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Chatbot Personality and Customer Satisfaction

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Preface

Before you lies the thesis “Chatbot Personality and Customer Satisfaction” and explores the role the former has on the latter. It has been written to meet the graduation requirements of my Information Science Bachelor at Utrecht University, and has been written from November 2017 to January 2018.

This research was conducted for and on behalf of Info Support, a Dutch technology firm, in the form of an internship. The research question was formulated together with my supervisor from Info Support, Joop Snijder. One of the hardest challenges while writing this thesis was the novelty of the research field and the accompanying lack of scientific literature on this topic. As a result, this thesis took a multidisciplinary approach in an attempt to explore the research question, to build a better understanding of the problem, and to lay the groundwork for future studies.

I would like to thank Joop Snijder for his guidance and support throughout my internship at Info Support. Our weekly meetings have always been very open and provided me with valuable feedback. I also wish to thank the other graduate students and colleagues at Info Support, who always have been very supportive these last few months.

Furthermore, I would like to thank my head supervisor Christof van Nimwegen for his valuable input and support throughout my graduation. Despite his air tight schedule, we had weekly meetings in which he would provide me with constructive feedback on my deliverables and useful insights. Moreover, I would like to thank Robbert Jan Beun for freeing up time reviewing my thesis as second supervisor.

Yet, I could not have written this thesis without another strong support group. First of all, I wish to thank my parents, who supported me with their love and understanding. Furthermore, I also would like to thank my friends for their enduring support and their interest. Finally, special thanks to Floortje Kipp for always having my back and for prepping my meals.

I hope you will enjoy reading this thesis.

Hayco de Haan

Veenendaal, February 2018.

Contents

1 Introduction

These days it seems that almost every business has adopted its own chatbot to communicate with either their customers, their own employees or with other businesses. To support this claim Haptik Inc. (2017), the company behind the application of the same name, recently published a report stating that there currently exist over 40,000 chatbots across multiple platforms and that the market size of chatbots can grow from $700 million in 2016 to $3 billion in 2021. Moreover, a survey by Oracle Inc. (2016) found that 80% of the 800 interviewed businesses were already using chatbots or planned to implement them into their businesses by 2020. Perhaps the best-known example of a chatbot implementation is Apple's Siri[1], which is a digital assistant that helps people with their request. Besides a digital assistant, chatbots also serve other ends such as accompanying dementia patients (Endurance[2]), placing online orders (Subway bot[3]), and offering financial advice based on spending habits (Erica[4]). Yet, it appears that most chatbots implementations are assigned customer service roles, assuming roles traditionally assigned to humans.

In a report published by Garter (2017), two main reasons are given for the adoption of chatbots within businesses. The first is increasing customer satisfaction, as chatbots have the potential to manage customer progress more effectively than humans by using efficient decision trees. The second is cost reduction, as chatbots will deliver customer satisfaction at significantly lower cost than human customer service agents. In turn, customer satisfaction leads to customer retention and eventually increases a business's profit (Anderson & Mittal, 2000). Besides the effects of customer satisfaction, factors influencing customer satisfaction have also been identified including helpful employees, quick service, and service quality (Hokanson, 1995). Additionally, earlier research that studied the relationship between personality, service quality, and customer satisfaction, concluded that some personality traits have a significant influence on customer satisfaction (Ekinci & Dawes, 2009; Hurley, 1998). These studies, however, merely considered human customer support representatives and its findings therefore cannot be directly applied to non-human representatives without any further thought. This leads to the formulation of the following main research question:

What role has the personality of chatbots on perceived customer satisfaction?

This question is then further divided into the following sub questions:

1: How can personality be categorized?
2: What models to customer satisfaction exists and are they influenced by personality?
3: Can earlier related research on customer satisfaction and personality also be applied to chatbots?

[1] https://www.apple.com/ios/siri/
[2] http://endurancerobots.com/azbnmaterial/chatbots-for-senior-people-and-patients-with-alzheimer-s-disease/
[3] https://www.cnbc.com/2017/04/18/subway-unveils-facebook-chatbot-for-ordering-as-it-looks-to-revamp-digital.html
[4] https://www.cnbc.com/2016/10/24/bank-of-america-launches-ai-chatbot-erica--heres-what-it-does.html

Since little to no scientific research on this specific topic exists, insights are primarily obtained by reviewing scientific literature from other domains related to the subject under study. This research has scientific relevancy, because it unites different aspects from core disciplines of information science, psychology, and marketing in order to contribute to the gap prevalent in the scientific knowledge.

This research project is performed for and on behalf of Info Support, a medium sized Dutch technology company located in Veenendaal, the Netherlands. They are specialized in developing, managing, and hosting custom software solutions with innovations being one of their core values. From its clients, Info Support receives an increasing number of requests with respect to chatbots recently. This is in line with McTaer's (2016) statement that the year 2016 marked a tipping point for chatbots as major companies started to invest heavily in the technologies required to develop sophisticated systems capable of interacting with users in a natural, conversational style. Earlier, cost reduction and customer satisfaction were identified as important reasons for a business to replace human representatives with chatbots. Moreover, other research identified that the personality of human service employees significantly influences customer satisfaction. The current study is carried out under the assumption that this is also the case for chatbots, however no current research exists to support this. In other words, these clients benefit from research concerning the personality of chatbots, emphasizing its practical relevance.

This research does not intend to offer a final and conclusive solution on the research question. It rather intends to explore the research question, to build a better understanding of the problem, and to lay the groundwork for future studies.

The remainder of this thesis is structured into seven sections. The next section will elaborate on the methodology prevalent in this study. The following three sections will clarify the theoretical background and will discuss the development of chatbots, personality models, and customer satisfaction theory. In the sixth section, the results of the conducted survey will be analysed. Section seven will discuss some of the ethical challenges associated with implementing chatbots within a firm. Finally, the overall results, limitations and future research agenda will be discussed in section eight.

2 Methodology

Since little research has been conducted on this topic, the following study will be explorative by nature. The research techniques used in this study consist of an explorative literature review complemented by a short survey distributed among businesses. The goal of the literature review is to explore available literature in an attempt to identify, evaluate and integrate the findings of relevant, high-quality studies that address one or more aspects of the research questions (Budgen & Brereton, 2006). Subsequently, the goal of the survey is then to validate these findings. Both techniques result in qualitative data which is not uncommon for studies of explorative nature.

2.1 Explorative literature study

In order to identify relevant literature, a keyword-search is performed on the following scholarly databases: Google Scholar, PubMed, Scopus, ResearchGate, JSTOR, Web of Science, and Ovid. The types of studies that are primarily selected are studies investigating personality traits, chatbots or conversational agents, or customer satisfaction. Moreover, the search is limited to sources published in 1900 and onwards, written in Dutch or English. This review mainly uses scientific literature (e.g. journal articles, conference proceedings, and books) as sources, however some insights are also obtained from suggestions made by other credible sources. Furthermore, the relevancy of the found sources depends on its contribution in answering the current topic under study and is determined by their scope, objectives, methods and findings. Finally, both backward and forward searching is performed in order to cover as much relevant literature as possible (Levy & Ellis, 2006). Backward searching has been applied in order to trace back research on which the found sources are based and forward searching in order to find more recent sources.

2.2 Survey

In addition to the literature study, a survey element is added to this research in order to obtain businesses' perspectives on this topic. The survey will be sent to sixty different businesses in ten different industries, including life insurance, public transport, retail, banking, and telecom organizations. Because of the exploratory nature of this study, guidelines cannot yet be derived from earlier studies in the formulation of a measure scale. Rather the questions are formulated using the theory from the literature review and with the research question in mind. In addition, the questions are independently evaluated by two other parties. Additionally, the NEO-PI-3 test (McCrae, Costa, Jr, & Martin, 2005) will be used to map the results of the survey with the according category. The businesses have been selected by means of purposive sampling, meaning that however the sample represents a large variety of businesses, the results are only generalizable to a certain extent. Moreover, this survey focusses on the perspectives of businesses rather than customers, since they probably have a clearer vision with respect to the preferred personality traits in their customer service representatives, leading to less ambiguity. See section 6.2 for a more detailed description of the survey.

2.3 Validity

With research, it is important to consider both the concepts of validity and reliability. Reliability is often referred to as "…the extent to which results are consistent over time and an accurate representation of the total population under study is referred to as reliability and if the results of a study can be reproduced under a similar methodology, then the research instrument is considered to be reliable" (Joppe, 2000, p. 1). However, if a research's results are reliable this does not necessarily imply that they are valid as well. Validity refers to "… whether the research truly measures that which it was intended to measure or how truthful the research results are" (Joppe, 2000, p. 1). However, Golafshani (2003) argues that these components only apply to quantitative research and not as much to qualitative research. Moreover, she argues that with qualitative research reliability and validity are conceptualized as trustworthiness, rigor and quality, which can be increased by means of triangulation. In this study triangulation is achieved by considering multiple different information sources (data triangulation) as well as using multiple qualitative methods (methodological triangulation).

