Bachelor Thesis

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Chatbots/Conversational Interfaces in the Context of the Stereotype Content Model (SCM)

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Management Summary

Virtual assistants in the form of chatbots are taking over today's technology industry. Companies have increasingly started integrating conversational agents into their customer support platforms and recorded millions of interactions. However, this technology has a high failure rate when it comes to correctly processing inquires. How can firms enhance a client's experience with their chatbot, aside from improving the technology that powers these bots?

The stereotype content model (SCM) theory postulates that people judge each other based on two dimensions: Warmth and competence. A person seen as highly warm and competent is admired and these two traits have a positive effect on trust. In practice, Casciaro and Sousa-Lobo developed archetypes based on the likability and competence dimensions. The "lovable star" is likeable and competent and thus great in demand. The "incompetent jerk" on the other hand lacks expertise and is seen as cold, therefore vastly avoided.

This thesis aims to find out whether the SCM can be applied to the domain of chatbots. In other words, is it possible to differentiate the concepts of "lovable star" and "incompetent jerk" on chatbots? Chatbots have the potential to replace millions of jobs in the future; it should therefore be interesting for businesses to transform their chatbots into popular "lovable stars". In order to answer the research question, stimulus material in the shape of avatar pictures were chosen and implemented into an online experiment with three experimental groups. A chatbot designed as "lovable star", one as "incompetent jerk" and a simple text chatbot without avatar as a control were exposed to subjects.

The empirical research revealed that people were able to successfully judge the chatbots on the warmth and competence dimensions. The "lovable" star chatbot was perceived as significantly more likable and credible than the "incompetent jerk" and the simpler bot. While the "lovable star" chatbot was experienced as more trustworthy than the "incompetent jerk", it was not seen as more trustworthy than the control variable, a simple text chatbot.

In conclusion, the SCM principle can be applied to the field of chatbots/conversational agents. Companies are therefore recommended to model their chatbots as admirable "loveable stars". Future research will have to focus on the trust aspects of a chatbot, as

the “lovable star” chatbot did not receive significantly higher trust scores than the plain chatbot.

Although the model is transferrable, businesses are advised to be upfront about their chatbot technology. Further findings show that consumers want to know that they are talking to a chatbot and not a real human. It is also suggested for firms to use a modern approach and illustrate cartoonish avatars in order to avoid the uncanny valley effect. Lastly, companies should aim to reduce a chatbot’s error rates, enable a fast processing of inquiries and offer individualized consulting sessions. They should be cautious about data privacy, particularly when it comes to asking consumers about sharing sensitive information with a bot.

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List of Abbreviations

SCM	Stereotype Content Model
AI	Artificial Intelligence
NLP	Natural Language Processing
ML	Machine Learning
DCA	Disembodied conversational agents
ECA	Embodied conversational agents
M	Mean
SD	Standard Deviation

1. Introduction

This thesis starts with an introduction and background information on chatbots. After that, the problem statement and the aim of this thesis are presented.

1.1. Background information

Intelligent virtual assistants in the form of chatbots, conversational interfaces or digital assistants are taking over today's technology industry (DALE, 2016, p. 811). The most famous technologies are the voice-driven virtual assistants such as the well-known Google Assistant, Apple's Siri, Amazon's Alexa and Microsoft's Cortana. The lesser known technology is the text-based chatbot which is taking over messaging apps and social media (DALE, 2016, p. 811). In less than a year, Facebook Messenger released over 100,000 chatbots (Johnson, 2017). On Pandorabots, a leading chatbot platform and community, over 300,000 chatbots have been created by more than 250,000 registered bot developers, as well as over six billion interactions with users have been recorded (Pandorabots & Inc, 2018). Microsoft's conversational artificial intelligence (AI) tools report a monthly activity of 30,000 bots (Dillet, 2018). Approximately 30 million messages are handled across thousands of company platforms, including UPS, Stack Overlow, Asiana Airlines, and many more (Dillet, 2018)

Bots can execute simple tasks such as booking hotel rooms and airline tickets, or complex tasks like financial aid, health and insurance advice or online shopping guidance. This form of AI can potentially replace millions of human worker jobs. According to a recent forecast study, chatbots might deliver the banking and insurance sectors up to $8 billion in cost savings per year by 2022 (Foye, 2017). It is also estimated that chatbots will take over 25 percent of customer service communication by the year 2020 (Gartner, 2018). In addition, by the year 2020, 80 percent of businesses will have implemented a form of chatbot technology into their processes (Business Insider, 2016).

1.2. Problem Statement

Making use of conversational interfaces has become a top priority for companies and consumers, as well as several scientific organizations (DALE, 2016). As companies increasingly utilize these conversational agents with customers, it becomes crucial to understand the influencing factors that drive consumers towards the use of chatbots. This calls for greater urgency especially since current reports show the drawbacks and high failure rates of chatbots implemented on social media and messaging apps (Knight, 2016). Facebook reported that its AI bots hit a failure rate of 70 percent since the launch of their bot API on its Messenger, e.g. not being able to answer correctly specific questions (Orlowski, 2017).

Furthermore, a PointSource report showed that 80 percent of users looking for healthcare or financial advice/products admitted that they would prefer talking to a human instead of a bot, even though 90 percent of the users believe that companies are ready to make use of the chatbot technology (Hopping, 2018). These examples show the need to prioritize the development of the chatbot technology.

The stereotype content model (SCM) proposes that humans use the two primary dimensions of warmth and competence to judge other humans in social interactions, preferring someone with high degree of likability (warmth) and competence (Fiske et al., 2007, p. 77). A study conducted by Casciaro and Sousa-Lobo (2005) shows that within organizations, people prefer to work with "lovable stars" (highly warm and competent). These two traits affect first impressions and trust. Customers are more likely to buy from businesses they trust and of which they have a good impression.

Combining the domains of chatbots and the SCM, the author theorizes that the SCM principle can be useful for businesses that want to launch more trustworthy and successful chatbots and also improve the area of human-computer communication. Since chatbots have the potential to replace millions human workers the future, it should be interesting for companies to transforms their chatbots into trustworthy "lovable stars".

1.3. Aim of the Thesis

The aim of this Bachelor's thesis is to answer the question whether the SCM can be applied to the domain of chatbots/conversational interfaces. It is concerned with the modeling of high warm and high competence conversational agents. The thesis examines whether the concepts of a "lovable star" and "incompetent jerk" can be differentiated on chatbots and whether high warmth and competence scores have a positive influence on the trustworthiness of a chatbot.

2. Theoretical Framework

This section presents existing studies of the general topic and subtopics of this thesis. It is designed to build an understanding of the contributions to the general problem being researched. A set of hypotheses was drawn from this literature review.

2.1. Chatbots

This part starts with the definition of a chatbot, since essential parts of this thesis draw on this subject. After defining what a chatbot is, the technology used to power chatbots is explained.

2.1.1. Definition

Chatbots (a.k.a. chatterbots) simulate text or speech based conversations with the human end-user (Pereira et al., 2016). A chatbot uses natural language to interact with users, powered by natural language processing (NLP) and machine learning (ML), both related to the field of AI (Pereira et al., 2016). The terms NLP and ML will be explained in detail in the next chapters. This form of technology was first developed in the 1960s to make users believe they were chatting with a real person. Some chatbots have avatars or talking heads to display more human-like characteristics. To engage in conversation, the bot accesses a large storage of response patterns. It usually replies to the user's input instead of taking the initiative to start a chat (McTear et al., 2016).

Chatbots on websites, messaging apps and social media are usually referred to as Disembodied conversational agents (DCAs) (Araujo, 2018). These bots generally use a text-based interface which allows the exchange of different media such as videos and images between the DCA and the user. Conversational agents may also be embodied. Embodied conversational agents (ECAs) usually have a non-static, virtual body (avatar) and human-like facial features that enables them to use nonverbal communication (body movements, facial expressions) (Araujo, 2018). The chatbot used in this study's empirical research is a disembodied conversational agent.

2.1.2. Natural Language Processing (NLP)

As mentioned in the previous section, chatbots use NLP to learn how to converse with humans. NLP is categorized in the field of computer science that focuses on computational techniques (Hirschberg & D. Manning, 2015). These computational techniques focus on learning, understanding, and creating human language content (Hirschberg & D. Manning, 2015).

Boutin (2017) explains that the "intent" of a user is captured and classified by the bot. The bot can then be trained with as many intents needed, depending on the purpose of the chatbot. An example of an intent could be "small-talk". One would start training by creating intents such as "how are you?", "it's nice weather today", or "when do we meet up?". NLP does not use keywords, instead it uses its understanding of pattern recognition, sentence structures and idioms to match the users intent with the previously classified intents (Boutin, 2017).

To enhance the performance of NLP, ML techniques are often used within it. ML can be described as a computer program automatically learning and improving their performance through experience. This is defined as "programming by example" (Mumford & Jain, 2009).

2.2. Nonverbal Communication

This section begins the definition of nonverbal communication and its components. Also, the concept of the SCM is presented to explain the two central social cognition dimensions which are essential for this thesis: warmth and competence.

2.2.1. Definition

Nonverbal communication is a set of conscious or unconscious behaviors. This includes gestures, facial expressions and the tonality of voice (Eunson, 2013, p. 256). Humans are communicating even when they are not talking. Albert Mehrabian (1981) found that communication is mainly expressed through nonverbal actions. 7% is conveyed verbally (words), 38% vocally (tone, pitch) and 55% visually (nonverbal) (Mehabian, 1981).

According to Dickson and Hargie (2013), nonverbal communication is complementary to verbal communication, strengthening the meaning of the message. It can also replace verbal communication when one is not able to talk. It alters the said words, conveys emotions and attitudes, shows identity through adornments and sets the framework in a social setting (Hargie, 2003).

Nonverbal communication is subjective and can be ambiguous. People make judgments based on what they think is correct, however, they could equally be wrong about their perception. In an online context, communication does not allow the use of nonverbal signals. With chat messengers, it is not possible to use body language and the tonality of voice. One possible method to decrease confusion and misinterpretation is the use of emoticons.

2.2.2. Nonverbal Warmth and Competence Cues

A person has some control over the impression he/she makes along the warmth and competence dimensions through nonverbal cues (Cuddy et al., 2011, p. 88). One could argue that in all social interactions, people are consistently projecting warmth/coldness and competence/incompetence through nonverbal cues (Cuddy et al., 2011, p. 88).

Nonverbal warm cues include smiling, leaning forward, nodding, leaning the body towards someone and relaxed hand gestures (Cuddy et al., 2011, p. 89). Contrarily, cold nonverbal cues are defined as having a tense posture, leaning backwards, shifting the body away from someone, and tense intrusive hand gestures (Cuddy et al., 2011, p. 89). Nonverbal competent cues are described as being dominant, expansive and open (e.g. using up more space, a firm hand shake) (Cuddy et al., 2011, p. 90) Finally, nonverbal incompetent cues include submissive poses and generally emitting low confidence (Cuddy et al., 2011, p. 90).

To show the importance of non-verbal communication in an online setting (pictures, avatars), the author will focus on three categories of nonverbal communication in particular: facial expressions, appearance and body language.

2.2.3. Facial Expressions

Facial expressions generate the most data in terms of expressing emotions (Oatley, 1992). They can have various meanings depending on the culture. For example, Japanese people are taught not to reveal their emotions to other people unless they have an intimate relationship with that person. This demonstrates self-control, which is highly valued in the Japanese culture. Smiling also has diverse meanings in different cultures. In the selling context, a study showed that a salesperson is perceived more capable and trustworthy when the salesperson smiled a lot (Wood et al., 2008).

However, there are particular facial expressions that are recognizable across cultures, which is known as the universality thesis (Russell, 1995). Russell categorizes two types of universal facial expressions: "easily recognized" and "specific emotion categories”. The latter category includes emotions such as happiness, fear, sadness and anger (Russell, 1995).

Additionally, research has shown that people can accurately detect the emotions of others through facial expressions even without personal contact, e.g. in the form of photographs (Ambady et al., 2006, p. 4)

2.2.4. Appearance

Appearance is an important factor in nonverbal communication. It carries information on the physical features of a person such as height, weight, age, sex and it offers insights into someone's personality (Urbaniak, 2005). It also includes accessories, clothes, environmental aspects and other adjustments on their appearance (Eunson, 2013).

Observers may identify personality traits about an individual through their dress style. For example, professors are assessed as more knowledgeable when dressed smartly (Morris et al., 1996). Teachers dressed casually were perceived as more entertaining (Morris et al., 1996). In a professional setting, it is essential to dress appropriately as a salesperson. By dressing smartly, salespeople are seen as more competent they are more likely to gain the trust of their client (Wood et al., 2008). A newer study shows that men and women are viewed more credible when dressed in smart attire. For instance, models dressed in a suit were judged more competent than those dressed in a casual manner (Gurney et al., 2017).

