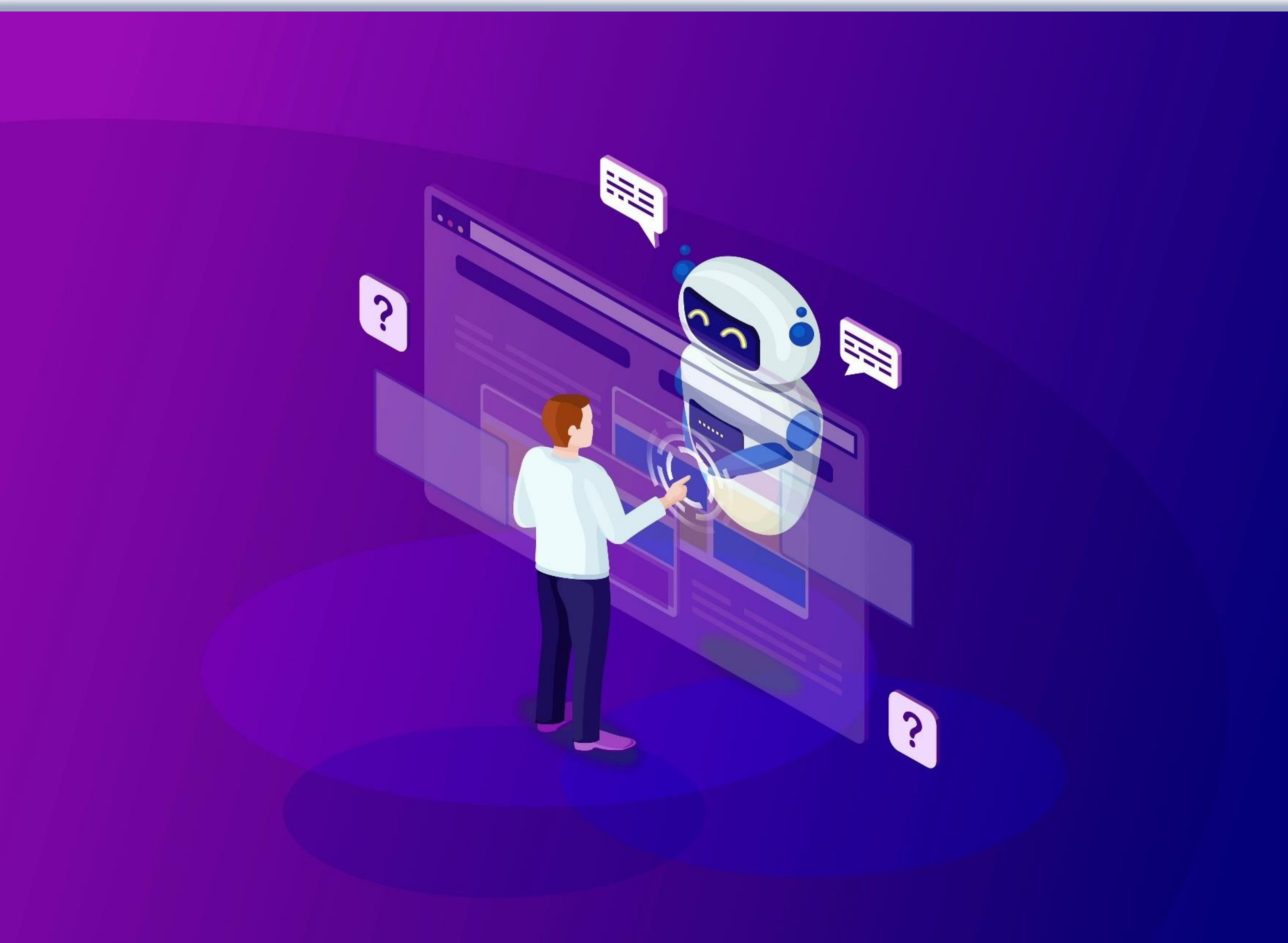
PERSONALIZED DYADIC CHATBOT CONVERSATIONS

The influence of human and chatbot personality on customer satisfaction within the e-commerce domain

Andrea Ciovati



Personalized Dyadic Chatbot Conversations

The influence of human and chatbot personality on customer satisfaction within the e-commerce domain

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Executive Summary

Chatbots have been considered as one of the leading technologies in the e-commerce domain as virtual shopping assistants able to guide customers throughout the entire shopping experience automatically. However, this technology is currently registering a high failure rate, and several users are still skeptical of its effectiveness. One of the reasons for this low performance lies in the fact that chatbots have a poor human-likeness that negatively influences customer perception of the technology. Secondly, the low level of personalization does not allow for tailored services based on customers' needs and requirements.

Previous studies discovered that it is possible to attach specific personality traits to chatbots in order to increase their human-likeness. Besides, other researchers have discovered the importance of service personalization as a distinctive requirement for successful e-commerce businesses. Depending on consumers' decision-making behaviour, scientists have found that different services lead to different levels of customer satisfaction.

The present study explored the two sides of Human-Computer Interaction with the final aim of understanding how to better align chatbot personality with human decision-making personality. Two different chatbot personalities (neutral and extravert) were created and randomly assigned to different users. During the experiment, participants had to complete a real chatbot conversation focused on dress shoes and were asked to conduct a post-interaction questionnaire to assess their satisfaction.

Results showed that it is possible to effectively attach an extravert personality into a chatbot conversation through the use of language, emoticons and GIFs. Moreover, participants with different personal decision-making behaviour and gender registered different levels of customer satisfaction. Finally, the chatbot neutral personality registered different level of customer satisfaction depending on gender and personal decision-making behaviour.

These findings support the literature by analyzing the complementary relationship between chatbot and human personalities. Future studies could use these findings to develop chatbot experiences that better fit with customer needs and requirements.

Preface

In the last few decades, the world has seen remarkable growth in e-commerce, which allows consumers to buy anything from their own mobile devices anywhere in the world. This new way of shopping has left customers progressively overwhelmed by the number of products available and with little ability on how to select the best option for them. This can be seen from Bill Watterson's description of the exasperated grocery shopper who is trying to buy a peanut butter:

~Look at this peanut butter! There must be three sizes of five brands of four consistencies! Who demands this much choice? I know! I'll quit my job and devote my life to choosing peanut butter! Is "chunky" chunky enough or not? Need extra chunky? I'll compare ingredients! I'll compare brands! I'll compare sizes and prices! Maybe I'll drive around and see what other stores have! So much selection, and so little time!

(Watterson, 1996, p.107) ~

Within this context, Chatbots might be considered the right technological solution that aims at supporting consumers while shopping online. This technology reduces customers decision-making time and makes them feel supported and less anxious for all the options available. The dream of developing a computer able to support and maintain a real interaction with humans has been inspiring developers since the early days of computers. Nowadays, several things have changed from the first chatbot. If ten years ago chatbots were compared to science fiction, today we hear or interact with them almost on a daily basis. The advent of smartphone, social media and enhanced computing capabilities have boosted the development of more intelligent bots, capable of proactively understand, process and react to natural language conversations.

This context has inspired my research for the last six months in which I have been able to develop a real chatbot from scratch, investigating how to develop more effective chatbot conversations for the e-commerce industry, with a focus on the interaction between the personality of both the user and the chatbot.

I would like to thank Dr. Laurens Rook for supervising and inspiring me during the last six months. His support for the thesis was crucial for the quality and caliber of the final document. I will always remember our insightful skype meetings both from the professional and personal perspective.

Secondly, I am very grateful to Prof. Frances Brazier for her unique and rigorous ability to help me understand and grasp the passion and the effort behind proper academic research. Her inspiring criticism was crucial for the completion of the document and undoubtedly influenced the outcome of this project.

I would also like to express my gratitude to my Deloitte supervisors Karine van Hal and Wessel Schot, who have proactively supported my project since the beginning and provided me with the right environment to create a successful result. This thesis would not have been developed without the Deloitte Cognitive Engagement team, which has allowed me to access the right resources and capabilities to excel in this project.

Last but not the least, I would like to thank my family and friends for always assisting me in my up and downs regardless of the physical distance. In particular, I am grateful to my girlfriend, Maria Chiara, for her love and emotional support that helped me overcome any obstacles in the last years.

To my dear grandma Anna Maria.

Although you are no longer of this world, your memories continue to regulate my life.

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1. Introduction

This chapter presents the background information of the thesis and identifies the concepts that have inspired the research and the literature review. The research scope section narrows down the focus of this research to chatbots as shopping assistants. It also introduces the research gap addressed in this thesis. A practical problem is identified about chatbot human-likeness and users personal decision-making behaviour within the e-commerce domain. Finally, a research objective and questions are formulated, followed by the designed research approach.

1.1. Background

The research domain of Human-Computer Interaction (HCI) focuses on the investigation of relationships between technology and individuals (Rica & Hutchison, 2013). Information and communication technologies have radically changed the way society behaves every-day, as well as how people interact with computers to accomplish their tasks (Dale, 2016). Graphical user interfaces that started from simple computer programs have evolved into mobile applications (Petter Bae & Asbjørn, 2018). With the advent of Artificial Intelligence (AI), the future of mobile applications lies on the development of new technologies that are not based upon the usual scrolling or swiping, but, instead, exploit the powerful capabilities of AI and natural language-based text strings (Følstad & Brandtzaeg, 2017).

One of the leading technologies of this new era is the *Chatbot* or *Conversational Agent* (BCG, 2019). Chatbots are defined as software-based systems that imitate communication experiences using the power of AI and natural language processing technologies (Abu Shawar & Atwell, 2007). Due to their ability to easily communicate with customers, chatbots have been applied in various sectors such as healthcare, education, e-commerce and entertainment (Io & Lee, 2018). According to research conducted by Wang, 57% of surveyed companies are going to develop a chatbot for their activities (2017). Moreover, Gartner predicted that a majority of companies would invest more in the development of chatbots than on traditional applications by 2021 (Gartner, 2019). These data show the popularity that this technology has gained in the last few years as well as its promise for the future.

Chatbots have been considered the most promising technology for businesses due to their powerful ability to handle complex processes and support multiple clients (Etlinger, 2017). This technology is able to interact with humans and support customers in their online activities, effectively replacing a human employee (Bakhasi, 2018). Considering the frequent interactions that they have with humans, it is relevant to assess the societal role that chatbots have during conversations (Al-Natour et al., 2011). As early as 1996, under the so-called 'CASA' paradigm or "Computer As Social Actors", Reeves and Nass posited that people treat computers and robots as real social actors with gender, values as well as personality (Reeves & Nass, 1996). Personality is defined as a set of personal behaviour and characteristics that makes it possible to distinguish among different people (Tausczik & Pennebaker, 2010). Besides, personality traits have been considered highly important in effective conversations (Tausczik & Pennebaker, 2010). Studies have shown that people tend to attach personality traits to chatbots as if they were discussing with a real human with a specific personality (Lortie & Guitton, 2011). Thus, studies have started to focus their attention on developing conversational agents personalities (also known as "*botsanalities*") (Smestad

& Volden, 2019). Among the psychological theories proposed, the "Five Factor" model or "Big Five" (extraversion, agreeableness, openness, conscientiousness and neuroticism) is the most widely used approach to develop chatbot personalities. Based on this model, academics have recently begun to design chatbot personalities with the aim of improving conversation effectiveness and the overall satisfaction of humans interacting with these agents (Ma et al., 2019).

However, a systematic methodology for the development of chatbot personality tailored to users has not yet been proposed (Duijst et al., 2017; J. Li et al., 2017). Therefore, this thesis aims to understand the role that chatbot personality plays within human-computer interaction and to explore in greater detail which personality traits perform better within this context. Understanding these concepts will help designers to develop more effective conversational agents, and enhance the overall customer experience.

1.2. Research Scope

This research focuses on the e-commerce domain, in which chatbots have been applied as shopping assistants that actively support customers during their online purchases (Y. Sun & Zhang, 2018). Chatbots seem to have a significant potential for online businesses due to two main advantages associated with this technology (Bhawiyuga et al., 2018). Firstly, chatbots are able to process natural language strings of text and to communicate with customers almost instantly. This speed of interaction significantly enhances the conversion rates (Bakhasi, 2018). Secondly, by automating the customer service process, this technology can help companies reduce their labour costs. In fact, chatbots are expected to help companies save $8 billion in cost for their operational activities by 2022 (JuniperResearch, 2017). Thus, chatbots might be considered an essential tool to enhance customers' perception of the e-commerce business (Chung et al., 2018).

Chatbot personality should also be taken into consideration while developing commercial chatbots aimed at achieving high levels of customer satisfaction (Lee et al., 2019). Although academics have studied chatbot personality in various domains, research is still lacking on the impact of personality on the appreciation of a shopping assistant chatbot. Thus, this research tries to shed light on the influence that chatbot personality might have on the overall customer satisfaction when chatbots are applied as shopping assistants. Interestingly, within the sales and marketing domain, studies have shown that the personality of salespeople often influences the final sales performances (DeYoung et al., 2007). Particularly, the extraversion dimension of the Five-Factor model is highly correlated to sales revenue (Grant, 2013). Academics have found that extravert salespeople register higher sales performances compared to others due to their ability to easily engage with customers (Grant, 2013). Therefore, this research focuses on extraversion as a pillar for the development of chatbot personality.

In addition to the chatbot personality domain, scientists have started to study how consumers behave while purchasing online. They discovered that it is possible to increase customer satisfaction and loyalty by personalizing online services, depending on the customers' personality (Bologna et al., 2013). Again, the chatbot literature is still lacking the analysis of the influence of users' personality on customer satisfaction after interacting with chatbots (Paredes et al., 2015). Previous studies have also found that gender is a critical variable to consider while developing personalized online services (Sarkar & Das, 2016). Males were found to have different decision-making behaviour more focused on maximizing their outcomes while purchasing online compared to females (Schwartz et al., 2002). Thus, different services can be developed by e-commerce websites depending on the gender of their customers.

In summary, this research focuses on the application of chatbots as real shopping assistants that support customers while purchasing online. Specifically, it aims to study the influence of chatbot personalities in relation to users' personality when customers are interacting with shopping assistant conversational agents while purchasing online.

1.3. Problem Definition

Although conversational agents may expand organizational opportunities and help companies save on cost, a major practical problem of chatbots is their poor performance when interacting with humans (Brandtzaeg & Følstad, 2018). They simply are unconvincing in their conversations with humans. As a result, most users are still skeptical of this technology (Elsner, 2017). Considering that chatbot interactions consist of humans and computer technology, the chatbots' high failure rate might be analysed from these two different perspectives. From the computer side, there is a low perceived chatbot human-likeness that decreases the connection that people have with the technology. On the human side, there is a low service personalization that does not allow for tailored services based on customer needs, personalities and gender. This problem is visualized in Figure 1 below:

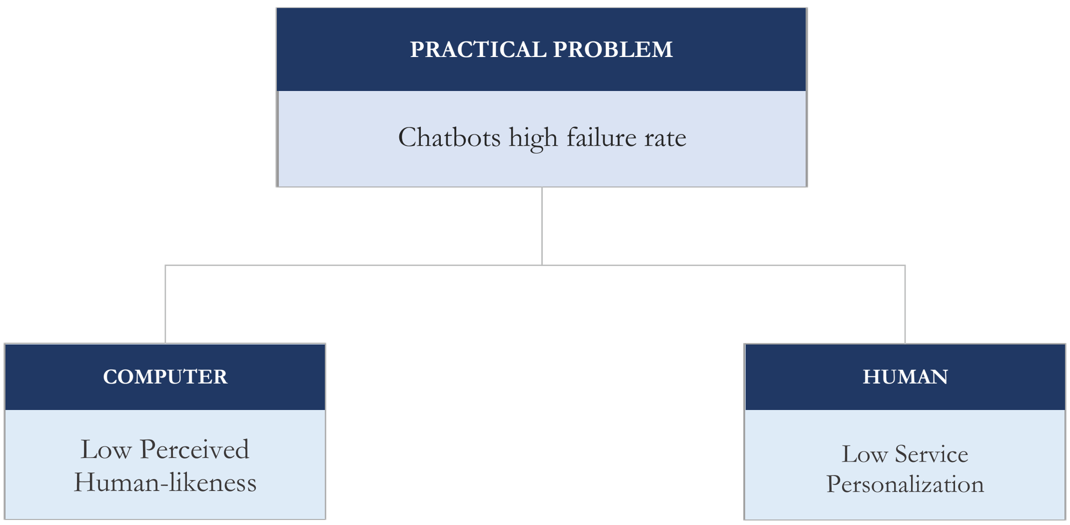


Figure 1: Practical Problems identified

1.3.1. The Need for Chatbot-human Likeness

Considering the chatbot perspective, users often believe that chatbots are un-intelligent and not able to maintain a real conversation with a human being (Smestad & Volden, 2019). Research shows that the answers a chatbot provides to users often feel unnatural and are not up to the standards usually expected from a real human interaction (Orf, 2016). A study from Capgemini confirmed that chatbots have a low perceived chatbot human-likeness, and people still prefer human-human interactions when reaching out for customer support (Garcia, 2018).

One of the variables influencing this low users' perception of chatbot human-likeness lies in the societal role that chatbots have during the interactions with users (Al-Natour et al., 2011). Under the so-called CASA paradigm, studies have shown that chatbots may unexpectedly exhibit specific personality traits that might influence users' perceived chatbots human-likeness (Paredes et al., 2015). Thus, specialists on cognitive engagement acknowledge the necessity to create psychologically realistic chatbots that imitate human behaviour (R. Sun & Hélie, 2013). The literature on chatbot personality has recently started, and academics have tried to come up with hypotheses on how to design chatbots' personalities that improve their human-likeness and provide enhanced customer experiences (Ma et al., 2019). For instance, some researchers (Back et al., 2010; Hirsh & Peterson, 2009) have focused their attention on specific language styles (such as related words categories or conversation styles), whereas others (Butterworth et al., 2019; Miltner & Highfield, 2017) have considered additional elements (such as images, videos, emojis or GIFs) to express specific personality traits.

However, a systematic methodology to effectively implement specific chatbot personalities has not been discovered yet (Duijst et al., 2017; J. Li et al., 2017). There is still room for improvement and methodologies to be discovered in order to implement powerful chatbot personalities that support the perception of a chatbot as real agents (Kim et al., 2019).

