companies seek to increase profits, and even though the experience itself is related with loyal relationships, a behaviour variable (e.g., attitude towards chatbots) should be studied, in order to give tangible and practical results to company managers.

In conclusion, implementing a chatbot is highly recommended to save costs in the customer service area. However, there are some aspects that should be carefully thought in order to avoid undesirable outcomes, such as the chatbot simplicity and functionality for customers.

In the future, it would be important to understand the impact of different types of bot and chatbots in consumer responses. Should consumers be informed and made aware that they are dealing with an AI mechanism? When should communication be directed to a human agent? It is important with improve chatbot communication capabilities, in order to be able to direct the interaction to a human assistant if the communication is not being effective and/or if the consumer is expressing frustration with the process.

5.3. Limitations and Future Research

Despite the valuable findings and insights described above, as this research is part of a master thesis, timeframe and resources are limited. Therefore, some limitations should be considered when interpreting results and conclusions.

Culture can influence customer attitudes and behaviours in service settings (Chan, Yim, & Lam, 2010), thus, this would be a fruitful area for further work since respondents were divided between 24 countries. Future research could analyse whether perceptions of chatbots would change according to their home country and their awareness of the concept. These insights could contribute to a more developed understanding of the process of acceptance of AI mechanisms.

One of the objectives of this study was to obtain a sample evenly distributed in terms of age, however, perhaps by the method of dissemination of the questionnaire (social networks), most respondents were between 18 and 25 years old (64,5%) – thus representativeness of other age groups is limited.

Another suggestion would be to make people interact before with a chatbot so that they could have a more vivid encounter with this AI mechanism and refer to that episode when answering, thus respondents would be basing their opinion on the same chatbot experience. If the

questionnaire were to be kept as it is in which it distinguishes at the beginning who has interacted with a chatbot and who has not - perhaps add an open question to know how their interaction was, in order to analyse whether their experience had an influence when answering to the concepts of the TAM model.

Despite this existing literature, there remains a need for further research on how consumers perceive chatbots as a form of service interaction. Indeed, the introduction of chatbots has fundamentally altered the nature of traditional service encounters online. The primary reasons for consumers to choose chatbots are time and cost related. Online entrepreneurs want to reduce the wait-time by delivering their visitors and customers fast answers (59%) and they also want to save more time on repetitive customer service tasks (43%) (Jovic, 2020). Chatbots, can provide unbiased information and consistent experience, as unlike humans, chatbots are free from fatigue (Huang & Rust, 2018). Hence, service interactions involving chatbots could be more consistent than traditional human-mediated interactions. In an era where convenience and speed are highly valued (Kaplan & Haenlein, 2019), the ability to address and respond to consumers' enquiries instantly can generate a huge advantage for firms (Tran, Pallant, & Johnson, 2021).

6. Bibliography

Agarwal, S., & Saif Al Qouyatahi, K. (2018). HRM Challenges in the Age of Globalisation. *International Research Journal of Business Studies, 10 (2)*, 89-98. Retrieved from http://www.irjbs.com/index.php/jurnalirjbs/article/view/1295/181

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Alduaij, M. (2019). Employing the Technology Acceptance Model to Explore the Trends of Social Media Adoption and its Effect on Perceived Usefulness and Perceived Ease of Use. *Journal of Information Technology Management, 11*(2), 129-143.

Alves, A., & Soares, A. M. (2013). Evaluating the use of avatars in e-commerce. *Portuguese Journal of Marketing/Revista Portuguesa de Marketing*, 31.

Alves, A., & Soares, A. M. (2014). L'introduction des Avatars comme facteur de sociabilité sur les sites de e-commerce: perspectives pour les petits détaillants. *Revue Française du Marketing*, 66-78.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., . . . Yang, H. (2018). Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. *Customer Needs and Solutions*(5(1-2)), 28-37. Retrieved April 15, 2020

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.

Barros, C. (2014). Recursos Humanos no século XXI: desafios e oportunidades - INFORH. Retrieved Setembro 25, 2019, from https://inforh.pt/recursos-humanos-no-seculo-xxi-desafios-e-oportunidades/

Barros, T., & Campomar, M. (2018). O Trade Marketing e suas atividades: Estudo de Casos no Setor Farmacêutico. *Revista de Gestão em Sistemas de Saúde*, 297-313.