2.2.5. Body Language

Body language sends out more authentic signals than just words. Subconsciously, the body will show different messages when lying or being insincere (Ekman, 2015). It reflects how someone feels about themselves, it can influence the perception of an audience and how the crowd views them in return (Cuddy, 2012).

A powerful, confident posture compared to a weak posture can make a person feel strong and make them have more confidence in themselves (Briñol et al., 2009). Research shows that when men displayed a power pose, they stated a change in behavior, feeling more powerful, taking more risks and even went through hormonal changes such as increased level of testosterone and reduced cortisol (Carney et al., 2010). Using power poses can make someone feel fitter and physically stronger (Hee Lee & Schnall, 2014) Making use of these poses also help achieve better results at job interviews (Cuddy et al., 2015). A positive relationship is therefore apparent between power poses and feelings of being strong.

Moreover, admiration through body language is expressed by mirroring the admired person's posture (Eunson, 2013, p. 267) This mimicry, the so called "chameleon effect", was important in human evolution to bond and build relationships with other humans (Lakin et al., 2003, p. 1).

2.3. First Impressions

A person needs less than 100 milliseconds of exposure to a face in order to make a judgment on them (Willis & Todorov, 2006). Additional exposure time increases confidence in judgments and allows for more differentiated impressions. Increased exposure time may allow for more individualized impressions of a person, however, the initial impression has already been set and anchored into a person's mind (Willis & Todorov, 2006).

Berg and Piner (1990) stated that during the first two minutes, interviewers report knowing whether a job candidate is suitable for the vacancy and people claimed knowing within the first thirty seconds whether a blind date will go well (as cited in Bartneck, 2007). Clients judge a salesperson within seconds of the first confrontation, deciding whether the salesperson is helpful or too pushy (Ambady et al., 2006). In the context of the SCM, warmth and competence judgments are made within the first few seconds of an encounter with another person (Fiske et al., 2007, p. 77).

Numerous studies have indicated that important judgments about others are made within seconds, if not milliseconds of meeting another person. Consequently, it is highly likely that people are also capable of making the same judgments on robots/virtual entities based on their first impression (Bartneck et al., 2007).

2.4. Stereotype Content Model (SCM)

This part starts with the definition, then explanation of the stereotype content model (SCM) and finally its application to practice.

2.4.1. Definition

The SCM is a theory in social psychology that categorizes interpersonal impressions and stereotypes based on the dimensions warmth and competence (Fiske et al., 2002). These two attributes make up 82% of the diversity in perception of everyday social interactions (Wojciszke et al., 1998).

According to Fiske et al. (2007) warmth is about good or bad intentions while competence is about ability to ratify those intentions. Both stereotypes are rooted in evolutionary pressures (Fiske et al., 2007, p. 77). This is because within seconds of the first encounter between two people, one decides whether the other has good or bad intentions (Fiske et al., 2007, p. 77). The next question would be whether the other person is able to act out on his/her intention (Fiske et al., 2007, p. 77). People who are seen as warm and competent evoke positive emotions and behavior, whereas those seen as lacking warmth and competence evoke negative feelings (Fiske et al., 2007, p. 77). When two people meet, they judge each other's warmth and competence first (Cuddy et al., 2008, p. 62). Evidence suggests that warmth is judged before competence, and causes stronger affective and behavioral responses (Fiske et al., 2007, p. 77). This makes sense because evaluating whether a person is a friend or foe is more important than whether a person can carry out his/her intentions (Fiske et al., 2007, p. 77).

Warmth judgments primarily affect our perception of trust in another person and competence judgments affect our perception of a person's ability to enact his/her intent (Cuddy et al., 2011, p. 74). There is a tendency to trust a person once it is apparent that the person has no ill intent or cannot realize that intent (Fiske et al., 2007, p. 77). In other words, perceived trustworthiness in others depends on a person's warmth and competence level (Fiske & Dupree, 2014, p. 13593).

2.4.2. The SCM Applied to Practice

The SCM theory has been tested and applied to practice before. Aaker et al. (2010) found that non-profit organizations are perceived warmer than for-profit organizations but also as less competent. Additionally, customers would rather buy a product from a for-profit than from a non-profit since they are seen as more competent (Aaker et al., 2010, p. 230). When a non-profit's perceived competence is improved, people are more willing to buy from them. Finally, when consumers perceive a high level of warmth and competence, they feel admiration for the company which then increases their willingness to buy (Aaker et al., 2010, p. 230).
Another study showed that high warmth and high competence interactively affect the intention to purchase, with competence being the more important driver of purchase intent (Aaker et al., 2012, p. 193). This is because consumers admire brands that are placed in the "golden quadrant" (highly warm and highly competent) (Aaker et al., 2012, p. 193).

Furthermore, Casciaro and Sousa-Lobo (2005) demonstrated in their study that when people can decide with whom to work with, they choose based on the criteria of competence (Does the person know what he/she is doing?) and likability (Is the person pleasant to work with?) (Casciaro & Sousa Lobo, 2005, p. 3). They used the two dimensions competence and likability and built a 2x2 matrix (see Figure 1).

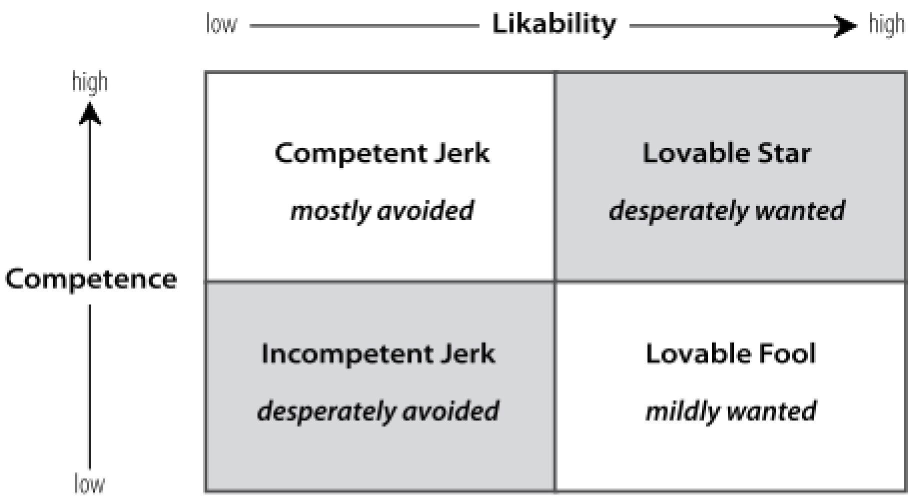

Figure 1: Model of Casciaro and Sousa-Lobo (2005)

Their study suggests that within an organization, people want to work with “lovable stars” and avoid working with “incompetent jerks”. “Lovable stars” are seen as highly warm and highly competent, whereas “incompetent jerks” are perceived as incompetent and not likable. The “competent jerks” are competent, but mostly avoided since they are not seen as warm/likable. The “lovable fools” are highly likable but incompetent, thus people only mildly want to work with them (Casciaro & Sousa Lobo, 2005, p. 5).

Other studies confirmed that the SCM can be applied to the domain of insurance agents (Seiler et al., 2015), as well as to the field of crowdfunding (Seiler et al., 2016). The crowdfunding study suggests that the competence dimension is more important than the warmth dimension, whether it is in a business context, consumer behavior context or connected to a brand/person (Seiler et al., 2016, p. 6).

2.5. Trust

This section defines what trust is since it plays an important role in the SCM theory. In addition, trust in an online context is discussed in this part.

2.5.1. Definition

Trust comes in many forms, e.g. in a friendship where secrets are exchanged, or in a business context where trust is essential for business partners, or a more recent topic of trust in an online context (cloud computing, social networks, data sharing, etc.) (Walterbusch et al., 2014).

There are various definitions of trust in literature, however, there is no common definition of trust (Rousseau et al., 1998, p. 393). For example, trust is from the perspective of an economist mainly calculative, whereas sociologist believe that trust lies within the characteristics of interpersonal relationships (Walterbusch et al., 2014). Trust can be defined as in Table 1.

Author(s)	Definition of trust
Rousseau et al. (1998, p. 395)	*“Trust is a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another.”*
(Sheppard & Sherman, 1998)	*"Trust entails the assumption of risks and some form of trust is inherent in all relationships."*
(Mayer et al., 1995)	*“Trust is the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part.”*

Table 1: Various definitions of trust

Furthermore, it is important to distinguish between trust and trustworthiness. Trust is something you place in someone or an object, while trustworthiness displays a characteristic of a person or object of trust (Corritore et al., 2003, p. 741).

2.5.2. Online Trust

In an online setting, trust plays a central role as it is a key element of success (Corritore et al., 2003, p. 737). It has been found that trust reduces the perceived risk in an online environment (Gefen, 2000).

Corritore et al. (2003) define online trust as the trust that develops for a person towards a transactional or informational website. Their definition is limited to websites only, and does not apply to chats, email, instant messengers or educational and gaming websites (Corritore et al., 2003, p. 740).

Corritore et al. (2003) model of online trust (see Figure 2) proposes that the factors credibility, ease of use, and risk have an influence on online trust. External factors may be related to the website, e.g. the interface design, accuracy of information, navigational architecture, and the level of risk or control of user interaction with the website (Corritore et al., 2003, p. 749). Four dimensions of credibility were identified for websites: honesty, expertise, predictability and reputation (Corritore et al., 2003, p. 750). The ease of use reflects how simple a website can be handled (Corritore et al., 2003, p. 751). Additionally, risk is a crucial factor for online trust as it is for offline trust (Corritore et al., 2003, p. 751).

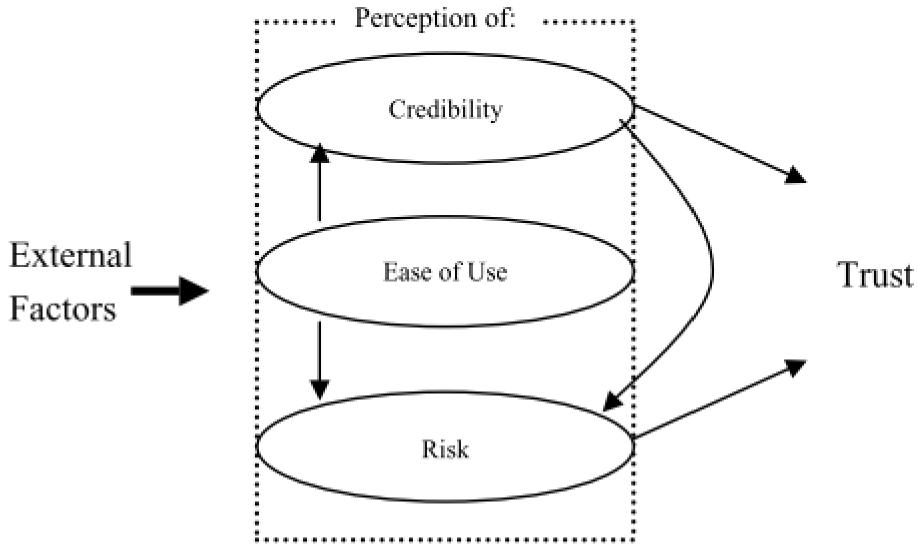

Figure 2: Model of Online Trust by Corritore et al. (2003)

2.5.3. Online Trust in Chatbots

In the context of chatbots, social presence plays an important role when choosing to interact with computer agents (Xu & Lombard, 2017, p. 152). Social presence can be described as a psychological state where virtual actors are perceived as real actors (Lee, 2004, p. 37). Lombard and Ditton (1997) identified two types of social presence: a virtual character presenting social cues within a medium and the medium itself presented as social actor (Lombard & Ditton, 1997). When the medium signals social cues, people are inclined to see the medium as a real person (Xu & Lombard, 2017, p. 155). Therefore, social presence is explained as the phenomenon where people feel as if they were interacting with a real human instead of a technology-driven entity (ISPR, 2009).

A study has shown that social presence of embodied avatars shown on company websites significantly influenced the perceived trust and emotional appeal of the website, if the avatars are perceived as pleasant (Etemad-Sajadi & Ghachem, 2015, pp. 84–85). It was found that social presence is a main driver of trust and online purchase intent (Lu et al., 2016, p. 225). Additionally, social presence was found to positively affect perceived trust in recommendation agents (Hess et al., 2009, p. 908).