1.3.2. The Need for E-commerce Service Personalization

Within the e-commerce literature, customer satisfaction has shown to be influenced not only by the chatbot personality and its perceived human-likeness but also by users' specific personalities (Bologna et al., 2013). Besides, gender was also found to play a role in customer satisfaction, since male users registered different decision-making behaviour compared to females (Iyengar et al., 2006). Indeed, customer services that consider users' personality traits have shown to ensure an increase in purchase probability (To et al., 2007). Such experiences are the result of so-called service personalization, the process of changing the functionalities of a system to better fit its activity with the user's personality and gender in order to increase his/her satisfaction (Fan & Poole, 2006). Notably, this concept was applied to e-commerce chatbots to develop better conversations that fit customer personalities (Duijst et al., 2017; Zhou et al., 2019). For instance, one study found that different extravert people are more willing to interact with a chatbot compared to introverts (Fang et al., 2018).

However, few studies have studied how to develop a personalized chatbot and how to align chatbot services with users' personalities and gender (Brandtzaeg & Følstad, 2018). There is a need to develop chatbots that better consider users' personality traits during their interaction (Duijst et al., 2017; Zhou et al., 2019). The main research focus of these personalized chatbot studies has always been based upon users' personality traits from the Five-Factor perspective, but not upon their decision-making behaviour or gender. To the author's knowledge, no research has looked into the influence of individuals' decision-making behaviour and gender while interacting with chatbots within the e-commerce domain. Understanding this relationship might help understand why chatbots are still registering a low level of personalization.

Maximization theory is a popular theory to study decision-making behaviour (Dar-Nimrod et al., 2009). This theory posits that people differ in their decision-making behaviour in terms of the way they make (purchasing) decisions (Schwartz et al., 2002). Maximization Theory distinguishes between two different types of behaviour. On the one hand, there are maximizers who seek to make the best decision possible and try to evaluate all the options available. On the other hand, there are satisficers*,* who seek to make decisions based on their preferences and standards instead (Schwartz et al., 2002). This difference was found to significantly influence customer satisfaction within the same purchasing experience, as maximizers might feel worse off as the options that they face an increase or they might be more sensitive to regret and feel less satisfied (Kokkoris, 2017). Besides, it was also found that gender influences personal maximizing tendency behaviour. Men often register a higher value of maximization compared to women (Schwartz et al., 2002). Thus, studying the influence that personal decision-making behaviour and gender has on chatbot interactions might shed light on the reasons why chatbots are still registering a low level of personalization and, thus, poor customer satisfaction.

In sum, it is a major challenge to develop more effective conversational agents that not only exhibit higher human-likeness through their personality but also take individuals' personalities, gender, and decision-making behaviour into consideration. Understanding how to better align chatbot and individuals' personalities will allow for the development of better shopping assistant chatbots that enhance the customer experience and, consequently, the overall customer satisfaction for men and women.

1.4. Research Objective

The literature discussed methods to attach personality traits to chatbots using the Five-Factor model (Lee et al., 2019). Research shows that people differ in maximizing or non-maximizing behaviour while buying products or services online – also based on gender differences. This is the reason why the present study aims to analyse the relationship between chatbot personality, individuals' personal maximizing tendency behaviour, and gender differences between them, with the following research objective:

To determine whether chatbot extraversion influences customer satisfaction within the e-commerce domain and, if so, whether this is influenced by personal maximizing tendency behaviour and gender

Accordingly, this thesis explores how people interact with digital shopping assistants and analyses the role that conversational agents have during their online purchasing experience. In addition, this research aims to assess the appreciation of perceived chatbot personality and the impact on overall customer satisfaction. From a business perspective, this research aspires to inform organizations about how to develop and personalize their conversational agents to achieve higher customer satisfaction.

1.5. Research Questions

This section presents the main research question of the thesis. Along with the research question, a group of sub-questions is presented with the aim of structuring the research, and to meet the research objective.

1.5.1. Main Research Question

Considering the research objective of studying the relationship between chatbot personality and satisfaction of male and female customers from the angle of the maximization theory, the following is the main research question identified:

RQ: *To what extent does chatbot extraversion influence customer satisfaction within an e-commerce domain and, do personal maximizing tendency behaviour and gender influence this relationship?*

In this question, the term chatbot extraversion refers to the extraversion dimension of the Five-Factor model. To better answer this question, a set of sub-questions is identified.

1.5.2. Sub-Research Questions

The following are the sub-research questions, of which the main research question is composed. Addressing these questions will help to answer the general research question and to fulfil the research objective. Considering the main focus of this thesis on e-commerce chatbots as virtual shopping assistants and the extraversion dimension, before answering the main research question, there is a need to understand how to effectively implement chatbot personalities (extraversion in this case) that are perceived as different than a neutral chatbot version. Hence, the following sub-research question is formulated:

SRQ1*: Can virtual conversations for chatbots be designed to make them extravert in nature?*

After the development of an effective personality-based conversational experience, the focus of the thesis will shift to the users of the technology, so as to understand the influence of chatbot extraversion on customer satisfaction. Accordingly, the following research question is formulated:

SRQ2*: Does the extravert nature of a chatbot influence customer satisfaction?*

Besides, considering that the literature categorizes users in different groups based on their personal maximizing tendency behaviour (in terms of *maximizers* and *satisficers*) and the documented gender differences in personal maximizing tendency behaviour, this research focuses on understanding whether there is any difference in the chatbot interaction between these groups. It will assess the overall effectiveness of the botsanality among them. The following sub-research questions will be answered using the results gathered through the experiment:

SRQ3: *To what extent do personal maximizing tendency behaviour and gender differences influence customer satisfaction of chatbot use?*

SRQ4*: To what extent do personal maximizing tendency behaviour and gender differences influence the relationship between chatbot extraversion and customer satisfaction?*

Answering these four sub-research questions will help clarify the relationship between chatbot personality, user characteristics, and decision-making behaviour.

1.6. Research Approach

To answer the research questions and fulfil the research objective, a structured research approach is followed with two main phases: Firstly, an extensive literature review to identify the relevant articles and existing studies related to the research topic, and knowledge gaps. Secondly, an experiment is performed with a real shopping assistant chatbot to analyse the influence of chatbot personality on customer satisfaction of men and women. The statistical results obtained from the experiment are used to answer the research questions. Table 1 presents an overview of the research approach and designated output for each of the sub-questions.

#	Research Question	Research Approach	Output
1	Can virtual conversations for chatbots be designed to make them extravert in nature?	Literature Review	Methodology on how to attach personality trait in virtual conversations
2	Does the extravert nature of a chatbot influence customer satisfaction?	Experiment and Statistical Analysis	Shopping assistant chatbot and statistical results
3	To what extent do personal maximizing tendency behaviour and gender differences influence the customer satisfaction of chatbot use?	Experiment and Statistical Analysis	Statistical results
4	To what extent do personal maximizing tendency behaviour and gender differences influence the relationship between chatbot extraversion and customer satisfaction?	Experiment and Statistical Analysis	Statistical Results

Table 1: Research Approach

This M.Sc. thesis is the result of a collaboration between the Delft University of Technology (in the context of the Management of Technology M.Sc. programme) in collaboration with Deloitte's Cognitive Engagement Department. Specifically, the research was part of a six-month internship at Deloitte in Amsterdam within the Cognitive Engagement (CE) team. This team focuses mainly on the identification and the development of chatbot strategies as well as their implementation within organizational processes. The main focus of the Deloitte team is on Virtual Agents (CVA), that have shown great potential for customer assistant applications (such as e-commerce applications or customer queries management) coupled with the internal business opportunity to support a firm's employees internally for maintenance, human resources and production processes. Hence, this research is supported by Deloitte's professional expertise as well as resources. This has enabled the author to perform experimentation required to answer the main research question and fulfil the overall objective.

1.7. Report Structure

This thesis is organized as follows. The first chapter has introduced the research scope and context, along with the research questions and approach. Chapter 2 presents the literature review in which the theoretical background of all the involved variables is described. Chapter 3 described the conceptual framework of the thesis, including the research gap and the hypothesis. Chapter 4 introduces the instrument design, delineating how the chatbot personality was developed as well as the chatbot software used in the study. Chapter 5 describes the research methodology with the participant description, the research procedure and the measurements. Chapter 6 presents the results of the statistical analysis. Chapter 7 discusses the implication and analyse the findings by delineating the consequences of the study, practical relevance and the limitations of the study. Chapter 8 includes the conclusion of the thesis and a brief summary of the findings.

2.
Literature Review

This chapter presents the literature review with the studies and theories relevant to this thesis. It provides a theoretical background to support the research and development of a conceptual framework. Firstly, this chapter presents a brief introduction of Human-Computer Interaction (HCI) and the role of chatbots in recommender systems. Secondly, this chapter explores the relationship between the two main subjects of HCI (chatbots and individuals) from a personality perspective. On the one hand, an extensive review of the previous studies on chatbot personality is given with a focus on the extraversion trait of the "Five-Factor" theoretical model. On the other hand, the importance of individuals' personality and gender in their decision-making behaviour is presented using "Maximization" theory. This chapter ends with the identification of the implications of this relationship on customers in terms of their satisfaction.

2.1. E-commerce Chatbots as Recommender Systems

Human-Computer Interaction (HCI) is defined as a scientific field, which focuses on the design and control of the relationship between computer technologies and humans (Lazar et al., 2017). For decades, the improvement of graphical user interfaces has been the main focus of research in this domain (Rica & Hutchison, 2013). Nowadays, the development of Artificial Intelligence (AI) technologies and the availability of messaging applications have shifted the nature of these interactions with computers from the usual swiping and scrolling-based applications towards natural language conversations (Etlinger, 2017). This advancement has inspired researchers to redirect their emphasis on text-based user interfaces, in which humans interact with computers using strings of natural language (Elsholz et al., 2019; Følstad & Brandtzaeg, 2017).

One of the leading technologies in language-based HCI studies is the *chatbot* or *conversational agent*, defined as a "computer program that interacts with users using natural language" (Abu Shawar & Atwell, 2007, p.29). Compared to previous solutions, chatbots have brought a new way of creating digital experiences, setting up conversation-based business models, in which users are directly interacting with agents in a way more similar to how they communicate naturally (Etlinger, 2017). The main advantage of this technology is the ability to process natural language strings of text and to provide almost instantly the most appropriate answer to customers depending on the chatbot's specific task (Kuligowska, 2015). Due to the ability to actively support customers throughout their online experience, chatbots have recently been developed in the e-commerce industry, in which businesses are always looking for innovative ways of guaranteeing a competitive advantage and enhancing the customer satisfaction (Bhawiyuga et al., 2018). Studies have shown that chatbot e-services allow for a more interactive and engaging service encounter by directly communicating with customers almost instantly (Chung et al., 2018).

Within the e-commerce domain, in parallel to the advancement of HCI studies, organizations have always been focused on the design and implementation of other innovative ideas that guarantee a competitive advantage by providing an enhanced customer experience – i.e. better supports consumers during their online purchases (Srinivasan et al., 2002). One of the technologies employed is "Recommender Systems" (RS), which refers to online systems that are able to provide advice to users during their decision-making processes. Examples are recommender systems that support users in the purchase of a new product or the selection of an online or offline service (e.g. a movie or holiday destination) (Ricci et al., 2015). The most important advantage of this technology is the ability to create recommendations tailored to different customers' needs (Foster & Oberlander, 2010). Thanks to the tailored services that they can provide, RSs have the ability to improve the success rate of e-commerce businesses and to enhance customer experience (Coba et al., 2019).

Given the high potential of RSs for e-commerce organizations, researchers have started to consider RS methodologies to improve the effectiveness and selling ability of chatbots. By applying RS processes in virtual conversations, researchers have found an increase in the conversion rate for online sales and, consequently, coined the term "Conversational Recommender Systems" (CoRS) (Narducci et al., 2019). This new technological integration benefits both systems (Y. Sun & Zhang, 2018). On the one hand, the ability to recommend products and services based on their preferences and standards enables chatbots to enhance the user experience. On the other hand, through conversation-based recommendations, RSs can gain important data on users that they would not be able to grasp otherwise (e.g. price preferences or indirect purchase intentions). Within the literature, several studies assess the overall effectiveness of CoRS systems (Iovine et al., 2020; Jusoh, 2018; Liu et al., 2019; Narducci et al., 2019). For instance, one study developed a methodology for the design of CoRS systems focused on persuasion features that can better fit e-customers' needs (Jusoh, 2018). Another study compared different types of CoRS (button-based, natural language-based or mixed), and found that the natural language version with specific closed questions was not assessed as better than the button-based mode in terms of perceived recommendation accuracy for online selling (Iovine et al., 2020). Flexibility and duration of interaction influenced these perceptions (Iovine et al., 2020).

Although researchers have started to analyse this domain, additional testing and development of CoRS methodologies are still lacking. There is a need for more reliable and robust data (Arteaga et al., 2019). CoRS are required to have an effective and reliable conversational strategy for online sales (Lee et al., 2019). One of the most crucial aspects for developing better conversational agents is the ability to attach personality trait to chatbots to increase their human-likeness (Gittens, 2018). The next paragraph focuses on the psychological side of conversations and underlines the importance of developing better chatbot personalities.

2.2. Chatbot Personality

One of the most important capabilities of e-commerce chatbots is their ability to manage complex processes and support customers while purchasing online, effectively replacing a real employee (Bakhasi, 2018). Chatbots actively participate and constantly interact with individuals, creating a sort of human-computer relationship with them (Go & Sundar, 2019). Hence, in order to better develop effective chatbots conversations, it is crucial to consider the societal role that this technology has among users (Al-Natour et al., 2011).

As mentioned in the introduction chapter, conversational agents are often considered to be real social actors with values, gender and personalities (Reeves & Nass, 1996). Researchers have found that chatbot human-likeness is a crucial aspect of influencing users' trust and perception of the technology (Følstad et al., 2018). This new concept has contributed to the development of a new field of study called *anthropomorphism*, which refers to the propensity to allocate human traits to conversational agents (Lortie & Guitton, 2011). This domain focuses on the identification of innovative ways of improving chatbots' human-likeness with the final aim of enhancing customer satisfaction (Araujo, 2018). Several studies have started exploring this new field of research (Elsner, 2017). Accordingly, physical representations such as avatars, voices and images have been added to conversational agents to increase human-likeness (extending simple text-based conversations), obtaining significant results in terms of enhanced user experience (Przegalinska et al., 2019). For instance, Kuligowska has found that adding a picture that presents the chatbot as a real person increases the overall customer satisfaction compared to a neutral conversation without any picture (2015).

Despite these relevant results, corporal appearance is not the only factor that affects the chatbot human-likeness perception as a good communication partner. Linguistic capabilities were found to play a crucial role in this context (Elsholz et al., 2019). Language has been defined as the most important humanness factor for machines, thanks to the famous studies on the Turing Test to assess whether computers exhibit intelligent behaviour (French, 2000). Language is also seen as an important factor for individuals to be considered as a good communicator (French, 2000). Accordingly, Lortie & Guitton discovered that linguistic capabilities influence a chatbot's perceived human-likeness by using common words as well as linguistics methodologies (2011). Thus, language is the main factor that can help develop chatbots that exhibit a higher level of human-likeness and are seen as real social actors by users (see also Elsholz et al., 2019).

Personality is defined as a group of features that uniquely identify people behaviour, motivations and cognitions (McTear et al., 2016). Personality plays a crucial role in how users perceive chatbots. It can be the main factor that determines whether individuals are willing to use the technology or not (Smestad & Volden, 2019). One study analysed the role of personality on the perception of chatbot human-likeness and discovered that attaching personality traits to conversation allows for a better consistency throughout the interaction, helping users perceive that they are talking to a real person with a specific personality (Callejas et al., 2011). Thus, given the importance of personality for language skills and the relevance of language for chatbot human-likeness, it is important to develop personalized conversational agents that exhibit personality traits through language-based conversations.

E-commerce applications have been used to test a conversational agent's effectiveness in relation to customer engagement (Chung et al., 2018). Nass discovered that customers that use a personality-matched chat with an agent feel an increased social presence as well as trust in the technology (Nass, 2019). Another study showed that chatbot personality positively influences users' assessment of the virtual shopping assistant (Paredes et al., 2015). Nevertheless, although these studies have shown that chatbot personality influences customer satisfaction, a systematic design methodology to attach personality traits to conversational agents has not been proposed yet (Kim et al., 2019). Thus, there is a need for discovering which personality traits perform better within a specific domain and chatbot task with the final aim of developing more effective chatbots (Duijst et al., 2017; Zhou et al., 2019).

In summary, although corporal factors and personality traits have shown to be crucial to increase chatbots anthropomorphic effect on users, there is still room for improvement to develop chatbots personalities that better fit users' needs and requirements. The following paragraphs present an in-depth exploration of the relevant personality theories in the literature and answer the first sub-research question by identifying the key differentiating personality trait for shopping assistant chatbots.

2.3. Personality Theories

Among the various personality theories available in the literature, one of the most famous and studied ones is the 'Five-Factor' or 'Big Five' personality model (DeYoung et al., 2007). The model was firstly introduced in 1932 by McDougall as a first attempt at systematically assessing individuals' personality (McDougall, 1932). However, the Five-Factor model, as it is currently known, was formally presented a few decades later by Norman, who reviewed the previous version and introduced five components (Norman, 1963). Accordingly, the Five-Factor theory nowadays includes Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism (Norman, 1963). Figure 2 below shows a graphical representation of the model with a brief description of each component (Vital, 2018).

