May AI help you?

A quantitative study investigating a potential means to overcome the disclosure paradox of chatbots in the service encounter

The use of artificial intelligence solutions such as chatbots in service encounters is gaining in popularity due to the potential efficiency gains from automating routine interactions. However, the desired benefits are dependent on the identity of the virtual service agent not being disclosed, as customers who know that they are interacting with a chatbot perceive it to be less competent and trustworthy, eliminating all efficiency gains. Yet the choice to omit disclosure is not only deceitful, but also increasingly restricted by law, leading to a disclosure paradox. A significant research gap exists since little attention has been paid to identity disclosure of chatbots. Since mere identity disclosure leads to negative attitudes, the purpose of this study is to explore whether a variant of the second-order disclosure can affect humans' resulting attitudes as compared to first-order disclosure. The proposed second-order disclosure includes the chatbot identity and a competence signal. A quantitative study with 1000 participants was conducted through an experiment that divided the treatment and control group based on whether the disclosure of the chatbot identity included a competence signal or not. The study found that the competence signal was unsuccessful in impacting attitudes. However, the importance of perceived competence and trust for attitude towards the chatbot and the brand was determined. The study found that perceived chatbot competence leads to a higher attitude towards the chatbot, through the mediating effect of trust, with spillover effects on brand liking and the intention to use the chatbot. The findings indicate the challenge and importance of further investigating means to overcome the disclosure paradox. Therefore, this study highlights theoretical implications of the practical dilemma.

Keywords: *trust, perceived competence, disclosure paradox, chatbot attitude, competence signal*

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Acronyms & Definitions

Algorithm: can be thought of as a set of step-by-step instructions to be followed in order to achieve a certain desired outcome and if often used in chatbot programming

Anthropomorphism: the assignment of human traits and characteristics to computers

AI: a computer science concept that combines computation and cognition with the aim of making programs "attempt to achieve some kind of intelligent behavior" (AI is an abbreviation for artificial intelligence)

Capacity trust: entails that the user believes the chatbot has the capability and competence to achieve the task at hand and thus trusting that an agent is capable of completing a task

Calculative trust: refers to assessing the other party's trustworthiness based on evidence

Chatbot: conversation automation solution with interface channels such as voice, text or a combination thereof, with potential visual cues such as avatars

Conversational AI: chatbot powered by AI (AI is technology, chatbot is solution)

Disclosure: disclosure of non-human nature of service agent to customer

Disclosure paradox: A proposed paradox resulting from the fact that companies have to disclose the identity of the chatbot whilst overcoming the negative effects resulting from such disclosure.

First-order disclosure: see definition for disclosure

HCI: Human-computer interaction

Second-order disclosure: disclosure and additional cue giving information regarding chatbot features

Text-based chatbot: single channel virtual agents (chatbots) without voice or avatars

Uncanny valley: the effect of not being able to fully distinguish between a human and technology which evokes uncomfortable feelings of eeriness and uneasiness

1. Introduction

This first section will provide an overview of the background of chatbots within the service encounter. The introduction will explain the proposed disclosure paradox and the importance for companies and researchers to explore ways to resolve it. The section also outlines the research gap, purpose of the study, expected contribution and delimitations.

1.1. Background

The importance of the service encounter for positive customer attitudes has been an established notion for decades (Hill & Alexander, 2000). A service encounter is a dyadic interaction between a customer and its service agent (Bitner, Booms & Tetreault, 1990). Customers' overall perception of a brand and its service encounter depend on, to a large extent, not only the quality of the service but also on the service agent's characteristics and attributes (Söderlund & Rosengren, 2008). "Indeed, previous studies of service encounters have identified a positive association between the customer's evaluation of the service employee and overall satisfaction with the firm for which the employee works" (Söderlund & Rosengren, 2008). In some regards, the agent representing the company is seen as equivalent with the company itself (Bitner et al., 1990; O'Cass & Grace, 2004; Söderlund & Rosengren, 2008; Wang, 2009).

Traditionally, the agent in the dyadic interaction of the service encounter has been human. However, the development of modern technology has made it possible to replace agents with computer-based solutions, impacting the dynamic. The communication between a human and a virtual agent is referred to as a human-computer interaction (HCI). Virtual agents, also known as chatbots, are conversation automation solutions with interface channels such as voice, text or a combination thereof, with potential visual cues such as avatars (Barr & Feigenbaum, 2014). Over time the intelligence of chatbots has become more complex and simple decision-tree solution paths have now been upgraded to solutions utilizing artificial intelligence (AI) technology. Such AI includes machine learning and natural language processing algorithms, which power the chatbot with computation and cognition in order to “attempt to achieve some kind of intelligent behavior” (Barr & Feigenbaum, 2014, p. 3). AI-powered chatbots can review past conversations and ‘learn’ to provide future improved and tailored responses to customer queries.

Since a chatbot has the ability to consistently improve, automate repetitive interactions and conduct service encounters at much higher speed and volumes 24/7, some claim that ”the future of customer service is AI-Human Collaboration” (Kannan & Bernoff, 2019; Toader et al., 2019). Since customer service is one of the most resource-intensive departments in a company, the desire to increase efficiency is high (Cui et al., 2017). Organizations “have recognized the far-reaching potential of chatbots for their commercial agendas” (Zarouali, Van den Broeck, Walrave & Poels, 2018, p. 2). The intention is not to replace human agents altogether, but rather automate routine encounters to free up time for human agents to handle more complex queries in order to achieve an overall more efficient and positive customer experience and higher satisfaction with how cases are handled (Kannan & Bernoff, 2019).

In 2019 the use of chatbots in sales grew by 136% and such use is predicted to continue to rise (Sweezey, 2019). Thus, chatbots will become increasingly important, and relevant in many service encounters. However, replacing a previously human agent with a chatbot will inherently have a significant impact on the relationship dynamic with the customer. Therefore, re-examining the customer-agent relationship through the lense of this new dynamic is an essential area of focus for companies and researchers attempting to understand how measures, such as attitudes towards the brand, may be impacted by the new agent and its attributes (Sweezey, 2019).