3 Chatbots

Until now the term chatbot has been loosely used without assigning a clear definition to it. However, to avoid ambiguity about the meaning of the term, a definition should be assigned to it. The definition adopted in the remainder of this study, results from synthesizing definitions used in different scientific works.

A chatbot, or conversational agent, is a software system which exploits natural language technologies to engage users in information-seeking and task-oriented dialogs (Kerly, Hall, & Bull, 2007; Lester, Branting, & Mott, 2004; Shawar & Atwell, 2007).

Natural Language Processing (NLP) is an area of research that explores the ability of computers to understand and manipulate natural language (e.g. English, Dutch, or Spanish) text or speech to do meaningful tasks (Chowdhury, 2003). Such tasks might include translating input to another language, interpreting the text and compile a summary, or to participate in an ongoing conversation with a human. Natural language technologies used in early work on chatbots (e.g. ELIZA) mainly concerned techniques based on textual input. However, as new technologies rapidly were developed over the last years, input by speech was also assigned a more significant role.

Moreover, the definition distinguishes two types of dialogs, *information-seeking dialogs* and *task-oriented dialogs. Information-seeking* systems*,* provide users with relevant information on their query. For instance, when a customer asks the system for the status of an order they earlier placed, the system will retrieve this information and present is to the user. *Task-oriented* systems, on the other hand, are designed to converse with its users in order to accomplish tasks. An example of this is online shopping, where users can tell the chatbot to place an order, which then is automatically executed. The user tells the system what he is looking for along with other preferences, whereupon the system asks the user for missing information. Once all details have been processed, the user gives his confirmation and the order is placed. Whereas the information-seeking system merely provides information about an order, the task-oriented system is more interactive and allows its users to place an order as well.

The remainder of this section will discuss: the development of chatbots, the different implementations of chatbots, how chatbots are used in businesses and its requirements, and the potential of chatbots.

3.1 Development of chatbots

The Imitation Game, sometimes referred to as the *Turing test*, was coined by Alan Turing (1950) and was designed to determine whether human behaviour could be imitated by computers. The original imitation game involves three actors: an interrogator (C), a man or woman (B), and computer (A). Moreover, the objective of the game is for the interrogator to distinguish A from B. The computer wins when the interrogator cannot reliably distinguish A from B. In line with the Turing test, chatbots are developed with the goal to deceive people into thinking they are chatting with a human being (De Angeli, Johnson, & Coventry, 2001).

Weizenbaum's ELIZA (1966) is often considered to be one of the first chatbots able to fool its users. ELIZA inspects the input message and flags important keywords. Subsequently, identified keywords then lead to a transformation of the user input according to an associated rule, and the resulting sentence is then returned to the user (De Angeli et al., 2001). For instance, if the input contains the keyword "concentration", ELIZA's response could be "have you recently had enough sleep?". ELIZA does not understand the reasoning behind the occurring transformation, but simply matches the identified keywords and provides the user with a standard response (Shawar & Atwell, 2007). Furthermore, Shawar and Atwell argued that although ELIZA had its shortcomings (i.e. it often did not understand the users' input), it nonetheless was the inspiration for many modern chatbots that aim to fool its users that they are conversing with another human.

3.2 Implementations of Chatbots

Recently, chatbots are found in a broad range of applications spanning a wide variety of domains. Chatbots used in education might for example improve a learners critical thinking skill (Goda, Yamada, Matsukawa, Hata, & Yasunami, 2014). Moreover, Kerry, Ellis and Bull (2009) argue that conversational agents that extend traditional education systems "are capable of offering bespoke support for each individual, and to recognise and build upon the strengths, interests and abilities of individuals in order to foster engaged and independent learners." Language-learning platform Duolingo, for instance uses chatbots to get people acquainted with new languages. As users speak to their chatbots it will learn from this conversation and responds according to the learners' abilities in order to keep users engaged and allow them to learn a language at their own pace[5]. In other words, chatbots are valuable to the educational system as they can be adopted to an individual's abilities and learning style. Eventually, this may accelerate the learning process or lead to improved grades. Another domain in which chatbots are successfully applied is healthcare, as they help people to lose weight (Kowatsch et al., 2017) and accompany elderly that suffer from dementia and struggle with loneliness (Shaked, 2017). Notice that the first chatbot, ELIZA, was also developed with the healthcare in mind, as it simulated real therapy conversations with people (Weizenbaum, 1966). A more recent example of a healthcare chatbot is Your.MD, which uses artificial intelligence (AI) to provide patients with the most relevant health information and to connect them to the right care professional, if needed[6]. Most noteworthy, however, is the fast adaption of chatbots in enterprises.

3.2.1 Chatbots in Enterprises

Recently, enterprises are using chatbots at different levels of their business. Fast food chain Subway, for instance integrated chatbots into their business so that customers could place an order more easily[7]. Whereas Marriott International, the hotel chain, allows users to apply for a job using their chatbot "Marriott Careers"[8]. According to Lester et al. (2004) there are five major families of business applications for which chatbots could assume an important role:

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[5] http://bots.duolingo.com, *accessed December 01, 2017*

[6] https://www.your.md, *accessed January 28, 2018*

[7] https://www.topbots.com/project/subway-food-ordering-bot-review/, *accessed February 2, 2018*

[8] http://news.marriott.com/2017/10/marriott-international-launches-careers-chatbot-facebook-messenger/, *accessed December 01, 2017*

- *Customer service:* answering customers' general questions about products and services (e.g. answering questions about how to configure a product)
- *Help desk:* internally responding to employees' questions (e.g. questions related to payslips)
- *Website navigation:* directing customers relevant portions of complex websites
- *Guided selling:* helping potential buyers to choose the product or service best fulfilling their needs and guiding them to a buying decision.
- *Technical support:* providing users assistance with technical problems (e.g. diagnosing software problems)

Moreover, he argues that two types of chatbot deployments exist for enterprises. In *customer-facing* deployments, chatbots interact directly with the customer in order to help them obtain answers to their questions. In *internal-facing* deployments, chatbots are used for matters within the company such as, training customer sales representatives.

This study primarily focuses on customer faced chatbot deployments, and customer service applications more specifically. It does so since this type of applications directly interacts with the customer and they often are a customers' first point of contact with a business. Therefore, by focusing on this type of applications probably leads to the clearest results when measuring customer satisfaction and therefor is most relevant for the subject under study. Furthermore, this study limits itself to chatbots that use textual inputs since this is the most commonly used sort of chatbot used by businesses.

3.2.2 Requirements for enterprise chatbots

When implemented within an enterprise a chatbot should gratify two sets of requirements to be effective, *natural language requirements (functional)* and *enterprise delivery requirements* (Lester et al., 2004). The first set of requirements are the system's functional requirements and specify what the system should be able to do. The latter set of requirements are the system's non-functional requirements and specify how the system should behave. As mentioned above, a chatbot is partially defined by its ability to process natural language. For a chatbot to productively engage in a conversation with users, accurate and efficient natural language processing is required. The other set of requirements involves the operational effectivity of chatbots in the enterprise, such as its scalability and reliability. Both sets of requirements will be further elaborated below according to Lester's et al. (2004) study.

Natural Language Requirements (functional)

For a conversational agent to respond appropriately to a user's input, it must 1) interpret the input, 2) determine what actions should be taken in response to the input, and 3) perform the actions, such as presenting steps to solve a problem or updating a database with a new order.

For instance, if the user's input were: "I would like to buy a train ticket" the agent must first determine the meaning of the sentence: the user wants to buy a train ticket. Moreover, the agent must sense the underlying goals the user is trying to achieve with the sentence. In this case, although the sentence is formulated as an assertion, it was probably intended as a request to buy a ticket.

After the agent interpreted the sentence, it should consider how to respond to it accordingly. This plan of action depends on the current goal of the agent (e.g. offering support or guide the selling process), the dialog history (previously used sentences by both the agent and user), and information in databases accessible to the agents (e.g. personal data of customers or specific information about products). Considering the train ticket scenario, if the agent's goal is selling, the user earlier specified the origin and destination of the journey, and the train is not completely booked, a proper response might be to present a booking form and ask the user to complete it. Whereas, if the train is completely booked, a proper response would be to offer the user an alternative choice.

Finally, the agent should execute the previously formulated plan of action. This execution can manifest itself by means of returning a sentence, presenting information in other modalities (e.g. video or pictures), and other actions (e.g. logging data to a database). If, for example, the proper response from the earlier formulated plan of actions was to present a booking form and ask the user to complete it. The agent should return a sentence such as "Alright! Please fill in the open fields to complete your booking" along with the form, and log the information into the database. Figure 3.1 depicts the data flow in a chatbot system. The three steps within the NLP layer actually consist of several sub-steps, however these will not be further explained as it is beyond the scope of this study. A more detailed explanation of these sub-steps can be found in Lester et al. (2004).