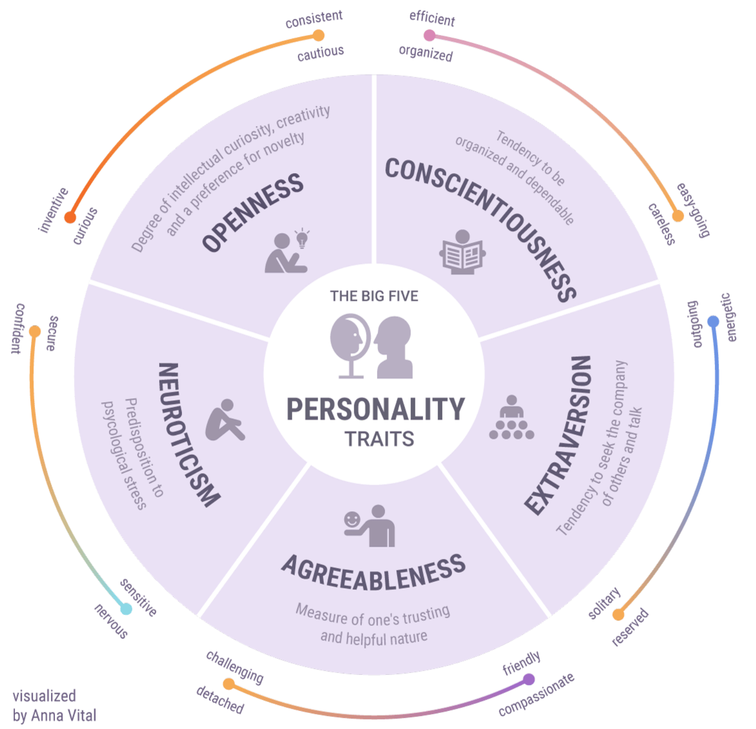


Figure 2: Big Five personality theory (Vital, 2018)

During the last fifty years, many studies have focused on the role and relevance of personality traits in human interpersonal interaction (L. Barrick et al., 1991; DeYoung et al., 2007; Mccrae & John, 1992; Weisberg et al., 2011). The Five-Factor model has related personality traits to job performance, to identify which personality trait performs better in which specific working environments (L. Barrick et al., 1991). As such, this model has been used by the majority of the studies within this domain (De Young et al., 2013).

As an alternative to the Five-Factor model, Freedman, Leary, Ossorio and Coffrey proposed the 'Interpersonal Circumplex', which refers to a circular model in which interpersonal actions and mechanisms are organized along two orthogonal dimensions (1951): affiliation (tendency to relate with others like sympathy) and assertiveness (tendency to influence others like suggestions or criticism) (Freedman et al., 1951).

Although this model differs from the Five-Factor in terms of origin, context and structure, the two variables used in the circumplex model were found to be strictly related to two dimensions of the Five-Factor personality model: extraversion and agreeableness (McCrae and Costa, 1989). Extraversion is significantly associated with the dynamic behaviour of social interactions (Cuperman & Ickes, 2009). People with high extraversion are characterized by a more dynamic, powerful and community-oriented behaviour, as opposed to introverts, who try to avoid interpersonal connections (Mccrae & John, 1992). Agreeableness is defined in the literature by concepts such as interpersonal warmth, empathy and friendliness (Funder & Sneed, 1993). Agreeableness may be more related to societal aspects and interpersonal interactions than the other personality dimensions as it refers to emotions and behaviour connected to altruism. Figure 3 depicts the graphical illustration of the interpersonal circumplex model with the extraversion and agreeableness dimensions from the Five-Factor framework (Park et al., 2016).

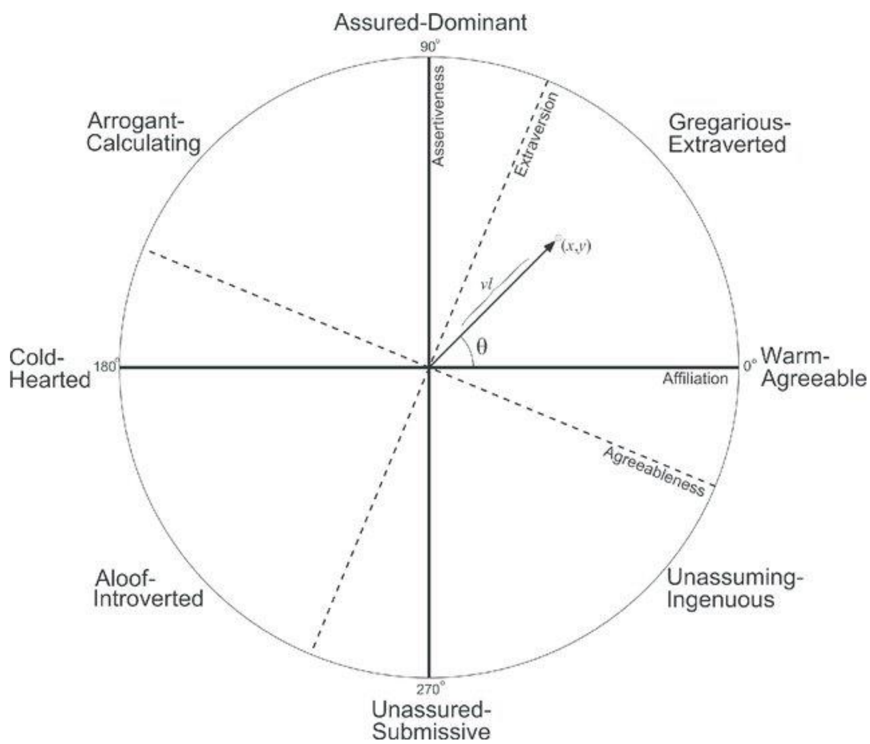


Figure 3: The interpersonal Circumplex with Big Five model dimensions (McCrae & Costa, 1989)

Given the focus of this thesis on the social interaction between humans and chatbots, especially the extraversion and agreeableness dimensions of the Big Five are considered to be relevant dimensions for interpersonal communication. Previous studies have found a moderate and positive correlation between agreeableness and extraversion (Rook et al., 2020). One study found strong personality configurations with both extraversion and agreeableness (Rentfrow et al., 2013). Thus, considering this proven relationship between these two personality traits, this thesis focuses only on the extraversion dimension as the most relevant trait for an e-commerce shopping assistant chatbot. The next paragraph explains more in detail the reason behind this decision.

Extraversion and Conversation styles

Extraversion has shown to be the most relevant trait in the Five-Factor framework to influence individual behaviour in dyadic social conversations (together with agreeableness) (Cuperman & Ickes, 2009). This personality trait was found to be significantly correlated to individual social behaviour and the ability to establish interpersonal relationships (L. Barrick et al., 1991). Highly extravert people tend to be more active and have a higher ability to engage in social interactions (Mccrae & John, 1992). Besides, extravert people are more comfortable talking to strangers and interacting with different people during their daily activities (Furnham, 1990).

As indicated above, throughout the last few decades, researchers have analysed the influence of specific personality traits for job performance based on the Five-Factor model (Barrick et al., 2001). Particularly, extraversion was found to be related to working positions such as marketing, sales and customer services (DeYoung et al., 2007). The reasons for this correlation are three-fold (Grant, 2013). First of all, extravert people easily engage with people and start a conversation with strangers without difficulties (Furnham & Fudge, 2008). Secondly, extravert people are usually more determined and persuasive and better able to convince customers to switch their behaviour or decisions (Stewart, 1996). Finally, throughout the selling activity, extraversion performs better in terms of enthusiasm compared to other personality traits (Vinchur et al., 1998). Accordingly, extraversion is usually correlated with high sales performances (Grant, 2013).

However, different studies criticized the relation between extraversion and sales performances based on the type of organisation involved (Grant, 2013). One study focused on manufacturing sales and found that extraversion was not significantly correlated to high performances (Barrick et al., 1993). Other researchers also found the same results for the healthcare industry (Adrian Furnham & Fudge, 2008) as well as in sales between businesses (Stewart, 1996). Thus, although extraversion may be related to high sales performances, it is vital to understand the context in which this personality trait is implemented – to avoid developing the wrong chatbot personality (Adrian Furnham & Fudge, 2008).

Considering the importance of extraversion for social interactions and sales activities, coupled with the focus of this thesis on shopping assistant chatbots, this specific Big Five dimension will be used to develop the shopping assistant chatbot's personality. Besides, in line with the extraversion and sales criticism, this research analyses the influence of chatbot extraversion for customer satisfaction. It identifies whether this personality trait influences sales performance and or customer satisfaction within the context of chatbot shopping assistants.

2.4. Chatbot-Users Personality Relationship

HCI studies not only focus on machines and computers, but they also take the human side into account, studying how users perceive technology as well as how different user profiles interact with the same technology (Hill et al., 2015). The main objective of HCI studies is to find the most appropriate solution for the interaction between humans and computers (Siricharoen, 2019). Hence, it is crucial to take into consideration how users react to different services encounter with the final aim of creating customer experiences that better fit users' needs and requirements (Paredes et al., 2015).

Recent studies have discovered that personality may influence consumer purchase intention and, thus, the overall satisfaction for specific customer experience (Tsao & Chang, 2010). Different users may have different perceptions of a product value depending on their personality (Olson & Olson, 2003). This concept was also applied within the e-commerce domain, in which customer satisfaction was found to be influenced not only by the chatbot personality and human-likeness but also by users' psychological trait (To et al., 2007). Customer services that consider users' personality traits have shown to ensure an increase in purchase probability (Bologna et al., 2013).

These services that suit customer's needs and wants are related to the well-known process of *service personalization,* defined as the "combined use of technology and customer information to tailor electronic commerce interactions between a business and each individual customer" (Fan & Poole, 2006). Personalized services are able to enhance the interaction between humans and computers, positively influencing overall customer satisfaction (Duijst et al., 2017; Siricharoen, 2019). Within the e-commerce domain, Tsao & Chang discovered that individuals with different personality traits and gender exhibit different shopping behaviour in terms of hedonic or utilitarian motivations, underlining the need to align better customer experience with users' expectation and needs (2010). This concept was also implemented in chatbot applications in which one study showed that users with a different personality from the Five-Factor model perceived chatbot in different ways in terms of trust and intention to use the technology (Paredes et al., 2015). Others found that users' extraversion predicts the evaluation outcome of the interaction with the chatbot, suggesting that different users should have different experiences tailored to their personality (Gratch, 2010).

However, the literature is still lacking a systematic methodology to align chatbots personalities with humans psychological traits and, thus, to enhance and tailor the customer experience (Duijst et al., 2017; J. Li et al., 2017). Previous attempts focused on understanding the influence of chatbot personality from the Five-Factor model perspective, and the literature falls short in analysing this relation from a different psychological perspective (Putri et al., 2019). The next paragraph proposes a personality model based on consumer behaviour as a different approach in understanding how human personality may influence the interaction with a chatbot.

2.5. Maximization Theory

With the advent of the e-commerce industry, people have been exposed to an intricate set of choices that influence their every-day decisions (Dalal et al., 2015). Such complex decision-making processes may positively or negatively influence consumer behaviour for two different reasons (Iyengar & Lepper, 2000). On the one hand, people might be more satisfied when they are exposed to several options due to a sense of freedom registered within this scenario (Reibstein et al., 1975). On the other hand, people may also feel overwhelmed when facing an enormous amount of data and options (Iyengar & Lepper, 2000; Miceli et al., 2018). This has inspired several researchers to explore how to support people decisions in different environments with the aim of coming up with a systematic overview of how people make decisions in different contexts (Dalal et al., 2015).

A popular theory in the decision-making domain is the so-called maximization theory, which distinguishes consumers based on their decision-making behaviour in terms of the way they make purchasing decisions (Schwartz et al., 2002). This theory states that people may be defined as maximizers or satisficers. On the one hand, maximizers are defined as people who seek for the best option available and always consider all of the alternatives before making a decision (Schwartz et al., 2002). On the other hand, satisficers are people who aspire to make choices that fit with their standards and preferences without spending too much time evaluating all the possible options (Schwartz et al., 2002).

This theory is the result of the dichotomy between two different contradictory theories (Cheek & Schwartz, 2016). The original theory of decision-making behaviour dates back to the 1940s, when Kuhn proposed rational choice theory, that posits that people have structured and specific set of preferences and they always behave to maximize their values and utilities (laying down the fundamental concepts for the current definition of maximizers) (Kuhn et al., 1944). In the 1950s, this theory was criticized by Herbert Simon, who proposed that people do not always behave as maximizers, but their every-day life decisions may be characterized by the satisficing principle (Simon, 1955). Particularly, human decision-making is restricted within a certain range (so-called 'bounded rationality'), and it is driven by individuals' needs, aspirations and existing available knowledge and computational capabilities (Simon, 1956). Accordingly, considering a large number of options available, consumers are not able to make the best possible decision due to their limited information processing abilities, but they usually end up making decisions that satisfy their personal goals and aspirations, exhibiting satisficing behaviour (Simon, 1956). Schwartz et al. proposed the maximization theory as a complementary framework that considers both theories and distinguishes between maximisers and satisficers (Schwartz et al., 2002).

With the introduction of maximization theory, Schwartz et al. also developed the first Maximization Scale (MS) to categorize individuals based on their personal maximizing tendency behaviour (PMTB) (Schwartz et al., 2002). One of the most popular and reliable revisions of the maximization scale is the work developed by Cheek and Schwartz, who posit that the personal maximizing tendency behaviour is composed by two different components: goal and strategy (Cheek & Schwartz, 2016). On the one hand, the maximization *goal* is defined as the ability to choose the best, which corresponds to the original definition of Simon to make the best decision and is considered as the definitional component of maximization (Simon, 1956). On the other hand, the maximization *strategy* refers to the procedure of seeking out options and comparing them, analysing the options available and contrasting them based on different variables. For clarity's sake, Figure 4 shows a graphical representation of the construct.

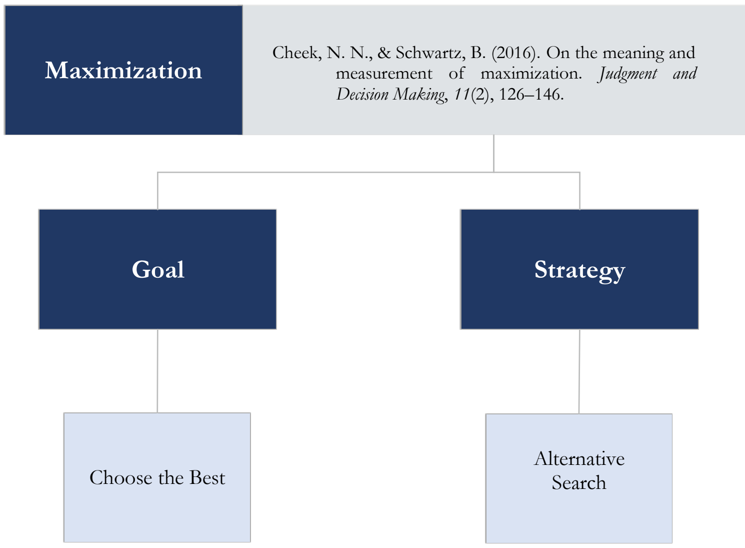


Figure 4: Maximization components (Cheek & Schwartz, 2016)

Maximization theory has been applied in the e-commerce industry, and it has been found to significantly influence customer satisfaction (Coba et al., 2019; Dar-Nimrod et al., 2009). For instance, maximizers may feel worse off as the options that they face increase, or they might be more sensitive to regret and feel less satisfied compared to satisficers (Kokkoris, 2017).

More interestingly, different studies have shown that gender is one of the variables influencing PMTB (Schwartz et al., 2002). Male customers registered different online shopping behaviour more focused on rational factors compared to women (Sarkar & Das, 2016). Male customers were found to exhibit different decision-making behaviour while shopping online and showed a higher tendency to maximize compared to female customers (Iyengar et al., 2006). Thus, these studies demonstrate that maximization theory and gender can play a role in influencing customer satisfaction and should be taken into consideration while developing online customer experiences.

Studying the influence that maximizing tendency behaviour and gender have on e-commerce interactions may shed light on why chatbots are still registering a low level of satisfaction and, thus, may help better understand how to achieve higher levels of service personalization.

2.6. E-commerce Customer Satisfaction

One of the most popular models used to assess the effectiveness of new technologies is the Technology Acceptance Model (TAM)(Al-Natour et al., 2011). This model was developed in 1989 by Davis, and it based on two fundamental factors (perceived ease of use and perceived usefulness) that influence technology acceptance behaviour (Davis, 1989). On the one hand, the perceived usefulness is defined as the "degree to which a person believes that using a particular system would enhance his or her job performance"(Davis, 1989, p. 320). This factor is considered an important mediator that it is still used in new versions of the TAM (Marangunić & Granić, 2015). On the other hand, the perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989, p. 320). Earlier versions of this model also include social influence as well as cognitive instrumental processes as factors influencing users' intention to use a technology (Venkatesh & Davis, 2000). This model was then completed with the intended and actual use of the technology factors, which were related together but were found to play a crucial role in the users' acceptance behaviour (Ajzen & Cote, 2008)

The TAM was used in several studies to assess whether chatbots were able to provide a sustained competitive advantage based on enhanced service quality (Kassim & Asiah Abdullah, 2010). One study found that a higher intention to use chatbots leads to higher customer engagement and user satisfaction from the service (J. Li et al., 2017). Accordingly, researchers found that chatbots significantly improved customer intention to use e-services and, thus, their overall satisfaction (Chung et al., 2018).

Hence, this thesis uses the TAM as the main theoretical background to evaluate the chatbot effectiveness for e-commerce applications due to the ability to assess the extent to which users like the technology as well as to predict their overall service satisfaction. The intention to use the technology coupled with customer satisfaction will be considered as the main dependent variables to assess customer perception of chatbots during the experiment.

3. Conceptual Framework

This chapter presents: (1) the research gap related to chatbot personality, maximization theory, and gender differences, (2) a conceptual framework and (3) a list of hypotheses related to the conceptual framework.

3.1. Conceptual Framework

Previous studies on e-commerce focus on the development of chatbot personalities to enhance customer experience and overall customer satisfaction (Gittens, 2018). In parallel, the role of humans in HCI studies has been emphasized (Tsao & Chang, 2010). Parades et al. have shown that specific personality traits may influence customer experience and experienced levels of satisfaction with the same service (Paredes et al., 2015). An analysis of the influence of an individual's personality from the perspective of personal decision-making behaviour has yet to be considered. This thesis explores the relationship between personal decision-making behaviour and chatbot personality.

Figure 5 shows the graphical framework (the identified knowledge gap), in which the chatbot personality literature is combined with maximization theory, delineating a new area of research, focused on the identification of the influence of chatbot personality on customer satisfaction.