A primary concern in this altered relationship is how to facilitate trust towards this new form of agent and ensure a positive evaluation of its attributes, given the direct brand impact of the customer's evaluation of the agent (Söderlund & Rosengren, 2008). Koehn (2003) outlines the condition of parties disclosing their identities and erring on the side of transparency when attempting to achieve trust in online interactions. The author argues that not disclosing an identity is a form of manipulation and disrespect to the customer, which is counter to trust-building. If there is any foreseeable customer confusion of mistaking a chatbot for a human, companies have an obligation to disclose the identity of the chatbot in advance (Koehn, 2003).

Chatbots were originally designed in the 1960s as an attempt to "determine whether chatbot systems could fool users into believing they were real humans" through the use of natural language and the possibility of such deceit was soon confirmed (Ciechanowski, Przegalinska, Magnuski & Gloor, 2019). A famous recent example of deceitful technology is that of Google's Duplex voice assistant, which is able to mimic a human voice to an eerie degree, resulting in the humans involved in testing of the assistant being unaware that a technological solution was conducting the conversation (Chen & Metz, 2019). Such lack of transparency and intentionally blurring the line between human and technology to fool the human party can be argued to be unethical.

Consequently, to merit any form of trust, chatbots "need to make themselves as transparent as is humanly possible" (Koehn, 2003, p. 11). Legal frameworks are also catching up with technological developments since legislation is being put in place in some countries forcing companies to disclose the nature of agents used (Lamo & Calo, 2019). Therefore, disclosure is a key component of chatbot implementation.

However, establishing the premise that chatbots must disclose their nature causes a dilemma. As mentioned earlier, chatbots are primarily used in service encounters in order to achieve efficiency and operational gains. Yet, disclosing the nature of a chatbot, as opposed to not being transparent with it, not only reduces but completely eliminates benefits of chatbot use (Hendriks, Amiri & Bockting, 2020; Ishowo-Oloko, Bonnefon & Soroye, 2019; Luo, Tong, Fang & Qu, 2019). For example, although chatbots are equally effective in sales performance in the banking industry as experienced workers and four times more effective than workers with little experience, mere identity disclosure leads to a 79.9% reduction of purchases from the chatbot (Luo et al., 2019). Although placing the disclosure after the interaction mitigates the negative effect (Luo et al., 2019), disclosure at the end rather than upfront ignores the ethical consideration of avoiding deceit to ensure a human is aware who they are interacting with in the first place. As a result, the authors of this study believe that a disclosure paradox is created, where honesty about the nature of a chatbot is needed to facilitate trust towards the chatbot, but the disclosure directly negatively affects the customer's perception of the chatbot and the service encounter.

In summary, in order for chatbots to provide the desired efficiency and brand image benefits for companies implementing chatbots in their service encounters, companies have to simultaneously disclose the identity of the chatbot whilst overcoming the negative effects resulting from such disclosure. In other words, companies must overcome the disclosure paradox of chatbots.

1.2. Research Gap

The chatbot concept was developed in the 1960s and it has thereafter been a heavily researched topic throughout various stages of its technological development and commercial applications.

However, the debate regarding the use of chatbots has largely concentrated on the intersections of humans and machines and whether chatbots are truly more effective than humans and how chatbots can be designed to increasingly mimic humanness through the use of anthropomorphic cues (Ciechanowski et al., 2019; Gong & Nass, 2007; Ishowo-Oloko et al., 2019; Lee & See, 2004; Luo et al., 2019; Mandell, Smith & Wiese, 2017; Wiese, Mandell, Shaw & Smith, 2019; Wiese & Weis, 2020; Weis & Wiese, 2017; Yamada, Kawabe & Ihaya, 2013). Further research to increase humanness may not only be superfluous, but also does not address the issue of the negative effects of disclosure of the technological identity of the chatbot. An ethical and legal stance to maintain the divide and distinction between human and chatbot customer service agents is being established as a premise and thus, must be included in academic research.

Yet findings from the few studies investigating whether to disclose the identity of a chatbot or not, detail the negative effects of disclosing chatbot nature to customers (Hendriks et al., 2020; Ishowo-Oloko et al., 2019; Luo et al., 2019). Therefore, potential means to overcome the proposed disclosure paradox needs further academic undertaking. There is an important inadequacy gap in the research that does not sufficiently explore the dimension in which disclosure is a premise from the outset. The focus needs to shift from whether a chatbot should disclose its nature, i.e. first-order disclosure, to how to disclose such nature in order to mitigate any negative effects and remain safely within the boundaries of ethics and legislation. The research on chatbots can no longer be binary, i.e. human versus chatbot or disclosure versus no disclosure, but should rather facilitate nuance and intricacy to reflect the complex synergy of the modern HCI environment. In other words, the problem has evolved from whether to disclose the real nature of chatbots to *how* chatbots should disclose their nature in an interaction with a human, without jeopardizing positive perceptions of the encounter.

To the knowledge of the authors, little academic research exists that specifically explores how to influence or alter the effects of the chatbot nature disclosure or how various forms of identity disclosure may be altered in order to affect customer perceptions. Thus, a study is needed to define how such transparency should be framed to affect the, otherwise negative, resulting customer perceptions and transform them into positive ones. Ishowo-Oloko et al. (2019) propose the term "*second-order*" disclosure, which entails not only providing a disclosure about the chatbots nature, but also including some sort of framing or additional information to potentially affect the resulting attitudes to the disclosure. To the knowledge of the authors, little to no research using the concept of the second-order disclosure of chatbots currently exists.

1.3. Purpose of Study

Given the dilemmas and research gap described above, the intention of this study is to dive deeper into the actual disclosure dimension and how to overcome the disclosure paradox. The purpose of this study is to explore whether a variant of the second-order disclosure can affect humans' resulting attitudes as compared to first-order disclosure. This thesis investigates the effects of the second-order disclosure of a chatbot and how the framing and information given by a chatbot in an interaction with a customer can affect such a customer's perception and attitudes to it, especially as regards improving the customer's attitude and trust towards the service encounter chatbot.

1.3.1. Research Question

Based on the background, research gap and purpose of the study, the research question of this thesis is as stated below.

To what extent can a second-order disclosure induce positive customer attitudes and increase trust towards service encounter chatbots?