Moreover, in order to generate trust with humans, a chatbot needs a face (Meadows, 2017). However, the effect of the "uncanny valley" can occur if the bot seems too realistic (Meadows, 2017). The uncanny valley theory proposes that the more human-like a robot is, the more it invokes positive human emotions towards them. This effect lasts up to a certain point, where emotions become negative when one is not able to differentiate between a real human and a robot (Bartneck et al., 2007, p. 368).

2.5.4. The SCM and Trust

Several studies have shown that warmth and competence have a positive effect on trust (Seiler et al. 2016; Seiler et al. 2015). Aaker et al. (2012) demonstrated that warmth and competence induce trust. Not only do high warmth and high competence lead to admiration of a brand, it also leads to a higher willingness to purchase since the brand is perceived more trustworthy (Aaker et al., 2012, p. 191). However, warmth has a bigger effect on trust than competence (Aaker et al., 2012, p. 194). This was confirmed by a study that showed that in a sales context between a salesperson and the customer, warmth is the primary dimension (Arndt et al., 2014, p. 19).

Other findings also illustrated that warmth is a main driver of preferences towards products or countries (Xu et al., 2013, p. 15). Moreover, the trust model by Martin (2014), displays that high affinity and high competence lead to higher trust (Martin, 2014, p. 47). One can therefore argue that companies should aim to build chatbots high in warmth and competence, in order to be deemed as trustworthy.

3. Hypothesis Statements

This part focuses on the hypotheses that were developed based on current literature. It presents the hypothesis statements that will either be rejected or accepted after the data analysis. The chatbot designs are based on Casciaro and Sousa Lobo's (2005) 2x2 matrix (see Figure 1).

3.1. SCM Theory

The SCM postulates that people are judged on the two primary dimensions: warmth and competence. This concept has been tested and applied to practice by Casciaro and Sousa Lobo (2005). They found out that in an organization, people prefer to work with "lovable stars" (highly warm and competent) and avoid the "incompetent jerk" (low warmth and low competence). Another study showed that consumers admire brands placed in the 'golden quadrant' (highly warm and competent) (Aaker et al., 2012). Based on these findings, the author theorizes following hypotheses relating to the domain of chatbots:

H1: Chatbot 1 (lovable star design) is perceived warmer than Chatbot 2 (incompetent jerk design)
H2: Chatbot 1 (lovable star design) is perceived more competent than Chatbot 2 (incompetent jerk design)
H3: Chatbot 1 (lovable star design) is perceived warmer than Chatbot 3 (simple text chatbot)
H4: Chatbot 1 (lovable star design) is perceived more competent than Chatbot 3 (simple text chatbot)

3.2. Trust

As mentioned in the theoretical framework of this thesis, the dimensions warmth and competence positively affect trust. Brands that are perceived as highly competent and warm are admired and inspire trust (Aaker et al., 2012, p. 191). Additionally, Martin's (2014, p. 47) trust model stipulates that high trust can be achieved through high affinity and high competence. The author therefore derives the following hypotheses on the "lovable star" (highly warmth and competent) connected to chatbots:

H5: Chatbot 1 (lovable star design) is perceived more trustworthy than Chatbot 2 (incompetent jerk design).
H6: Chatbot 1 (lovable star design) is perceived more trustworthy than Chatbot 3 (simple text bot).

4. Methodology

Based on current literature, six hypotheses were developed. In order to test the hypotheses, an online experiment and questionnaire were conducted. The participants were randomly assigned to three groups, each showing a different type of chatbot. The intention was to use avatar designs that reflect the respective high/low warmth and competence characteristics based on the social dimensions model proposed by Casciaro and Sousa-Lobo (2005).

For stimulus material, pictures of sales agents used in a previous study on the "experimental validation of the warmth and competence dimensions in the context of insurance consultants" were used as avatars (Seiler et al., 2016). This study confirmed that the SCM theory is applicable to the domain of insurance consultants, which is why the pictures were selected.

Participants were shown screenshots of a scenario with an insurance agency chatbot (see Appendix 9.2). Chatbot 1 was designed based on high warmth and high competence attributes. Chatbot 2 was based on low warmth and low competence attributes, whereas Chatbot 3 was designed as simple text chatbot to serve as a control. Participants were randomly assigned to one of the chatbots. The text in all scenarios was the same; the only difference was the avatar. This was to make sure that the participants focused on the appearance of the chatbot.

4.1. Research Design

In order to determine whether the SCM theory can be applied to the context of chatbots, a web-based experiment and a questionnaire were developed. The online experiment and questionnaire were created with the online survey tool Unipark.

A questionnaire is used in descriptive research while an experiment is a method used in causal research. The main principle of an experiment is the manipulation of an independent variable(s) and then measures/observation of the effect(s) on the dependent variable (Aaker et al., 2013, p. 324). Experimental research consists of one or more experimental groups and one or more control groups. The experimental group is exposed to the experimental treatment (e.g. low exposure level or medium exposure level in an advertising experiment) while the control group is not exposed to the experimental treatment (Aaker et al., 2013, p. 330). A concept to increase the reliability of an experiment is randomization. Randomization is a process where subjects are randomly assigned to experimental groups (Aaker et al., 2013, p. 331).

4.2. Structure of the Experiment

At the beginning of the questionnaire, the subjects had to answer demographic and psychographic questions. Then, the subjects were randomly assigned to one of the three experimental groups including one control group. The first part of the questionnaire was designed to answer the hypotheses H1 to H6 (see Figure 3). They had to fill out questions concerning the aspects of warmth/likability, competence, and trust. The aim was to find out whether the warmth and competence concept can be applied to the domain of chatbots. In other words, will the subjects rate Chatbot 1 as warm and competent and Chatbot 2 as incompetent and cold? The variable "trust" is the dependent variable in this experiment. The question asked here is whether high warmth and high competence positively affect the perceived trust of a chatbot. In the second part of the questionnaire, general questions were asked.

4.2.1. Manipulation Check

A manipulation check was included after the first part of the questionnaire. The question used as manipulation check was "What is the chatbot's name?". People who answered the question wrongly were excluded from the study.

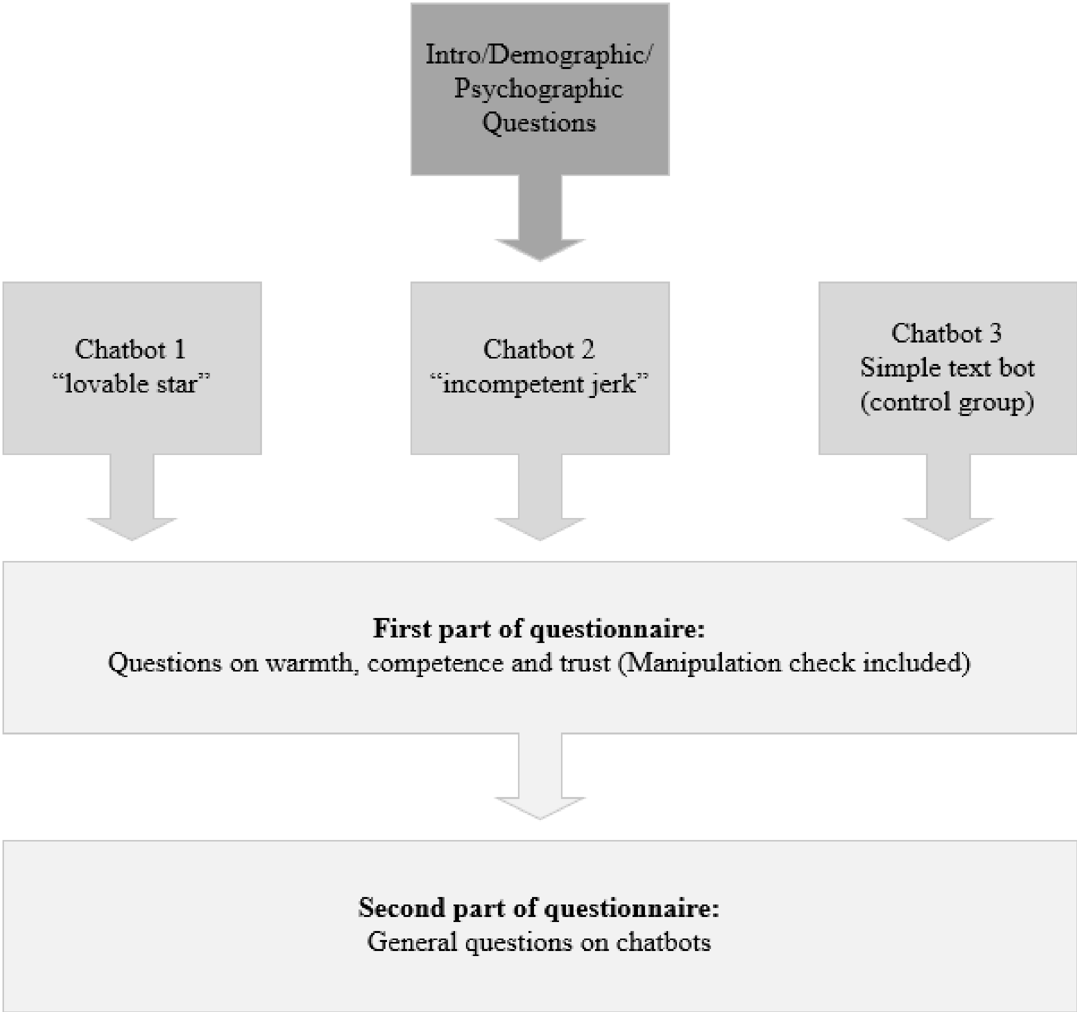

Figure 3: Structure of the experiment

4.3. Questionnaire

The questionnaire (see Appendix 10.1) was designed based on the literature used in the theoretical framework of this thesis. In first part of the questionnaire, only previously tested and reliable multiple-item scales were used. Multiple-item scales were selected since they have a clear advantage over single item scales in terms of predictive validity (Diamantopoulos et al., 2012, p. 434). A seven point semantic differential and Likert scale were used for the majority of the questions. Likert scales are widely used in research and in practice since quantitative data can be analyzed with relative ease (Kuss, 2012, p. 93).

Another widespread scale used in marketing research is the semantic differential. It is used for measuring the attitudes or feelings of the participants by using a pair of contrasting adjectives (Kuss, 2012, p. 96).

The author translated the scales taken from previous studies from English to German, in order to generate more responses. This is because the experiment/questionnaire was sent to a mainly German-speaking sample. A native English speaker was consulted to ensure an accurate translation.

4.3.1. Demographic questions

The demographic questions at the beginning of the questionnaire contained items about age, gender, marital status, education, job status, workload, postal code and canton (see Appendix 10.1). In order not to upset the participants, the option “not applicable” was added to the mandatory questions.

At the end of the demographics part, four psychographic questions were asked. A seven point Likert scale was used to ask whether the participant agreed/disagreed on being technology-oriented, an early adopter of technology, whether he/she is up to date on digital news and whether he/she regularly uses social media. These questions were asked to gain more insight into the practical use of chatbots.

4.3.2. Warmth items

The variable warmth/likability was measured with the scale used by Reinhard, Messner and Sporer (2006, p. 254). The scale used was a seven point semantic differential.

ID	**Scale**
W1	Dislikable - Likable
W2	Unfriendly – Friendly
W3	Awful – Nice
W4	Unkind - Kind

Table 2: Warmth scale used by Reinhard, Messner and Sporer (2006)

4.3.3. Competence items

Competence was measured with the construct "expertise" used by Reinhard, Messner and Sporer (2006, p. 254) on a seven point semantic differential scale.

ID	Scale
C1	Inexpert – Expert
C2	Inexperience – Experienced
C3	Unknowledgeable – Knowledgeable
C4	Unqualified – Qualified
C5	Unskilled - Skilled

Table 3: Competence scale used by Reinhard, Messner and Sporer (2006)

4.3.4. Trust items

Measured on a seven point semantic differential scale as well, the trust items were drawn from Reinhard, Messner and Sporer (2006, p. 254), as shown in Table 4.

ID	Scale
T1	Not dependable – Dependable
T2	Dishonest – Honest
T3	Unreliable – Reliable
T4	Insincere – Sincere
T5	Untrustworthy - Trustworthy

Table 4: Trust scale used by Reinhard, Messner and Sporer (2006)

4.3.5. General questions

The second part of the questionnaire was composed of general questions about chatbots. A Likert scale was used for all questions except for one open-ended question at the end of the questionnaire. The same seven point Likert scales were consistently used throughout the questionnaire in order to statistically examine the relationship between the variables across the questionnaire.