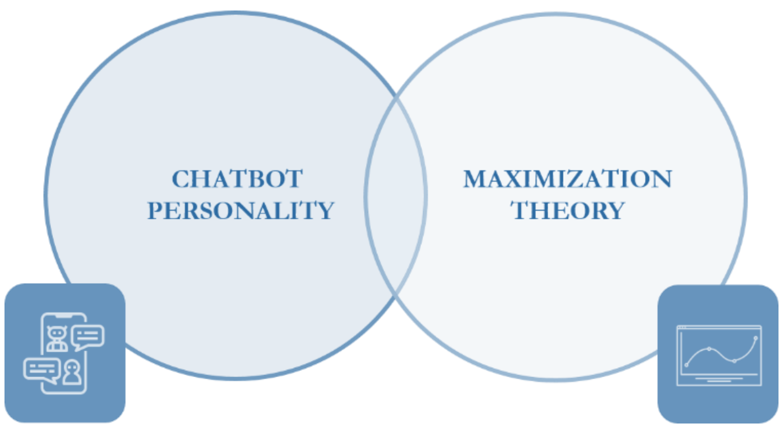


Figure 5: Identified research gap framework

Based on this theoretical background, an extravert shopping assistant chatbot is developed and used to evaluate customer satisfaction. Besides, this thesis determines whether this relationship is influenced by personal maximizing tendency behaviour. Figure 6 graphically represents the conceptual framework for this research. The personal maximizing tendency behaviour refers to the two constructs identified in the literature as strategy and goal. Considering its relevance for decision-making behaviour, gender will be considered as an additional variable in the experiment to test whether there is any difference in customer satisfaction for male and female (Dalal et al., 2015).

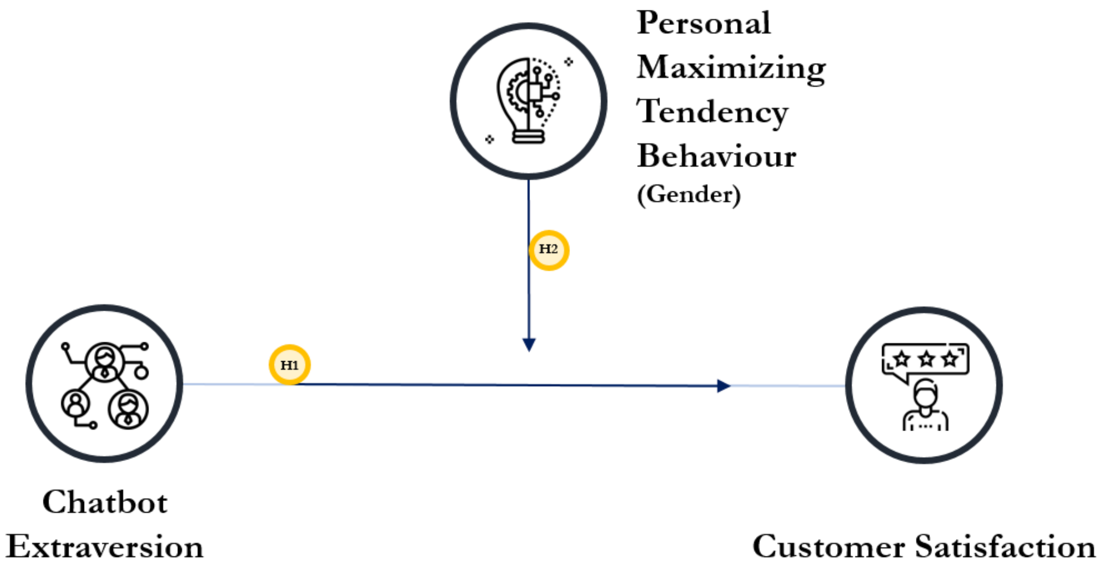


Figure 6: The identified conceptual framework

3.2. Hypothesis Development

Based on the maximization theoretical background, this research predicts that customer satisfaction will be influenced by chatbot personality. Two chatbot personalities are distinguished: extravert and neutral. Based on the literature, it is hypothesized that chatbot extraversion will lead to higher customer satisfaction:

Hypothesis 1: An extrovert chatbot personality increases customer satisfaction compared

to a neutral chatbot personality

Personal maximizing tendency behaviour is included as a moderator between chatbot personality and customer satisfaction. The influence of maximization decision-making behaviour on online chatbot conversations is explored. The following hypotheses are the focus of the second part of this research:

Hypothesis 2: Personal maximizing tendency behaviour and gender differences influence customer satisfaction

Hypothesis 3: The relationship between chatbot extraversion and customer satisfaction is influenced by personal maximizing tendency behaviour and gender differences

4. Instrument Design

This chapter presents the instrument design for the experiment. First, the approach used for the experimental manipulation of chatbot personality will be introduced. Second, the chatbot development platform is introduced.

4.1. Chatbot Personality Development

Two different versions of the chatbot (extravert vs neutral) were developed to explore the main research question. This section explains the operationalization of this specific personality trait and its control in the chatbot's conversations. Afterwards, the methodology used to implement the extraversion dimension is presented.

Express Personality Through Conversation: The Existing Literature

To design virtual conversations that successfully reflect extraversion, previous studies have built chatbot extraversion by means of language, emoticons and GIFs.

Firstly, semantic content is a crucial social cue to express personality, behaviour or mood during a social conversation (Walker et al., 2007). Pennebaker et al. discovered that extravert people use more tentative words (such as "sort of", "quite", "it seems that") than introvert people (1999). Also, extravert people use more informal language than introverts (Furnham, 1990) to exaggerate more and to be more concerned about the hearer (DeYoung et al., 2007). These findings were also found in online conversations or blogs (Foster & Oberlander, 2010). Using the Linguistic Inquiry and Word Count (LIWC) software, extravert people were found to use more social and emotional words, less complicated language and fewer significant words than introverts (Qiu et al., 2012).

Researchers have used these findings to develop a chatbot conversation that expresses specific personality traits, including extraversion (Ma et al., 2019). Table 2 presents a summary of the relevant findings on the extraversion language.

Introvert Findings	**Extrovert Findings**	**Studies**	**Parameters + Examples**
Tentative words (high)	Tentative words (Low)	(Pennebaker & King, 1999)	Softener Hedges: *(Sort of, somewhat, quite, rather, it seems that, like)*
Formal Language (low)	Informal Language (high)	(A Furnham, 1990)	Acknowledgement: *(Yeah, right, ok, I see, Well)*
Realism	Exaggeration	(Oberlander & Gill, 2004)	Emphasize Hedges: *(Really, Basically, Actually, Just)*
Not sympathetic (Low)	Sympathetic, concerned about hearer (High)	(Hirsh & Peterson, 2009)	Tag Questions
Strict Selection	Think out loud	(A Furnham, 1990)	Repetition and Openness
LIWC Categories			
Low scores on these categories	You, social, family, space, Number of words, question marks	(Tausczik & Pennebaker, 2010)	

Table 2: Findings on language cues for Extraversion

Second, with the advent of social media and online instant-messaging platforms, *emoji* or *emoticons* have become popular additions to textual communication (Butterworth et al., 2019). Emoticons are pictographs that can be used in virtual conversations to express an emotional context. They can strengthen the interpretation and meaning of a specific message (Ganster et al., 2012). Marengo et al. found that several emoticons significantly are related to three personality traits, including extraversion (2018). One study discovered that when a sales assistant uses emoticons during an online conversation, customers are more likely to feel warmth and satisfaction with the service encountered (X. Li et al., 2019). Considering these advantages, emoticons were used as an additional cue for the chatbot to express extraversion in the conversation. Table 3 presents the set of emoticons used in the experiment.

Extravert Emoticons	Findings	Studies
Positive emotion emojis		**(X. Li et al., 2019)**; **(Bai et al., 2019)**

Table 3: Emoticons related to extraversion:

Finally, Animated Graphical Interchange Formats (GIFs; short animated image sequences which convey a specific message to the end-user), see (Chen et al., 2017) allow for higher user engagement compared to other digital contents. This is due to their ability to quickly and intuitively express emotions and moods within virtual environments (Bakhshi et al., 2016; Yang et al., 2019). Researchers from the Media Lab of the MIT have developed a database of emotion-related GIFs (Rich et al., 2014) that is widely used to study the effectiveness of GIFs (Chen et al., 2017). In the present research GIFs from this database were included in the extravert chatbot conversations as a way to better engage with users, as well as to express the extraversion dimension more efficiently. Figure 7 presents an example of a sequence of images from a GIF included in the chatbot conversation.

Figure 7: Sequence of images from GIFs used within the chatbot conversations

Chatbot Personality Development

Taken together, linguistic cues, emoticons and GIFs were used to develop an extravert chatbot for the experiment. Figure 8 presents the comparison of the first message of the two different versions of the chatbot (extravert and neutral) and a few examples of the extravert conversations.

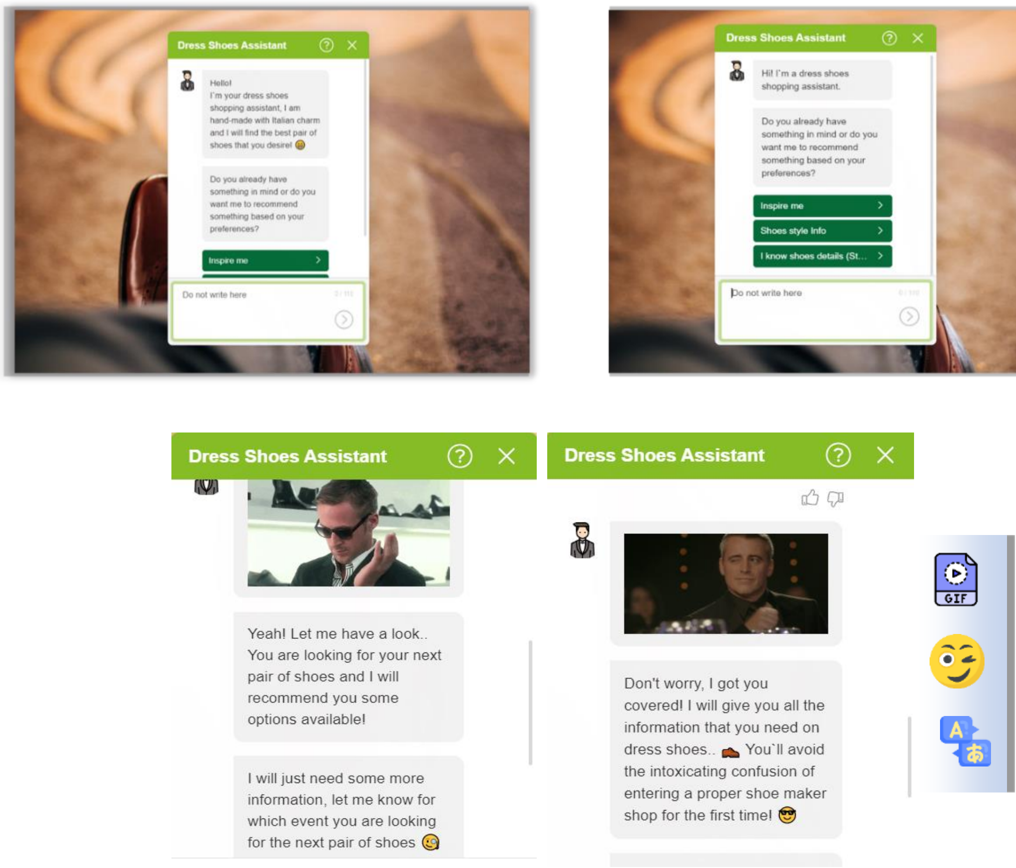


Figure 8: Example of extravert chatbot conversation compared to the neutral version

4.2. Chatbot development platform

The online experiment on which this thesis reports used a dedicated website in which participants interacted with a button-based e-commerce shopping assistant chatbot. The chatbot was designed to recommend a specific pair of formal dress shoes. The task users were asked to fulfil was to find/choose a pair of shoes for one of the user's male friends. The design and implementation of the chatbot conversations were conducted in the online conversational Artificial Intelligence (AI) platform Boost.ai®. This software was made available by Deloitte's Cognitive Engagement department. This platform provides solutions for the banking, insurance as well as in the e-commerce domain.

Two different versions of the chatbot (one extravert and the other neutral) were developed to answer the main research question. These two versions were created using the intent-based hierarchy technology included in the platform. Intents are the pre-defined topics on which information can be provided and used to structure conversations in a hierarchical way – i.e., to simplify and rationalize the development of a conversation. Figure 9 presents the intent hierarchy used to structure both of the two different types of chatbot conversations distinguished in this thesis.

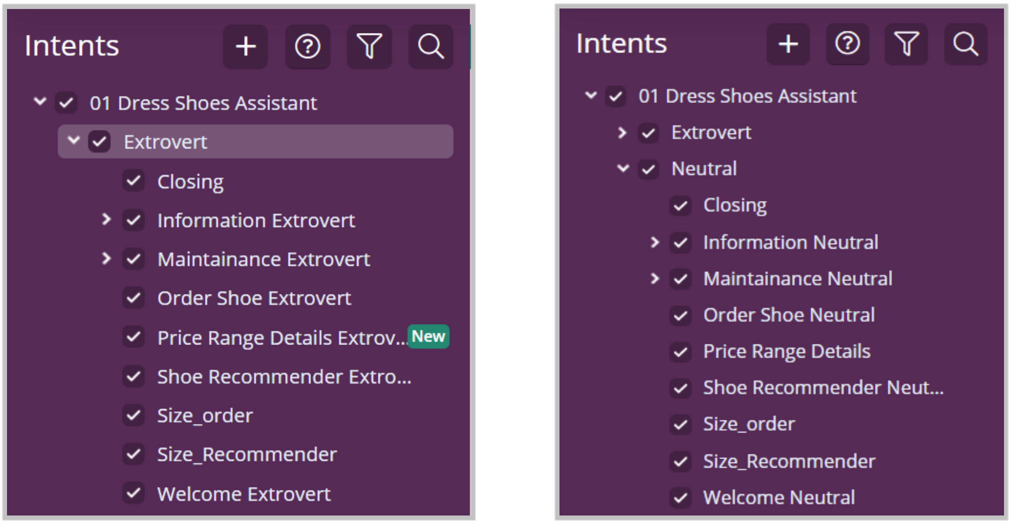


Figure 9: Intent hierarchy used for the experiment

Three different recommendation strategies were distinguished: First, an "Inspire me" storyline that proactively provides users with a recommendation for a specific pair of shoes based on their needs and preferences (based on specific events, suit colour and preferred decoration style). Second, an "I know shoe details" storyline designed to interact with users who know (believe they) what they are looking for. In this last case, users are prompted to select a preferred pair of shoes based on shoe details (such as style, decoration and colour). Third, an "Inform Me" part to allow unknowledgeable users to gain information about the different style of shoes available.

These strategies were implemented in conversations using the so-called 'Entity Extraction' methodology. Each strategy extracts words from the user's input to determine the right recommendation to be provided to the user based on the shoe logic. For example, when a user selects the "Inspire me" strategy and selects a pair of shoes for a "wedding", "with a "Blue suit" and a "Plain Style", the chatbot is able to recommend a "Plain Black Oxford" shoe based on the designed shoe logic. Figure 10 depicts a graphical representation of the process flow of conversations.

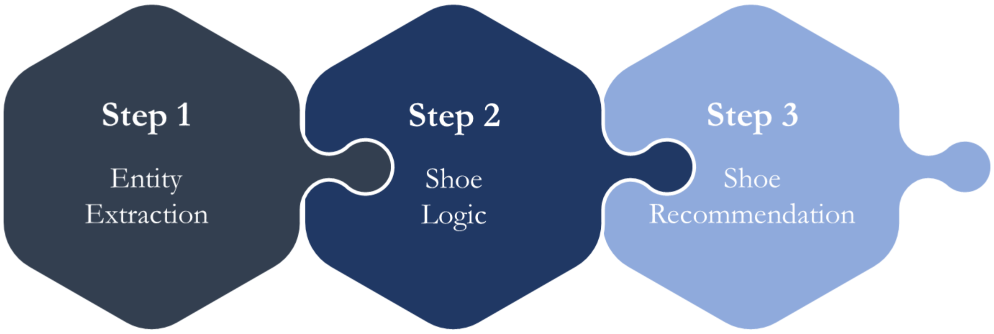


Figure 10: Chatbot process flow

This structure enables the chatbot to recommend different shoe styles depending on users' specific needs. Table 4 presents a list of the specific entities related to each of the recommendation strategies.

Recommendation strategy	Entity Name	Description	Options Available
Inspire me	Event	For which event the shoes will be used (Pennebaker & King, 1999)	Business Casual, Business Professional, Date Night, Formal-ish Event, Job Interview
	Suit colour	Refers to which suit colour shoes need to be matched for the event	Blue, Black, Grey, Brown
	Decoration	Different shoe decoration style	Plain, Brogue
	Price	Shoe price range	100€-150€, 250€-300€
I know shoe details	Style	Style of shoes	Oxford, Derby, Monk Strap, Chukka, Chelsea
	Decoration	Type of decoration	Wingtip, Brogue, Whole cut, Cap Toe, Single/Double Strap, Plain
	Price	Shoe price range	100€-150€, 250€-300€
Inform me	Style	Style of shoes	Description of the different shoe styles
	Decoration	Type of decorations	Description of the different decorations available

Table 4: Three recommendation strategies

5.

Research Methodology

This chapter presents the research design and methodology used for this research. Based on the literature review and the proposed conceptual framework, an online experiment was delineated to answer the main research question. First, the experimental design, the procedure, and the main components of the study are introduced. Second, the measures are presented.

5.1. Ethics Approval

This experiment and the protocol received official approval by the Human Research and Ethics Committee (HREC) of TU Delft.

5.2. Research Design and Participants

This study was conducted as an online experiment, in which participants interacted with a button-based e-commerce shopping assistant chatbot. Participants were asked to virtually order one pair of shoes for one of their male acquaintances based on their preferences. Participants were randomly assigned to one of the two versions of a chatbot (neutral or extravert). In both cases, the chatbot recommended a specific pair of formal dress shoes for one of a user's male acquaintances. Interactions with the chatbot varied only in terms of the amount of extraversion. Table 5 shows the distribution of chatbot personalities among participants.

Chatbot Personality

		Frequency	Percent
Personality	Extravert	58	48.3
	Neutral	62	51.7
	Total	120	100.0

Table 5: Chatbot personality distribution

Participants were recruited through the author's personal and professional network, including co-workers, friends, university colleagues, as well as acquaintances. Participation in the experiment was on a voluntary basis, and participants were not paid to complete the experiment. Considering the limited time and resources available, the classic rule of thirty participants per chatbot and user personality was used (O'Gorman & Macintosh, 2014). The initial sample consisted of 130 participants. The data of participants with missing values and outliers (N=10, 7.7%) was omitted from the research sample. The final sample size consisted of 120 participants (41 female and 79 male, the majority of which between 18 and 34 years old). The following tables present the descriptive statistics for the final sample.