1.4. Expected Contribution

This thesis aims to contribute theoretically by conducting research within the relatively unexplored domain of chatbot disclosure and how forms of such transparency affect the dynamics of customer-chatbot relationships and customer perceptions in the service encounter. Ciechanowski et al. (2019) argue that further investigating the user's side and what drives their perceptions, which has been much neglected in HCI literature, is necessary as chatbots become increasingly popular. Through such a focus, the authors hope to shed light on this dimension of the domain and initiate a discussion on how to increase the transparency in HCI without compromising efficiency as well as clarifying the blurred line between human and chatbot to facilitate trust in the technology. As chatbots are deemed to be the commercial future of customer service by some, it is important to academically establish how customers perceive the increasingly complex and prominent technology as well as what factors may affect their perceptions and trust towards it. Hancock et al. (2011b) posit that "the issue of trust in technology systems will be as influential on social development as it is in our own human-human relationships" (Hancock et al, 2011b, p. 523).

Additionally, the study will empirically test an example of a second-order disclosure in order to initiate the exploration of how chatbots can provide information in practice to achieve desired commercial and managerial outcomes within ethical and legislative parameters of transparency. Therefore, the intended practical contribution is to investigate a potential managerial solution to improving customer attitudes towards chatbots in the service encounters to allow for efficiency gains through an academic and empirical undertaking. Lastly, the authors recognize that the contributions acquired as a result of this study may not facilitate a practically viable solution alone, but rather the attempt is to initiate a discussion that leads to contributions from others.

1.5. Delimitations

Although the literature review and theory is inspired by a wider array of adjacent studies and domains of marketing, computer science and psychology, a number of delimitations are made in terms of the scope of the experiment and resulting discussion in this study in order to investigate a specific environment that is practically relevant and in line with a real use case, as opposed to a study on the general chatbot technology in all applications.

The first delimitation of the study is narrowing the scope to HCI within the customer service context of a service provider since such encounters provide a strong environment for examining relationships and attitudes due to the mutual nature of the interaction, as opposed to those seen in goods providers (Wang, Baker, Wagner & Wakefield, 2007).

A second delimitation is made in terms of industry selection of the banking sector. The relevance of chatbots in customer service is especially evident in the banking industry. Capgemini found that 49% of the top 100 performers in the retail banking and insurance industry were already using chatbot assistants in 2019, compared with only 23% in the consumer products and retail sector. 53% of consumers in the study had also used chatbots previously for customer service and queries related to banking (Taylor et al., 2019). Another reason why the banking industry is especially relevant and interesting for a study of attitudes to chatbots is because the nature of interactions within banking often require a higher degree of complexity and trust, compared to e.g. customer service interactions in retail (Boateng, 2019). In fact, trust is the most defining construct of an engaging relationship within the banking sector and a customer's intention to use the service (Agariya & Singh, 2011; Angenu, Quansah & Okoe, 2015; Benamati & Serva, 2007; Boateng, 2019). Concerns about security and privacy are also especially salient factors related to the need for strong trust between customer and agent in online banking due to the more sensitive nature of information handled in the customer service inquiries (Lai, Leu & Lin, 2018). Therefore, the banking industry provides a strong environment for testing the role of attitudes and trust in an interaction between a customer and a service chatbot.

The third delimitation is to narrow the form of service encounter chatbots used in this study to text-based chatbots, i.e. single channel agents without voice or avatars. A key limitation in studies testing multi-channel chatbots is that it is difficult to isolate changes in attitude to variations within specific channels of communication (Ciechanowski et al., 2019; Gong & Nass, 2007). Thus, further exploration is needed regarding changes in attitudes within single channels, such as variations in just text, which is a main medium for many commercial customer service chatbots. Furthermore, Ciechanowski et al. (2019) finds that simpler text-based chatbots are perceived to be less competent. Since Toader et al. (2019) links perceived competence to trust towards the technology, it means that there is a need to understand what drives the competence perception of text-based chatbots and how it can potentially be improved to facilitate trust.

The fourth delimitation made is that the sample is confined to Swedish customers for the main study due to time and resource constraints, as well as the fact that the platform used to distribute the survey only reaches Swedish nationals. All sampling decisions and specifications are further detailed in section 3.4.1.

2. Theoretical Framework & Hypothesis Generation

The purpose of this section is to dive deeper into the existing literature on chatbots in HCI in order to get a better overview of the research gap. The literature review and initial theory will begin by describing what perceptions customers have of chatbots and their underlying technology, in order to further understand the current attitudes in HCI. Thereafter, a theoretical framework will be established to clarify how trust is defined in this study, what factors it includes in the chatbot context and how such factors can be communicated and signaled to customers in a systematic manner. Finally, how such a signal affects attitudes, intention to use and brand liking will be summarized from a theoretical perspective. The theoretical framework outlined in this section will guide the hypotheses generation and the remainder of the thesis.

2.1. Chatbots as Social Actors

Since HCI is becoming an increasing part of people's daily communications, researchers try to understand how such interactions are perceived by people and what affective reactions, i.e. mental feeling processes, are evoked in connection therewith (Bagozzi, Gopinath & Nyer, 1999). Although one party in the HCI is non-human, people apply the same heuristics, cognitive processes and overlearned social behaviors to chatbots as they would in a social interaction with a human counterpart (Eyssel & Hegel, 2012; Hendriks et al., 2020; Nass & Moon, 2000; Reeves & Nass, 1996). According to the equivalence hypothesis, "people psychologically engage with chatbots as they do with people, resulting in similar disclosure processes and outcomes" (Ho, Hancock & Miner, 2018).

However, as the human instinct is to treat chatbots socially and to apply social heuristics, the cognitive struggle to categorize an inhumane party in an otherwise social interaction can cause challenges. A classic concept in the field of HCI relating to people's reaction to technology is that of the 'uncanny valley' effect discussed by Mori (1970). Although there is a general positive correlation between humanness and familiarity, Mori found that not being able to fully distinguish between a human and technology evokes uncomfortable feelings of eeriness and uneasiness. This sensitivity is especially strong for defects when the technology is near-human but not perfectly mimicking a human.