No tested and reliable scales on measuring the characteristics/usage of a chatbot were found. Instead, questions were grouped by the most relevant topics, based on extensive literature research from scientific journals and websites. The lack of tested scales can be explained by the fact that the chatbot technology is relatively new.

5. Collection of Primary Data

The questionnaire was first sent to a group of six people in order to receive feedback on it. Some questions were changed and inconsistencies removed after receipt of their feedback. The final version of the questionnaire was sent to family, friends and ZHAW students on April 24, 2018. It was open for responses until May 3, 2018.

5.1. Sample selection

The aim was to have at least n=30 subjects in all three experimental groups. This is because of the central limit theorem which states that if the sample size is large enough, then the distribution of the sample means will be approximately normal (Kuss, 2012, p. 218). A sample size of at least 30 usually leads to a normal distribution of sample means (Kuss, 2012, p. 218).

A total of n=140 subjects have fully completed the questionnaire. A sample of n=46 people were assigned to Chatbot 1, n=44 to Chatbot 2 and n=50 people saw Chatbot 3. Since there are at least n=30 subjects per group, a normal distribution of the sampling means in all three groups can be assumed.

6. Analysis of Data

In this section the primary data collected from the experiment/questionnaire is analyzed. An introduction to the statistical methods used is given and the hypotheses will be tested using these methods. Additional statistical analysis is carried out to provide more insight into the relationship between the variables.

6.1. Data Preparation

For the analysis of the data, only subjects who completed the entire questionnaire and successfully passed the manipulation check were considered. Those who failed to pass the manipulation check were removed as it is assumed that they did not pay enough attention to the pictures and questions.

This leaves Chatbot 1 with n=38 subjects, Chatbot 2 with n=41 and Chatbot 3 with n=50 subjects, since all participants assigned to Chatbot 3 passed the manipulation check. A total of n=129 responses were considered for the data analysis. A normal distribution of the sample means is still assumed since there is a minimum of n=30 subjects per group.

The software "IBM SPSS Statistics 24" was used for the evaluation of the data. All responses generated from Likert and semantic differential scales have a numeric value. The numbers all run in the same direction and ranging from 1 (Strongly disagree/Not important) to 7 (Strongly agree/Very important). The semantic differential scales range from 1 to 7 from one adjective to the other.

6.2. Statistical Methods

The statistical methods used for the hypothesis testing are described in this section.

First, it is important to consider the type of data when choosing a statistical technique (Aaker et al., 2013, p. 413). Scales of measurements can be sorted into nominal, ordinal, interval and ratio scales (Aaker et al., 2013, p. 413).

The nominal scale (nonmetric data) is made up of categorical data such as gender and age (Aaker et al., 2013, p. 413). Only a few statistical analyses can be performed with this type of data. The chi-square test is one of them and will be used in this thesis. It measures the independence of two categorical variables to see if there is a relationship between them (Aaker et al., 2013, p. 431).

The most useful type of data for statistical analysis are interval and ratio (metric) data (Aaker et al., 2013, p. 413). The Likert and semantic differential scales used in this thesis are classified as interval scales. Metric data can be tested using a set of statistical tests explained in the next paragraphs.

To test difference between two sample means, an independent sample t-test was used (Field, 2013, p. 365). A significance level of $p \leq 0.05$ was chosen (Kuss, 2012, p. 221). The same level of significance ($p \leq 0.05$) was used for the Levene's test (Field, 2013, p. 193).

To determine the strength of association between two variables, Pearson correlation coefficient *r* is used (Kuss, 2012, p. 207). The coefficient value can range from +1 to -1 (perfect positive or negative correlation) and a value of 0 indicates no correlation between the variables (Kuss, 2012, p. 210).

6.3. Descriptive Statistics

After cleaning the data, a total of 129 responses were recorded. A number of 38 participants saw Chatbot 1, 41 people were assigned to Chatbot 2 and 50 people saw Chatbot 3 as shown in Table 5.

	Number of people	**Percent**
Chatbot 1	38	29.46%
Chatbot 2	41	31.78%
Chatbot 3	50	38.76%
Total	129	100%

Table 5: Number of participants per experimental group

Participants were 60 women (46.5 percent), 66 men (51.2 percent) and 3 people (2.3 percent) preferred not to state their gender (see Table 18) The age of participants ranged from 19 to 54 with an average age of 27.41 years after the removal one outlier, a reported value of 322 years (see Table 19). A chi-square test of independence was calculated comparing the frequency of men and women per experimental group (see Table 20). No association between gender and experimental group was observed ($\chi^2(2) = 1.059$, $p = 0.588$). The results were calculated with Excel as an exception.

The majority of the participants indicated that their marital status is single (87.6 percent, n=113), 8.5 percent of the participants are married (n=11), 1.6 percent are divorced (n=2), and 2.3 percent (n=3) did not state their marital status (see Table 21).

As highest level of education, 45.7 percent (n=59) of the subjects indicated that they have a high school degree. This is followed by a degree from a university of applied sciences with 26.4 percent (n=34). Next, 9.3 percent (n=12) of the participants completed an apprenticeship and 7.8 percent (n=10) have a Swiss federal diploma of higher education and also 7.8 percent (n=10) have a degree from a state recognized Swiss university or a polytechnic institute. Some did not indicate their highest level of education (3.1 percent, n=4) (see Table 22).

Most participants are part-time students with a job (48.8 percent, n=63). With 20.9 percent (n=27), some participants are employed on a full-time basis. There are 15.5 percent (n=20) full-time students with a job, 8.5 percent (n=11) full-time students without a job, 1.6 percent (n=1) part-time students without a job and 1.6 percent (n=2) did not state their current occupation (see Table 23).

Regarding the workload of the participants, 25.6 percent (n=33) of the subjects work on a part-time basis of 80 percent. Then, 20.9 percent (n=27) work on a full-time basis of 100 percent. This is followed by a workload of 60 percent (14.7 percent, n=19). The subjects indicated working on a part-time basis of 40 percent (7 percent, n=9), 0 percent (6.2 percent, n=8), 50 and 20 percent (4.7 percent, n=6), 70 percent (2.3 percent, n=3), 10 percent (1.6 percent, n=2), 30 percent (.8 percent, n=1) and finally 7 percent (n=9) did not share their workload (see Table 25).

The participants were asked in which Swiss canton they reside. The question about the postal code was excluded as it is similar to the question about the residential canton. With 69 percent (n=89), most subjects live in the canton of Zurich. Others live in the canton of

Thurgau with 7.8 percent (n=10), followed by the canton St. Gallen with 4.7 percent (n=6) then the canton of Schwyz with 3.9 percent (n=5), canton Schaffhausen and Aargau with both 3.1 percent (n=4), Glarus with 2.3 percent (n=3), Basel-Stadt and Zug with each 1.6 percent (n=2), and lastly the cantons Appenzell Ausserrhoden, Graubünden, and Wallis with each .8 percent (n=1) participants (see Table 24).

6.4. Psychographic Information

Continuing from the demographic information, a set of four psychographic questions were asked. Participants were asked to indicate on a seven point Likert scale to which extent they agree (1 for strongly disagree to 7 for strongly agree) to the questions in Table 6.

A comparison of the means (see Table 6) show that participants agree the most with regularly using social media (M = 4.94, SD = 1.90), followed by being technology-oriented (M = 4.77, SD = 1.53), then being up to date with digital trends (M = 4.03, SD = 1.69), and finally they agree the least with being an early adopted (M = 3.52, SD = 1.61).

	Descriptive Statistics			
		Mean	Std. Deviation	N
PSY1	I am technology-oriented	4.77	1.534	129
PSY2	I am an early adopter (first person to acquire new technology)	3.52	1.611	129
PSY3	I follow digital trends (always up to date)	4.03	1.686	129
PSY4	I regularly use social media	4.94	1.899	129
	Valid N			129

Table 6: Psychographic information

6.5. Reliability

The reliability of the items scales were tested by using Cronbach's alpha. An alpha value of larger than 0.7 or 0.8 indicates good reliability (Field, 2013, p. 715). All construct values range from .777 to .942 (see Table 7). The analysis is continued with these constructs since no items need to be excluded.

Construct		Cronbach's Alpha	Number of Items
Warmth	Chatbot 1	.823	4
	Chatbot 2	.824	4
	Chatbot 3 (Control group)	.777	4
Competence	Chatbot 1	.942	5
	Chatbot 2	.916	5
	Chatbot 3 (Control group)	.925	5
Trust	Chatbot 1	.917	5
	Chatbot 2	.940	5
	Chatbot 3 (Control group)	.874	5

Table 7: Cronbach's Alpha Values

6.6. Hypothesis Testing

In this part the hypotheses stated in section 3.1-3.2 will be tested using the statistical methods described in section 6.2.

6.6.1. Hypothesis 1

Hypothesis 1 states that Chatbot 1 (lovable star design) is perceived warmer than Chatbot 2 (incompetent jerk design).

An independent-samples t-test (see Table 26) indicated that warmth scores were significantly higher for Chatbot 1 ($M = 4.59$, $SD = 1.57$) than for Chatbot 2 ($M = 3.13$, $SD = 1.390$), $t(314) = 8.72$, $p < .001$. Therefore, hypothesis number 1 is accepted.

6.6.2. Hypothesis 2

To test whether there is a significant difference between perceived competence in Chatbot 1 and 2, the same procedure used for H1 is applied for H2 test (see Table 27).

Scores on the competence scale were higher for Chatbot 1 ($M = 5.01$, $SD = 1.45$) than for Chatbot 2 ($M = 4.29$, $SD = 1.563$), $t(393) = 4.72$, $p < .001$. As this result is significant, hypothesis number 2 is accepted.

6.6.3. Hypothesis 3

For hypothesis number 3, an independent-samples t-test was used to examine the warmth scores of Chatbot 1 and Chatbot 3 (Table 28).

The result showed that scores on the warmth scale were significantly higher for Chatbot 1 ($M = 4.59$, $SD = 1.57$) than for Chatbot 3 ($M = 3.82$, $SD = 1.604$), $t(350) = 4.51$, $p < .001$). This supports hypothesis number 3, which is thus reported as accepted.

6.6.4. Hypothesis 4

Hypothesis number 4 hypothesizes that Chatbot 1 is judged as more competent than Chatbot 3 (see Table 29).

The independent-samples t-test indicated that perceived competence was higher for Chatbot 1 ($M = 5.01$, $SD = 1.45$) than for Chatbot 3 ($M = 3.97$, $SD = 1.43$), $t(438) = 7.52$, $p < .001$). This shows support of hypothesis number 4, leading it to be accepted.

6.6.5. Hypothesis 5

In order to examine the differences between the trust scores of Chatbot 1 and Chatbot 2, an independent-samples t-test was used (see Table 30).

The result indicated that Chatbot 1 ($M = 4.51$, $SD = 1.58$), received significantly higher trust ratings than Chatbot 2 ($M = 4.15$, $SD = 1.59$), $t(393) = 2.25$, $p < .05$). Chatbot 1 is perceived more trustworthy and thus hypothesis number 5 is accepted.

6.6.6. Hypothesis 6

Hypothesis number 6 states that Chatbot 1 (lovable star design) is seen more trustworthy than Chatbot 3 (simple text bot). The same t-test was used for hypothesis 6 (see Table 31).

There was no significant difference in the perceived trust of Chatbot 1 ($M = 4.51$, $SD = 1.58$) and Chatbot 3 ($M = 4.43$, $SD = 1.30$), $t(438) = .599$, $p > .05$. Therefore, hypothesis number 6 is rejected.

6.6.7. Results

After testing all hypotheses, the following results (see Table 8) have been generated.

Number	Hypothesis	Result
1	Chatbot 1 (lovable star design) is perceived warmer than Chatbot 2 (incompetent jerk design)	Accepted
2	Chatbot 1 (lovable star design) is perceived more competent than Chatbot 2 (incompetent jerk design)	Accepted
3	Chatbot 1 (lovable star design) is perceived warmer than Chatbot 3 (simple text chatbot)	Accepted
4	Chatbot 1 (lovable star design) is perceived more competent than Chatbot 3 (simple text chatbot)	Accepted
5	Chatbot 1 (lovable star design) is perceived more trustworthy than Chatbot 2 (incompetent jerk design).	Accepted
6	Chatbot 1 (lovable star design) is perceived more trustworthy than Chatbot 3 (simple text bot).	Rejected

Table 8: Results overview of the hypothesis testing

6.7. Further Analysis

In the second part of the questionnaire, general questions about chatbots were asked. The author grouped the questions by usage, purpose, characteristics of a chatbot (Avatar, design, and privacy policy), sharing personal information, and reasons not to use a chatbot. A seven point Likert scale was used for all items except for one last open ended question. The means will be compared to analyze the data.