Nationality

	Frequency	Percent
Belgium	1	.8
China	1	.8
Colombia	1	.8
Estonia	7	5.8
Germany	2	1.7
Greece	4	3.3
India	7	5.8
Indonesia	9	7.5
Italy	46	38.3
Mexico	1	.8
Netherlands	29	24.2
Pakistan	1	.8
South Africa	1	.8
Spain	3	2.5
Sweden	1	.8
Switzerland	2	1.7
Syrian Arab Republic	1	.8
Turkey	1	.8
United Kingdom	1	.8
Viet Nam	1	.8
Total	120	100.0

Age Range

	Frequency	Percent
18 - 24	51	42.5
25 - 34	67	55.8
35 - 44	1	.8
55 - 64	1	.8
Total	120	100.0

Gender

		Frequency	Percent
Valid	Female	41	34.2
	Male	79	65.8
	Total	120	100.0

Education

	Frequency	Percent
Bachelor degree	46	38.3
College	3	2.5
Doctorate	2	1.7
High school graduate	12	10.0
Master degree	57	47.5
Total	120	100.0

5.3. Research Procedure

Participants received an URL link that directed them to the landing page of the experiment hosted in Qualtrics and the chatbot platform. Participants were introduced to the research and were required to provide informed consent for their data to be used for research purposes. The experiment was divided into three different parts: demographic questions, chatbot interaction and post-interaction questionnaire. First, participants were asked to provide their demographic information (including age, gender, nationality, education level, e-commerce and chatbot experience), that was used to create their profiles. Next, participants were introduced to the experiment as follows:

DRESS SHOES SHOPPING ASSISTANT
Shortly, you will be redirected to a webpage in which you will interact with a button-based shopping assistant chatbot for dress/formal shoes that will recommend you some shoes based on your preferences.
You will be asked to 'order' one pair of dress shoe **for one of your *Male* acquaintances (brother, father, friend, boyfriend, etc.)** and select the recommended options based on your preferences:
Once you complete the ***virtual order*** and the interaction, you will be redirected to the second part of the experiment for a ***post-interaction questionnaire.***

IMPORTANT PRE-INTERACTION DECISIONS:
- **FIRST:** please decide to whom you would like to order the pair of shoes
- **SECOND:** we would like you to start the research by identifying a specific situation in which your *male* acquaintance needs a formal dress shoe between the following categories: (please select only one based on your preferences or what you think best fits his needs):
1) Job interview
2) Business Casual (everyday business, office outfit, versatile, etc.)
3) Date Night
4) Business Formal (Client meetings, official meetings, corporate gatherings, etc.)
5) Formal-ish events (Weddings, ceremonies, etc.)

- **THIRD:** Once you place a virtual order, you will be redirected to the second part of the survey

! REMINDERS

- *For the sake of the research objective, you are only allowed to press buttons on the conversation. Please **DO NOT write** any text in the text input space.*

- *The virtual order that you are placing is fictitious, does not have any payment involved and it is meant for the purpose of this research only.*

- *The research assumes that all of the shoe sizes are available and ready for your order.*

The website redirected them to the chatbot conversation website, in which the participant was requested to interact with the chatbot, and virtually place an order for dress shoes for their acquaintance based on their preferences. Participants were randomly assigned to one of the chatbot personality versions (neutral vs extravert). Figure 11 represents a picture of the user interface that participants used during the interaction (extravert version).

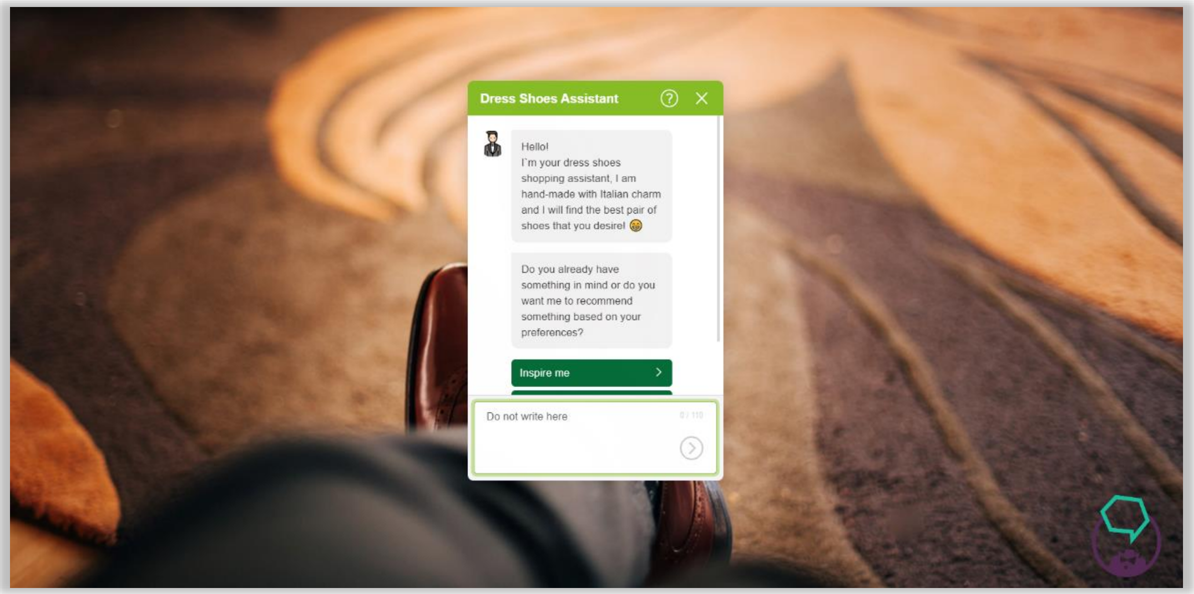


Figure 11: Chatbot interaction website

Once participants had "virtually" ordered a pair of shoes, they were automatically redirected to a post-interaction questionnaire. In this section, participants were asked to evaluate the chatbot personality based on their interaction and to complete a customer satisfaction section and two personality measures. The details are presented in the following paragraphs. The experiment took about 10-15 minutes to complete depending on the amount of time spent on the chatbot conversation.

5.4. Measures

This section presents the measurement scales used in the research to measure the relevant variable of the conceptual framework. Firstly, the approach used for manipulation of the chatbot personality is presented. Afterwards, the scales for extraversion, maximization tendency behaviour and operationalization of customer satisfaction are presented, together with the related literature.

Extraversion Scale

To assess chatbot extraversion, the Extraversion items of the International Personality Item Pool (IPIP) were used (Goldberg, 1992). Participants were asked to answer to what extent they agree or disagree on ten different statements describing the chatbot extraversion on a five-point Likert scale (from 1: "Very Inaccurate" to 5: "Very Accurate") as shown in Appendix A. The ten items related to the extraversion had high reliability (Cronbach's $\alpha = 0.908$), and consistently loaded on one factor (Appendix B).

Personal Maximizing Tendency Behaviour Scale

Personal maximizing tendency behaviour (PMTB) was measured for two different aspects: maximization goals and maximization strategy (Cheek & Schwartz, 2016) as follows:

PMTB (Goal): PMTB goal was measured using the seven-item Maximizing Tendency Scale (MTS-7; Turner et al., 2012). The items in the scale were measured on a five-point Likert scale (from 1: "Strongly Disagree" to 5: "Strongly Agree") as shown in Appendix A. The scale was reliable (Cronbach's $\alpha = 0.843$).

PMTB (Strategy): PMTB (Strategy) was measured using the twelve-item 'Alternative Search' subscale of the Maximization Inventory (Turner et al., 2012). Again, the items in the scale were measured on a five-point Likert scale (from 1: "Strongly Disagree" to 5: "Strongly Agree") as shown in Appendix A. The scale was reliable (Cronbach's $\alpha = 0.907$).

Confirming the different aspects of PMTB, both scales recorded high loadings on two different constructs, confirming the two factors structure (Appendix B). Only the item *"I never settle"* did not register high loadings.

Dependent Measures

The outcomes in the experiment relate to customer satisfaction. The dependent variable was operationalized in three different ways: using a Customer Satisfaction measure, with the help of the Intention to Use the Technology measure, and via the Net Promoter Score (NPS).

Customer Satisfaction

The scale developed by Chin et al. for evaluation of human-computer interfaces (Chin et al., 1988; Lee & Choi, 2017) was used to assess customer satisfaction. The scale showed high loadings on one factor (Appendix B). Participants assessed customer satisfaction using the original seven-point Likert scale (from 1: "Strongly Agree" to 7: "Strongly disagree") presented in Appendix A. The scale had a high level of reliability (Cronbach's $\alpha = 0.868$).

Intention to Use the Technology

A modified version of the scale developed by Davis in 1992 was used (Benbasat & Wang, 2005; Davis et al., 1992) to measure intention to use. This scale was adapted from the original version (Cronbach's α of 0.89) to assess the intention to use the technology for conversational agents (Benbasat & Wang, 2005). All items registered high loadings on one component, confirming previous findings (Appendix B). The scale was assessed using the seven-point Likert scale (from 1: "Strongly Agree" to 7: "Strongly Disagree") that is presented in Appendix A. The scale was reliable (Cronbach's α = 0.893).

Net Promoter Score

Finally, the Net Promoter Score (NPS) was used to test whether users were willing to recommend the chatbot to a friend or a colleague (Reichheld, 2003). The score of this scale ranges from 0 to 10 and divides customers into three different categories: Detractors, Passives and Promoters. Detractors are people that scored lower than six on the NPS and are not willing to recommend the technology. Passives are people that are indifferent on the technology and can easily switch to competitors or other products. Promoters are extremely satisfied with the interaction and likely to encourage other people to use the technology (Reichheld, 2003). The NPS is computed as the difference between the percentage of promoters and the percentage of detractors. Within this study, in line with the original NPS scale, participants were asked to answer the question "how likely are you to recommend the chatbot to a friend or colleague?" on a scale from 1 to 10.

6. Results

This chapter presents the results obtained from the experiment. The chapter starts with the manipulation check for the chatbot personality, and then presents the descriptive statistics, correlations and overall distributions. Finally, the hypothesis testing is reported introduced with the results for customer satisfaction.

6.1. Manipulation Check

To assess to what extent participants had perceived chatbot extraversion or chatbot neutrality as such, they were asked to identify the chatbot's personality. Table 6 shows the results from the ANOVA table with an F-test. A Levene's test or equality of variances revealed that the variances in the two conditions (extravert and neutral) were equal (Sig.>.05). The 58 participants that interacted with the extravert chatbot ($M_{Extravert}$=4.0879, $SD_{Extravert}$=.648) compared to the 62 in the control group ($M_{Neutral}$=2.985, $SD_{Neutral}$=.824) registered a significantly higher level of perceived chatbot personality, $F(1,116)=65.337$, $p<0.001$.

Tests of Between-Subjects Effects
Dependent Variable: CP_Mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	36.987[a]	3	12.329	22.073	.000	.363
Intercept	1499.403	1	1499.403	2684.423	.000	.959
MTB Goal	.009	1	.009	.015	.902	.000
MTB Strategy	.271	1	.271	.485	.488	.004
Personality Chatbot	**36.494**	**1**	**36.494**	**65.337**	**.000**	**.360**
Error	64.793	116	.559			
Total	1587.220	120				
Corrected Total	101.780	119				

a. R Squared = .363 (Adjusted R Squared = .347)

Table 6: F-test table for chatbot personality

These results show that participants were able to distinguish between an extravert chatbot and a neutral version, confirming a successful manipulation of chatbot personality.

6.2. Sample Characteristics, Correlations and Overall Distribution

Table 7 shows that the majority of participants (98.4%) purchased at least one purchase online in the past, and had had at least one chatbot interaction (83.2%) prior to this experiment.

Online Purchase Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	123	98.4	98.4	98.4
	No	2	1.6	1.6	100.0
	Total	125	100.0	100.0	

Chatbot Usage Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	21	16.8	16.8	16.8
	Yes	104	83.2	83.2	100.0
	Total	125	100.0	100.0	

Table 7: Frequencies Online Purchase Experience and Chatbot Usage

Table 8 shows the descriptive statistics for the variables included in the research, including the arithmetic means, standard deviations, skewness and kurtosis. For all of the variables involved, the level of kurtosis and skewness registered value within the acceptance range for a normal distribution with skewness levels between -1 and 1, and kurtosis levels between 1 and -1. Thus, the variables included in the experiment were normally distributed (Field, 2008). Appendix D shows the histograms for the three research factors.

Descriptive Statistics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Intention to Use	120	4.8226	1.00641	-.535	.221	-.010	.438
Customer Satisfaction	120	5.5604	.76060	-.634	.221	-.204	.438
MTB (Strategy)	120	3.7833	.80065	-.610	.221	-.413	.438
MTB (Goal)	120	3.5036	.74149	-.562	.221	.080	.438

Table 8: Descriptive Statistics for research factors

Table 9 shows the correlation matrix for all of the variables. As expected from the literature, customer satisfaction was significantly correlated to the intention to use the technology (r = 0.732). Second, both components of maximizing tendency behaviour were strongly correlated (r = 0.9).

Correlations

		1.	2.	3.	4.	5.	6.
1.	Customer Satisfaction	1					
2.	Chatbot Personality	.136	1				
3.	Intention to Use	**.732****	.092	1			
4.	Maximizing tendency behaviour (Goal)	.047	-.029	.062	**.902****	1	
5.	Maximizing tendency behaviour (Strategy)	.046	.042	.063	**.908****	.638**	1

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

Table 9: Summary of correlations for scores on Customer Satisfaction, Intention to Use and PMTB (Goal and Strategy)

6.3. Hypotheses Testing

An Analysis of Covariance (ANCOVA) was conducted to determine to what extent personal maximizing tendency behaviour (PMTB) (Goal and Strategy) and gender moderated the relationship between chatbot personality and customer satisfaction or intention to use (Aiken & West, 1991). PMTB Goal and Strategy were separately entered as covariates in the model and analysed for both customer satisfaction and intention to use. Besides, the ANCOVA analysis was used to determine whether there was a significant main effect between chatbot personality and PMTB on customer satisfaction and intention to use (Aiken & West, 1991). The following paragraphs present the results of the analysis and hypotheses testing.

6.3.1. Customer Satisfaction

An ANCOVA revealed a moderation effect of PMTB Goal on the influence of chatbot personality and user's gender on customer satisfaction, $F(1, 112)=4.367$, $p=.039$, partial $\eta^2=.038$ (Figure 12). Customer satisfaction differed between male and female, and it was influenced by the chatbot personality and the consumer's PMTB Goal. The PMTB Goal negatively influences customer satisfaction for the neutral chatbot personality (for female) and the extravert chatbot (for male). Besides, when male used the neutral version, the PMTB Goal positively influenced customer satisfaction. Simple effect analysis showed a significant effect of PMTB Goal and gender for the neutral chatbot, F(1,112)=5.857, *p*=.017, but not for the extravert chatbot, F(1,112)=.229, *ns*. These findings confirm Hypothesis 3 on the moderation effect from the perspective of PMTB Goal factor and customer satisfaction. No significant results were found with the PMTB Strategy (Appendix E).

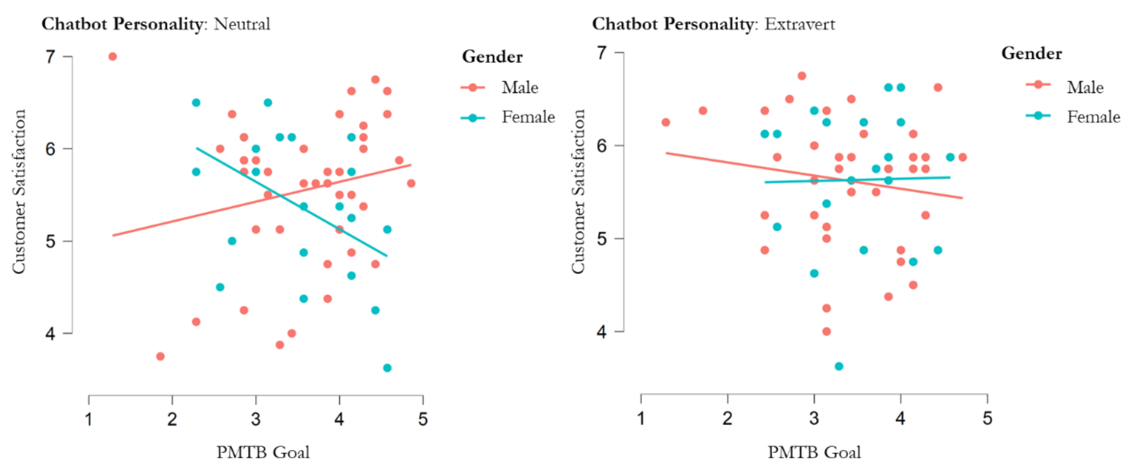


Figure 12: Scatter Plot for customer satisfaction, PMTB, chatbot personality and gender

In addition, the main effect of chatbot personality on customer satisfaction did not register significant results, F(1,112)=.043, *ns*. Also, the main effect of PMTB Goal, F(1,112)=.948, *ns,* and the main effect of PMTB Strategy, F(1,112)=.0018, *ns,* did not register any significant result on customer satisfaction (Appendix E). Thus, from the perspective of customer satisfaction, Hypothesis 1 and 2 need to be rejected.

6.3.2. Intention to Use

An ANCOVA revealed a significant main effect of PMTB Goal with gender on Intention to Use, F(1,112)=5.352, p=.023, partial η^2 =.046 (Figure 13). As shown in Figure 13, PMTB Goal negatively influenced intention to use for female users, whereas PMTB Goal positively influenced the intention to use the chatbot for male users. This finding allows for the acceptance of Hypothesis 2 from the perspective of PMTB Goal, gender and intention to use.