A cognitive conflict arises when there is ambiguity about the humanness of the stimuli due to increased processing costs of attempting to categorize the ambiguity (Mandell et al., 2017; Wiese et al., 2019; Wiese & Weis, 2020; Weis & Wiese, 2017; Yamada et al., 2013). Ciechanowski et al. (2019) found that less complex chatbots with only text, compared to complex multi-channel chatbots (text, audio and avatar), induce less intense affective reactions because such less complex chatbots are perceived to be less uncanny and ambiguous overall. However, the less human-like the chatbot is perceived to be is also closely correlated to lower competence perceptions (Ciechanowski et al., 2019). This finding is important as perceived competence is directly correlated to trust towards the agent as well as customer service encounter satisfaction levels (Toader et al., 2019). Consequently, a trade-off seems to exist in the sense that although negative affective reactions towards text-based chatbots are mitigated, customer's perception of their competence, and therefore, trustworthiness, is also lower.

2.2. Chatbot Trust Challenges

Since perceptions and attitudes towards chatbots are largely social, the willingness to interact and rely on such technology is essentially dependent on a sort of trust in the capability of the chatbot to uphold their purpose or function in the interaction (Dietvorst, Simmons & Massey, 2015; Hancock, Billings & Schaefer, 2011a; Lee & See, 2004). Trust means the "perceptions about others' attributes and a related willingness to become vulnerable to others" (McKnight, Choudhury & Kacmar, 2002). This indicates that trust helps a customer overcome the risk-perceptions in HCI, encouraging them to interact with the agent and is dependent on the customer's perception of their counter-party (Holmes, 1991; Luhmann, 1979; Mayer et al., 1995; McKnight et al., 2002; Rousseau et al., 1998; Zand, 1972). In particular, trust is a mechanism for relying on automation when it is difficult to understand the complexities of the underlying technology (Lee & See, 2004). Therefore, trust is a key component of customers being willing to interact with chatbots since the programming and algorithms can be quite complex (Lee & See, 2004; Yen & Chiang, 2020). Since trust towards chatbots is a central factor affecting customers' propensity to rely on them and is essential in building a positive relationship with customers of banks, it is important to delve deeper into what current levels of trust have been found in literature as a starting point (Agariya & Singh, 2011; Angenu, Quansah & Okoe, 2015; Benamati & Serva, 2007; Boateng, 2019; Lee & See, 2004).

Past studies show a nuanced account of trust towards chatbots. Humans are more likely to break promises regarding cooperation in prisoner's dilemma games with human-like computers (text with human avatar) than either humans or simple text-based computers (Kiesler, Sproull & Waters, 1996). However, promises are kept towards text-based computers to the same extent as to human counterparts (Kiesler et al., 1996). Such findings entail that when the cognitive dissonance and uncanny valley dilemmas are reduced by only using a text-based channel, there is potential for trust in the chatbot. However, although there is potential for trust, there are also a number of challenges due to distrust towards the underlying programming of chatbots, namely algorithms. There is a tendency for people to choose human-made forecasts over that of algorithms (Dietvorst et al., 2015). Multiple studies aggregated prove that algorithms are objectively more superior and accurate at forecasting in a number of fields like medicine, employment trends as well as product demand analyses (Beck et al., 2011; Dawes, 1971; Dawes, 1979; Dawes, Faust, & Meehl, 1989;

Grove et al., 2000; Highhouse, 2008; Meehl, 1954; Schweitzer & Cachon, 2000; Thompson, 1952; Wormith & Goldstone, 1984). Yet despite this multitude of performance superiority evidence and even when the subjects in the study witnessed the superior performance first hand, people still prefer and have a higher tolerance towards their own forecasts (Dietvorst et al., 2015).

Humans have a tendency to expect algorithms to make mistakes due to their limited accounts of reality with preset factors that can never capture the full complexity of the human world, consequently quickly losing faith in an algorithm (Einhorn's, 1986). Small mistakes by algorithms are weighed heavier than larger mistakes by humans, who are more easily forgiven and granted the benefit of the doubt (Dietvorst et al., 2015). In other words, people have higher expectations of perfection in algorithms than they would of a human and consequently, more is required to build and maintain trust towards them. Furthermore, text-based chatbots are seen as less competent which is inherently linked to their trustworthiness, indicating that the underlying distrust towards algorithms could be amplified when humans are interacting with simpler chatbot interfaces (Ciechanowski et al., 2019; Toader et al., 2019).

In summary, there is an underlying concern that technology can never truly comprehend or respond to the intricate complexities of reality and much higher expectations are placed on an algorithm than is expected of a human. In turn, this implies that replacing a human customer service agent with a chatbot in an interaction will impact expectations, attitudes and perceptions towards the agent. A detailed definition of trust and its components is needed to explore what it would take for the creation of a more systematic trust in chatbots, especially in the banking customer service context (Lee & See, 2004). Therefore, a more thorough account of the components of chatbot trust is outlined in the theoretical framework below.

2.3. Chatbot Trust & Competence

To reiterate, trust means the "perceptions about others' attributes and a related willingness to become vulnerable to others" and thus, the willingness to interact with them by overcoming risk perceptions (Holmes, 1991; Luhmann, 1979; Mayer et al., 1995; McKnight, Choudhury & Kacmar, 2002; Rousseau et al., 1998; Zand, 1972). The trust definition consists of two components; the perception of attributes referred to as *trusting beliefs*, as well as the willingness and intention to make oneself vulnerable to the company, called *trusting intentions* (McKnight et al., 2002). However, a positive perception precedes intentions (Davis, Bagozzi & Warshaw, 1989; Fishbein, 1963; Fishbein & Ajzen, 1975), meaning that the trusting belief is a starting point for the theoretical framework with the trusting intention explored in later sections 2.2.4.1.