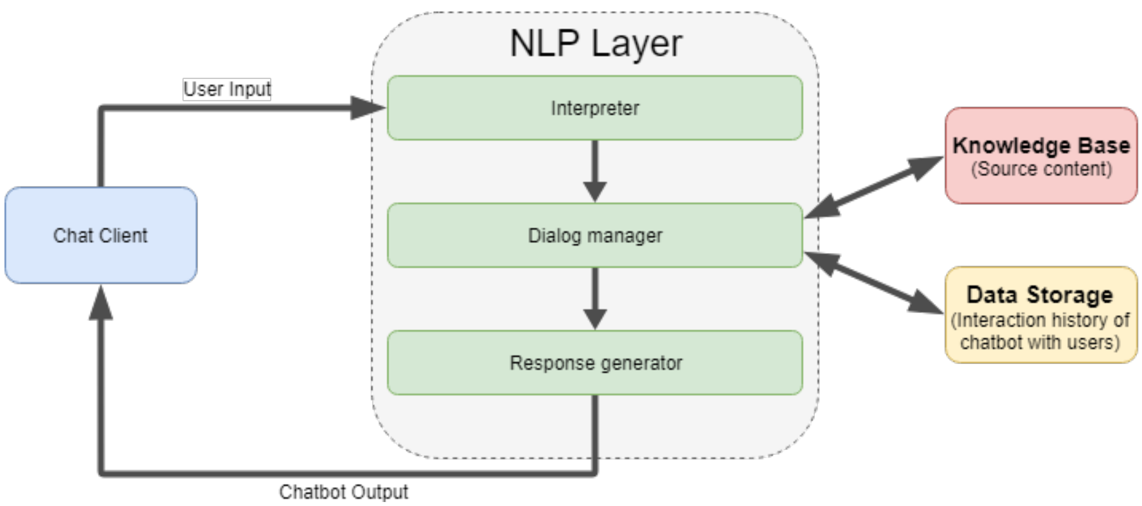

Figure 3.1. Data flow in a chatbot, adopted from Lester et al. (2004)

Enterprise Delivery Requirements (non-functional)

In contrast with the previous treated set of requirements, this set of requirements is more concerned with the integration of chatbots into the enterprise and concerns non-functional requirements. Only chatbots that are scalable, secure, reliable, integrated without much effort and achieve high performances can be used within large enterprises.

Scalability: Chatbots deployed by enterprises must scale well to accommodate the exceptional high volumes of inbound contacts typically associated with them. Chatbots must be designed to handle continuing expanded roll-outs to address increased capacity. Additionally, since volumes can increase exponentially during periods of crisis, chatbots must be able to respond dynamically to different levels of demand.

Performance: Chatbot performance is measured in two ways. First, chatbots must be able to supply a conversational throughput that matches the demand. They must be able to process hundreds of requests per minute, with peak rates in the thousands. Second, the chatbot must be able to handle large numbers of simultaneous conversations in a timely matter. For example, if the chatbot processes all the pending requests consecutively, it meets the first aspect. However, as it processes the requests one by one, it probably will not be able to ensure adequate response times and therefor does not meet the second criteria.

Reliability: Chatbots should be able to reliably answer users' questions considering software and hardware failures. Failure mechanisms should be in place, such that if a chatbot server goes down this will not affect the active conversation. This can be accomplished by other servers taking over pending and new conversations from the defunct server.

Security: Chatbots should meet the same security criteria as the site on which it is implemented. Nevertheless, as conversations could contain sensitive and critical information, chatbots should support standard authorization and authentication mechanisms and sent conversations over encrypted channels.

Integration: Chatbots should integrate neatly with the enterprise infrastructure that is already in place, represented by different layers. In the application layer, it is key that they easily integrate with all important business rules. In the data storage level, they should be able to smoothly integrate with back-office data such as product catalogs and databases holding information about customer profiles. Lastly, in the presentation layer, chatbots should properly integrate with content management systems and personalization engines.

Interestingly, however, is the recent development of personality as a chatbot's requirement. Enterprise user experience professional Ultan O'Broin (2017) argues that "The job to be done by your chatbot is vital because it provides the reason for botifying a task in someone's life …" However, "… now the style, tone, and attitude of the chatbot —the personality— encountered along the journey to getting that job done really makes or breaks a great overall user experience. And a satisfying UX that resonates personally is a powerful strategy for creating more customers". Moreover, by designing a personality for a chatbot it becomes more relevant, trustworthy, and relatable to its users (Thoms, 2017). In other words, personality is also expected to be an important non-functional requirement for chatbots as it contributes to the overall quality of the service. In fact, when observing the historical development of software systems, personality can be regarded as an additional non-functional requirement. With traditional software systems, it was mainly important that they did what they had to do. For instance, word processors are expected to process text, and they do not need personality to be able to do this. However, within modern software systems, such as chatbots, user experience (UX) has been assigned a more significant role. As aforementioned personality is the tool to improve the UX of a chatbot.

Personality in general, the different aspects to it, and its implications will be discussed more extensively in section four.

3.3 Potential of Chatbots

Chatbots are expected to assume a dominant position into people's lives, with technology research and consultancy firm Gartner (2016) even predicting that "By 2020, the average person will have more conversations with bots than with their spouse." Moreover, a study examining chatbots in the retail, e-commerce, banking and healthcare sector prognoses that in 2022 chatbots will be responsible for cost savings of more $8 billion per year, compared to $20 million this year (Foye, 2017). Elaborating on the business context, chatbots show the potential to improve the customer service offered by a business as they are not bounded by time and therefor have the ability to offer customer support 24/7, positively impacting customer satisfaction. Additionally, chatbots provide businesses with the opportunity to monitor and anticipate to customer behaviour more closely since the conversations between them and the chatbot can be analysed more extensively. As the AI behind chatbots will keep improving itself in the near future, this will probably result in improved analysis of conversations, more sophisticated responses, and new opportunities for developers to create even better conversational experiences.

4 Personality

Personality can be defined as the relatively enduring styles of thinking, feeling, and acting that characterize an individual (Costa & McCrea, 1995). However, personality is not something universal and according to Goldberg (1990) the variety of individual differences is nearly boundless. However, one way to look at personality is that of psychological traits (or personality traits). Psychological traits are characteristics that describe ways in which people are different from each other or define ways in which people are similar (Larsen & Buss, 2009). The remainder of this section will first briefly summarize the development of a shared taxonomy on personality. Then, the taxonomy adopted in this study will be further elaborated on, describing how it conceptualizes personality. Finally, this section will end by discussing the habit humans have of assigning non-human objects a personality.

4.1 Taxonomy on Personality

For over decades researchers have been exploring the concept of personality in order to formulate a shared taxonomy (Digman, 1990). In their book, Srivastava and John (1999) argued that a taxonomy on personality should provide a systematic framework for distinguishing, ordering, and naming types and characteristics of individuals. One of the first attempts to formulate such a personality framework was done by Thurstone (1934). In his work, he found that sixty adjectives, that are in common use for describing people, could be accounted for by only five independent common factors. Almost a decade later, Cattell (1943, 1947, 1948) also developed a taxonomy on personality, resulting in a complex system consisting of sixteen primary factors and five second-order factors (Cattell & Mead, 2008). However, most researchers seem to favor the five-factor model (FFM) on personality, due to their unsuccessful attempts to replicate Cattell's findings and their own data supporting the five-dimensional view (e.g. Digman, 1990; Fiske, 1949; Tupes & Christal, 1961). This thesis also adopts the five-factor model on personality since its validity is proven by various studies and the reasons described above.

4.2 The Five Dimensions

Within the developed body of literature consensus concerning the number of factors seems to be reached. However, there is much disagreement over the interpretation of each of those factors. Norman (1963), for instance, labels the five dimensions as follows:

I) Extraversion or Surgency
II) Agreeableness
III) Conscientiousness
IV) Emotional Stability
V) Culture

However, some others for instance have labelled Dimension IV as neuroticism (Digman, 1990; Eysenck, 1970; McCrae et al., 2005) and Dimension V as intellect (e.g. Digman, 1990; Fiske, 1949). In the remainder of this study the factor names used in the Neuroticism-Extraversion-Openness Personality Inventory 3 (NEO PI-3) developed by Costa, McCrea & Martin (2005) will be adopted — Extraversion (E); Neuroticism (N); Openness to Experience (O); Agreeableness (A); and Conscientiousness (C) — also known under the acronym OCEAN. This questionnaire was chosen as it is considered as one of the most widely used and researched tool for the operationalization of the five-factor model (Hoekstra & Filip, 2014).