Bart, Y., Shankar, V., Sultan, F., & Urban, L. (2005). Are the Drivers and Role of Online Trust the Same for All Web Sites and Consumers? A Large-Scale Exploratory Empirical Study. *Journal of Marketing, 69*(4), 133-152.

Brandtzaeg, P. B., & Følstad, A. (2017). Why people use chatbots. *In International Conference on Internet Science*, 377-392.

Cappelli, P., Tambe, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *SSRN*, pp. 15-42. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3263878#references-widget

Carter, R. (2019). Retrieved September 20, 2020, from UC Today: https://www.uctoday.com/contact-centre/how-do-bots-and-chatbots-

work/#:~:text=A%20bot%20is%20a%20program,would%20converse%20with%20another%20person.

Chan, K., Yim, C., & Lam, S. (2010). Is Customer Participation in Value Creation a Double-Edged Sword? Evidence from Professional Financial Services across Cultures. *Journal of Marketing, 74*(3), 48-64.

Cheng, Y., & Jiang, H. (2020). 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. doi:https://doi.org/10.1080/08838151.2020.1834296

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018, April). Retrieved Abril 1, 2020, from McKinsey Global Institute: https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-applications-and-value-of-deep-learning

Chung, M., Ko, E., Joung, H., & Kim, S. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research, 117*, 587–595.

Columbus, L. (2019). Retrieved March 18, 2020, from Forbes: https://www.forbes.com/sites/louiscolumbus/2019/07/07/10-charts-that-will-change-your-perspective-of-ai-in-marketing/amp/

Corti, K., & Gillespie, A. (2016). Co-constructing intersubjectivity with artificial conversational agents: people are more likely to initiate repairs of misunderstandings with agents represented as human. *Computers in Human Behavior, 58*, 431-442.

Cyr, D., Hassanein, K., Head, M., & Ivanov, A. (2007). The role of social presence in establishing loyalty in e-service environments. *Interacting with Computers, 19*(1), 43-56.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24-42. doi:https://doi.org/10.1007/s11747-019-00696-0

Dávila, H., Palacios, I., Peña, H. C., & Valencia, J. A. (2019). Trade marketing como estrategia de posicionamiento empresarial. *Revista de Ciencias Sociales*, 130-145.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

De Cicco, R., Costa, S., & Alparone, F. (2020). Millennials' attitude toward chatbots: an experimental study in a social relationship perspective. *International Journal of Retail & Distribution Management, 48*(11), 1213-1233.

De Cicco, R., Costa, S., & Alparone, F. (2020). Millennials' attitude toward chatbots: an experimental study in a social relationship perspective. *International Journal of Retail & Distribution Management*.

Eskildsen, J. (2009). The satisfied customer: Winners and losers in the battle for buyer preference. *Total Quality Management & Business Excellence*(20(5)), 581–582. doi:https://doi.org/10.1080/14783360902925421

Ferraty, F., Laksaci, A., Tadj, A., & Vieu, P. (2010). Rate of uniform consistency for nonparametric estimates with functional variables. *Journal of Statistical planning and inference, 140*(2), 335-352.

Field, A. (2005). *Discovering statistics using SPSS* (2nd ed.). London: Sage Publications.

Fisher, C. (1989). Current and Recurrent Challenges in HRM. *Journal of Management*.

Garcia, K. (2018, November 7). *Insider Intelligence*. Retrieved March 26, 2021, from eMarketer: https://www.emarketer.com/content/consumers-still-prefer-humans-over-chatbots

Garcia, K. (2018). *Insider Intelligence*. Retrieved March 26, 2021, from eMarketer: https://www.emarketer.com/content/customer-service-seekers-prefer-bypassing-humans?_ga=2.43491437.994207160.1616770742-1685722996.1616770742

Garcia, K. (2019). *Insider Intelligence*. Retrieved March 26, 2021, from eMarketer: https://www.emarketer.com/content/chatbots-may-ease-consumers-customer-service-concerns?_ga=2.5703803.994207160.1616770742-1685722996.1616770742

Gefen, D., & Straub, D. (2003). Managing user trust in B2C e-services. *e-service Journal, 2*(2), 7-24.