6.7.1. Usage

A comparison of the means (see Table 9) shows that the majority of the participants have used/interacted with a chatbot before (M = 4.60, SD = 2.68), while some have never used/interacted with a chatbot (M = 3.37, SD = 2.61). Only a few regularly interact with a chatbot (M = 2.23, SD = 1.51).

When splitting the seven-point Likert scale into one bottom half (Ratings from 1-3, strongly disagree to disagree) and one upper half (Ratings from 4-7, agree to strongly agree), the responses can be turned into categorical data which yielded the following results:

With 39.6 percent, participants indicated that they have never used a chatbot before. Whereas 62.8 percent said that they have used a chatbot before, but only 23.3 percent of the subjects regularly use a chatbot.

	Descriptive Statistics			
		Mean	Std. Deviation	N
U1	I have never used a chatbot	3.37	2.610	129
U2	I have used a chatbot before	4.60	2.682	129
U3	I regularly use chatbots	2.23	1.508	129
	Valid N (listwise)			129

Table 9: Comparison of means - Usage of chatbots

6.7.2. Purpose

Looking at the means of Table 10, participants mainly use chatbots as part of a customer support service (LiveChat) platform (M = 3.64, SD = 2.49). The second most common usage of a chatbot is for online shopping (M = 1.81, SD = 1.51).

	Descriptive Statistics			
		Mean	Std. Deviation	N
P1	Weather information	1.3178	.90125	129
P2	Online shopping	1.8140	1.51435	129
P3	Booking flights	1.6589	1.40031	129
P4	Booking hotels	1.6202	1.33577	129
P5	Insurance advice	1.6822	1.50512	129
P6	Financial aid	1.5039	1.31769	129
P7	Customer Service (LiveChat)	3.6434	2.48684	129
	Valid N (listwise)			129

Table 10: Comparison of means - Reasons for using a chatbot

Other reasons indicated for using a chatbot were IT-Support, testing, social media / online games, tourism inquiries, and planning a language stay.

6.7.3. Avatar

The subjects were asked about the most important aspects of a chatbot avatar (see Table 11). The most important trait is that the avatar fits to the company (M = 5.08, SD = 2.15). It is somewhat important for a chatbot to have an avatar at all (M = 3.43, SD = 2.22), but less important that the avatar shows a real person (M = 3.03, SD = 2.10). It is rather unimportant to show a static avatar picture (M = 2.60, SD = 1.79), be animated (M = 2.36, SD = 1.79), or to be cartoonish (M = 2.29, SD = 1.59).

	Descriptive Statistics			
		Mean	Std. Deviation	N
A1	The chatbot has an avatar	3.43	2.218	129
A2	The avatar shows a real person	3.03	2.095	129
A3	The avatar is cartoonish	2.29	1.587	129
A4	The avatar is animated (can speak and move)	2.36	1.785	129
A5	The avatar is static (only a an image, no sound/movement)	2.60	1.792	129
A6	The avatar fits to the company	5.08	2.146	129
	Valid N (listwise)			129

Table 11: Comparison of means – Avatar

6.7.4. Characteristics

A set of questions regarding the characteristics of a chatbot were asked (see Table 12) The results show that it is very important for a chatbot to process inquiries correctly (M = 6.53, SD = 1.23) and fast (M = 6.31, SD = 1.18). An open communication is important for the people, meaning that it is shown that the client is now talking to a chatbot and not a real person (M = 5.89, SD 1.489). It is also quite important to show a data privacy policy at the beginning of the interaction (M = 5.35, SD = 1.79). Other factors considered as rather important is that the chat windows has a modern design (M = 5.04, SD = 1.67) and that it is big enough (M = 4.81, SD = 1.56).

	Descriptive Statistics			
		Mean	Std. Deviation	N
CR1	The chat window is big enough	4.81	1.562	129
CR2	The chat window has modern design	5.04	1.670	129
CR3	Inquiries are processed correctly	6.53	1.225	129
CR4	Inquiries are processed fast	6.31	1.178	129
CR5	The chatbot lets you know that you are chatting with a bot	5.89	1.480	129
CR6	Data privacy policy is shown on the screen	5.35	1.788	129
	Valid N (listwise)			129

Table 12: Comparison of means – Characteristics

6.7.5. Consulting / Personal information

The subjects were questioned about a chatbot's consulting service and whether they would share personal information during a consulting session (see Table 13).

People see a great potential for the chatbot technology (M = 4.45, SD = 1.858), and they are willing to take advice from a chatbot (M = 4.40, SD = 1.96). They believe that companies are somewhat ready for this technology (M = 3.75, SD = 1.72) However, the people are clearly averse to sharing their personal information. They are more willing to share their date of birth (M = 3.09, SD = 1.98) than pictures (M = 2.74, SD = 1.86), or their address (M = 2.57, SD = 1.79). The participants are especially reluctant to share their payment details with a bot (M = 1.80, SD = 1.35).

	Descriptive Statistics			
		Mean	Std. Deviation	N
CP1	I would take advice from a chatbot (e.g. customer service, insurance or financial advice, usw.).	4.40	1.958	129
CP2	I would share payment details in the chat window	1.80	1.354	129
CP3	I would share pictures in the chat window	2.74	1.859	129
CP4	I would share address data in the chat window	2.57	1.789	129
CP5	I would share my date of birth in the chat window	3.09	1.978	129
CP6	I see great potential for this technology	4.45	1.858	129
CP7	Companies are ready for this technology	3.75	1.723	129
	Valid N (listwise)			129

Table 13: Comparison of means – Consulting

6.7.6. Reasons not to use a chatbot

When asked about the reasons why the subjects would not use a chatbot, people reported that they still value and prefer human contact (M = 5.35, SD = 1.72). This is followed by the fact that people still prefer to look for information on a company's website by themselves (M = 4.82, SD = 1.684). A high error rate (M = 3.94, SD = 1.56) and the trust in the technology (M = 3.61, SD = 1.69) were only moderate factors. Landing in the middle of the scale, people indicated that they have no concerns and would take advice from a chatbot (M = 3.5, SD = 1.82). The means are reported in Table 14.

	Descriptive Statistics			
		Mean	Std. Deviation	N
NU1	I prefer human contact	5.35	1.721	129
NU2	I do not trust this technology	3.61	1.692	129
NU3	The error rate is too high	3.94	1.560	129
NU4	I prefer looking for information on the website by myself	4.82	1.684	129
NU5	I am scared of chatbots	2.44	1.794	129
NU6	I have no concerns and would take advice from a chatbot	3.50	1.816	129
	Valid N (listwise)			129

Table 14: Comparison of means – Reasons not to use a chatbot

6.7.7. Reasons not to share private information

Data privacy is of great concern for the participants (see Table 15). The results report that people do not want their data to be shared with third parties (M = 5.85, SD = 1.69), nor collected at all (M = 5.36, SD = 1.92). People also do not trust the chatbot technology (M = 4.12, SD = 1.92). Additionally, the subjects denied having no concerns about sharing private information with a bot (M = 2.23, SD = 1.46).

	Descriptive Statistics			
		Mean	Std. Deviation	N
NP1	I do not trust this technology	4.12	1.920	129
NP2	I do not want my data to be collected	5.36	1.924	129
NP3	I do not want my data to be shared with third parties	5.85	1.687	129
NP4	I have no concerns and would share private information	2.23	1.455	129
	Valid N (listwise)			129

Table 15: Comparison of means – Private information

6.7.8. Improving Chatbots

At the end of the questionnaire, participants were asked what companies should improve so they would use their chatbot service more often. The question was open-ended. The answers were categorized and ranked in the following order, starting with the most mentioned suggestion for companies:

1. Lower error rates
2. More personalized advice
3. Faster process of inquiries
4. Open communication, reveal that you are now talking to a bot
5. Modern interface
6. Data privacy policy

The suggestions are in line with the findings in section 6.7.4., where the most important feature of a chatbot was chosen to be the correct processing of inquiries. Additionally, individualized advice from a chatbot is highly regarded. This personalized advice includes the bot's ability to answer to specific questions and coming across more personal (No standard/robotic replies to questions).

A fast process was mentioned often, which is also one of the findings in section 6.7.4. Moreover, transparency is important when interacting with a chatbot. People indicated that they were frightened when a bot unexpectedly addressed the person by his/her name. The bot should not pretend to be a real person. Furthermore, people welcome a modern and responsive design when it comes to the chatbot technology. Lastly, data privacy is a crucial matter, as people prefer not to have their data collected without their permission.

6.8. Correlations

To examine the relationships between the variables, several correlation analyses were conducted in this section.

6.8.1. Psychographic Information / Usage

The four psychographic questions were correlated with the items concerning the usage of chatbots (see Table 32).

There is a significant negative relationship between PSY3 and U1 ($r = -.316$, $p<0.05$), as well as a significant positive relationship between PSY3 and U2 ($r = .357$, $p<0.05$). Furthermore, PSY4 significantly correlates with U1 ($r = -.401$, $p<0.01$), and with U2 ($r = .377$, $p<0.05$), and also with U3 ($r = .407$, $p<0.05$).

6.8.2. Psychographic Information / Avatar

Correlations between the perception of chatbot avatars and psychographic information were conduction to analyze the relationships between the variables (see Table 33).

The results show a significant positive relationship between PSY1 and A6 ($r = .298$, $p<0.05$). Additionally, the variable PSY3 significantly correlates with A3 ($r = .320$, $p<0.05$).

6.8.3. Psychographic Information / Characteristics

The characteristics items were correlated with the psychographic items A significant relationship exists between PSY1 and CR1 ($r = .312$, $p<0.05$), as well as between PSY1 and CR2 ($r = .312$, $p<0.05$), between PSY1 and CR3 ($r = .280$, $p<0.05$), and between PSY1 and CR5 ($r = .332$, $p<0.05$). Moreover, a high correlation between PSY3 and CR2 ($r = .422$, $p<0.01$) was detected. All correlations are illustrated in Table 34.

6.8.4. Psychographic Information / Personal Information

All correlations between psychographic questions and the questions about consulting and sharing personal data can be seen in Table 35.

The highest significant correlations are between the items PSY2 and CP3 ($r = .401$, $p<0.01$), PSY2 and CP6 ($r = .394$, $p<0.01$) and between the items PSY1 and CP4 ($r = .360$, $p<0.05$).

6.8.5. Psychographic Information / Reasons Not to Use a Chatbot

The relationship between reasons not to use a chatbot and psychographic information were analyzed and summed up in Table 36.

A significant negative relationship exists between the variables PSY3 and NU2 ($r = -.378$, $p<0.01$) and between the items PSY2 and NU2 ($r = -.339$, $p<0.05$). In addition, PSY1 correlates with NU6 ($r = .340$, $p<0.05$).

6.8.6. Psychographic Information / Reasons Not to Share Information

Finally, the psychographic items were correlated with reasons not to share private information (Table 37).

There is a significant negative correlation between PSY2 and NP1 ($r = -.390$, $p<0.01$) and a significant positive relationship between PSY3 and NP1 ($r = -.299$, $p<0.05$).

7. Discussion

This part shows an overview of the results found in the data analysis part in section 6. It discusses and interprets the findings of this study.

7.1. Discussion of Hypotheses H1 to H6

The results show that Chatbot 1 (Lovable star design) is perceived significantly warmer than Chatbot 2 (Incompetent jerk design), as well as Chatbot 3 (Simple text bot as a control). Furthermore, Chatbot 1 is also rated more competent than Chatbot 2 and Chatbot 3, since the outcome displayed a statistically significant difference between the perceived competences. Consequently, the hypotheses H1 to H4 have all been accepted. Hypothesis H5 was accepted, as Chatbot 1 is seen as more trustworthy than Chatbot 2. However, hypothesis H6 is rejected since there was no significant difference between the trust scores of Chatbot 1 and Chatbot 3.

Despite hypothesis H6 being rejected, the participants were still able to successfully judge the chatbots on the dimensions warmth and competence (Casciaro & Sousa Lobo, 2005; Fiske et al., 2007), which is suggested through the acceptance of hypotheses H1 to H4.

The rejection of hypothesis H6 may be explained by a lack of transparency. The findings of this study show that open communication by a bot is important ($M = 5.89$). If the participants are not certain whether they are talking to a bot or a real human (Chatbot 1 showed a real person as avatar), it may negatively impact their trust towards the technology/company.