- *Openness to Experience* is characterized by having an active imagination, being artistic, having attention to inner feelings, preferring variety, and being intellectual curious (McCrae & John, 1992). People who score high on openness have more difficulty ignoring previously experienced stimuli, exhibit less prejudice, and tend to remember their dreams more. Facets associated with openness are fantasy, aesthetics, feelings, actions, ideas, and values (McCrae et al., 2005)
- *Conscientiousness* implies the desire to take obligations to others seriously and to do a task well (Thompson, 2008). Conscientious individuals tend to be more passionate and perseverated for long-term goals, are having more stable and secure relationships, and have greater job satisfaction and security (Larsen & Buss, 2009). Facets corresponding to this trait are competence, order, dutifulness, achievement striving, self-discipline, and deliberation (McCrae et al., 2005)
- *Extraversion* reflects people's desire to be with other people and to draw energy from them (Toegel & Barsoux, 2012). Extraverts frequently engage in social interaction, take the lead in livening up dull gatherings, and enjoy talking a lot (Larsen & Buss, 2009). Research on extraversion suggests that extraverts tend to be happier, more involved and more cooperative than introverts are (Larsen & Buss, 2009). Warmth, gregariousness, assertiveness, activity, excitement seeking, and positive emotions are facets associated with extraversion (McCrae et al., 2005).
- *Agreeableness* is manifested in behavioural characteristics that are perceived as sympathetic, cooperative, kind, considerate and warm (Thompson, 2008). Agreeable individuals get along well with others, are well liked, avoid conflict, and prefer professions in which their likability is an asset (Larsen & Buss, 2009; Toegel & Barsoux, 2012). Facets that belong to this personality trait are trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness (McCrae et al., 2005).
- *Neuroticism* (or emotional instability), results from a lower threshold for activation in the limbic system, responsible for emotions such as fear, anxiety, anger, and distress (Rusting & Larsen, 1997). Neurotic individuals tend to overreact to unpleasant events, take longer to return to a normal state after being upset, are easily irritated, worry about many things, and seem to be constantly complaining (Larsen & Buss, 2009). Moreover, to identify persons high on neuroticism, facets like anxiety, angry hostility, depression, self-consciousness, impulsiveness, and vulnerability are useful (McCrae et al., 2005).

4.3 Anthropomorphism

Interestingly, such human-like characteristics are not only attributed to humans, but humans also tend to attribute such characteristics to non-lifelike artefacts. This process of attributing human-like characteristics to non-lifelike artefacts is called anthropomorphism, or personification, and helps people to rationalize the artefact's actions (Duffy, 2003). A great effort in this field of research has been contributed by computer scientists, who for over a decade have been studying anthropomorphism and its role in the design of human-robot interaction (HRI) and socially interactive robots (Duffy, 2003; Fink, 2012; Nowak & Rauh, 2005). Anthropomorphism is not bounded to the technological domain, however, and can also be found in other domains such as nature (Tam, Lee, & Chao, 2013), animals (Horowitz & Bekoff, 2007), and religion (Barrett & Keil, 1996; Barrett & Richert, 2003). In their search for why people tend to anthropomorphise, Epley, Waytz and Cacioppo (2007) identified three constructs.

The first construct, *elicited agent knowledge,* implies that knowledge about humans in general, or the self in particular, functions as the known and often readily accessible base for induction about the properties of unknown agents. As knowledge about non-human agents is acquired, however, knowledge about humans or the self will most likely be substituted (Epley et al., 2007). In other words, in situations when people have a lack of understanding of the non-human agent, mainly due to missing information, they tend to supplement this gap with their general knowledge about humans or specific knowledge about themselves. In sum, elicited agent knowledge is about the accessibility and applicability of human centred knowledge (Epley et al., 2007).

The second construct, *sociality motivation,* describes the need and desire to establish social connections with other humans. Anthropomorphism enables social satisfaction by representing non-human agents as sources of humanlike social connection. In short, when people feel socially disconnected from other humans, they construct sources of connection by creating humanlike agents out of non-humans through anthropomorphism non-human order to satisfy their motivation for social connection (Epley et al., 2007; Waytz et al., 2010).

The last construct, *effectance motivation,* entails a desire for understanding, predicting, and controlling one's environment (Waytz et al., 2010). When people face an unknown agent for the first time, it is likely to assume that they are unfamiliar with its behaviour and motivations. As aforementioned, in such situations people tend to use their general knowledge about humans or specific knowledge about themselves to create a better understanding of the agent. In line with this, anthropomorphism may also increase peoples sense of control over the unknown agents and making its actions more predictable. In short, effectance motivation entails the motivation to understand and explain the behaviour of other agents (Epley et al., 2007).

Besides the fact that people anthropomorphize objects in order to make sense of an otherwise uncertain environment, numerous researchers have also studied other effects that result from anthropomorphizing nonhuman agents. For instance, Blanchard and Mcnincht (1984) discovered that anthropomorphism enhances the learning and retention of words among children. Another study, investigating the effect of brand anthropomorphism, found that people are likely to take on the behaviours they associate with a brand image when this brand is anthropomorphised (Aggarwal & McGill, 2011). Yet, research more related to the information science domain found that anthropomorphizing technology especially influences its credibility and trustworthiness (Nowak & Rauh, 2005; Waytz, Heafner, & Epley, 2014).

5 Personality and Customer Satisfaction

As mentioned before, enterprises are using chatbots at different levels in their business. Yet, this thesis focuses on customer-facing chatbot applications, and particularly customer support (or customer service) applications. Goffin & New (2001) identified several reasons for businesses to employ customer support services, such as achieving higher customer satisfaction, providing a competitive advantage, and increasing the success rate of new products.

The remainder of this section will discuss the influence of personality from service employees on customer satisfaction. First, it will cover customer satisfaction in a more general way along with the antecedents that play an important role in it. Then, once a better understanding of customer satisfaction has been created, earlier research investigating the influence of personality on customer satisfaction will be discussed.

5.1 Customer Satisfaction

A popular view on customer satisfaction is the disconfirmation paradigm which explains customer satisfaction by means of four constructs: expectations, performance, disconfirmation, and satisfaction. Customers' expectations are confirmed when a product or service functions as expected, negatively disconfirmed when the product or service functions dissatisfy expectations, and positively disconfirmed when the product or service exceeds expectations (Churchill & Surprenant, 1982). For instance, when a customer buys a new mobile phone he or she has certain expectations of the phone. However, after receiving the mobile phone, it does not perform as anticipated and therefore underperforms the customers' original expectations. As the customers' expectations are now negatively disconfirmed, this could lead to increased dissatisfaction with the product. In other words, customer satisfaction is "the number of customers, or percentage of total customers, whose reported experience with a firm, its products, or its services … exceeds specified goals" (Farris, Bendle, Pfeifer, & Reibstein, 2010, p. 57). Figure 5.1 depicts the process of reaching satisfaction within the disconfirmation framework, as described by numerous studies (e.g. Anderson & Sullivan, 1993; Churchill & Surprenant, 1982; Oliver, 1980; Yi, 1993). The direct lines from both expectations and performance to satisfaction are dotted because they do not always exist, but rather depend on the ambiguity of the product or service (Yi, 1993).

As aforementioned, within businesses customer support services play an important role in achieving higher customer satisfaction goals. Such customer support services are often the only contact point a customer has with a company and can greatly influence customers' impression about the company. In their updated IS Success Model, Delone and McLean (2003) identify three important dimensions that affect customer satisfaction within an information system (IS): *system quality*, *information quality*, and *service quality.* System quality refers to the quality of information processing itself, including software and data components, and measures the technical soundness of the system (e.g. ease of use, whether or not the system contains bugs, or quality of documentation) (Gorla, Somers, & Wong, 2010). Information quality is concerned with the quality of the information system outputs such as web pages or reports. Items associated with information quality are: accuracy, relevance, usability, conciseness, and understandability (Petter, DeLone, & McLean, 2008). Service quality represents the quality of the support that users receive from the IT support personnel and is often defined as the degree of discrepancy between what users expect of a service and the performance of that service (Gorla et al., 2010; Petter et al., 2008). The first two constructs are primarily concerned with the technical aspect of an IS, whereas the latter construct is more concerned with the relational aspect of an IS. This study limits itself to the service quality as it focusses on the relational aspect of a customer service and is believed to be the core criterion for overall customer service, and thus matches best with the scope of the research (Parasuraman, Berry, & Zeithaml, 1991).

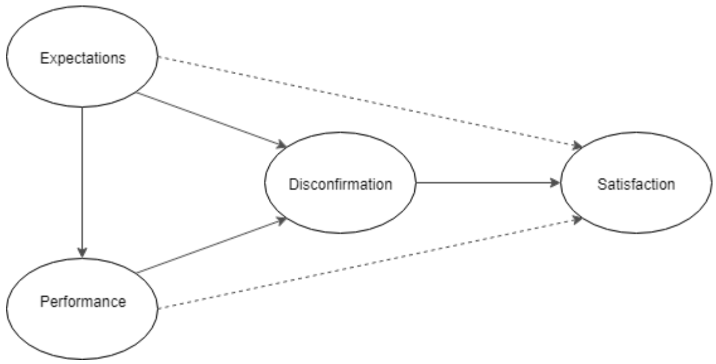

Figure 5.1. The disconfirmation paradigm, adopted from Yi (1993)

5.1.1 Service Quality Models

Numerous conceptualisations of the service quality dimension have been proposed over the years. Grönroos' *Nordic Model* (1984) was one of the first to formulate such a model and was based on the earlier discussed disconfirmation paradigm. This implicates that service quality result from comparing expected performance with perceived performance. Moreover, Grönroos identified two service quality dimensions, functional quality (how the service is delivered) and technical quality (what the service delivers). However, the Nordic model was limited in the dimensions to be measured and did not offer techniques to measure either its quality- or functional dimension. Later, Rust and Oliver (1994) refined Grönroos' model by adding another dimension to it. Their three-component model consists of, the service product (comparable to technical quality), the service delivery (functional quality), and service environment. However, they did not test their model.