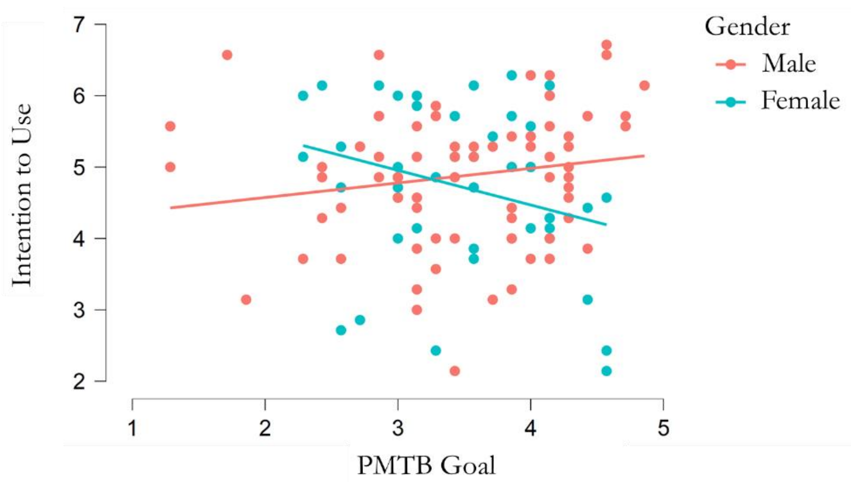


Figure 13: Scatter plot for Intention to Use and PMTB Goal

A main effect of gender on the intention to use also registered a significant result, F(1,112)=4.525, p=.036, partial η^2 =.039. As shown in Figure 14, contrast analysis confirmed that male had a higher level of intention to use the technology (M=4.883, SD=0.923) compared to women (M=4.716, SD=1.122), F(1,112)=7.343, p=.007.

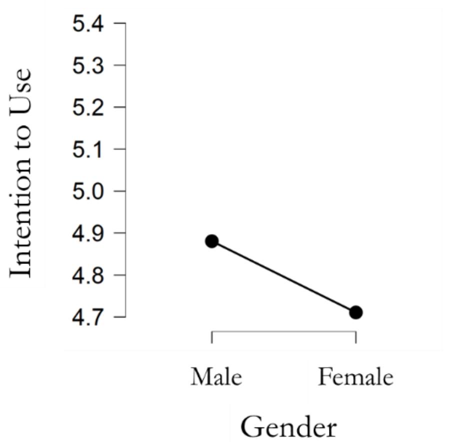


Figure 14: Gender on Intention to Use

The main effect of chatbot personality did not register any significant results, F(1,112)=.368, *ns*, rejecting Hypothesis 1 from the intention to use perspective. The moderation effect of PMTB Goal, F(1,112)=2.737, *ns*, and PMTB Strategy, F(1,112)=.948, *ns*, did not register any significant results (Appendix E). Thus, Hypothesis 3 also needs to be rejected from the perspective of the intention to use the chatbot.

6.4. Net Promoter Score

Finally, the experiment results for the Net Promoter Score (NPS) are presented (Table 10). The NPS scores for the extravert and the neutral version were compared. Table 10 presents the frequencies for the NPS scores. On the one hand, for the extravert chatbot, Detractors (participants who evaluate the chatbot between 1 and 6) were 11 (19%). Passive participants (scored 7 or 8) were 36 (62%), whereas Promoters (scores 9 or 10) were 11 (19%). Thus, the NPS for the extravert version has a value of 0, calculated by subtracting the percentage of Promoters with the percentage of Detractors. On the other hand, for the neutral chatbot, Detractors were 21 (33.9%). Passive participants were 30 (48.4%), whereas Promoters were 11 (17.7%). Thus, the NPS for the neutral version is -16.2. The extravert chatbot registered a higher NPS score compared to the neutral version. These results suggest that, although it registered an NPS of 0, the extravert chatbot is more likely to be recommended and promoted by users to friends or colleagues compared to the neutral version. Thus, chatbot personality influenced customer satisfaction from the perspective of the NPS.

NPS Extravert chatbot

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	1	1.7	1.7	1.7
	4	1	1.7	1.7	3.4
	5	2	3.4	3.4	6.9
	6	7	12.1	12.1	19.0
	7	17	29.3	29.3	48.3
	8	19	32.8	32.8	81.0
	9	9	15.5	15.5	96.6
	10	2	3.4	3.4	100.0
	Total	58	100.0	100.0	

NPS Neutral chatbot

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	1	1.6	1.6	1.6
	3	1	1.6	1.6	3.2
	4	2	3.2	3.2	6.5
	5	4	6.5	6.5	12.9
	6	13	21.0	21.0	33.9
	7	17	27.4	27.4	61.3
	8	13	21.0	21.0	82.3
	9	9	14.5	14.5	96.8
	10	2	3.2	3.2	100.0
	Total	62	100.0	100.0	

Table 10: Net Promoter Score for chatbot personalities

7. Discussion

The main objective of this research was to understand to what extent chatbot extraversion influences customer satisfaction within the e-commerce domain for a dress shoes shopping assistant chatbot. This thesis also explored if the relationship between these two variables is related and influenced by personal maximizing tendency behaviour (PMTB), and gender differences in users. The following paragraphs present the scientific implications of the results obtained in the experiment, the practical relevance, the research limitations, and suggestions for future research.

7.1. Chatbot Extraversion Recognition

The first relevant variable for the study was the chatbot extraversion. Overall, users were able to recognize the chatbot extraversion and distinguish it from the neutral version. These findings have different implications. Firstly, these results have shown that social cues extracted from human activities (offline and online conversations) can be used to express specific personality traits (in this case, extraversion) while developing online chatbots. Secondly, this study has confirmed previous findings on the ability of informational cues (such as linguistic capabilities, emoticons and GIFs) to infer the extraversion personality trait in online conversations (Butterworth et al., 2019; Chen et al., 2017; Tausczik & Pennebaker, 2010). Thus, although this research has not come up with a systematic methodology for developing chatbot personality, it has shed some lights on which kind of conversational cues future research should focus on while designing chatbot personalities. The fact that users were able to distinguish between the two chatbot versions enabled to reliably compare the two versions, test whether the chatbot extraversion influenced the customer satisfaction and assess whether this relationship was influenced by the personal maximizing tendency behaviour and gender. This result enables to answer the first sub-research question and confirms that it is possible to develop virtual conversations for chatbots that are extravert in nature.

7.2. Personal Maximizing Tendency Behaviour Scale

This research has used the two-component model of maximization developed by Cheek and Schwartz (2016) to express PMTB. The results obtained in the experiment have replicated the high reliability of the scales used and the existence of two components for the personal maximizing tendency behaviour. Thus, this study has confirmed the results obtained in previous research and has confirmed the high reliability of this two-component model for maximization (Cheek & Schwartz, 2016). Future research can use this model to measure personal maximizing tendency behaviour.

7.3. Scientific Relevance

This study hypothesized that (1) an extravert chatbot leads to higher customer satisfaction, (2) that maximizers (with different gender) have different customer satisfaction compared to satisficers and (3) that PMTB (together with gender) is moderating the relationship between chatbot extraversion and customer satisfaction. The following paragraphs present the implications of the obtained results and discuss the scientific relevance of each hypothesis.

7.3.1. Chatbot Extraversion and Customer Satisfaction

This study hypothesized that an extravert chatbot would lead to increased customer satisfaction. However, the extravert chatbot did not perform better than the neutral version in terms of customer satisfaction (or intention to use). This is in line with previous studies on Human-Computer Interaction (HCI), which did not find any significant results for this main effect (Smestad & Volden, 2019; Zhou et al., 2019). Thus, this result rejects Hypothesis 1 on the main effect of chatbot personality and customer satisfaction.

7.3.2. Personal Maximizing Tendency Behaviour and Satisfaction

Before checking for the moderation effect, Hypothesis 2 was developed to understand whether PMTB and gender directly influence customer satisfaction. Results showed that after controlling for PMTB Goal, male participants were more willing to use the technology than female participants. Male maximizers registered a higher level of intention to use the technology than satisficers, whereas female satisficers registered a higher level of intention to use than maximizers. Previous studies found that the desire of choosing the best is particularly relevant when shopping online since satisficers in that case just buy the first thing that matches their limited standards (i.e. brand name or price). Maximizers, on the other hand, continue to look for the best option even after they found one that matches their numerous standards (Cheek & Schwartz, 2016). Considering that the focus of the research was on the end goal of the purchasing experience rather than on the decision-making process, it is clear how the influence of choosing the best option (PMTB Goal factor) was more relevant for the experiment.

Therefore, the results obtained in the experiment confirm Hypothesis 2 from the perspective of PMTB Goal, gender and intention to use the technology. The chatbot application for male dress shoes differently influenced the intention to use the technology for men and women, and a participant registered a different level of intention to use depending on their level of PMTB Goal.

7.3.3. The Moderation Effect of PMTB

Hypothesis 3 on the moderation effect of PMTB was formulated as the main hypothesis. Results showed that, for male participants, the neutral version of the conversation registered a higher level of customer satisfaction for maximizers, while the extravert version performed better with satisficers. For female participants, only the neutral version registered a higher level of customer satisfaction for satisficers. From the perspective of male satisficers, the fact that the extravert version of the chatbot performed better than the neutral version confirms findings in previous studies about the higher persuasion ability of extravert salespeople (Grant, 2013).

Therefore, these findings confirm Hypothesis 3 from the perspective of the PMTB Goal factor and gender. Personalizing the chatbot personality depending on customers' PMTB is a successful tool to enhance customer satisfaction and, thus, the overall customer experience.

7.4. Practical Relevance

This research studied the influence of chatbot extraversion on customer satisfaction for applications within e-commerce. First of all, this study showed that it is possible to attach extraversion traits in online conversations, which are also recognized as such by users interacting with those chatbots. This finding has practical relevance because the insight can be used to increase customer engagement and human-likeness of the chatbot by attaching specific personality trait to the conversations. As mentioned in the literature, successfully attaching a personality trait to a chatbot increases its human-likeness and overall customer satisfaction (J. Li et al., 2017).

In addition, this research showed the importance of the personality trait PMTB Goal on customer satisfaction and chatbot personality. Developers should align chatbot personality with a user's PMTB Goal to better improve online customer experiences for the e-commerce domain. For instance, an e-commerce platform with many female clients characterized by high PMTB Goal should adjust the personality of the chatbot according to the findings of this research in order to offer an enhanced service personalization.

7.5. Limitations

First of all, the experiment was conducted in an uncontrolled space without any supervision (i.e., it was administered in an online form). Participants were able to complete the experiment wherever and whenever they wanted to. Experiments developed in a lab tend to be more reliable due to the ability to control any external variable that might influence the results (Sekaran & Bougie, 2016). On the other hand, this online format was closer to the real-life search, browse, and shopping experiences that people nowadays have in e-commerce. Secondly, this research used self-report questionnaires to measure the different variable involved in the research. However, such approaches only measure the perception of what people think they are, and it might not truly reflect how they actually behave (Hoskin, 2012). Thirdly, there might have been sampling issues in this online research. The selection of the sample was conducted through a convenience sampling, using people related to the author's personal network. Thus, individuals in the population did not have equal chances of being selected within the sample, and this might have influenced the final results (Sekaran & Bougie, 2016). Finally, the experiment was developed completely in English, and some participants might not have had sufficient language fluency to understand all the contents due to a different primary language. This deficiency should be taken into consideration for future research since it might have influenced the perception and interpretation of participants of specific parts of the research (Sekaran & Bougie, 2016).

7.6. Future Research

This research is one of the first attempts at understanding the interaction between a chatbot and users' personality, and it has shed some lights on the role of the alignment between chatbot and users' personality within the e-commerce domain. First of all, future research could focus on other personality traits in order to understand which dimension is crucial for a chatbot personalization in e-commerce apart from the extraversion dimension.

Secondly, future research might integrate the chatbot conversation with an existing e-commerce website in order to exploit the capabilities of both tools and allow customers to interact with both the chatbot and the website. The chatbot interaction in the present study happened in a dedicated interface focused only on the conversation. However, chatbots are usually implemented in an existing website (in this case, dress shoes websites) as small pop-up windows.

Thirdly, this study has explored a dedicated and specific chatbot application, and design focused on male dress shoes and button-based interactions. Future research could focus on different design and applications in order to test the generalization of these results and compare them with different contexts. For instance, later studies could focus on different products or applications (i.e. government services) or on developing a natural language-based chatbot that enables consumers to interact with it by typing messages similar to how they are currently communicating with other real people (i.e., virtual chat). These analyses will help to understand which personality traits perform better depending on different chatbot applications and designs.

8. Conclusion

The advent of chatbots in e-commerce has introduced a new way of thinking about how to communicate online with customers. The ability to simultaneously and automatically reach numerous customers allowed for the development of new business models based on innovative conversational strategies. However, chatbots also come with several problematic issues. Customers are increasingly complaining about their high failure rate and low human-likeness. One of the main solutions to increase chatbot effectiveness is the ability to attach to the agent specific personality traits in order to make them more similar to humans. However, chatbot personality has revealed to be only one side of effective chatbot interactions due to the major influence of users' personalities while interacting with chatbots. Specifically, developers should take into consideration how different chatbot personalities interact and perform with different users' personality. Thus, there is a need to understand how to better align chatbot and users' personality in order to develop enhanced chatbot conversations that better fit customers' needs and wants.

This thesis has developed an experiment that tried to shed some light on the complementary interaction between chatbot and users' personalities. Considering the focus on shopping assistant chatbots, the extraversion dimension of the Five-Factor model has been selected as the most relevant personality trait for salespeople. Besides, the users' personality was analysed from the perspective of Personal Maximizing Tendency Behaviour (PMTB). The main objective was to "*determine whether chatbot extraversion influences customer satisfaction within the e-commerce domain and, if so, whether this is influenced by personal maximizing tendency behaviour and gender*". In order to fulfil the main objective, a real male dress shoe, button-based chatbot was developed with two different personalities (extravert and neutral), and users were able to interact through a dedicated website. Customer satisfaction was measured with an online questionnaire, and statistical analysis was conducted to test the hypotheses.

This study registered a significant result for the moderation effect of PMTB and gender on the relationship between chatbot extraversion and customer satisfaction. Table 11 presents the results for the three hypotheses formulated for the experiment. Significant results were found for the predicted higher-order interaction effects of chatbot personality, PMTB, gender and customer satisfaction. PMTB (only the Goal factor) was found to influence customer satisfaction with differences in gender, confirming Hypothesis 2 from the perspective of gender. Besides, this study discovered that PMTB Goal (together with gender) moderated the relationship between chatbot personality and customer satisfaction confirming Hypothesis 3. Maximizers/Satisficers Male or Female registered a different level of customer satisfaction depending on the chatbot personality they interacted with during the experiment.

#	Hypothesis	Result
1	An extrovert chatbot personality increases customer satisfaction compared to a neutral chatbot personality	**Rejected**
2	Personal maximizing tendency behaviour and gender differences influence customer satisfaction	**Accepted**
3	The relationship between chatbot extraversion and customer satisfaction is influenced by personal maximizing tendency behaviour and gender differences	**Accepted**

Table 11: Research Result

Thus, these results have shown that chatbot personality does not directly influence customer satisfaction, but customers' gender and personal maximizing tendency behaviour while shopping online play a crucial role as moderating variables in the relationship between chatbot personality and customer satisfaction. This study aims at inspiring future research on a deeper understanding of the relationship between chatbot and users personalities. The ability to effectively adjust chatbot services to different customers depending on their personalities will allow companies to achieve a greater level of customer experiences and will ensure them a secure and reliable competitive advantage.

Appendix

Appendix A: Measurement Scales

Construct	Item
Extraversion	1. The chatbot might be the life of a party 2. The chatbot feels comfortable around people 3. The chatbot starts conversations 4. The chatbot talks to a lot of different people at parties 5. The chatbot does not mind being the centre of attention 6. The chatbot does not talk a lot 7. The chatbot keeps in the background 8. The chatbot has little to say 9. The chatbot does not like to draw attention to itself 10. The chatbot is quiet around strangers
Customer Satisfaction	1. I was satisfied with the experience of using a dialogue with the chatbot to complete tasks 2. I am satisfied with the chatbot's recommendation service 3. Interacting with the chatbot was a pleasant and satisfactory experience 4. The dialogue with the chatbot gave me useful information 5. I am satisfied with asking the chatbot for information because it is easier than trying to find it myself 6. I feel that the chatbot is an expert 7. The chatbot's responses in the interaction were appropriate 8. The overall assessment of conversing with the chatbot was satisfactory
Intention to use	1. I would use the chatbot again 2. I would recommend the chatbot to others 3. If this chatbot is commercially available, I will purchase it 4. I would like the chatbot to assist me in making decisions 5. I am satisfied with using the chatbot because it is easy to use and better than having to do it my self 6. When looking for dress shoes, I will watch the content recommended by the chatbot 7. If I had the chance to use this chatbot again, I want to talk a lot with it
Maximizing Tendency Scale (MTS-7)	1. I don't like having to settle for good enough 2. I am a maximizer 3. No matter what I do, I have the highest standards for myself 4. I will wait for the best option, no matter how long it takes 5. I never settle for second best 6. I never settle 7. No matter what it takes, I always try to choose the best thing
'Alternative Search' subscale Maximizing Inventory (MI)	1. I can't come to a decision unless I have carefully considered all of my options 2. I take time to read the whole menu when dining 3. I will usually continue shopping for an item until it reaches all of my criteria 4. I usually continue to search for an item until it reaches my expectations 5. When shopping, I plan on spending a lot of time looking for something 6. When shopping, if I can't find exactly what I'm looking for, I will continue to search for it 7. I find myself going to many different stores before finding the thing I want 8. When shopping for something, I don't mind spending several hours looking for it 9. I take the time to consider all alternatives before making a decision 10. When I see something I want, I always try to find the best deal before purchasing it 11. If a store doesn't have exactly what I'm shopping for, then I will go somewhere else 12. I just won't make a decision until I am comfortable with the process

Appendix B: Factor Analysis

Component Matrix for Chatbot Extraversion (IPIP)

	Component
	1
The chatbot might be the life of the party	**.644**
The chatbot feels comfortable around people	**.727**
The chatbot starts conversations	**.755**
The chatbot talks to a lot of different people at parties	**.659**
The chatbot does not mind being the centre of attention	**.713**
The chatbot does not talk a lot	**.832**
The chatbot keeps in the background	**.738**
The chatbot has little to say	**.805**
The chatbot does not like to draw attention to itself	**.803**
The chatbot is quiet around strangers	**.708**