Gourraud, P.-A. (2020). Differences Between Europe and the United States on AI/Digital Policy: Comment Response to Roundtable Discussion on AI. *Gender & the Genome, 4*, 1-2. Retrieved April 02, 2020

Grabner-Kraeeter, S. (2002). The role of consumers' trust in online-shopping. *Journal of Business Ethics, 39*, 43-50.

Guariglia, M. (2020). *What to Know Before You Buy or Install Your Amazon Ring Camera*. Retrieved February 04, 2021, from https://www.eff.org/deeplinks/2020/02/what-know-you-buy-or-install-your-amazon-ring-camera

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*(61(4)), 5-14. doi:https://doi.org/10.1177/0008125619864925

Hair, J., Joe, F., Wolfinbarger, M., Money, A., Samouel, P., & Page, M. (2015). *Essentials of Business Research Methods.* New York: Routledge.

Harding, K. (2017). *Objective*. Retrieved April 11, 2020, from https://objectiveit.com/blog/use-ai-and-machine-learning-for-predictive-lead-scoring/

Hayes, A. (2019). *The Unintended Consequences of Self-Driving Cars*. Retrieved March 15, 2020, from https://www.investopedia.com/articles/investing/090215/unintended-consequences-selfdriving-cars.asp

Hill, J., Ford, W. R., & Farreras, I. G. (2015). Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. *Computers in human behavior, 49*, 245-250.

Holland, C. P., & Mandry, G. D. (2013). Online Search and Buying Behaviour in Consumer Markets. *46th Hawaii International Conference on System Sciences*, 2918-2927.

Holzwarth, M., Janiszewski, C., & Neumann, M. (2006). The Influence of Avatars on Online Consumer Shopping Behavior. *Journal of Marketing, 70*(4), 19-36.

Huang, M., & Rust, R. (2018). Artificial Intelligence in Service. *Journal of Service Research*(21 (2)), 155-172.

Illescas-Manzano, M., Vicente, N., Afonso, N., & Cristofol, C. (2021). Implementation of Chatbot in Online Commerce, and Open Innovation. *Journal of Open Innovation, 7*(2), 125.

Jarcenpaa, S., Tractinsky, N., & Vitale, M. (2000). Consumer trust in an Internet store. *Information Technology and Management, 1*(2), 45-71.

Jovic, D. (2020). *Smallbizgenius*. Retrieved March 26, 2021, from https://www.smallbizgenius.net/by-the-numbers/chatbot-statistics/#gref

Kaplan, A. M., & Haenlein, M. (2016). Higher education and the digital revolution: About MOOCs, SPOCs, social media, and the Cookie Monster. *Business Horizons*(59(4)), 441-450. Retrieved April 20, 2020

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15-25. doi:https://doi.org/10.1016/j.bushor.2018.08.004

Kartika, T., Firdhaus, A., & Najib, M. (2019). Contrasting the drivers of customer loyalty; financing and depositor customer, single and dual customer, in Indonesian Islamic bank. *Journal of Islamic Marketing, 11*(4), 933-959.

Keating, J., & Nourbakhsh, I. (2018). Teaching artificial intelligence and humanity. *Communications of the ACM*(61(2)), 29-32. doi:https://dl.acm.org/doi/10.1145/3104986

Keni, K. (2020). How Perceived Usefulness and Perceived Ease of Use Affecting Intent to Repurchase? *Jurnal Manajemen, 24*(3), 481–496.

Kim, J., Merrill, K., & Collins, C. (2021). AI as a Friend or Assistant: The Mediating Role of Perceived Usefulness in Social AI vs. Functional AI. *Telematics and Informatics, 64*(101694), 101694. doi:https://doi.org/10.1016/j.tele.2021.101694

Kitto, K., & Knight, S. (2019). Practical Ethics for Building Learning Analytics. *British Journal of Educational Technology*(50(6)), 2855-2870.