Another prominent model that is also based on the disconfirmation paradigm, is the SERVQUAL model developed by Parasuraman, Zeithaml and Berry (1985, 1988). They argue that, irrespective of the type of service, consumers assess service quality using the same generic criteria, which can be arranged into the following five dimensions:

- *Reliability:* the ability to accurately and dependably perform the promised service.
- *Assurance:* employees' ability to express confidence and trust along with their knowledge and courtesy
- *Tangibles:* the presence of physical communication material, equipment, and personnel.
- *Empathy:* measure of the care and attention provided to customers.
- *Responsiveness:* the readiness to help customers and to offer fast service.

Yet, despite the models' popularity among academics it was also greatly criticized. For an extensive review of the SERVQUAL model and its critiques refer to Buttle (1996). However, the most heard critique is its dimensionality problem. For instance, the model states that the service offered should be reliable, but does not specify what needs to be reliable (Brady & Cronin, 2001). Responding to SERVQUAL's shortcomings, Dabholkar, Thorpe and Rentz (1966) proposed a multidimensional conceptualization of retail service quality, the Retail Service Quality Scale (RSQS). This model consisted of three levels: 1) overall perceptions of service quality, 2) a dimensional level consisting of five primary dimensions, and 3) a sub dimensional level consisting of six sub dimensions (see Figure 5.2). According to Martinez and Martinez (2010) this model distinguishes itself from previous models as they argue that service quality is not formed by but defined by several dimensions. However, its limitation lies in the fact that it is specifically designed for a retail setting and therefore cannot be generalized.

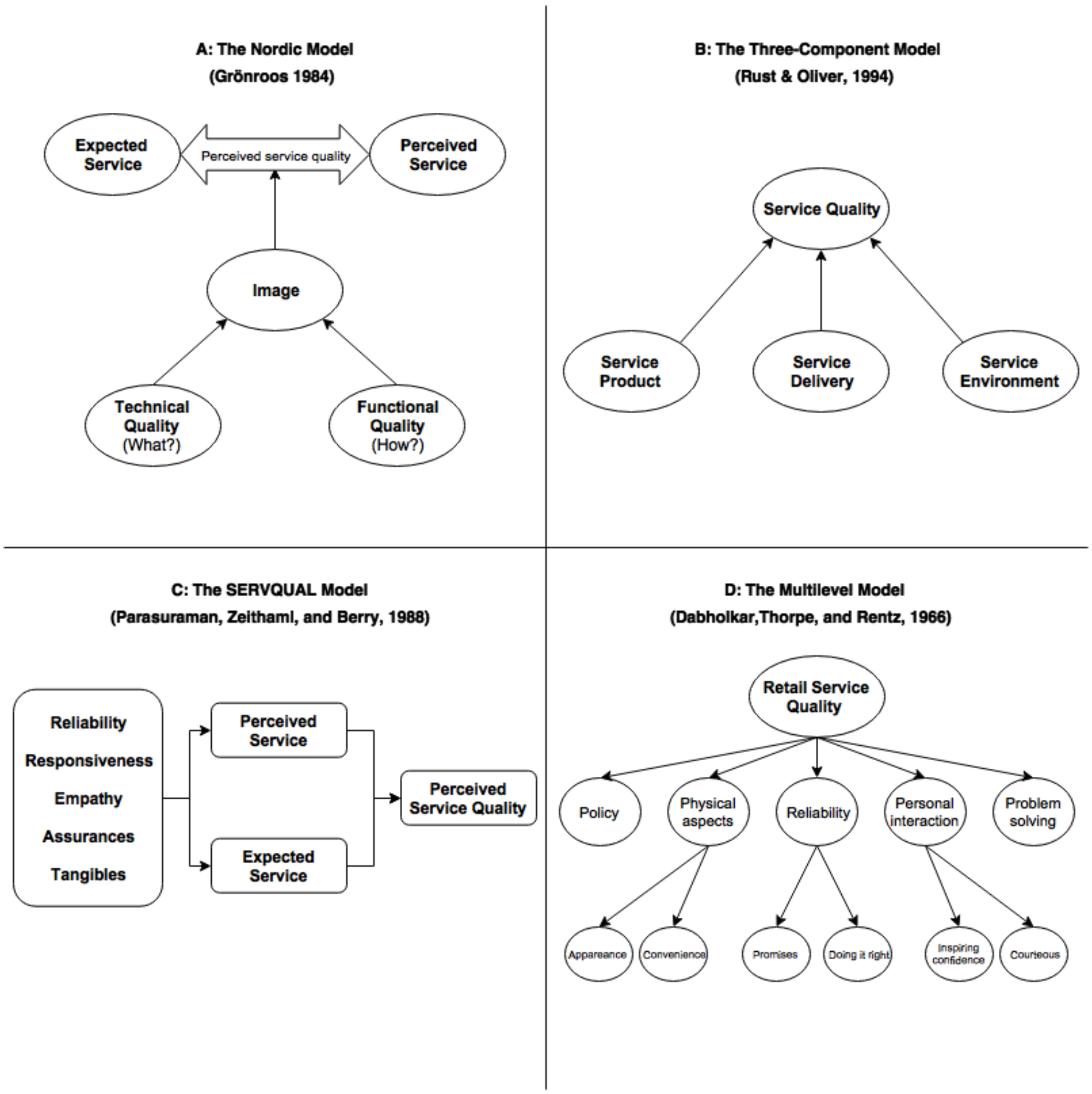

Figure 5.2. Overview of Service Quality Models, adopted from Brady & Cronin (2001)

The last model is a combination of the three-component model from Rust and Oliver (1994) with the multilevel model proposed by Dabholkar et al. (1996), suggested by Brady and Cronin (2001). They argue that service quality is determined by three primary dimensions which are defined by nine sub dimensions. The first primary dimension, *interaction quality*, refers to the interpersonal interactions that take place between an employee and a customer. Moreover, Brady and Cronin (2001) indicate that attitude, behaviour, and expertise are the three sub dimensions that influence customer perceptions of interaction quality. The second primary dimension, *environmental quality,* refers to the environment in which the service encounter takes place and its quality is influenced by ambient conditions (e.g. temperature and music), facility design (functional or aesthetic layout), and social factors (number, type, and behaviour of people)(Brady & Cronin Jr, 2001). The last primary dimension, *output quality,* refers to the actual product the customer receives when the process has been completed and is associated with valence (degree to which the service outcome is considered good or bad), tangibles (physical results), and waiting time (Brady & Cronin Jr, 2001). In turn, these sub dimensions are evaluated by using some of the SERVQUAL dimensions (see Figure 5.3). Moreover, perceptions of an organization's performance on each of the three primary dimensions is formed by combining customers' evaluation of the sub dimensions. An overall service quality perception is then formed by aggregating those perceptions.

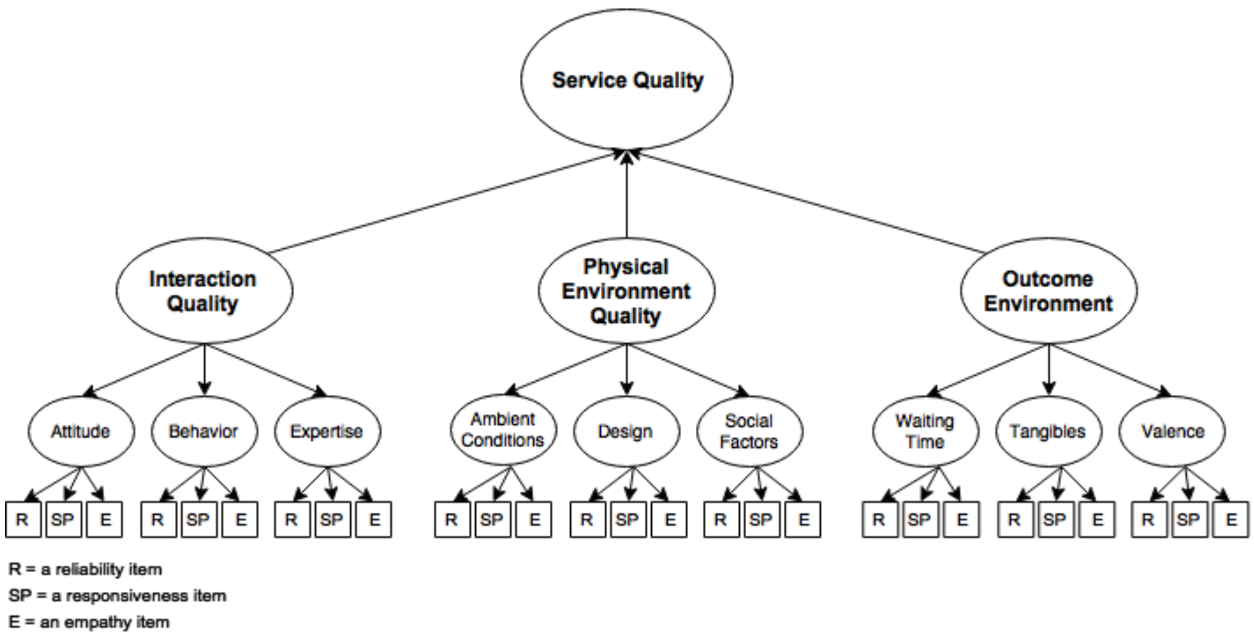

Figure 5.3. The Hierarchical Service Quality Model, adopted from Brady and Cronin (2001)