The trusting belief means that the customer, or truster, perceives that the trustee has attributes that are beneficial to them (McKnight et al., 2002). There are three such beliefs that are used most often, namely, the perception of the trustee to deliver on what the trustee needs, i.e *competence*, caring and motivational attributes to act in truster's best interest i.e. *benevolence*, and honesty and promise keeping attributes i.e. *integrity* (Butler, 1991; Bhattacherjee, 2002; Gefen, 1997; Mayer et al., 1995; McKnight et al., 2002). Although chabots are treated as social actors, the primary attributes related to their trustworthiness is predictability and reliability, excluding 'human trust' aspects such as benevolence and integrity (Corritore, Kracher & Wiedenbeck, 2003; Hancock et al., 2011a; Lee & See, 2004; Schaefer, 2013; Ullman & Malle, 2018).

Performance and reliability can be summarized as ‘capacity trust’, which entails that the user believes the chatbot has the capability and competence to achieve the task at hand and thus, is trustworthy (Corritore et al., 2003; Hancock et al., 2011a; Lee & See, 2004; Schaefer, 2013; Ullman & Malle, 2018). Complementing McKnight et al.’s (2002) definition of competence mentioned earlier, the Stereotype Content Model (SCM) defines it as a subjective variable that “reflects traits that are related to perceived ability, including intelligence, skill, creativity and efficacy”. The model explains how humans use interpersonal impressions to assess a stereotype of a counterparty based on a number of attributes or items (Fiske, 2018; Fiske, Cuddy & Glick, 2006).

Therefore, the trusting belief, and interpersonal assessment of interest in this study is the subjective perception of the competence level of chatbots (Fiske, 2018; Fiske, Cuddy & Glick, 2006; McKnight et al., 2002). An important aspect to point out in this regard is that the focus is not on objective competence of the chatbot but rather the customers’ perception of competence (Corritore et al., 2003; Deutsch, 1958; Giddens, 1990; Kee & Knox, 1970; Luo et al. 2019; Muir & Moray, 1996; Rotter, 1980). In other words, it is evident that companies should not only aim to achieve objective competence of chatbots for efficiency and functionality purposes but also have to ensure that customers perceive it as competent in order for customers to trust it and be willing to use the chatbot.

Apart from McKnights et al.’s (2002) trust definition components, Koehn (2003) outlines four bases and mechanisms for trust in online interactions; goal-based, calculative, knowledge-based and respect-based. Goal-based trust entails that two parties in an interaction believe that they share the same common goal with little interest in the identity or character of the other party and where the end justifies all means. Calculative trust refers to assessing the other party's trustworthiness based on evidence. Knowledge-based trust is founded in frequent interactions leading to familiarity, and finally, respect-based trust is created based on the belief that one's interaction partner is praiseworthy and influential. Koehn (2003) explains that goal-based trust should not be sought after due to the interaction being seen as a tool rather than an enduring relationship. Instead, respect-based trust is the most lasting form that should be the ultimate goal of a company. However, until that type of trust is viable, calculative and knowledge-based trust should be the aim as a proxy in the meantime.

Given the fact that a positive perception is a prerequisite for intention to use technology (Davis et al., 1989), calculative trust must be the starting point when attempting to establish any form of trust. Only thereafter can intention to use a chatbot increase, enabling familiarity. Therefore, calculative trust of a customer towards a chatbot in the service encounter may be facilitated by providing competence evidence that positively impacts the customer's view about the bank's chatbot ability to satisfy their needs reliably (Boateng, 2019; Brun, Durif & Ricard, 2014; Brun, Rajaobelina & Ricard, 2014; Urban, Amyx & Lorenzo, 2009). Toader et al. (2019) found that perceived competence mediates the impact of anthropomorphic design cues on chatbot trust, thus other cues that impact competence perception may potentially lead to similar positive effects on chatbot trust.

Finally, Hancock et al. (2011) presented a model of trust in bots describing the mechanism for trust facilitation. The trust model is built on three elements; a transmitter of information, a receiver of that information as well as a communication channel between them. The outcomes of this interplay then provide a feedback loop leading to an adjustment of the trust level over time based on performance and updated perceptions of the receiver of information towards the transmitter. By combining this model with Koehn's (2003) calculative trust dimension and the position that a positive attitude is a prerequisite for actual use (Davis et al., 1989), it is intuitive to assume that providing evidence of trustworthiness could in theory be a proxy for performance in the feedback loop within the model. Therefore, evidence can, in theory, be presented to impact a customer's perception about the chatbot's attributes and trustworthiness, leading to an increased willingness to interact with it.

Thus, the next step is defining what must be included in such evidence and how it can be conveyed to impact a customer's trust belief and competence perception of the chatbot.

2.4. Signaling Chatbot Competence

Due to the clear distinction that it is perceived competence rather than objective competence that impacts customer trust towards a chatbot, a large emphasis is placed on the cues relayed to the customer in order to impact their perceived level of chatbot competence (Corritore et al., 2003; Deutsch, 1958; Giddens, 1990; Kee & Knox, 1970; Luo et al. 2019; Muir & Moray, 1996; Rotter, 1980; Toader et al., 2019). Such competence cues may be the necessary evidence and cognitive heuristics needed to create capacity trust towards a customer service chatbot (Ullman & Malle, 2018; Corritore et al., 2003). However, in order for these competence cues to be internalized by the customer to cause the desired effect of facilitating trust and a positive attitude, they must be signaled and received by the customer successfully.

Michael Spence's (1973) article about job-market signaling presented a theory describing how an agent can overcome information asymmetry by credibly conveying a 'signal' about his or her own ability to the principal that does not have access to the same information. If the signal is credible and convincing, it overcomes the information asymmetry and enables the principal to reliably distinguish between various agents' abilities. Signaling as a concept has been applied to areas such as buyer-seller relationships and marketing towards customers, where the company attempts to convey information about brand, product or service quality to the customer through signals in order to attempt to manipulate the customer's perceptions of attribute levels (Boateng, 2019; Kirmani, 1997; Kirmani & Rao, 2000). During recent years, such signals are increasingly being conveyed through technology such as e.g. machine learning algorithms, often used in chatbots, to allow for personalized recommendations that signal the intent to create a personal and tailored relationship with the customer (Boateng, 2019).

The relationship between principal (customer) and agent (chatbot) works in a feedback loop where the principal updates their expectations as new information becomes available and the principal experiences the agent’s capabilities as they relate to the signals. Through this loop probabilistic beliefs are adjusted and signals must be updated accordingly (Spence, 1973). Such a feedback mechanism works in a similar fashion to Hancock et al.’s (2011) model of trust (presented in section 2.2.1), in the sense that perceptions are adjusted over time through the communication feedback loop between the transmitter and receiver of information.