Kram, K. (1985). *Mentoring at Work: Developmental Relationships in Organisational Life.* Boston: University Press of America.

Larson, K. (2019). Retrieved March 21, 2020, from Medium: https://medium.com/@Smalltofeds/data-privacy-and-ai-ethics-stepped-to-the-fore-in-2018-4e0207f28210

Lengnick-Hall, M. (2003). Human Resources Management in the Knowledge Economy. Retrieved September 24, 2019, from https://books.google.pt/books?id=t8RLT77_VHMC&pg=PA1&hl=pt-PT&source=gbs_toc_r&cad=4#v=onepage&q&f=false

Levin, S. (2017). *The Guardian*. Retrieved April 16, 2020, from https://www.theguardian.com/technology/2017/sep/07/new-artificial-intelligence-can-tell-whether-youre-gay-or-straight-from-a-photograph

Li, H. (2019). Special Section Introduction: Artificial Intelligence and Advertising. *Journal of Advertising*(48(4)), 333. Retrieved April 31, 2020

Lin, X., Bu, T., He, Q., & Liang, Y. (2019). A study on the impact of positive and negative comments on consumers' perceived usefulness. *16th International Conference on Service Systems and Service Management*.

Lu, B., Fan, W., & Zhou, M. (2016). Social presence, trust, and social commerce purchase intention: An empirical research. *Computers in Human Behavior, 56*, 225–237. doi:https://doi.org/10.1016/j.chb.2015.11.057

Luo, J. T., McGoldrick, P., Beatty, S., & Keeling, K. A. (2006). On-screen characters: their design and influence on consumer trust. *Journal of Services Marketing*.

Magalhães, S. (2018). Impacto da Era Digital em algumas Práticas de Gestão de Recursos Humanos e nos Perfis dos Gestores e Técnicos de Recursos Humanos. Retrieved September 24, 2019, from https://repositorium.sdum.uminho.pt/bitstream/1822/59290/1/Susana%2bMagalha_es_tesefinal03.12.2018.pdf

Marras, J. P. (2016). *Administração de Recursos Humanos: do Operacional ao Estratégico* (15 ed.). São Paulo: Saraiva.

Maryanto, R., & Kaihatu, T. (2021). Customer Loyalty as an Impact of Perceived Usefulness to Grab Users, Mediated by Customer Satisfaction and Moderated by Perceived Ease of Use. *Binus Business Review, 12*(1), 31-39.

McKnight, D., & Chervany, N. (2001). What Trust Means in ECommerce Customer Relationships: An Interdisciplinary Conceptual Typology. *International Journal of Electronic Commerce, 6*(2), 35-59.

McKnight, D., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: a trust building model. *Journal of Strategic Information Systems, 11*(3), 297–323.

Melo, P., & Machado, C. (2013). Human Resources Management in small and medium enterprises in Portugal: rhetoric or reality? Retrieved September 25, 2019, from https://repositorium.sdum.uminho.pt/bitstream/1822/44262/1/IJESB200107%20MELO.pdf

Menidjel, C., Benhabib, A., & Bilgihan, A. (2017). Examining the moderating role of personality traits in the relationship between brand trust and brand loyalty. *Journal of Product & Brand Management, 26*(6), 631-649.

Miao, F., Kozlenkova, I., Wang, H., Xie, T., & Palmatier, R. (2021). An Emerging Theory of Avatar Marketing. *Journal of Marketing*, 1-24.

Miller, G. (2016). Retrieved March 18, 2020, from Medium: https://chatbotnewsdaily.com/bots-chatbots-and-artificial-intelligence-what-the-evolution-is-all-abot-about-a7e148dd067d

Moon, J., & Kim, Y. (2001). Extending the TAM for a WorldWideWeb context. *Information and Management, 38*(4), 217-230.