The conceptualization of service quality used in this study is the hierarchical model proposed by Brady and Cronin (2001) because it has been used in numerous studies that found strong support for this model (e.g. Akter, D'Ambra, & Ray, 2013; Wu & Ko, 2013; Zhao, Lu, Zhang, & Chau, 2012). Additionally, Brady and Cronin (2001) argue that neither perspective (two-dimensional or multi-dimensional) is wrong, but is incomplete without the other instead. Therefore, it can be seen as an improvement on both perspectives. Finally, the focus of this study is on interaction quality rather than the other two dimensions since the interpersonal interactions that take place during service delivery often influence service quality perceptions the most (Ekinci & Dawes, 2009).

5.2 Personality Influencing Customer Satisfaction

So far, little research has been published concerning the effects of front-line employee personality on service quality and thus on customer satisfaction. However, it is argued that front-line service employees play an important role in developing high satisfaction among customers as employees' attitudes, skills, behaviours, and personalities influence customers perceptions of service quality (Bowen & Schneider, 1985; Ekinci, Dawes, & Massey, 2008). Moreover, Ekinci and Dawes (2009) suggest that customer-oriented service behaviours (e.g. responding, smiling, and helping) are likely to be influenced by the personality traits of service employees.

Hurley (1998) was one of the first to explore the effect of personality on service quality among front-line employees. The results of his research indicated that service quality is influenced by personality and that superior service providers show higher levels of extraversion and agreeableness. Additionally, Liao and Chuang (2004) investigated the impact of four personality dimensions (extraversion, conscientiousness, agreeableness, and neuroticism) on service performance (employees' behaviour) and customer outcomes (e.g. customer satisfaction and customer loyalty). They found that conscientiousness and extraversion had a significant positive relationship with service performance and positively influenced customer satisfaction. They excluded the openness to experience dimension from their study as there was no convincing evidence to support a relationship between openness to experience and service performance.

More recently, Ekinci and Dawes (2009) examined the relationship between frontline service employee personality traits, interaction quality, and customer satisfaction. They proposed a model in which the effects of the five earlier described personality dimensions – openness to experience, conscientiousness, extroversion, agreeableness, neuroticism (section 4.2) – on customer satisfaction was mediated by interaction quality. Additionally, they argued that employee personality traits can be conceived as direct determinants of interaction quality since they appear to be related to employee attitudes and customer orientation, both of which have been identified as determinants of interaction quality. The results of their research showed that customer satisfaction is indeed influenced by the personality of employees. However, they only found support for four of the five traits. Extraversion, conscientiousness, and agreeableness were found to have a significant impact on interaction quality, whereas openness to experience was found an important (direct) predictor of customer satisfaction.

By comparing these three studies, it becomes apparent that they show overlapping results for three of the five aforementioned personality dimensions. Hurley (1998) identified extraversion and agreeableness as important traits for superior service providers, Liao and Chuang (2004) found that conscientiousness and extraversion positively influenced customer satisfaction, and the most extensive and recent research on this topic from Ekinci and Dawes (2009) concluded that extraversion, agreeableness, and conscientiousness were strong predictors on interaction quality and thus customer satisfaction. In other words, there is scientific evidence that the personality traits of service employees are likely to be key determinants of customer satisfaction, extraversion, agreeableness, and conscientiousness in particular.

6 Personality in Chatbots: survey

In the previous section, some studies that investigated the influence of a service employees' personality on perceived customer satisfaction have been outlined. These studies found that certain personality traits of customer support representatives are more likely to influence customer satisfaction than others. Moreover, as mentioned before personality is not exclusively attributed to humans, but is also attributed to non-human artefacts in order to rationalize its actions. Additionally, earlier research indicated that anthropomorphism plays a role in the design of socially interactive robots (Duffy, 2003; Fink, 2012; Nowak & Rauh, 2005). More recently, some contributions have been made with respect to anthropomorphising chatbots that, for instance, suggest that humanizing chatbots affects their trustworthiness (Seeger & Heinzl, 2018). Nevertheless, research on the personality of a chatbot remains scarce in the scientific literature.

Despite the fact that this topic is currently scientifically misrepresented, some internet sites have been writing about assigning a personality to chatbots. Chatbot Magazine is probably the most popular source for information about chatbots and have recently also published some articles about the personality of a chatbot. For instance, one of their articles gave a superficial description about how people could design a chatbot's personality, whereas another article reasoned why chatbots benefit from having a personality (Shinde, 2016; Zilnik, 2016). Yet, other sites also share Chatbot Magazine's interest in this topic. Technology firm Xandra, for instance, published a guide to developing chatbot personalities, including why they are so important and an enumeration of things to considers when building a chatbot with personality (Thoms, 2017). Award-winning chatbot platform 'The Personality Forge' even lets people build their own chatbot with personality using their AI engine, which integrates memories, emotions, knowledge of hundreds of thousands of words, sentence structure, unmatched pattern-matching capabilities, and a customized scripting language[9].

To summarize, there is evidence that the personality of human customer support representatives has an impact on customer satisfaction and that personality is also attributed to non-human artefacts, such as chatbots. Therefore, it is plausible to assume that the personality of chatbot customer support representative also influences customer satisfaction.

The remainder of this section will discuss the results of the survey as well as the survey itself, that was send to businesses in order to validate the aforementioned hypothesis by capturing their perspectives.

6.1 Survey: methodology

Participants

As mentioned in section 2.2, this survey was distributed among sixty businesses employing a customer support. These businesses were selected by means of purposive sampling and they were all located in the Netherlands. The businesses were chosen so that they covered a wide variety of industries and included businesses active in telecom, retail, finance, energy, aviation, consumer electronics, insurances, and public transport. It was chosen to distribute this survey among businesses rather than customers, as businesses probably maintain a communication policy that informs their employees about how they should behave in interaction with the

[9] https://www.personalityforge.com, accessed January 25, 2018

customer. This should lead to less ambiguity. Only five businesses have been included in the results, as the other fifty-five businesses either did not complete the survey or did not respond.

Materials

The survey consists of 16 items including 3 items about demographics, 4 items about customer support, and 9 items about personality traits (see Appendix A for an overview of all items). Because of the exploratory nature of this study, guidelines cannot yet be derived from earlier studies in the formulation of a measure scale. Rather the questions are inspired by the theory originating from the literature review and with the research question in mind. In addition, the questions are independently evaluated by two other parties. Depending on the answers given by participants, participants have to complete paths of different lengths, ranging from seven items to ten items (see Appendix A). Table 6.1 gives an overview of the seven most important items of the survey, the demographic items were left out as they were not filled out by all participants and therefore are less meaningful. Also, it should be noted that in the last question the neuroticism dimension was reversed to better fit with the other dimensions and to avoid confusion. The NEO PI-3 (Costa & McCrae, 2005) was used to map specific personality traits to the corresponding dimension. The NEO PI-3 is a 240-item questionnaire, with a 5-point Likert scale assessing an individual's' personality in terms of the big five personality dimensions (e.g. O: Our ideas of right and wrong may not be right for everyone in the world; C: I'm picky about how jobs should be done; E: I act forcefully and energetically; A: Human need is more important than economics; N: I feel awkward around people).

Table 6.1

Sample of questions from the survey.

1. *What is the main reason to employ a customer support service within your company?*
2. *What kind of customer support representatives does your business employ?*
3. *What kind(s) of channels for customer support service(s) does your business employ?*
4. *Which personality traits does your company value in your human customer support representatives?*
5. *Which personality traits does your company value in your chatbot customer support representatives?*
6. *In the (hypothetical) case that your company uses chatbots as customer support representatives, would it then value other traits for chatbots than for its current representatives?*
7. *Rank (drag & drop) the following five personality dimensions on its importance, considering your customer support representatives*

Procedure
The businesses were contacted by either e-mail or Facebook messenger and the invitation included a letter (as can be seen in Appendix B). This letter contained the request to participate, information about the relevance, the tasks the businesses would have to perform, the workload, as well as the confidentiality and anonymity of the study. If businesses did not respond, a reminder was sent after a week. The questionnaire was accessible by means of a link that was also included in the letter. Before the actual questionnaire was shown, a brief introduction appeared with some information about the research, the anonymity and the confidentiality.