In the context of this study, information asymmetry exists in terms of the competence of the customer service chatbot as there is a discrepancy between objective and perceived competence. Objective competence cannot be altered without altering the actual functioning of the chatbot. “Signals, on the other hand, are alterable and therefore potentially subject to manipulation”

(Spence, 1973, p. 358). Hence, chatbots should emit a credible signal about their competence to the principal customers in order to provide evidence for calculative trust and improved trusting beliefs. As such, the first hypothesis is the following;

H1: Signaling chatbot competence has a positive effect on trust

The question arises how such a cue should be formed for it to be credible enough to signal trustworthiness. Firstly, considerations about the type of content included in the chatbot disclosure messages must be taken into account to ensure it conveys competence. Competence cues can be found in information relating to expertise, efficiency, the ability to provide comprehensive and accurate information, honesty about capabilities and limitations as well as lack of bias (Corritore et al., 2003; Fogg et al., 2001; Folstad, Nordheim & Bjorkli, 2018; Lee, Kim & Moon, 2000). Secondly, banks must communicate appropriate and useful signals to customers in order to positively influence trust, irrespective of the technology being used to emit the signals (Boateng, 2019; Corritore et al., 2003). Thus, an effective competence signal of the customer service chatbot to the customer must be credible, appropriate, useful and most importantly received and properly understood by the customer for it to have an effect (Boateng, 2019; Mavlanova, Benbunan-Finch & Lang, 2016).

Finally, a key prerequisite in Spence's (1973) signaling theory is that a signal should be costly so that it cannot be easily replicated by agents that do not possess the same skills but wish to mimic the signal in order to be granted the same opportunities. Costly does not entail merely monetary value but "are to be interpreted broadly to include psychic and other costs, as well as the direct monetary ones" (Spence, 1973, p. 359). If a customer perceives the signal from the chatbot as easily replicated, it will not be of much value and will therefore, not be properly received and interpreted as a credible signal of competence.

To summarize, the variant of second-order disclosure of a chatbot proposed through this theoretical framework should include the chatbot's identity along with a credible competence signal to influence customer perceptions of chatbot competence.

2.5. Chatbot Attitudes

In order to fully understand attitudes towards a chatbot, the processes and mechanisms underlying the reactions must be defined. Affective reactions, earlier defined as 'mental feeling processes', are an umbrella concept for mental states of moods, emotions and attitudes (Bagozzi et al., 1999; Zhang, 2013). Moods and emotions are often difficult to distinguish, but the former are generally longer lasting mental states of readiness, non-intentional and not coupled with action tendencies in the same way that emotions are (Bagozzi et al., 1999). Attitudes and emotions are different in the sense that emotions do not provide information about the world, instead they indicate how we are affected by the external world in the moment, whereas attitudes are based on internal cognitive evaluations of information that are relatively enduring (Spears & Singh, 2004). Since there is a positive association between the customer's evaluation of the service employee and overall satisfaction with the firm represented by the agent (Söderlund & Rosengren, 2008), the component of interest in this study is primarily attitude and the associated evaluation of the chatbot.

The multi-attribute attitude model defines attitudes as "a learned predisposition to respond in a consistently favorable or unfavorable manner with respect to a given object" (Fishebin, 1963; Fishbein & Ajzen, 1975, p. 6). Such a learned predisposition is a function of an individual's internal evaluation of the object based on their salient beliefs about the object (Fishbein, 1963;

Fishbein & Ajzen, 1975; Mitchell & Olson, 1981). Such beliefs are subjective associations between any two distinguishable concepts, where salience implies the association that is activated and considered by the person based on memory (Fishbein & Ajzen, 1975; Mitchell & Olson, 1981). Many different background variables, such as age, gender, experience, nationality, socio-economic status, values and group membership can theoretically impact the beliefs that people hold (Ajzen, 2005, p. 134). These background variables can be categorized as personal (e.g. values), social (e.g. education) and informative (e.g. experience). Although the importance of background variables is recognized, there is no necessary direct connection between such factors and beliefs. Due to the multitude of potential factors, the context must guide the selection of relevant background factors, if any (Ajzen, 2005, p. 134). Therefore, there is no precise rule for how and which background factors are relevant for salient beliefs but it is possible that they have an impact to some extent based on the context of a study.

The theoretical connection between beliefs and attitudes has been explored extensively. There is overwhelming support for the correlational relationship and empirical support has also been found for the causality chain between attitudes and intentions (Ajzen, 2014; Armitage & Conner, 1999; Sussman & Gifford, 2018). The established strength of the relationship implies relevance of exploring the relationship and investigating further proof of it.

In order to affect attitudes, the salient beliefs must be changed (Fishbein & Ajzen, 1975; Lutz, 1975). The salient beliefs can be altered by either creating new beliefs, attempting to alter the existing beliefs or convincing the customer to re-evaluate their beliefs (Lutz, 1975). Important to note is that a change will only occur if the belief is already included in the salient belief hierarchy or if it becomes salient as part of an influence attempt (Fishbein & Ajzen, 1975 p. 397). In other words, an association must be activated and considered in the customer's cognitive processes in order for the belief to be salient and therefore, for an attitude change to occur.

One potential mechanism to change salient beliefs is through marketing stimulus, i.e. advertising (Holbrook, 1978; Mitchell & Olson, 1981). Although beliefs about product attributes have been found to not be the sole mediators, they are a major mediating factor of advertising content effect on brand attitudes and thus, worth exploring further (Mitchell & Olson, 1981). Holbrook (1978) defined how advertising content can affect beliefs through persuasive communication consisting of factualness and evaluativeness. Factualness consists of objective verifiable descriptions and information about features, whereas evaluativeness entails content related to emotional and subjective aspects of the object. As such, beliefs can be affected by either cognition or affection, which consequently, are mediators of attitude formation driven by beliefs (Holbrook, 1978).