Motyka, S., Grewal, D., Puccinelli, N. M., Roggeveen, A. L., Avnet, T., Daryanto, A., . . . Wetzels, M. (2014). Regulatory fit: A meta-analytic synthesis. *Journal of Consumer Psychology*(24 (3), 394-410. doi:https://doi.org/10.1016/j.jcps.2013.11.004

Oracle. (2019). Retrieved August 03, 2020, from What is a chatbot?: https://www.oracle.com/solutions/chatbots/what-is-achatbot/

Pallant, J. (2016). *Survival Manual: A step by steo guide to data analysis using IBM SPSS* (6th ed.). Open University Press.

Parekh, J. (2018). *Why Programmatic provides a better digital marketing landscape*. Retrieved April 15, 2020, from https://www.adweek.com/programmatic/why-programmatic-provides-a-better-digital-marketing-landscape/

Park, S., & M.C. (2016). Human Resource Management. (J. J., & X. H., Edits.) *Encyclopedia of Tourism*.

Pavlou, A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology. *International Journal of Electronic Commerce, 7*, 101-134.

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: an extension of the technology acceptance model. *Internet res, 14*(3), 224-235.

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of management information systems, 25*(4), 145-182.

Robinson, M. (2017). *Business Insider*. Retrieved April 13, 2020, from https://www.businessinsider.com/knightscope-security-robots-microsoft-uber-2017-5

Shankar, V. (2018). How Artificial Intelligence (AI) Is Reshaping Retailing. *Journal of Retailing, VI-XI*, 94(4). doi:https://doi.org/10.1016/S0022-4359(18)30076-9

Shawar, A., & Atwell, E. (2005). Using corpora in machine-learning chatbot systems. *International Journal of Corpus Linguistics, 10*, 489-516.

Sienkiewicz, A. (2021). *Tidio*. Retrieved March 27, 2021, from https://www.tidio.com/blog/chatbot-statistics/#customer-experience-expectations

Soares, A. M., Pinho, J. C., Heath, T., & Alves, A. (2020). *Can Virtual Customer Service Agents Improve Consumers' Online Experiences? The Role of Hedonic Dimensions.* IGI Global.

Stone, D. L., & Deadrick, D. L. (2015, Janeiro). Human Resource Management Review. *Challenges and opportunities affecting the future of Human Resource Management*, pp. 139–145.

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*(69), 135-146. doi:https://doi.org/10.1016/j.indmarman.2017.12.019

Tran, A., Pallant, J., & Johnson, L. (2021). Exploring the impact of chatbots on consumer sentiment and expectations in retail. *Journal of Retailing and Consumer Services, 63*(102718).

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*, 91-111.

Turing, A. (1950). Computing machinery and intelligence. *Mind*(59(236)), 433-460. Retrieved April 21, 2020

Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Wainer, J., Feil-Seifer, D. J., Shell, D. A., & Mataric, M. J. (2006). The role of physical embodiment in human-robot interaction. *ROMAN 2006 - The 15th IEEE International Symposium on Robot and Human Interactive Communication*, (pp. 117-122). doi: https://doi.org/10.1109/ROMAN.2006.314404

Wang, Y., & Emurian, H. (2005). An overview of online trust: concepts, elements, and implications. *Computers in Human Behavior, 21*(1), 105-125.

Weber, R. M. (2019). Hey, Siri! Is Artificial Intelligence the Ultimate Oxymoron? *Journal of Financial Service Professionals*(73(4)), 46-50. Retrieved April 24, 2020

Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? *International Journal of Market Research* (60(5)), 435-438. doi:https://doi.org/10.1177/1470785318776841

Wu, J.-H., & Wang, S.-C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Information & Management, 42*, 719-729.