Pattern Matrix for personal maximizing tendency behaviour (strategy and goal construct)

	Component	
	1	2
I don't like having to settle for good enough	-.022	**.744**
I am a maximizer	-.006	**.825**
No matter what I do, I have the highest standards for myself	-.093	**.864**
I will wait for the best option, no matter how long it takes	.476	**.442**
I never settle for second best	.327	**.553**
I never settle	.341	.201
No matter what it takes, I always try to choose the best thing	.355	**.499**
I can't come to a decision unless I have carefully considered all of my options	**.787**	-.093
I take time to read the whole menu when dining	**.590**	.164
I will usually continue shopping for an item until it reaches all of my criteria	**.698**	.108
I usually continue to search for an item until it reaches my expectations	**.718**	.125
When shopping, I plan on spending a lot of time looking for something	**.809**	-.051
When shopping, if I can't find exactly what I'm looking for, I will continue to search for it	**.676**	.221
I find myself going to many different stores before finding the thing I want	**.596**	.167
When shopping for something, I don't mind spending several hours looking for it	**.713**	.022
I take the time to consider all alternatives before making a decision	**.835**	-.185
When I see something I want, I always try to find the best deal before purchasing it	**.568**	-.095
If a store doesn't have exactly what I'm shopping for, then I will go somewhere else	**.505**	.229
I just won't make a decision until I am comfortable with the process	**.694**	-.138

Component Matrix for customer satisfaction

	Component
	1
I was satisfied with the experience of using a dialogue with the chatbot to complete tasks	**.861**
I am satisfied with the chatbot's recommendation service	**.766**
Interacting with the chatbot was a pleasant and satisfactory experience	**.835**
The dialogue with the chatbot gave me useful information	**.691**
I am satisfied with asking the chatbot for information because it is easier than trying to find it myself	**.655**
I feel that the chatbot is an expert	**.535**
The chatbot's responses in the interaction were appropriate	**.574**
The overall assessment of conversing with the chatbot was satisfactory	**.856**

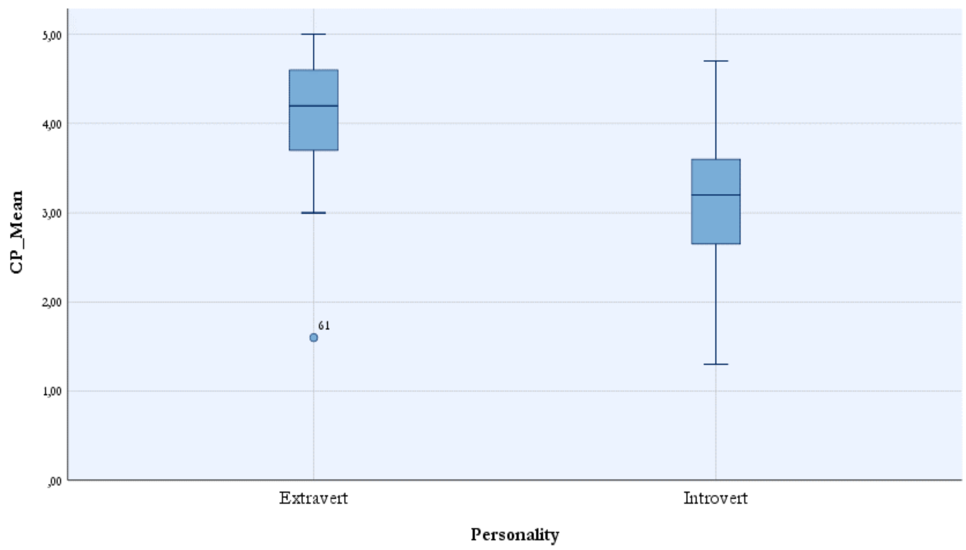
Component Matrix for intention to use the technology

	Component
	1
I would use the chatbot again	**.818**
I would recommend the chatbot to others	**.883**
If this chatbot is commercially available, I will purchase it	**.762**
I would like the chatbot to assist me in making decisions	**.772**
I am satisfied with using the chatbot because it is easy to use and better than having to do it my self	**.842**
When looking for dress shoes, I will watch the content recommended by the chatbot	**.766**
If I had the chance to use this chatbot again, I want to talk a lot with it	**.655**

Appendix C: Manipulation check analysis

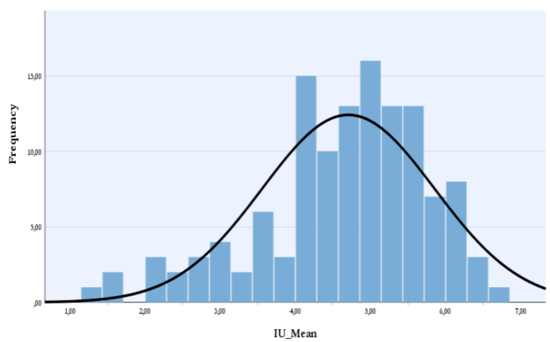
Descriptive Statistic Chatbot Personality

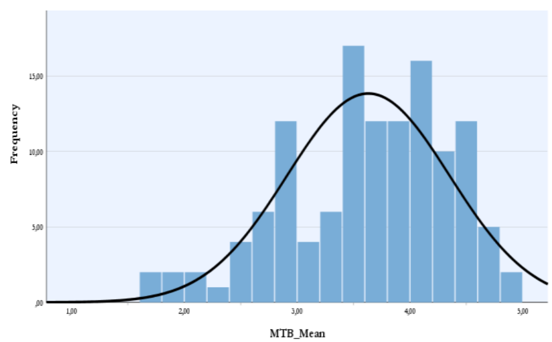
	Personality Chatbot	N	Mean	Std. Deviation	Std. Error Mean
CP_Mean	Neutral	63	2.9952	.82098	.10343
	Extravert	62	4.1016	.63672	.08086

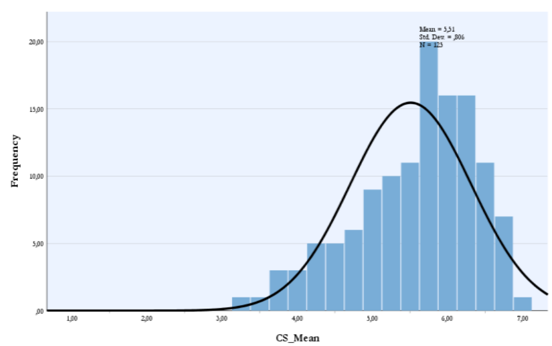


Boxplot with perceived chatbot personality and actual personality

Appendix D: Distributions







Appendix E: ANCOVA Results

ANCOVA – Customer Satisfaction

Cases	Sum of Squares	df	Mean Square	F	p	η²
Personality_Chatbot	0.025	1	0.025	0.043	0.835	3.489e -4
Gender	0.833	1	0.833	1.467	0.228	0.012
MTBG_Mean	0.538	1	0.538	0.948	0.332	0.008
Personality_Chatbot ✻ Gender	2.130	1	2.130	3.754	0.055	0.030
Personality_Chatbot ✻ MTBG_Mean	0.102	1	0.102	0.180	0.672	0.001
Gender ✻ MTBG_Mean	0.984	1	0.984	1.734	0.191	0.014
Personality_Chatbot ✻ Gender ✻ MTBG_Mean	**2.478**	**1**	**2.478**	**4.367**	**0.039**	**0.035**
Residuals	63.559	112	0.567			

Note. Type III Sum of Squares

ANCOVA – Customer Satisfaction

Cases	Sum of Squares	df	Mean Square	F	p	η²
Personality_Chatbot	0.016	1	0.016	0.027	0.870	2.275e -4
Gender	0.098	1	0.098	0.166	0.684	0.001
MTBS_Mean	1.070e -4	1	1.070e -4	1.818e -4	0.989	1.540e -6
Personality_Chatbot ✻ Gender	1.455	1	1.455	2.473	0.119	0.021
Personality_Chatbot ✻ MTBS_Mean	0.073	1	0.073	0.124	0.726	0.001
Gender ✻ MTBS_Mean	0.157	1	0.157	0.268	0.606	0.002
Personality_Chatbot ✻ Gender ✻ MTBS_Mean	1.743	1	1.743	2.963	0.088	0.025
Residuals	65.900	112	0.588			

Note. Type III Sum of Squares

ANCOVA – Intention to Use

Cases	Sum of Squares	df	Mean Square	F	p	η²
Personality_Chatbot	0.390	1	0.390	0.388	0.535	0.003
Gender	1.212	1	1.212	1.205	0.275	0.010
MTBS_Mean	0.134	1	0.134	0.133	0.716	0.001
Personality_Chatbot ✻ Gender	0.638	1	0.638	0.634	0.428	0.005
Personality_Chatbot ✻ MTBS_Mean	0.105	1	0.105	0.104	0.747	8.907e -4
Gender ✻ MTBS_Mean	1.665	1	1.665	1.656	0.201	0.014
Personality_Chatbot ✻ Gender ✻ MTBS_Mean	0.954	1	0.954	0.948	0.332	0.008
Residuals	112.615	112	1.005			

Note. Type III Sum of Squares

ANCOVA – Intention to Use

Cases	Sum of Squares	df	Mean Square	F	p	η^2
Personality_Chatbot	0.096	1	0.096	0.100	0.752	7.868e -4
Gender	**4.328**	**1**	**4.328**	**4.525**	**0.036**	**0.035**
MTBG_Mean	0.715	1	0.715	0.747	0.389	0.006
Personality_Chatbot ✻ Gender	2.088	1	2.088	2.183	0.142	0.017
Personality_Chatbot ✻ MTBG_Mean	6.757e -4	1	6.757e -4	7.065e -4	0.979	5.535e -6
Gender ✻ MTBG_Mean	**5.119**	**1**	**5.119**	**5.352**	**0.023**	**0.042**
Personality_Chatbot ✻ Gender ✻ MTBG_Mean	2.618	1	2.618	2.737	0.101	0.021
Residuals	107.124	112	0.956			

Note. Type III Sum of Squares

Bibliography

Abu Shawar, B., & Atwell, E. (2007). Chatbots: are they really useful? *LDV-Forum: Zeitschrift Für Computerlinguistik Und Sprachtechnologie*, *22*(1), 29–49.

Aiken, L., & West, S. (1991). Multiple Regression: Testing and Interpreting Interactions.

Ajzen, I., & Cote, G. (2008). Attitudes and the prediction of behavior.

Al-Natour, S., Benbasat, I., & Cenfetelli, R. (2011). The adoption of online shopping assistants: Perceived similarity as an antecedent to evaluative beliefs. *Journal of the Association for Information Systems*, *12*(5), 347–374. https://doi.org/10.17705/1jais.00267

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

Arteaga, D., Arenas, J., Paz, F., Tupia, M., & Bruzza, M. (2019). Design of information system architecture for the recommendation of tourist sites in the city of Manta, Ecuador through a Chatbot. *Iberian Conference on Information Systems and Technologies, CISTI*, *2019-June*(June), 19–22. https://doi.org/10.23919/CISTI.2019.8760669

Azucar, D., Marengo, D., & Settanni, M. (2018). Predicting the Big 5 personality traits from digital footprints on social media: A meta-analysis. *Personality and Individual Differences*, *124*(September 2017), 150–159. https://doi.org/10.1016/j.paid.2017.12.018

Back, M. D., Stopfer, J. M., Vazire, S., Gaddis, S., Schmukle, S. C., Egloff, B., & Gosling, S. D. (2010). Facebook profiles reflect actual personality, not self-idealization. *Psychological Science*, *21*(3), 372–374. https://doi.org/10.1177/0956797609360756

Bai, Q., Dan, Q., Mu, Z., & Yang, M. (2019). A Systematic Review of Emoji: Current Research and Future Perspectives. *Frontiers in Psychology*, *10*(October). https://doi.org/10.3389/fpsyg.2019.02221

Bakhasi, N. (2018). Chatbots Point of View. *Deloitte. Digital*, *March*, 1–26. https://doi.org/10.1097/BRS.0000000000002434

Bakhshi, S., Song, Y., Shamma, D. A., Juan, P. De, & Kaye, J. J. (2016). Fast , Cheap , and Good : Why Animated GIFs Engage Us.

Barrick, L., MURRAY, R., & Mount, M. (1991). the Big Five Personality Dimensions and Job Performance: a Meta-Analysis. *Personnel Psychology*, *44*(1), 1–26. https://doi.org/10.1111/j.1744-6570.1991.tb00688.x

Barrick, M. R., Mount, M. K., & Judge, T. A. (2001). Personality and Performance at the Beginning of the New Millennium: What Do We Know and Where Do We Go Next? *International Journal of Selection and Assessment*, *9*(1&2), 9–30. https://doi.org/10.1111/1468-2389.00160

Barrick, M. R., Mount, M. K., & Strauss, J. P. (1993). Conscientiousness and performance of sales representatives: Test of the mediating effects of goal setting. *Journal of Applied Psychology*, *78*(5), 715–722. https://doi.org/10.1037//0021-9010.78.5.715

BCG. (2019). How to Future-Proof Your Workforce. https://www.bcg.com/featured-insights/how-to/workforce-of-the-future.aspx?utm_source=linkedin&utm_medium=social&utm_campaign=how_to&utm_descr

iption=organic&utm_topic=ht_futureproof&utm_geo=global&utm_content=how_to_future proof&linkId=76993878&redir=true

Benbasat, I., & Wang, W. (2005). Trust In and Adoption of Online Recommendation Agents. *Journal of the Association for Information Systems*, *6*(3), 72–101. https://doi.org/10.17705/1jais.00065

Bhawiyuga, A., Fauzi, M. A., Pramukantoro, E. S., & Yahya, W. (2018). Design of E-commerce chat robot for automatically answering customer question. *Proceedings - 2017 International Conference on Sustainable Information Engineering and Technology, SIET 2017*, *2018-Janua*, 159–162. https://doi.org/10.1109/SIET.2017.8304128

Bologna, C., De Rosa, A. C., De Vivo, A., Gaeta, M., Sansonetti, G., & Viserta, V. (2013). Personality-based recommendation in E-commerce. *CEUR Workshop Proceedings*, *997*.

Brandtzaeg, P. B., & Følstad, A. (2018). Chatbots: User changing needs and motivations. *Interactions*, *25*(5), 38–43. https://doi.org/10.1145/3236669

Butterworth, S. E., Giuliano, T. A., White, J., Cantu, L., & Fraser, K. C. (2019). *Sender Gender Influences Emoji Interpretation in Text Messages*. *10*(April), 1–5. https://doi.org/10.3389/fpsyg.2019.00784

Callejas, Z., López-Cózar, R., Ábalos, N., & Griol, D. (2011). Affective conversational agents: The role of personality and emotion in spoken interactions. *Conversational Agents and Natural Language Interaction: Techniques and Effective Practices*, *2003*, 203–222. https://doi.org/10.4018/978-1-60960-617-6.ch009

Cheek, N. N., & Schwartz, B. (2016). On the meaning and measurement of maximization. *Judgment and Decision Making*, *11*(2), 126–146.

Chen, W., Rudovic, O. O., & Picard, R. W. (2017). *GIFGIF + :* Collecting Emotional Animated GIFs with Clustered Multi-Task Learning.

Chin, J. P., Diehl, V. A., & Norman, K. L. (1988). Development of an instrument measuring user satisfaction of the human-computer interface. *Conference on Human Factors in Computing Systems - Proceedings*, *Part F1302*, 213–218. https://doi.org/10.1145/57167.57203

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *September*, 1–9. https://doi.org/10.1016/j.jbusres.2018.10.004

Coba, L., Rook, L., & Zanker, M. (2019). Choosing between hotels: impact of bimodal rating summary statistics and maximizing behavioral tendency. *Information Technology and Tourism*, *0123456789*. https://doi.org/10.1007/s40558-019-00156-z

Cuperman, R., & Ickes, W. (2009). Big Five Predictors of Behavior and Perceptions in Initial Dyadic Interactions: Personality Similarity Helps Extraverts and Introverts, but Hurts "Disagreeables." *Journal of Personality and Social Psychology*, *97*(4), 667–684. https://doi.org/10.1037/a0015741

Dalal, D. K., Diab, D. L., Zhu, X. S., & Hwang, T. (2015). Understanding the Construct of Maximizing Tendency: A Theoretical and Empirical Evaluation. *Journal of Behavioral Decision Making*, *28*(5), 437–450. https://doi.org/10.1002/bdm.1859

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

Dar-Nimrod, I., Rawn, C. D., Lehman, D. R., & Schwartz, B. (2009). The Maximization Paradox:

The costs of seeking alternatives. *Personality and Individual Differences*, *46*(5–6), 631–635. https://doi.org/10.1016/j.paid.2009.01.007

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

DeYoung, C. G., Quilty, L. C., & Peterson, J. B. (2007). Between Facets and Domains: 10 Aspects of the Big Five. *Journal of Personality and Social Psychology*, *93*(5), 880–896. https://doi.org/10.1037/0022-3514.93.5.880

Deyoung, C. G., Weisberg, Y. J., Quilty, L. C., & Peterson, J. B. (2013). Unifying the aspects of the big five, the interpersonal circumplex, and trait affiliation. *Journal of Personality*, *81*(5), 465–475. https://doi.org/10.1111/jopy.12020

Duijst, D., Sandberg, J., & Buzzo, D. (2017). Can we Improve the User Experience of Chatbots with Personalisation ? *University of Amsterdam*, *July*, 1–23. https://doi.org/10.13140/RG.2.2.36112.92165

Elsholz, E., Chamberlain, J., & Kruschwitz, U. (2019). Exploring language style in chatbots to increase perceived product value and user engagement. *CHIIR 2019 - Proceedings of the 2019 Conference on Human Information Interaction and Retrieval*, *March*, 301–305. https://doi.org/10.1145/3295750.3298956

Elsner. (2017). *Chatbots in the UK.*

Etlinger, S. (2017). the Conversational Business: How Chatbots Will Reshape Digital Experiences. *Altimeter Group - Research Reports*, 1–29. http://www.redi-bw.de/db/ebsco.php/search.ebscohost.com/login.aspx%3Fdirect%3Dtrue%26db%3Dbuh%26AN%3D123922391%26site%3Dehost-live

Fan, H., & Poole, M. S. (2006). What is personalization? perspectives on the design and implementation of personalization in information systems. *Journal of Organizational Computing and Electronic Commerce*, *16*(3–4), 179–202. https://doi.org/10.1207/s15327744joce1603&4_2

Fang, H., Cheng, H., Sap, M., Clark, E., Holtzman, A., Choi, Y., Smith, N. A., & Ostendorf, M. (2018). *Sounding Board: A User-Centric and Content-Driven Social Chatbot*. 96–100. https://doi.org/10.18653/v1/n18-5020

Field, A. (2008). Discovering Statistics Using SPSS. In *Advances in Experimental Medicine and Biology* (Vol. 622). https://doi.org/10.1007/978-0-387-68969-2_13

Følstad, A., & Brandtzaeg, P. B. (2017). Chatbots and the New World of HCI. *Interactions*, *24*(4), 38–42. https://doi.org/10.1145/3085558

Foster, M. E., & Oberlander, J. (2010). User preferences can drive facial expressions: Evaluating an embodied conversational agent in a recommender dialogue system. *User Modeling and User-Adapted Interaction*, *20*(4), 341–381. https://doi.org/10.1007/s11257-010-9080-6

Freedman, M. B., LEARY, T. F., OSSORIO, A. G., & GOFFEY, H. S. (1951). The Interpersonal Dimension of Personality. *Journal of Personality*, *20*(2), 143–161. https://doi.org/10.1111/j.1467-6494.1951.tb01518.x

French, R. M. (2000). The turing test: The first 50 years. *Trends in Cognitive Sciences*, *4*(3), 115–122.

https://doi.org/10.1016/S1364-6613(00)01453-4

Funder, D. C., & Sneed, C. D. (1993). Behavioral Manifestations of Personality: An Ecological Approach to Judgmental Accuracy. *Journal of Personality and Social Psychology*, *64*(3), 479–490. https://doi.org/10.1037/0022-3514.64.3.479

Furnham, A. (1990). Language and personality. *Handbook of Language and Social Psychology*.