In order to determine which component of beliefs should be targeted primarily, one should address the motivational basis of the attitude, as proposed by the functional theory of attitudes (Katz, 1960). Attitudes can serve different functions and are therefore, the reason for changing the attitude is directly related to the function. The theory identifies a number of functions; utilitarian, value-expressive, ego-defensive and knowledge-based. Since trusting beliefs in the chatbot context are driven by competence perceptions and evaluations that focus on the chatbot's performance and reliability, applying the functional theory of attitudes appears to indicate that customers have a utilitarian motivation for their attitudes in this context. Furthermore, persuasive messages are more likely to be accepted as evidence by rational consumers evaluating the stimuli if they are seen as factual, thus influencing their perceived credibility (Holbrook, 1978). Therefore, an attempt to impact the salient trusting beliefs of customers, i.e. perceived competence, must focus on stimulating cognition through factualness to create a persuasive communication.

The theoretical framework thus far implies that current customer perceptions of competence and therefore, trusting beliefs towards chatbots, are closely connected to attitudes. This creates a potential opportunity since attitudes can be altered by influencing their underlying salient beliefs, as is often done with product attributes in marketing, indicating that the same could be done for trusting attributes of the chatbot. Combining the need for evidence to form calculative trust towards the chatbot (section 2.2.1) through credible signaling of competence (section 2.2.2) with the possibility of affecting salient beliefs through factual marketing stimulus mentioned in this section, it is evident that communication may impact a customer's attitude towards a chatbot. Consequently, the hypothesis follows;

H2: Signaling chatbot competence has a positive effect on chatbot attitude

Since the intention of signaling chatbot competence is to impact the evaluation of the salient trusting belief towards the chatbot, changes in trusting beliefs should in turn impact the overall attitude towards the chatbot. The following hypothesis is postulated;

H3: Trust will mediate the positive effect of signaling chatbot competence on chatbot attitude

Fishbein (1963) proposes that the formulated attitude consists of the summation of the object evaluation responses and on future occasions the evaluation responses will elicit the attitude toward the object. Hence, the future evaluation responses should be based on the previous evaluation formulation, i.e. previous accumulated attitudes toward that object. Hypotheses 2 aims to ignite a change in attitude towards chatbots through persuasive communication. However, attitudes held by the subject a priori the influence attempt are likely to affect the success of impacting salient beliefs. Therefore, the following hypothesis is proposed;

H4: Previous chatbot attitude moderates the effect of signaling competence on chatbot attitude

2.6. Variables Impacted by Chatbot Attitude

2.6.1. Intentions to Use Chatbot

Earlier, trust was defined as consisting of trusting beliefs and trusting intentions (McKnight et al., 2002). Trusting beliefs were explored in section 2.2.1., but the second component must also be investigated for the creation of a comprehensive theoretical framework. Trusting intentions imply a willingness and decision to interact with the counterparty based on their trusting beliefs and risk perception of the interaction (McKnight et al., 2002). In other words, beliefs and resulting attitudes towards a behavior impacts the intention of the behavior, i.e. the subjective probability that a person will perform a behavior (Fisbhein & Ajzen, 1975, p. 288). Intentions are seen as a 'conative' factor of attitude, indicating a strong relation between intention and attitude (Fishbein & Ajzen, 1975, p. 288). This intention in turn precedes the actual behavior (Fishbein & Ajzen, 1975). "Many studies have substantiated the predictive validity of behavioral intentions", meaning that as a general rule the more favorable an attitude, the stronger the intention, which in turn is seen as an immediate antecedent of behavior (Ajzen, 2005, p. 100). Therefore, when actual behavioral observation is not possible, it ought to be sufficient to measure intention as a reliable predictor of consumer behavior.

When investigating the relationship between attitudes and intentions in technological contexts, such as through the consumer acceptance of technology (CAT) model and the technology acceptance model (TAM) (Davis, 1989; Kulviwat, Bruner, Kumar, Nasco & Clark, 2007), the dependent variable measured is the intention to use the technology. Although these models include slight variations of predictors of attitude in order to fit their contexts, the main causal link from attitude to intention resulting in behavior remains. As posited by the multi-attribute attitude model causality chain, the intention to use a technology is the starting point in attempting to increase actual use and ultimately, achieving any benefits of such use to the company (Davis et al., 1989). Building on hypothesis 2 and given the strong relation between attitude and intention, the following hypothesis is proposed;

H5: Signaling chatbot competence has a positive effect on intention to use the chatbot

2.6.2. Brand Liking

Persuasive communication messages may impact not only attitudes towards a product or service but also perceptions towards the brand behind it (Mitchell & Olson, 1981; Olson & Dover, 1978). Brand liking is “the customers’ entire perception of a brand and its associations connected to it” (Keller, 2008). As defined in the introduction, customer service agents are virtually equivalent with the brand in the eyes of customers (Bitner et al., 1990; O’Cass & Grace, 2004; Söderlund & Rosengren, 2008; Wang, 2009). Furthermore, “classical conditioning principles suggest that if a brand is repeatedly paired with a positively evaluated stimulus a “direct transfer” of that evaluation to the brand might occur” (Mitchell & Olson, 1981). In particular, positively evaluated stimuli messages contribute to a positive brand evaluation and changes in the strength of salient beliefs are consistent with changes in brand attitudes (Mitchell & Olson, 1981). Such findings indicate that a persuasive communication signal may not only affect the underlying internal evaluation of attitudes impacting intention to use the chatbot but also measures related to the brand itself, such as brand liking (Mitchell & Olson, 1981). In other words, there are multiple potential effects of one communication stimulus. Measures of brand attribute beliefs are particularly useful in defining the effectiveness of a persuasive communication (Mitchell & Olson, 1981). Therefore, the final hypothesis is proposed;

H6: Signaling chatbot competence has a positive effect on brand liking

2.7. Summary of Theoretical Framework & Hypotheses

To summarize the theoretical framework guiding this study, given the fact that trusting beliefs are based on competence perceptions and identity disclosure of chatbots reduces competence perceptions, the suggested model proposes an added competence signal to the disclosure. The identity disclosure with a competence signal is a variant of second-order disclosure of the chatbot, the efficiency of which to overcome the disclosure paradox will be tested in this study.