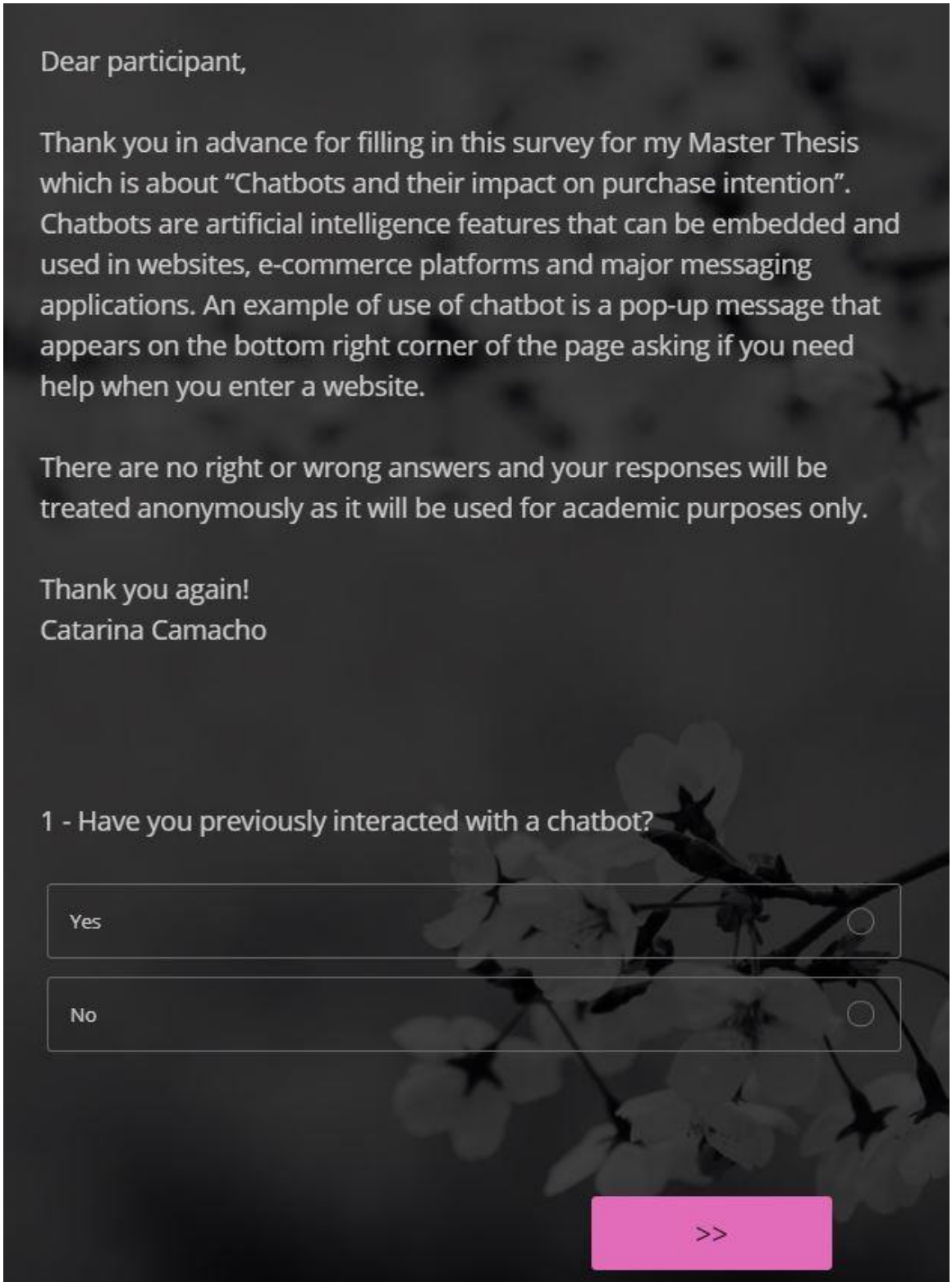
Xia, L., & Bechwati, N. (2008). Word of Mouse: The Role of Cognitive Personalization in Online Consumer Reviews. *Journal of Interactive Advertising, 9*(1), 108-113.

Xia, L., & Bechwati, N. (2021). Maximizing what? The effect of maximizing mindset on the evaluation of product bundles. *Journal of Business Research*(128), 314-325.

Zarmpou, T., Saprikis, V., Markos, A., & Vlachopoulou, M. (2012). Modeling users' acceptance of mobile services. *Electron Commer Res, 12*(2), 225-248.

7. Appendices

Appendix 1 - Questionnaire



2 - Please rate on a scale of 1-7, your degree of agreement with the following statements:

(1 = Strongly disagree/ 7 = Strongly agree).