Another explanation would be that the participants experienced the "uncanny valley effect" with Chatbot 1, which negatively affects trust. This reason is in line with a study that showed how a simpler text chatbot is perceived as less uncanny than a more complex chatbot (Ciechanowski et al., 2018, p. 1). Modelling an avatar with a less realistic face can decrease the uncanny valley effect (Meadows, 2017). However, it should be noted that the uncanny effect is associated with appearance and movements of a robot, whereas in this study a disembodied chatbot with static avatar was used.

7.2. Discussion of the General Questions

The findings report that 62.8 percent of the people have used a chatbot before, however, only 23.3 percent regularly use a bot. This shows how the chatbot technology has not yet reached a widespread adoption. Additionally, the chatbots used are mostly in connection with a customer live chat service provided by a company. Other types of chatbots are not quite known nor utilized, such as bots for insurance and financial advice or for booking flights/hotels.

Moreover, the results show that it is important to have a chatbot avatar that suits the company's image (M = 5.08). This result is in accordance to another study which found that an online avatar should accurately reflect a firm's corporate identity in order to enhance the perception of the website's quality (Etemad-Sajadi & Ghachem, 2015, p. 85). Having an avatar at all is rather unimportant to the subjects (M = 3.43), and it is even slightly less important that the avatar shows a real person (M = 3.03).

According to the questionnaire's responses, the two most important characteristics a chatbot should have is the correct and fast processing of a customer's inquiry. A recent survey conducted in the USA had similar results where 30 percent of the respondents worry about the chatbot making a mistake and 75 percent of the people expect an immediate response from a bot (Devaney, 2018).

Generally, the participants have a positive attitude towards taking advice from a bot and they see a great potential for this technology in the future. However, they are opposed to sharing personal information with a bot, especially when it comes to payment details. While chatbots have existed for some time, they are still new to many consumers and recent cybercrime activities around the world have raised concerns about data privacy. The findings of this study reveal that people do not want their data to be collected or shared with others.

Furthermore, the subjects still prefer human contact over a bot and they prefer looking for information on the website themselves. The survey results from Devaney (2018) also showed that people prefer dealing with a real-life assistant (43 percent) and they favor using a normal website (26 percent).

7.3. Discussion of the Correlations

There is a negative correlation between PSY4 and U1, as well as a positive correlation between PSY3 and U2. This suggests that people who indicated using social media regularly and people who follow digital trends, are more likely to have interacted with a chatbot before. Additionally, those who follow digital trends are more likely to appreciate a cartoon-ish looking chatbot avatar. This can be explained by the fact that a cartoon-ish avatar is more modern and appeals to people with a digital mindset. A correlation between PSY3 and CR2 also shows a preference of a modern chat window design by participants who follow digital trends.

A positive correlation exists between being an early adopter of technology (PSY2) and sharing pictures with a chatbot (CP3). PSY2 also correlates with CP6, which means early adopters are more open to the chatbot technology.

The variables PSY3 and NU2 negatively correlate, suggesting that people who follow digital trends, are more inclined to trust chatbots. The items PSY2 and NP1 also correlate, which implies that early adopters tend to have more faith in the chatbot technology.

Importantly, while some correlations were significant, they did not exceed a value of -.5 or .5. These numbers implicate rather low correlations and therefore the results should be treated with caution – using them only as a pointer in the right direction.

7.4. Conclusion and Implications for Practice

The aim of this Bachelor thesis is to find out whether the SCM theory can be applied to the domain of chatbots. Stimulus material in the form of chatbot avatar pictures were chosen and implemented into an online experiment/questionnaire with three experimental groups, including one control group.

Hypotheses H1 to H4 all postulate that Chatbot 1, which is designed as a “lovable star” (highly warm and competent), is perceived warmer and more competent than Chatbot 2 and Chatbot 3. As opposed to Chatbot 1, Chatbot 2 is designed as “incompetent jerk” (incompetent and cold), while Chatbot 3 is a simple text chatbot (control variable). The results revealed that Chatbot 1 was rated significantly warmer and more competent than Chatbot 2 and Chatbot 3.

Moreover, past studies have shown that warmth and competence positively affect trust. This statement is only partially confirmed with the acceptance of hypothesis H5, where Chatbot 1 received significantly higher trust scores than Chatbot 2. Hypothesis H6 on the other hand was rejected, as Chatbot 1 was not perceived as significantly more trustworthy than Chatbot 3.

In conclusion, with the acceptance of the hypotheses H1 to H4, this study suggests that the SCM principle can be applied to the domain of chatbots. Should a company decide to launch a chatbot with avatar, it is therefore recommended to model their avatars as "lovable stars", as they are seen as highly warm and competent. However, with regard to the rejected hypothesis number 6, it is suggested for businesses to be upfront about their chatbot technology. Consumers want to know that they are talking to a chatbot and not a real human. In order to avoid the uncanny valley effect, it is recommended to use a less realistic, cartoon-like avatar as a modern approach.

The findings further reveal that an avatar should suit the company's image and corporate identity. Firms should aim to reduce the chatbot's failure rates, enable a fast processing of inquiries and offer more personalized consulting sessions. The participants do not appreciate standardized responses. In addition, data privacy is an important matter for the subjects. They are averse to sharing personal information and the collection of their data. Companies should therefore be cautious about asking their clients for sensitive information, particularly when it comes to payment details.

To summarize, this study is the first to investigate whether the SCM theory can be transferred to the context of text-based chatbots/converstational agents. Based on the findings, the author claims that it is possible to apply the SCM to the domain of chatbots. As a result, this thesis contributes to closing the research gap in this field. It is a small step to improving human-computer communication by displaying highly warm and competent chatbots. Future research will have to focus on the trust aspects of a chatbot, as the "lovable star" chatbot was not seen as significantly more trustworthy than the simpler text chatbot.

8. Limitations

For this web-experiment, Casciaro and Sousa-Lobo's (2005) model was used as a basis for the chatbot designs. However, only two of the four quadrants were considered in this research. Further studies in the area of chatbots/conversational agents need to be made with regard to the two other quadrants “competent jerk” and “lovable fool”. Additionally, this Bachelor thesis only focuses on the appearance of a chatbot. The explicit content (text) and the tonality of a bot were not examined.

Furthermore, it should be noted the participants were not able to actually interact with a chatbot, instead, they were exposed to screenshots of a conversation with a bot. The missing interaction could be an important factor for future studies to consider. Another aspect to point out is that the majority of subjects who took part in the experiment/questionnaire are part-time students with jobs, residing in the canton of Zurich.

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10. Appendices

10.1. Questionnaire

ID	Question/Scale	Source
DEM1	How old are you?	Own item
DEM2	What is your gender?	Own item
DEM3	Marital status	Own item
DEM4	Highest level of education	Own item
DEM5	Occupation	Own item
DEM6	Please indicate your workload	Own item
DEM7	Please indicate your postal code	Own item
DEM8	Please indicate the canton you live in	Own item
PSY1	I am technology-oriented	Own item
PSY2	I am an early adopter (first person to acquire new technology)	Own item
PSY3	I follow digital trends (always up to date)	Own item
PSY4	I regularly use social media	Own item
W1	Dislikable - Likable	Reinhard, Messner and Sporer (2006, p. 254)
W2	Unfriendly – Friendly	Reinhard, Messner and Sporer (2006, p. 254)
W3	Awful – Nice	Reinhard, Messner and Sporer (2006, p. 254)
W4	Unkind - Kind	Reinhard, Messner and Sporer (2006, p. 254)
C1	Inexpert – Expert	Reinhard, Messner and Sporer (2006, p. 254)
C2	Inexperience – Experienced	Reinhard, Messner and Sporer (2006, p. 254)
C3	Unknowledgeable – Knowledgeable	Reinhard, Messner and Sporer (2006, p. 254)

C4	Unqualified – Qualified	Reinhard, Messner and Sporer (2006, p. 254)
C5	Unskilled - Skilled	Reinhard, Messner and Sporer (2006, p. 254)
T1	Not dependable – Dependable	Reinhard, Messner and Sporer (2006, p. 254)
T2	Dishonest – Honest	Reinhard, Messner and Sporer (2006, p. 254)
T3	Unreliable – Reliable	Reinhard, Messner and Sporer (2006, p. 254)
T4	Insincere – Sincere	Reinhard, Messner and Sporer (2006, p. 254)
T5	Untrustworthy - Trustworthy	Reinhard, Messner and Sporer (2006, p. 254)
MC	What is the bot's name?	Own item
U1	I have never used a chatbot	Own item
U2	I have used a chatbot before	Own item
U3	I regularly use chatbots	Own item
P1	Weather information	Own item
P2	Online shopping	Own item
P3	Booking flights	Own item
P4	Booking hotels	Own item
P5	Insurance advice	Own item
P6	Financial aid	Own item
P7	Customer Service (LiveChat)	Own item
A1	The chatbot has an avatar	Own item
A2	The avatar shows a real person	Own item
A3	The avatar is cartoonish	Own item
A4	The avatar is animated (can speak and move)	Own item
A5	The avatar is static (only a an image, no sound/movement)	Own item
A6	The avatar fits to the company	Own item

CR1	The chat window is big enough	Own item
CR2	The chat window has modern design	Own item
CR3	Inquiries are processed correctly	Own item
CR4	Inquiries are processed fast	Own item
CR5	The chatbot lets you know that you are chatting with a bot	Own item
CR6	Data privacy policy is shown on the screen	Own item
CP1	I would take advice from a chatbot (e.g. customer service, insurance or financial advice, usw.).	Own item
CP2	I would share payment details in the chat window	Own item
CP3	I would share pictures in the chat window	Own item
CP4	I would share address data in the chat window	Own item
CP5	I would share my date of birth in the chat window	Own item
CP6	I see great potential for this technology	Own item
CP7	Companies are ready for this technology	Own item
NU1	I prefer human contact	Own item
NU2	I do not trust this technology	Own item
NU3	The error rate is too high	Own item
NU4	I prefer looking for information on the website by myself	Own item
NU5	I am scared of chatbots	Own item
NU6	I have no concerns and would take advice from a chatbot	Own item
NP1	I do not trust this technology	Own item
NP2	I do not want my data to be collected	Own item
NP3	I do not want my data to be shared with third parties	Own item
NP4	I have no concerns and would share private information	Own item

IMP	What do companies have to improve with the chatbot technology, in order for you to use it more often? (E.g. lower failure rate, faster service, personalized advice)	Own item

Table 16: All Questionnaire Items in English

ID	Question/Scale in German	Source
DEM1	Wie alt sind Sie?	Own item
DEM2	Bitte geben Sie Ihr Geschlecht an.	Own item
DEM3	Familienstand	Own item
DEM4	Was ist Ihr höchster Bildungsabschluss?	Own item
DEM5	Berufstätigkeit	Own item
DEM6	Bitte geben Sie Ihr Arbeitspensum an.	Own item
DEM7	Bitte geben Sie Ihre Postleitzahl an (Wohnort)	Own item
DEM8	Bitte wählen Sie Ihren Wohnkanton aus.	Own item
PSY1	Ich bin technikaffin	Own item
PSY2	Ich bin ein Early Adopter (Nutzer, die als erste neue technische Errungenschaften erwerben)	Own item
PSY3	Ich verfolge digitale Trends (immer auf dem laufenden sein)	Own item
PSY4	Ich benutze regelmässig Social Media	Own item
W1	Unsympathisch - Sympathisch	Reinhard, Messner and Sporer (2006, p. 254)
W2	Unfreundlich - Freundlich	Reinhard, Messner and Sporer (2006, p. 254)
W3	Gemein - Nett	Reinhard, Messner and Sporer (2006, p. 254)
W4	Lieblos - Lieb	Reinhard, Messner and Sporer (2006, p. 254)

C1	Anfänger -Experte	Reinhard, Messner and Sporer (2006, p. 254)
C2	Unerfahren - Erfahren	Reinhard, Messner and Sporer (2006, p. 254)
C3	Unfähig - Sachkundig	Reinhard, Messner and Sporer (2006, p. 254)
C4	Unqualifiziert - Qualifiziert	Reinhard, Messner and Sporer (2006, p. 254)
C5	Ungeschickt - Geschickt	Reinhard, Messner and Sporer (2006, p. 254)
T1	Unzuverlässig - Zuverlässig	Reinhard, Messner and Sporer (2006, p. 254)
T2	Unehrlich - Ehrlich	Reinhard, Messner and Sporer (2006, p. 254)
T3	Unverantwortlich - Verantwortlich	Reinhard, Messner and Sporer (2006, p. 254)
T4	Unaufrichtig - Aufrichtig	Reinhard, Messner and Sporer (2006, p. 254)
T5	Nicht vertrauenswürdig - Vertrauenswürdig	Reinhard, Messner and Sporer (2006, p. 254)
MC	Wie heist der Bot?	Own item
U1	Ich habe noch nie einen Chatbot genutzt	Own item
U2	Ich habe schon einmal einen Chatbot genutzt	Own item
U3	Ich benutze regelmässig einen Chatbot	Own item
P1	Das Wetter abfragen	Own item
P2	Online Shopping	Own item
P3	Flüge buchen	Own item
P4	Hotels buchen	Own item
P5	Versicherungsfragen	Own item
P6	Finanzielle Fragen	Own item
P7	Customer Service (LiveChat)	Own item
A1	Ein Avatar ist vorhanden	Own item