Analysis
It is expected that the results of this survey replicate those of the previous literature study, which means that extraversion, agreeableness, and conscientiousness will be identified as the most important personality dimensions influencing customer satisfaction. Moreover, it is expected that businesses will value the same personality traits for their chatbot representatives as they do for their human representatives.

6.2 Survey: results

When analysing the results of the survey, it becomes apparent that businesses most often (80%) maintain an internal customer support service in order to provide customers with information and help them with their questions about the provided services. One of these businesses specifically identified a positive Netto Promoter Score (NPS), resulting from an increase in customer satisfaction, as a reason for having customer support. Only one of the participated businesses stated to employ both human and chatbot customer support representatives, whereas the other businesses only employ human representatives. Within the sample all businesses maintain a telephone communication channel as well as a social media presence, whereas mail was used by all but one and communicating by chat being the least common as only three businesses offer this option. To the question which personality traits businesses deemed most important for their human representatives, resulted in varied answers (see Table 6.3). However, empathetic ability was mentioned most often as personality trait valued in human customer support representatives. After mapping the given traits to its accompanying dimension, it also became apparent that most of these traits could be placed within the agreeableness dimension, whereas only one trait corresponded to the extraversion dimension (see Table 6.2). Only one business replied to the question about which personality traits they deemed important for chatbot representatives, as they were the only business in the sample to have chatbots as customer support representatives. However, the other businesses had to answer an alternative question about the hypothetical case in which they would have chatbot representatives. On both questions businesses answered that they do not value different personality traits for chatbots as they do for humans. Business 1, which currently implements a chatbot, did add “proactive thinking in finding solutions” as a valued trait for chatbots (see Table 6.3). However, they later stated that they also deem this an important trait for human representatives, but according to them this was self-evident. The last question, that asked the participants to rank the different personality dimensions on their importance, also resulted in varying outcomes. Nevertheless, extraversion was by all businesses identified as the least important dimension, whereas openness to experience and agreeableness were most often placed within the top three.

Table 6.2

Mapping of identified personality traits into the accompanying dimension

Big Five dimension	**Outcomes**	
Openness	Proactive thinking (actions)	(1x)
	Resourceful (ideas)	(1x)
	Knowledge (ideas)	(1x)
Conscientiousness	Client- and solution oriented (competence)	(2x)
	Accurate (competence)	(1x)
	Independent (self-discipline)	(1x)
Extraversion	Accessibility (gregariousness)	(1x)
Agreeableness	Empathic ability (tender-mindedness)	(3x)
	Friendliness (altruism)	(1x)
	Respectful (straightforwardness)	(1x)
	Helpfulness (altruism)	(1x)
Neuroticism	-	

Table 6.3

Survey Results

Questions	Business 1	Business 2	Business 3	Business 4	Business 5
What is the main reason to employ a customer support service within your company?	Gaining customer satisfaction, which results in a positive Netto Promoter Score (NPS)	Retail chain, so much contact with its customers.	Necessary for service	Provide the customer with information and support about their services.	Helping our customers with their questions
What kind of customer support representatives does your business employ?	Humans and chatbots	Humans	Humans	Humans	Humans
What kind(s) of channels for customer support service(s) does your business employ?	Telephone Chat Social media	Telephone Mail Social media	Telephone Chat Mail Social Media	Telephone Mail Social media	Telephone Chat Mail Social Media
Which personality traits does your company value in your human customer support representatives?	Client- and solution-oriented Empathic ability with a commercial approach	Empathic ability	Knowledge Friendliness Helpfulness Accessibility	Empathetic Respectful Accurate Independent Resourceful	Service oriented and respond to the needs of the customer
Which personality traits does your company value in your chatbot customer support representatives?	Proactive thinking in finding solutions. Client- and solution-oriented. Empathic ability with a commercial approach.	N/A	N/A	N/A	N/A
In the (hypothetical) case that your company uses chatbots as customer support representatives, would it then value other traits for chatbots than for its current representatives?	N/A	No	No	No	No
Rank (drag & drop) the following five personality dimensions on its importance, considering your customer support representatives:	1) Openness 2) Neurotiscm 3) Agreeableness 4) Concientiousness 5) Extraversion	1) Neurotiscm 2) Agreeableness 3) Concientiousness 4) Openness 5) Extraversion	1) Concientiousness 2) Agreeableness 3) Openness 4) Neuroticsm 5) Extraversion	1) Agreeableness 2) Concientiousness 3) Openness 4) Neuroticsm 5) Extraversion	1) Openness 2) Agreeableness 3) Neurotiscm 4) Concientiousness 5) Extraversion

7 Chatbots and Ethics

Chatbots are a promising technology that offer organizations a lot of new opportunities, such as improving learners critical thinking skills, enriching game interaction with players and helping people lose weight. However, as with any new technology it has ethical challenges and implications that need to be considered to warrant that it is used in a responsible way.

An example of a chatbot that was not used in a responsible way was Microsoft's chatbot "Tay". Tay was an experiment that was meant to converse with people on Twitter by learning from their input. At first the conversations were kind and friendly but soon changed to offensive and racist. This change in mood was caused by users who were supplying the chatbot with input filled with offensive and racist content.

Another important consideration in the use of chatbots is transparency. First of all, it is important to let customers know when they are communicating with a chatbot rather than an actual human. Bridget Botelho (2017), from technology marketing company TechTarget, explained that "consumers expect a level of trust, and when they find out a company is using a machine to interact with them, they could feel betrayed and may even turn against the brand …" This phenomenon is similar to the "uncanny valley effect", which proposes that as robots become more human, people's emotional response to those robots first increased, but then sharply declined (Mori, 1970). Just as with robots, people have high expectations of chatbots when they present themselves as humans. However, when a chatbot not exactly behaves like a real human being, these expectations are then replaced with distrust. Moreover, ownership of information and privacy should be clearly communicated with customers. If a chatbot assembles a shopping list based on earlier orders and user preferences, does it then belong to the chatbot or the user? Can user information retrieved from conversations with chatbots be sold to third parties? If so, should the user then be informed about this? According to Trips Reddy (2017), senior content manager at IBM, businesses that want to implement their own chatbot should address these issues and should be transparent in communicating their terms of service, privacy policy, and whether or not the user is conversing with a chatbot.

Yet, probably one of the biggest challenges concerning chatbots lies in their great potential to replace human beings in their job. Researchers predict that all human jobs will be automated within 120 years and that there is a 50% probability that this could even happen within the next 45 years (Grace, Salvatier, Dafoe, Zhang, & Evans, 2017). Nevertheless, it is argued that the highest efficiency can be achieved when chatbots and humans work together (von Malitz, 2016). Chatbots can be used to answer simple queries in a far more efficient and quickly manner than an actual human, whereas humans can take over from chatbots when the situations become more complex. For instance, chatbots are able to conduct the initial interaction with customers and record the customers' information and details on the incident, after which it is forwarded to the most qualified human agent. Additionally, history shows that technological advances, such as chatbots, do not result higher unemployment rates, but rather boosts employment by creating jobs in new sectors (Stewart, De, & Cole, 2015). In other words, as chatbots are still in its infancy they are not expected to take over jobs from humans for the foreseeable future, rather it is suggested that both human and machine will need to work together and complement each other in order to attain the highest efficiency. Moreover, even if chatbots eventually take over jobs from humans, history shows that such technological revolutions in the end always result in higher employment rates.

8 Discussion and conclusion

The aim of this research project was to investigate what role the personality of a chatbot has on the perceived customer satisfaction. In order to do so, first a literature study was performed after which the findings of this study were tested in a short experimental research.

Since current scientific research on this topic is scarce, the literature study was mainly conducted on the individual components that made up the main research question. Literature on chatbots was reviewed and used for assigning it with a clear definition, an overview of its development, stating requirements for enterprise implementations, and ascribing its potential. To answer the first research sub-question about how personality can be categorised, literature on personality was searched for theories about how personality can be defined and measured. This resulted in the adoption of the five-factor model, categorizing personality in five dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Yet, another interesting finding from this review was that it identified people's habit of human characteristics, such as personality, to non-human artefacts. At last, in order to answer the second research sub-question, marketing literature was reviewed to identify existing models to customer satisfaction and to identify earlier research that studied the relationship between personality and customer satisfaction. Interestingly, earlier research studying this relationship indeed existed and identified that the extraversion, agreeableness and conscientiousness dimensions had the greatest impact on customer satisfaction. However, these findings apply to human representatives and therefore cannot be directly applied to chatbots without any further consideration.

In order to answer the last research sub-question about whether this earlier research on customer satisfaction and personality can also be applied to chatbots, a short experimental research, in the form of a survey, was conducted. From the literature study, it was hypothesized that this would be the case as people would humanize chatbots and thus ascribe a personality to it. The findings of the survey indeed showed that the participating businesses did not value different personality traits for human customer support representatives than for chatbot representatives. This is in accordance with Fong, Nourbakhsh and Dautenhahn's (2003) statement that "the common, underlying assumption is that humans prefer to interact with machines in the same way that they interact with other people." Therefore, it appears that the aforementioned research can also be applied to chatbots. However, the results did not exactly replicate those of the previous studies regarding the personality dimensions. Extraversion, agreeableness and conscientiousness were by earlier research identified as most important dimensions influencing customer satisfaction. Yet, in this study businesses did not consider all dimensions as important and even ranked extraversion as the least important dimension.