	1 - Strongly disagree	2 - Disagree	3 - Somewhat disagree	4 - Neither agree nor disagree	5 - Somewhat agree	6 - Agree	7 - Strongly agree
I think using chatbots makes it easier for me to shop for products.	○	○	○	○	○	○	○
I think using chatbots makes it easier for me to follow up on my orders.	○	○	○	○	○	○	○
I think using chatbots enables me to shop for products online quicker.	○	○	○	○	○	○	○
I think using chatbots enables me to shop for products online more effectively.	○	○	○	○	○	○	○
I find chatbots very useful in shopping for a product.	○	○	○	○	○	○	○

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3 - Please rate on a scale of 1-7, your degree of agreement with the following statements:

(1 = Strongly disagree/ 7 = Strongly agree).

	1 - Strongly disagree	2 - Disagree	3 - Somewhat disagree	4 - Neither agree nor disagree	5 - Somewhat agree	6 - Agree	7 - Strongly agree
I think learning to use a chatbot is easy.	○	○	○	○	○	○	○
I think becoming skilful at using a chatbot is easy.	○	○	○	○	○	○	○
I think using a chatbot is easy.	○	○	○	○	○	○	○

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4 - Please rate on a scale of 1-7, your degree of agreement with the following statements:

(1 = Strongly disagree/ 7 = Strongly agree).

	1 - Strongly disagree	2 - Disagree	3 - Somewhat disagree	4 - Neither agree nor disagree	5 - Somewhat agree	6 - Agree	7 - Strongly agree
The websites that use chatbots appear to be more trustworthy than other similar websites I have visited.	○	○	○	○	○	○	○
The websites that use chatbots represent a company that will deliver on promises made.	○	○	○	○	○	○	○
The websites that use chatbots provide information that deserves my trust.	○	○	○	○	○	○	○
I trust the recommendations given to me by a chatbot on a website.	○	○	○	○	○	○	○

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5 - Please rate on a scale of 1-7, your degree of agreement with the following statements:

(1 = Strongly disagree/ 7 = Strongly agree).

	1 - Strongly disagree	2 - Disagree	3 - Somewhat disagree	4 - Neither agree nor disagree	5 - Somewhat agree	6 - Agree	7 - Strongly agree
Using chatbots is a good idea.	○	○	○	○	○	○	○
Chatbots make online shopping more interesting.	○	○	○	○	○	○	○
Using a chatbot is fun.	○	○	○	○	○	○	○
I would like online shopping with chatbots.	○	○	○	○	○	○	○

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6 - Please rate on a scale of 1-8, your degree of agreement with the following statements:

1 = Strongly disagree/ 8 = Not applicable).

	1 - Strongly disagree	2 - Disagree	3 - Somewhat disagree	4 - Neither agree nor disagree	5 - Somewhat agree	6 - Agree	7 - Strongly agree	8 - Not applicable
In general I am satisfied with using a chatbot.	○	○	○	○	○	○	○	○
In general I am content with using a chatbot.	○	○	○	○	○	○	○	○
The chatbot does a good job.	○	○	○	○	○	○	○	○
The chatbot does what I expect.	○	○	○	○	○	○	○	○
In general I am happy with using a chatbot.	○	○	○	○	○	○	○	○
In general I am satisfied with the experience of talking with the chatbot.	○	○	○	○	○	○	○	○

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7 - Please rate on a scale of 1-7, your degree of agreement with the following statements:

1 = Strongly disagree/ 7 = Strongly agree).

	1 - Strongly disagree	2 - Disagree	3 - Somewhat disagree	4 - Neither agree nor disagree	5 - Somewhat agree	6 - Agree	7 - Strongly agree
I am very likely to buy from a seller that uses a chatbot.	○	○	○	○	○	○	○
I would consider buying from a seller that uses a chatbot in the future.	○	○	○	○	○	○	○
I intend to buy from a seller that uses a chatbot.	○	○	○	○	○	○	○

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8 - What is your gender?

- Male
- Female
- Prefer not to say

9 - What is your nationality?

10 - What is your age?

11 - What is the highest degree or level of education you have completed?

- Primary School
- Secondary School
- Bachelor
- Master
- PhD

I thank you for your time spent taking this survey.

Your response has been recorded.