A2	Der Avatar zeigt einen realen Menschen	Own item
A3	Der Avatar ist Cartoon-artig	Own item
A4	Der Avatar ist animiert (Kann sich bewegen und sprechen)	Own item
A5	Der Avatar ist statisch (Nur ein Bild, keine Bewegungen/Audio)	Own item
A6	Der Avatar passt zum Unternehmen	Own item
CR1	Das Chatfenster ist gross genug	Own item
CR2	Das Chatfenster hat ein modernes Design	Own item
CR3	Anfragen werden korrekt bearbeitet	Own item
CR4	Anfragen werden schnell bearbeitet	Own item
CR5	Der Chatbot gibt sich zu erkennen (z.B. "Sie chatten jetzt mit einem Bot")	Own item
CR6	Datenschutzerklärung wird zu Beginn angezeigt	Own item
CP1	Ich würde mich von einem Chatbot beraten lassen (z.B. im Customer Service LiveChat, Versicherungsberatung, usw.).	Own item
CP2	Ich würde Zahlungsangaben im Chatfenster angeben	Own item
CP3	Ich würde Bilder im Chatfenster teilen	Own item
CP4	Ich würde Adressdaten im Chatfenster angeben	Own item
CP5	Ich würde Geburtsdatum im Chatfenster angeben	Own item
CP6	Ich sehe ein grosses Potential für diese Technologie	Own item
CP7	Unternehmen sind bereit für diese Technologie	Own item
NU1	Ich bevorzuge Kontakt mit einem Menschen	Own item
NU2	Ich traue dieser Technologie nicht	Own item
NU3	Die Fehlerquote von Chatbots ist mir zu hoch	Own item

NU4	Ich suche lieber selbst nach Infos auf der Webseite	Own item
NU5	Chatbots machen mir Angst	Own item
NU6	Ich habe keine Bedenken und würde mich von einem Chatbot beraten lassen	Own item
NP1	Ich traue dieser Technologie nicht	Own item
NP2	Ich will nicht, dass man meine Daten sammelt	Own item
NP3	Ich will nicht, dass meine Daten weitergegeben werden	Own item
NP4	Ich habe keine Bedenken und würde private Daten angeben	Own item
IMP	Was müssten Unternehmen an der Chatbot Technologie verbessern, damit Sie diese häufiger nutzen? (z.B. tiefere Fehlerquoten, schneller Service, individualisierte Beratung, usw.)	Own item

Table 17: All questionnaire items in German

10.2. Stimulus Material

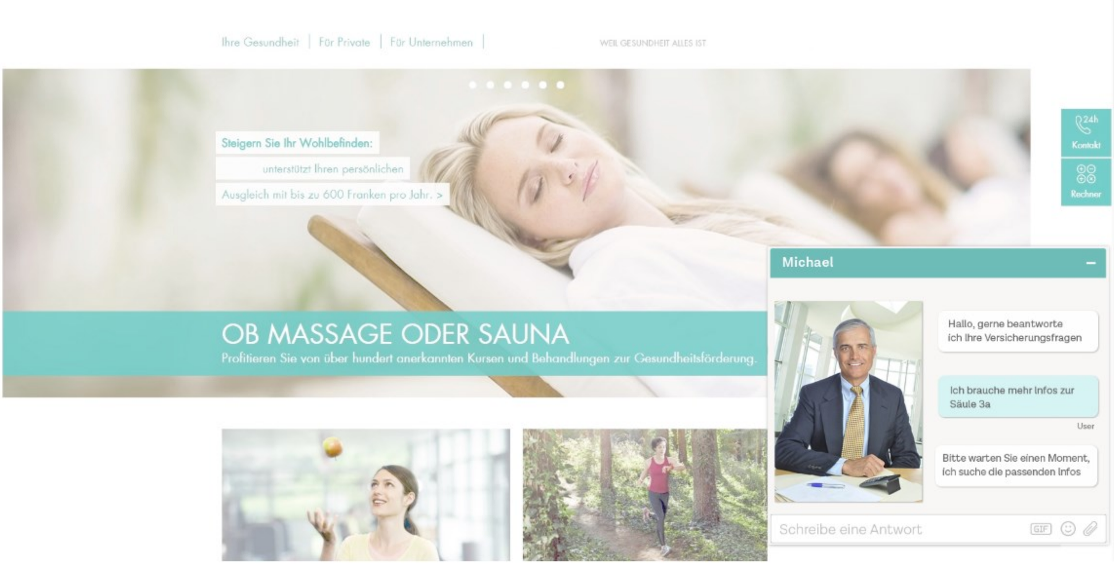

Figure 4: Stimulus Material for Chatbot 1, part 1

Figure 5: Stimulus material for Chatbot 1, part 2

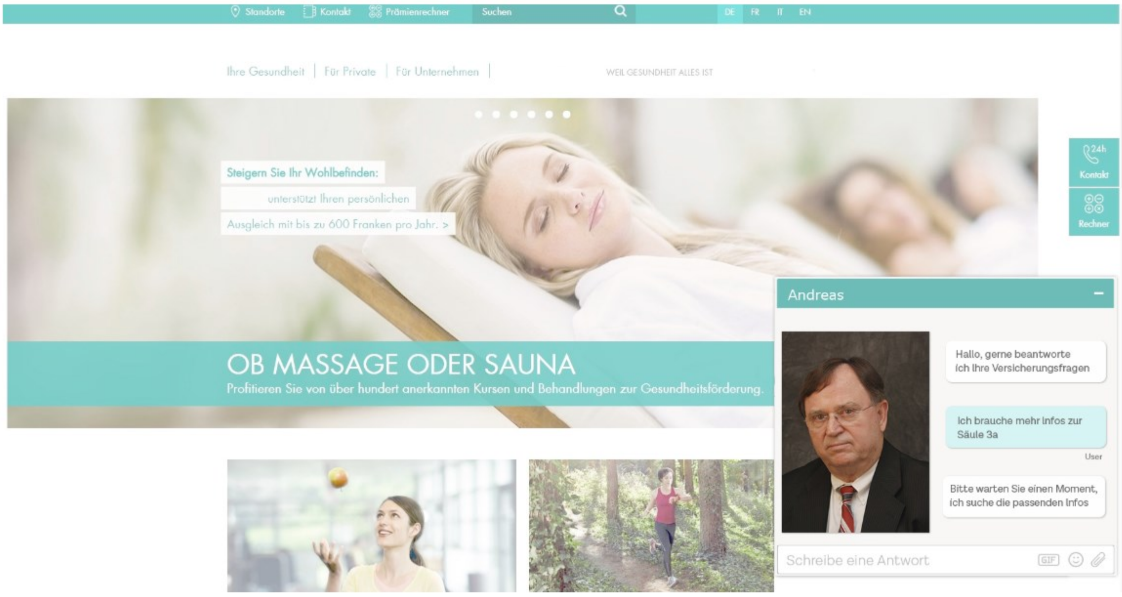

Figure 6: Stimulus material for Chatbot 2, part 1

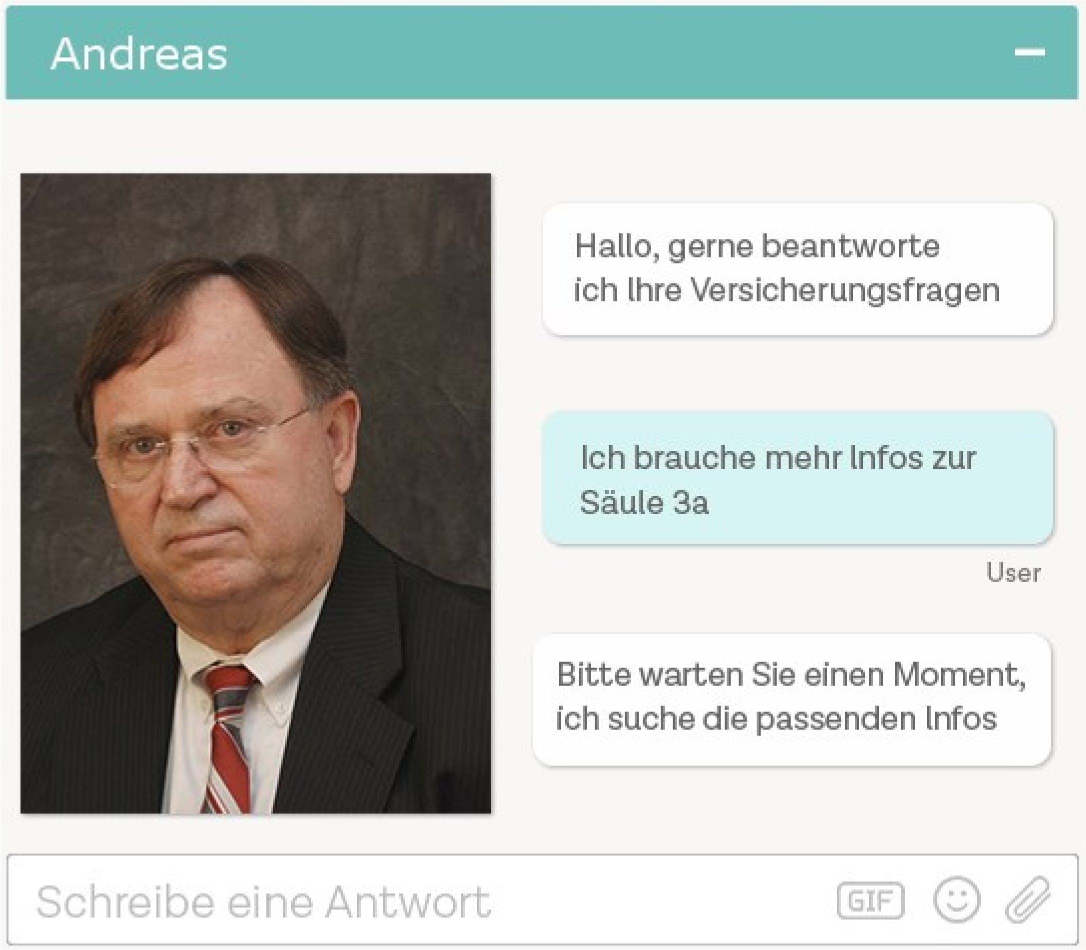

Figure 7: Stimulus material for Chatbot 2, part 2

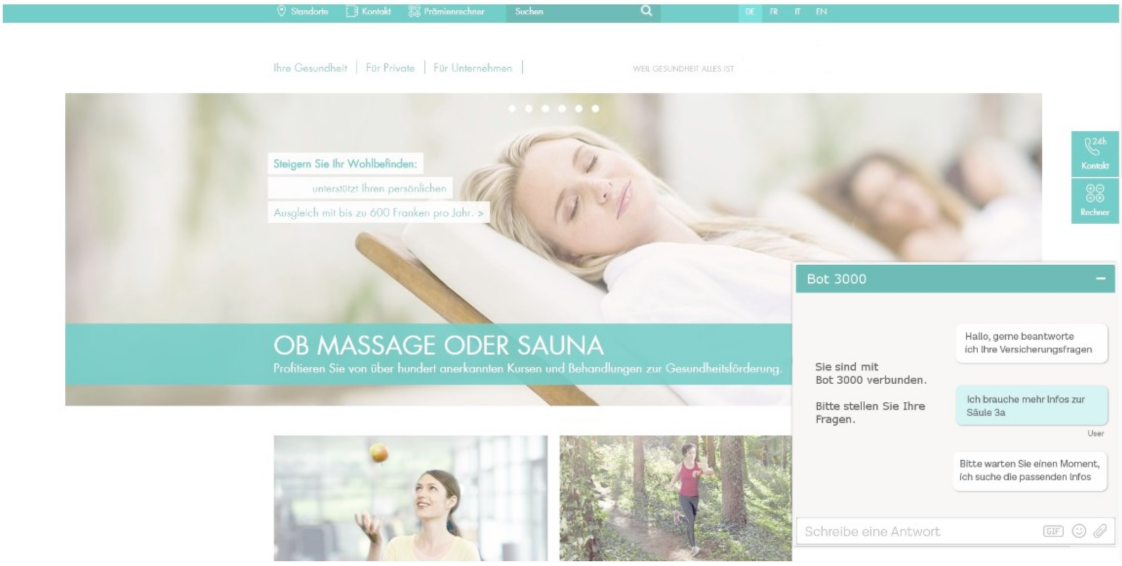

Figure 8: Stimulus material for Chatbot 3, part 1

Figure 9: Stimulus material for Chatbot 3, part 2

10.3. Data Analysis

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	66	51.2	51.2	51.2
	Female	60	46.5	46.5	97.7
	N/A	3	2.3	2.3	100.0
	Total	129	100.0	100.0	