Furnham, Adrian, & Fudge, C. (2008). The Five Factor Model of Personality and Sales Performance. *Journal of Individual Differences*, *29*(1), 11–16. https://doi.org/10.1027/1614-0001.29.1.11

Ganster, T., Eimler, S. C., & Krämer, N. C. (2012). Same same but different!? the differential influence of smilies and emoticons on person perception. *Cyberpsychology, Behavior, and Social Networking*, *15*(4), 226–230. https://doi.org/10.1089/cyber.2011.0179

Garcia, M. (2018). Consumers want chatbots to feel human, not look human.

Gartner. (2019). Chatbot Prediction. 373426.

Gittens, C. L. (2018). A Psychologically-Realistic Personality Model for Virtual Agents. 81–99. https://doi.org/10.1007/978-3-319-76430-6_4

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, *97*(January), 304–316. https://doi.org/10.1016/j.chb.2019.01.020

Goldberg, L. (1992). The development of markers for the Big-Five factor structure. *Psychological Assessment, 4(1), 26–42*. https://psycnet.apa.org/record/1992-25730-001

Grant, A. M. (2013). Rethinking the Extraverted Sales Ideal: The Ambivert Advantage. *Psychological Science*, *24*(6), 1024–1030. https://doi.org/10.1177/0956797612463706

Gratch, J. (2010). How Our Personality Shapes Our Interactions with Virtual Characters - Implications for Research and Development .

Hill, J., Randolph Ford, W., & 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. https://doi.org/10.1016/j.chb.2015.02.026

Hirsh, J. B., & Peterson, J. B. (2009). Personality and language use in self-narratives. *Journal of Research in Personality*, *43*(3), 524–527. https://doi.org/10.1016/j.jrp.2009.01.006

Hoskin, R. (2012). *The dangers of self-report.*

Io, H. N., & Lee, C. B. (2018). Chatbots and conversational agents: A bibliometric analysis. *IEEE International Conference on Industrial Engineering and Engineering Management*, *2017-Decem*, 215–219. https://doi.org/10.1109/IEEM.2017.8289883

Iovine, A., Narducci, F., & Semeraro, G. (2020). Conversational Recommender Systems and natural language:: A study through the ConveRSE framework. *Decision Support Systems*, *131*(January). https://doi.org/10.1016/j.dss.2020.113250

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, *79*(6), 995–1006. https://doi.org/10.1037/0022-3514.79.6.995

Iyengar, S. S., Wells, R. E., & Schwartz, B. (2006). Doing better but feeling worse looking for the "Best" job undermines satisfaction. *Psychological Science*, *17*(2), 143–150.

https://doi.org/10.1111/j.1467-9280.2006.01677.x

JuniperResearch. (2017). Chatbot Infographic Statistics. https://www.bevytechnologies.com/infographic-chatbots-key-statistics-2017/

Jusoh, S. (2018). Intelligent Conversational Agent for Online Sales. *Proceedings of the 10th International Conference on Electronics, Computers and Artificial Intelligence, ECAI 2018*, 1–4. https://doi.org/10.1109/ECAI.2018.8679045

Kassim, N., & Asiah Abdullah, nor. (2010). The effect of perceived service quality dimensions on customer satisfaction, trust, and loyalty in e-commerce settings: A cross cultural analysis. *Asia Pacific Journal of Marketing and Logistics*, *22*(3), 351–371. https://doi.org/10.1108/13555851011062269

Kim, H., Lee, G., Lim, Y. K., Koh, D. Y., & Park, J. M. (2019). Designing personalities of conversational agents. *Conference on Human Factors in Computing Systems - Proceedings*, 1–6. https://doi.org/10.1145/3290607.3312887

Kokkoris, M. D. (2017). When the purpose lies within: Maximizers and satisfaction with autotelic choices. *Marketing Letters*, *29*(1), 73–85. https://doi.org/10.1007/s11002-017-9443-4

Kuhn, H. W., von Neumann, J., Morgenstern, O., & Rubinstein, A. (1944). *Theory of Games and Economic Behavior*.

Kuligowska, K. (2015). Commercial Chatbot: Performance Evaluation, Usability Metrics and Quality Standards of Embodied Conversational Agents. *Professionals Center for Business Research*, *2*(02), 1–16. https://doi.org/10.18483/pcbr.22

Lazar, J., Hochheister, H., & Feng, H. (2017). Research Methods in Human-Computer Interaction.

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

Lee, S. Y., Lee, G., Kim, S., & Lee, J. (2019). Expressing personalities of conversational agents through visual and verbal feedback. *Electronics (Switzerland)*, *8*(7). https://doi.org/10.3390/electronics8070794

Li, J., Zhou, M. X., Yang, H., & Mark, G. (2017). Confiding in and listening to virtual agents: The effect of personality. *International Conference on Intelligent User Interfaces, Proceedings IUI*, *May 2018*, 275–286. https://doi.org/10.1145/3025171.3025206

Li, X., Chan, K. W., & Kim, S. (2019). Service with emoticons: How customers interpret employee use of emoticons in online service encounters. *Journal of Consumer Research*, *45*(5), 973–987. https://doi.org/10.1093/jcr/ucy016

Liu, Z., Long, C., Lu, X., Hu, Z., Zhang, J., & Wang, Y. (2019). Which Channel to Ask My Question?: Personalized Customer Service Request Stream Routing Using Deep Reinforcement Learning. *IEEE Access*, *7*, 107744–107756. https://doi.org/10.1109/ACCESS.2019.2932047

Lortie, C. L., & Guitton, M. J. (2011). Judgment of the humanness of an interlocutor is in the eye of the beholder. *PLoS ONE*, *6*(9), 1–7. https://doi.org/10.1371/journal.pone.0025085

Ma, X., Yang, E. Y., & Fung, P. (2019). Exploring perceived emotional intelligence of personality-driven virtual agents in handling user challenges. *The Web Conference 2019 - Proceedings of the World Wide Web Conference, WWW 2019*, 1222–1233. https://doi.org/10.1145/3308558.3313400

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

Mccrae, R. R., & John, O. P. (1992). The five-factor model: issues and applications. *Journal of Personality*, *60*(2), 175–532. http://www.ncbi.nlm.nih.gov/pubmed/1635040

McDougall, W. (1932). of the Words Character and Personality. *Journal of Personality*, *1*(1), 3–16. https://doi.org/10.1111/j.1467-6494.1932.tb02209.x

McTear, M., Callejas, Z., & Griol, D. (2016). The conversational interface: Talking to smart devices. In *The Conversational Interface: Talking to Smart Devices*. https://doi.org/10.1007/978-3-319-32967-3

Miceli, S., de Palo, V., Monacis, L., Di Nuovo, S., & Sinatra, M. (2018). Do personality traits and self-regulatory processes affect decision-making tendencies? *Australian Journal of Psychology*, *70*(3), 284–293. https://doi.org/10.1111/ajpy.12196

Miltner, K. M., & Highfield, T. (2017). Never gonna GIF you up: Analyzing the cultural significance of the animated GIF. *Social Media and Society*, *3*(3). https://doi.org/10.1177/2056305117725223

Narducci, F., Basile, P., de Gemmis, M., Lops, P., & Semeraro, G. (2019). An investigation on the user interaction modes of conversational recommender systems for the music domain. In *User Modeling and User-Adapted Interaction*. Springer Netherlands. https://doi.org/10.1007/s11257-019-09250-7

Nass, K. M. L. C. (2019). Social-Psychological Origins of Feelings of Presence: Creating Social Presence with Machine-Generated Voices. *Journal of Chemical Information and Modeling*, *53*(9), 1689–1699. https://doi.org/10.1017/CBO9781107415324.004

Norman, W. T. (1963). Toward an adequate taxonomy of personality attributes: Replicated factor structure in peer nomination personality ratings. *Journal of Abnormal and Social Psychology*, *66*(6), 574–583. https://doi.org/10.1037/h0040291

O'Gorman, K., & Macintosh, R. (2014). Research Methods for Business. *Creative Research*, *2014*, 2020. https://doi.org/10.5040/9781474247115.0048

Oberlander, L., & Gill, A. (2004). Language generation and personality: Two dimensions, two stages, two hemispheres?

Olson, G. M., & Olson, J. S. (2003). Human-Computer Interaction: Psychological Aspects of the Human Use of Computing. *Annual Review of Psychology*, *54*(1), 491–516. https://doi.org/10.1146/annurev.psych.54.101601.145044

Orf, D. (2016). Facebook chatbots are frustrating and useless.

Paredes, H., Fernandes, H., Sousa, A., Fernandes, L., Koch, F., Fortes, R., Filipe, V., & Barroso, J. (2015). The Influence of Users' Personality on the Perception of Intelligent Virtual Agents' Personality and the Trust Within a Collaborative Context. *Communications in Computer and Information Science*, *541*(August 2016), 66–76. https://doi.org/10.1007/978-3-319-24804-2

Park, G., Yaden, D. B., Schwartz, H. A., Kern, M. L., Eichstaedt, J. C., Kosinski, M., Stillwell, D., Ungar, L. H., & Seligman, M. E. P. (2016). Women are Warmer but No Less Assertive than Men: Gender and Language on Facebook. *PLoS ONE*, *11*(5). https://doi.org/10.1371/journal.pone.0155885

Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology*, *77*(6), 1296–1312. https://doi.org/10.1037/0022-

3514.77.6.1296

Petter Bae, B., & Asbjørn, F. (2018). Why do People use chatbots? 3–5. https://www.researchgate.net/profile/Asbjorn_Folstad/publication/318776998_Why_people_use_chatbots/links/5a016a99a6fdcc82a318416a/Why-people-use-chatbots.pdf

Przegalinska, A., Ciechanowski, L., Stroz, A., Gloor, P., & Mazurek, G. (2019). In bot we trust: A new methodology of chatbot performance measures. *Business Horizons*, *62*(6), 785–797. https://doi.org/10.1016/j.bushor.2019.08.005

Putri, F. P., Meidia, H., & Gunawan, D. (2019). Designing intelligent personalized chatbot for hotel services. *ACM International Conference Proceeding Series*, 468–472. https://doi.org/10.1145/3377713.3377791

Qiu, L., Lin, H., Ramsay, J., & Yang, F. (2012). You are what you tweet: Personality expression and perception on Twitter. *Journal of Research in Personality*, *46*(6), 710–718. https://doi.org/10.1016/j.jrp.2012.08.008

Reeves, B., & Nass, C. I. (1996). The media equation : how people treat computers, television, and new media like real people and places. https://openlibrary.org/books/OL982672M

Reibstein, D. J., Youngblood, S. A., & Fromkin, H. L. (1975). Number of choices and perceived decision freedom as a determinant of satisfaction and consumer behavior. *Journal of Applied Psychology*, *60*(4), 434–437. https://doi.org/10.1037/h0076906

Reichheld, F. (2003). The One Number You Need to Grow. https://hbr-org.tudelft.idm.oclc.org/2003/12/the-one-number-you-need-to-grow

Rentfrow, P. J., Gosling, S. D., Jokela, M., Stillwell, D. J., Kosinski, M., & Potter, J. (2013). Divided we stand: Three psychological regions of the united states and their political, economic, social, and health correlates. *Journal of Personality and Social Psychology*, *105*(6), 996–1012. https://doi.org/10.1037/a0034434

Rica, C., & Hutchison, D. (2013). Human Computer Interaction -. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 8278 LNCS* (Issue December).

Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender System Handbook. In *The American Journal of Medicine* (Vol. 32, Issue 1). https://doi.org/10.1016/0002-9343(62)90176-6

Rich, T., Hu, K., & Tome, B. (2014). *GIFGIF Dataset.*

Rook, L., Sabic, A., & Zanker, M. (2020). Engagement in proactive recommendations: The role of recommendation accuracy, information privacy concerns and personality traits. *Journal of Intelligent Information Systems*, *54*(1), 79–100. https://doi.org/10.1007/s10844-018-0529-0

Sarkar, R., & Das, S. (2016). The role of gender in online shopping. *International Journal of Scientific Development and Research*, *1*(5), 3–7. www.ijsdr.org865

Schwartz, B., Ward, A., Lyubomirsky, S., Monterosso, J., White, K., & Lehman, D. R. (2002). Maximizing versus satisficing: Happiness is a matter of choice. *Journal of Personality and Social Psychology*, *83*(5), 1178–1197. https://doi.org/10.1037/0022-3514.83.5.1178

Sekaran, U., & Bougie, R. (2016). Research Methods for Business. *Psychology Applied to Work: An Introduction to Industrial and Organizational Psychology, Tenth Edition Paul*, *53*(9), 1689–1699. https://doi.org/10.1017/CBO9781107415324.004

Simon, H. A. (1955). A Behavioral Model of Rational Choice Author (s): Herbert A . Simon Published by : Oxford University Press. *The Quarterly Journal of Economics*, *69*(1), 99–118.

http://www.jstor.org/stable/1884852

Simon, H. A. (1956). Rational choice and the structure of the environment. *Journal of Experimental Psychology: General*, *143*(5), 2000–2019. https://doi.org/10.1037/xge0000013

Siricharoen, W. (2019). Understanding Social Interaction with Human Computer Interaction (HCI) Adaptation. *EAI Endorsed Transactions on Context-Aware Systems and Applications*, *6*(18), 160762. https://doi.org/10.4108/eai.13-7-2018.160762

Smestad, T. L., & Volden, F. (2019). Chatbot personalities matters: Improving the user experience of chatbot interfaces. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11551 LNCS*, 170–181. https://doi.org/10.1007/978-3-030-17705-8_15

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer loyalty in e-commerce: An exploration of its antecedents and consequences. *Journal of Retailing*, *78*(1), 41–50. https://doi.org/10.1016/S0022-4359(01)00065-3

Stewart, G. (1996). Reward structure as a moderator of the relationship between extraversion and sales performance. *Journal of Applied Psychology*.

Sun, R., & Hélie, S. (2013). Psychologically realistic cognitive agents: Taking human cognition seriously. In *Journal of Experimental and Theoretical Artificial Intelligence* (Vol. 25, Issue 1). https://doi.org/10.1080/0952813X.2012.661236

Sun, Y., & Zhang, Y. (2018). Conversational recommender system. *41st International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2018*, 235–244. https://doi.org/10.1145/3209978.3210002

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, *29*(1), 24–54. https://doi.org/10.1177/0261927X09351676

To, P. L., Liao, C., & Lin, T. H. (2007). Shopping motivations on Internet: A study based on utilitarian and hedonic value. *Technovation*, *27*(12), 774–787. https://doi.org/10.1016/j.technovation.2007.01.001

Tsao, W., & Chang, H. (2010). Exploring the impact of personality traits on online shopping behavior. *African Journal of Business Management*, *4*(9), 1800–1812.

Turner, B. M., Rim, H. Bin, Betz, N. E., & Nygren, T. E. (2012). The maximization inventory. *Judgment and Decision Making*, *7*(1), 48–60.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model : Four Longitudinal Field Studies. *46*(2), 186–204.

Vinchur, A. J., Schippmann, J. S., Switzer, F. S. . I., & Roth, P. L. (1998). A meta-analytic review of predictors of job performance for salespeople. *Journal of Applied Psychology*, *83*(4), 586–597. https://doi.org/10.1037//0021-9010.83.4.586

Vital, A. (2018). Big Five Personality Traits – Infographic. https://blog.adioma.com/5-personality-traits-infographic/

Walker, M. A., Mehl, M. R., & Moore, R. K. (2007). *Using Linguistic Cues for the Automatic Recognition of Personality in Conversation and Text. 30*, 457–500.

Wang, L. (2017). Gender differences in online purchasing behavior. 31. https://ssrn.com/abstract=3056732

Wang, X. (2017). Chatbots Are Transforming Marketing.

Watterson, B. (1996). It`s A Magical World.

Weisberg, Y. J., De Young, C. G., & Hirsh, J. B. (2011). Gender differences in personality across the ten aspects of the Big Five. *Frontiers in Psychology*, *2*(AUG), 1–11. https://doi.org/10.3389/fpsyg.2011.00178

Yang, Z., Yixuan, Z., & Luo, J. (2019). Human-centered Emotion Recognition in Animated GIFsH.

Zhou, M. X., Mark, G., Li, J., & Yang, H. (2019). Trusting virtual agents: The effect of personality. *ACM Transactions on Interactive Intelligent Systems*, *9*(2–3). https://doi.org/10.1145/3232077