Overall, based on both earlier research and the results evident in this research project, it is assumed that the personality of a chatbot influences customer satisfaction. Since chatbots are an effective addition to a firm's customer support and the personality of such a chatbot is likely to influence customer satisfaction, businesses should explore their options on how chatbots with a personality can be successfully exploited within their firm. Nevertheless, additional research needs to be performed to further investigate how customer satisfaction is exactly being influenced by a chatbot's different personality dimensions.

8.1 Limitations and directions for future research

As does any research project, this study has some limitations. A key one is the use of purposive sampling as sampling technique. This sampling technique is considered to be effective when time available is limited and only a limited number of people can serve as primary data source. However, it is a non-probability sampling method and therefor the resulting research findings cannot be generalized. Another factor that hinders generalization of this study's findings is the small sample size. Accordingly, future research should consider adopting a more comprehensive sampling design and using a larger sample so that the sample will be more representative for the entire population.

Since no scientific research existed on this topic, guidelines and scales for measuring the relationship between the personality of chatbot and customer satisfaction still need to be developed. The items present in this study resulted from the previous literature review and were drafted with the research question in mind. Nevertheless, the instrument has yet to be tested on its validity and reliability. Therefore, for future research it would be relevant to develop an appropriate, valid instrument that measures the relationship between a chatbot's personality and customer satisfaction.

It should also be mentioned that a measurement error might have occurred in the results. The item that asked the participants to rank the personality dimensions on their importance did not specifically specify whether the number one referred to the most important dimension and number five to the least important dimension, or vice versa. Although there is enough reason to assume that this did not happen, future research will need to demonstrate whether the results from this item are indeed reliable.

According to Ekinci and Dawes (2009) marketing research uses personality traits to study a variety of behaviours from two perspectives: personality psychology and social psychology. The former perspective is from the point of view from employees' and businesses, whereas the latter perspective adopts a consumers' point of view. This study employed the latter perspective as it investigated the influence of business perceptions of frontline employee personality traits on customer satisfaction. That is, businesses were asked for the personality traits they valued most in their customer support representatives. However, for future research it is recommended to adopt the former perspective, and thus capture the customer's perspective. In the end, this may lead to more relevant findings as it directly involves the subject from which customer satisfaction originates.

Another consideration in developing and implementing chatbots with a personality is its adaptivity. In this research, personality was examined through the scope of personality dimensions and which dimensions in general were most likely to influence customer satisfaction. However, this does not have to mean that the same dimensions are equally applicable in every situation, rather it may be that in one situation other dimensions are of more importance than in another scenario. For instance, conscientiousness and agreeableness might be the most important dimensions for a chatbot representing a financial organization, whereas extraversion and openness may be of greater importance for a chatbot interacting with younger people. Therefore, further research should be conducted on the adaptivity of a chatbots' personality and how it affects customer satisfaction.

Another research avenue could be to investigate how personality can be manifested in chatbots. Earlier research has found that a person's personality is reflected in the way they write, speak, and behave has found that the style in which a text is written reflects the personality of the author (Ball & Breese, 2000; Luyckx & Daelemans, 2008; Polzehl, 2014). For instance, extravert people tend to use more words and pronouns in their messages, whereas neurotic peoples' messages contain more negative emotion words and acronyms (Holtgraves, 2011). More specific to the human computer interaction (HCI) domain, it was found that robots are also able to express personalities through gestures (Kim, Kwak, & Kim, 2008). Future research could examine whether this also applies to chatbots and may identify additional ways for a chatbot to reflect its personality.

In line with this view, the following research questions could be investigated by future studies: (1) How do customer's perceptions of a customer support chatbot influence perceived customer satisfaction? (2) Do customers assess chatbot personality differently in different contexts (i.e. industries, cultures, or age)? (3) How can personality effectively be established in chatbots?

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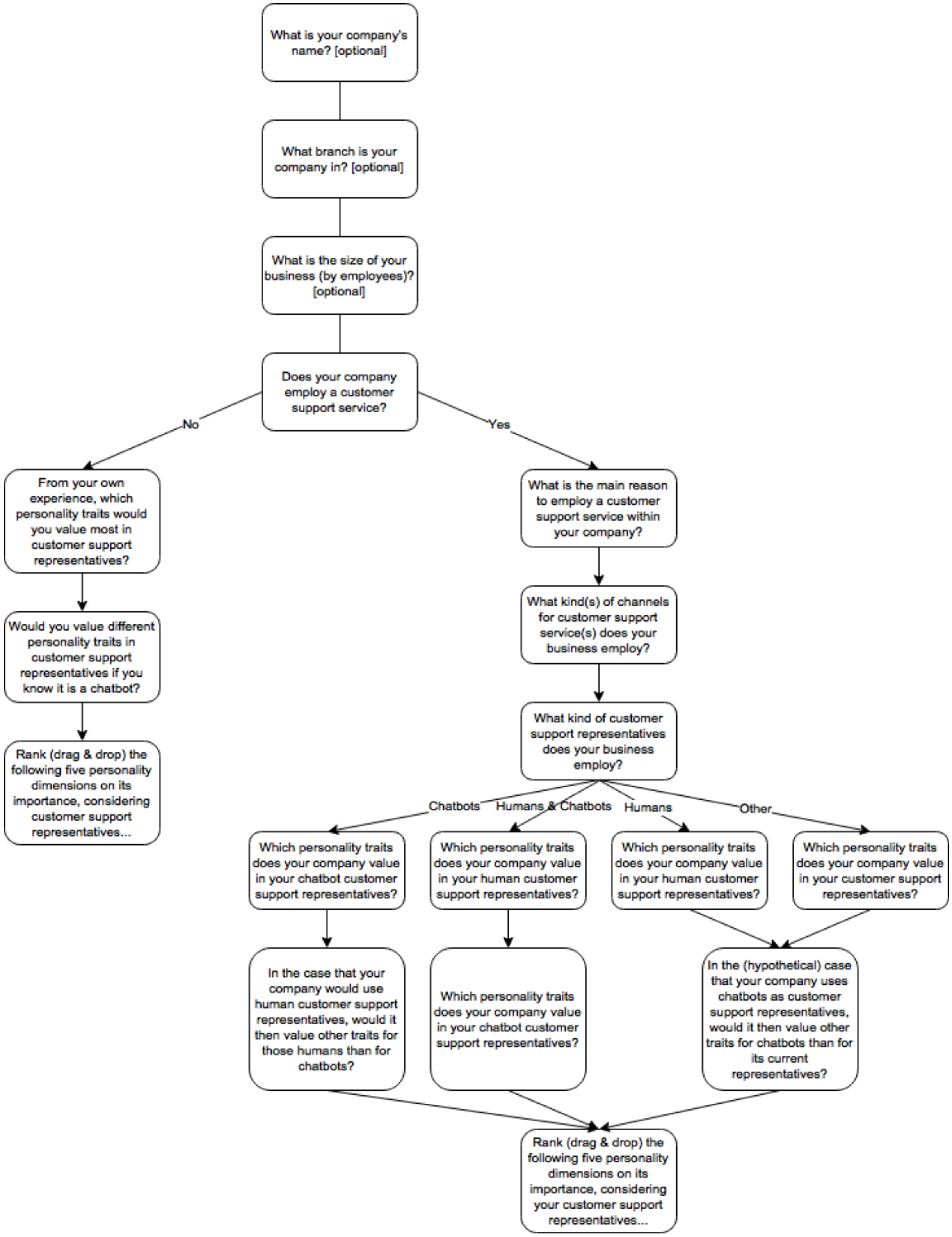
Appendix A

A hierarchical overview of the items and the different paths



Appendix B

Invitation letter send to businesses

Utrecht University

Dear Sir or Madam,

By sending this mail, I would like to ask for your participation in my bachelor thesis. My research will focus on the personality of chatbots and its influence on customer satisfaction. As you might know, implementing chatbots within companies lead to an increase in the effectiveness of your customer support services and a decrease costs associated with those services.

Moreover, customer satisfaction may be influenced by personality traits of customer support representatives. The right personality could result in an increase in customer satisfaction. With this in mind, I would like to ask you to fill out the questionnaire accessible through the following URL:

https://qtrial2017q4az1.az1.qualtrics.com/jfe/form/SV_bDfbebprXocCnqJ

This survey will ask for some general questions about your company and the customer support services your company employs. The survey only takes 5 minutes to complete and its results will be kept in confidentiality.

The survey is not only aimed businesses that are using chatbots as customer support representatives, but is also at businesses that have human, or other kinds of, customer support representatives.

I look forward to seeing your response. If you have any questions in the meantime, you can contact me via h.dehaan@students.uu.nl.

Yours faithfully,

Hayco de Haan

Supervisor: *Christof van Nimwegen* (Faculty of Science, Information Sciences, University Utrecht)