Table 18: Gender

Statistics

Age

N	Valid	128
	Missing	1
Mean		27.41
Median		26.00
Std. Deviation		6.545
Range		35
Minimum		19
Maximum		54

Table 19: Age

Chi-Square test

	Observed	Expected	$(O-E)^2$	$(O-E)^2/E$
Chatbot 1 Male	17	19.380952	5.6689342	0.2925003
Chatbot 1 Female	20	17.619048	5.6689342	0.3217503
Chatbot 2 Male	21	20.952381	0.0022676	0.0001082
Chatbot 2 Female	19	19.047619	0.0022676	0.000119
Chatbot 3 Male	28	25.666667	5.4444444	0.2121212
Chatbot 3 Female	21	23.333333	5.4444444	0.2333333
			X^2	1.0599324
			P Value	0.5886249
			df = 2	

Table 20: Chi-square test of independence – Gender and group

Marital status

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Single	113	29.2	87.6	87.6
	Married	11	2.8	8.5	96.1
	Divorced	2	.5	1.6	97.7
	N/A	3	.8	2.3	100.0
	Total	129	33.3	100.0	
Missing	System	258	66.7		
Total		387	100.0		

Table 21: Marital status

Highest level of education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	University / ETH	10	2.6	7.8	7.8
	University of Appl. Sciences	34	8.8	26.4	34.1
	Federal diploma of higher education	10	2.6	7.8	41.9
	High school degree (Matura)	59	15.2	45.7	87.6
	Apprenticeship	12	3.1	9.3	96.9
	N/A	4	1.0	3.1	100.0
	Total	129	33.3	100.0	
Missing	System	258	66.7		
Total		387	100.0		

Table 22: Highest level of education

Occupation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Full-time student without job	11	2.8	8.5	8.5
	Part-time student without job	2	.5	1.6	10.1
	Full-time student with job	20	5.2	15.5	25.6
	Part-time student with job	63	16.3	48.8	74.4
	Employed on a full-time basis	27	7.0	20.9	95.3
	N/A	2	.5	1.6	96.9
	Employed on a part-time basis	4	1.0	3.1	100.0
	Total	129	33.3	100.0	
Missing	System	258	66.7		
Total		387	100.0		

Table 23: Occupation

Canton

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Aargau	4	1.0	3.1	3.1
	Appenzell Ausserrhoden	1	.3	.8	3.9
	Basel-Stadt	2	.5	1.6	5.4
	Bern	1	.3	.8	6.2
	Glarus	3	.8	2.3	8.5
	Graubünden	1	.3	.8	9.3
	St. Gallen	6	1.6	4.7	14.0
	Schaffhausen	4	1.0	3.1	17.1
	Schwyz	5	1.3	3.9	20.9
	Thurgau	10	2.6	7.8	28.7
	Wallis	1	.3	.8	29.5
	Zug	2	.5	1.6	31.0
	Zürich	89	23.0	69.0	100.0
	Total	129	33.3	100.0	
Missing	System	258	66.7		
Total		387	100.0		

Table 24: Canton

Workload

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0%	8	2.1	6.2	6.2
	10%	2	.5	1.6	7.8
	20%	6	1.6	4.7	12.4
	30%	1	.3	.8	13.2
	40%	9	2.3	7.0	20.2
	50%	6	1.6	4.7	24.8
	60%	19	4.9	14.7	39.5
	70%	3	.8	2.3	41.9
	80%	33	8.5	25.6	67.4
	90%	6	1.6	4.7	72.1
	100%	27	7.0	20.9	93.0
	N/A	9	2.3	7.0	100.0
	Total	129	33.3	100.0	
Missing	System	258	66.7		
Total		387	100.0		

Table 25: Workload

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Chatbot 1 vs. 2 Warmth	Equal variances assumed	1.222	.270	8.722	314	.000	1.451	.166	1.124	1.779
	Equal variances not assumed			8.682	302.512	.000	1.451	.167	1.122	1.780

Table 26: Independent samples t test, warmth rating of Chatbot 1 vs. Chatbot 2

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Chatbot 1 vs. 2 Competence	Equal variances assumed	2.569	.110	4.715	393	.000	.718	.152	.418	1.017
	Equal variances not assumed			4.727	392.993	.000	.718	.152	.419	1.016

Table 27: Independent samples t test, competence rating of Chatbot 1 vs. Chatbot 2

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Chatbot 1 vs. 3 Warmth	Equal variances assumed	2.569	.110	4.715	393	.000	.718	.152	.418	1.017
	Equal variances not assumed			4.727	392.993	.000	.718	.152	.419	1.016

Table 28: Independent samples t test, warmth rating of Chatbot 1 vs. Chatbot 3

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Chatbot 1 vs. Chatbot 3 Competence	Equal variances assumed	.356	.551	7.524	438	.000	1.04253	.13855	.77021	1.31484
	Equal variances not assumed			7.505	403.087	.000	1.04253	.13891	.76946	1.31560

Table 29: Independent samples t test, competence rating of Chatbot 1 vs. Chatbot 3

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Chatbot 1 vs. Chatbot 2 Trust	Equal variances assumed	.434	.510	2.248	393	.025	.359	.160	.045	.674
	Equal variances not assumed			2.249	391.242	.025	.359	.160	.045	.673

Table 30: Independent samples t test, trust rating of Chatbot 1 vs. Chatbot 2

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Chatbot 1 vs. Chatbot 3 Trust	Equal variances assumed	5.138	.024	.599	438	.549	.083	.138	-.188	.353
	Equal variances not assumed			.584	362.364	.559	.083	.141	-.195	.360

Table 31: Independent samples t test, trust rating of Chatbot 1 vs. Chatbot 3

10.4. Correlations

Correlations

Pearson Correlation

	PSY1	PSY2	PSY3	PSY4	U1	U2	U3
PSY1	1	.735**	.707**	.234**	-.260	.185	.032
PSY 2	.735**	1	.719**	.120	-.144	.191	.126
PSY 3	.707**	.719**	1	.203*	-.316*	.357*	.289
PSY 4	.234**	.120	.203*	1	-.401**	.377*	.407**
U1	-.260	-.144	-.316*	-.401**	1	-.809**	-.483**
U2	.185	.191	.357*	.377*	-.809**	1	.555**
U3	.032	.126	.289	.407**	-.483**	.555**	1

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

*. Correlation is significant at the 0.05 level (2-tailed).

Table 32: Psychographic / Usage

Correlations

Pearson Correlation

	PSY1	PSY2	PSY3	PSY4	A1	A2	A3	A4	A5	A6
PSY1	1	.735**	.707**	.234**	.157	.176	.117	.163	.117	.298*
PSY2	.735**	1	.719**	.120	.095	-.031	.261	.017	.177	.142
PSY3	.707**	.719**	1	.203*	.124	.088	.320*	.169	.121	.203
PSY4	.234**	.120	.203*	1	.079	.218	.118	.253	.077	.224
A1	.157	.095	.124	.079	1	.561**	.368**	.255	.395**	.488**
A2	.176	-.031	.088	.218	.561**	1	.201	.227	.188	.405**
A3	.117	.261	.320*	.118	.368**	.201	1	.531**	.239	.370**
A4	.163	.017	.169	.253	.255	.227	.531**	1	.011	.397**
A5	.117	.177	.121	.077	.395**	.188	.239	.011	1	.405**
A6	.298*	.142	.203	.224	.488**	.405**	.370**	.397**	.405**	1

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

*. Correlation is significant at the 0.05 level (2-tailed).

Table 33: Psychographic / Avatar

Correlations

Pearson Correlation

	PSY1	PSY2	PSY3	PSY4	CP1	CP2	CP3	CP4	CP5	CP6	CP7
PSY1	1	.735**	.707**	.234**	.252	.177	.350*	.360*	.261	.353*	.204
PSY2	.735**	1	.719**	.120	.243	.249	.401**	.283*	.135	.394**	.141
PSY3	.707**	.719**	1	.203*	.194	.279*	.320*	.222	.084	.325*	.266
PSY4	.234**	.120	.203*	1	.280*	.102	.140	.021	.166	.070	.194
CP1	.252	.243	.194	.280*	1	.095	.384**	.285*	.341*	.641**	.317*
CP2	.177	.249	.279*	.102	.095	1	.522**	.514**	.461**	.263	.125
CP3	.350*	.401**	.320*	.140	.384**	.522**	1	.760**	.612**	.529**	.261
CP4	.360*	.283*	.222	.021	.285*	.514**	.760**	1	.724**	.459**	.259
CP5	.261	.135	.084	.166	.341*	.461**	.612**	.724**	1	.422**	.347*
CP6	.353*	.394**	.325*	.070	.641**	.263	.529**	.459**	.422**	1	.429**
CP7	.204	.141	.266	.194	.317*	.125	.261	.259	.347*	.429**	1

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

*. Correlation is significant at the 0.05 level (2-tailed).

Table 34: Psychographic / Characteristics

Correlations

Pearson Correlation

	PSY1	PSY2	PSY3	PSY4	CR1	CR2	CR3	CR4	CR5	CR6
PSY1	1	.735**	.707**	.234**	.312*	.312*	.280*	.181	.332*	.026
PSY2	.735**	1	.719**	.120	.133	.326*	.167	.149	.185	.025
PSY3	.707**	.719**	1	.203*	.233	.422**	.237	.164	.143	-.072
PSY4	.234**	.120	.203*	1	.219	.124	.297*	.242	.263	.071
CR1	.312*	.133	.233	.219	1	.581**	.397**	.378**	.294*	.294*
CR2	.312*	.326*	.422**	.124	.581**	1	.401**	.476**	.228	.187
CR3	.280*	.167	.237	.297*	.397**	.401**	1	.755**	.510**	.301*
CR4	.181	.149	.164	.242	.378**	.476**	.755**	1	.342*	.221
CR5	.332*	.185	.143	.263	.294*	.228	.510**	.342*	1	.360*
CR6	.026	.025	-.072	.071	.294*	.187	.301*	.221	.360*	1

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

*. Correlation is significant at the 0.05 level (2-tailed).

Table 35: Psychographic / Consulting

Correlations

Pearson Correlation

	PSY1	PSY2	PSY3	PSY4	NP1	NP2	NP3	NP4
PSY1	1	.735**	.707**	.234**	-.232	-.065	.054	.264
PSY2	.735**	1	.719**	.120	-.390**	-.103	-.015	.182
PSY3	.707**	.719**	1	.203*	-.299*	-.115	-.042	.037
PSY4	.234**	.120	.203*	1	.061	-.040	-.123	.175
NP1	-.232	-.390**	-.299*	.061	1	.545**	.439**	-.170
NP2	-.065	-.103	-.115	-.040	.545**	1	.838**	-.087
NP3	.054	-.015	-.042	-.123	.439**	.838**	1	.112
NP4	.264	.182	.037	.175	-.170	-.087	.112	1

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

*. Correlation is significant at the 0.05 level (2-tailed).

Table 36: Psychographic / Reasons not to use a bot

Correlations

Pearson Correlation

	PSY1	PSY2	PSY3	PSY4	NP1	NP2	NP3	NP4
PSY1	1	.735**	.707**	.234**	-.232	-.065	.054	.264
PSY2	.735**	1	.719**	.120	-.390**	-.103	-.015	.182
PSY3	.707**	.719**	1	.203*	-.299*	-.115	-.042	.037
PSY4	.234**	.120	.203*	1	.061	-.040	-.123	.175
NP1	-.232	-.390**	-.299*	.061	1	.545**	.439**	-.170
NP2	-.065	-.103	-.115	-.040	.545**	1	.838**	-.087
NP3	.054	-.015	-.042	-.123	.439**	.838**	1	.112
NP4	.264	.182	.037	.175	-.170	-.087	.112	1

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

*. Correlation is significant at the 0.05 level (2-tailed).

Table 37: Psychographic / Reasons not to share information