The competence signal intends to act as a stimulus impacting the salient trusting competence beliefs of the customer towards the chatbot, which in turn will impact the internal evaluation and resulting attitude towards the chatbot. The causal link in multi-attribute attitude model suggests that if the competence signal is successful in influencing salient beliefs, the changed attitude ought to impact both intention to use the chatbot and overall brand liking as a result. Past attitudes towards the chatbot are hypothesized to moderate the strength of the impact of the competence signal due to the increased strength of salient beliefs resulting from accumulated past attitudes impacting current attitudes. The model is graphically visualized below in Figure 1, with the corresponding hypotheses placed along the hypothesized relationships between measures. The proposed model includes six hypotheses, summarized in table 1.

	Summary of Hypotheses
H1	Signaling chatbot competence has a positive effect on trust
H2	Signaling chatbot competence has a positive effect on chatbot attitude
H3	Trust will mediate the positive effect of signaling chatbot competence on chatbot attitude
H4	Previous chatbot attitude moderates the effect of signaling competence on chatbot attitude
H5	Signaling chatbot competence has a positive effect on intention to use the chatbot
H6	Signaling chatbot competence has a positive effect on brand liking

Table 1. *Summary of hypotheses derived from theoretical framework*

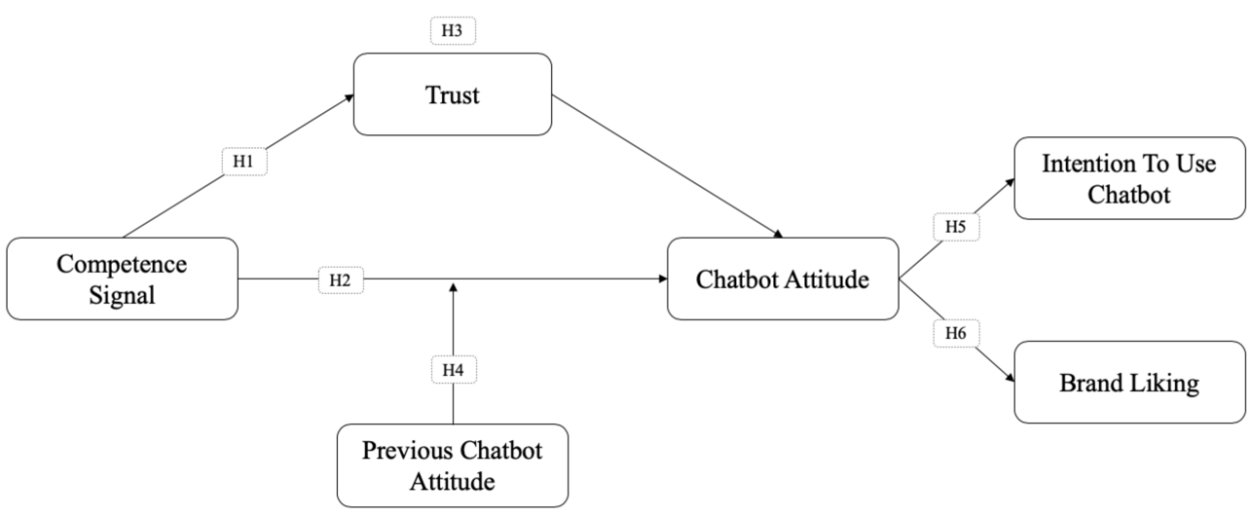

Figure 1. *Conceptual model of theoretical framework*

Finally, the content and communication efficiency of the competence signal in the proposed model is also guided by the theoretical framework outlined above. The signal content should primarily highlight factualness due to the utilitarian function driving the trusting belief and resulting attitude. Factualness can include information relating to expertise, efficiency, ability to provide comprehensive and accurate information, honesty about capabilities and limitations as well as lack of bias to communicate competence (Corritore et al., 2003; Fogg et al., 2001; Folstad et al., 2018; Lee et al., 2000). In order to relay this signal as a persuasive communication, it must be signaled and perceived to be credible by the customer. This entails that the signal cannot be easily replicated by 'incompetent' chatbots and that the signal must be perceived to be appropriate and useful. Most importantly, it must be received and properly understood by the customer for it to achieve the desired effect (Boateng, 2019; Mavlanova et al., 2016; Spence, 1973).

3. Methodology

This section will focus on explaining the scientific approach and design of the study. It will describe the process of formulating the stimuli as well as preparatory studies undertaken prior to the execution of main study. Questionnaire design will also be discussed. Lastly, the quality of the data will be examined.

3.1. Scientific Approach to the Research Design

A quantitative strategy is used in this study, building on the authors' realist ontological view and empiricist epistemology. As the state of theory related to the research question is mature and includes a number of related established fields, including marketing, computer science and psychology, a deductive method was applied (Edmondson & McManus, 2007). A weakness of the deductive approach is the possibility of forming incomplete presumptions regarding the true relationships between variables of interest which can create misguidance for the researcher in his/her work (Alvesson & Sköldberg, 1994). A thorough review of existing theories and findings across the domains was therefore considered important to create a holistic understanding of the topic and existing theories from various angles to facilitate hypotheses-generation on well-grounded theory. All articles were evaluated based on impact score and ABS ranking; higher ranking journals were prioritized in final literature selection to ensure information quality in the review. Exploring theories in all three relevant fields created the possibility of deducing new hypotheses within the intersection of the domains based on prior academic findings. These were then tested empirically within the delimited context of this study.

This paper employs a one-way between-subjects experimental design manipulating the signal of chatbot competence. The experiment consisted of showing a screenshot of a chatbot communication interface with a brief chatbot introduction to the subjects. The treatment group was exposed to a chatbot signaling its competence through an additional message in the chatbot interface, whilst the control group received no such signaling and only received a first-order disclosure of the chatbot's identity. Respondents were randomly assigned to either treatment or control group ensuring that any between-subjects variations could be attributed to the manipulation (Bryman & Bell, 2015). By comparing a treatment group with a control group, ceteris paribus, differences can be attributed to the independent variable of interest, perceived competence, strengthening internal validity (Bryman & Bell, 2015).

The experiment was carried out as an online self-reporting questionnaire where participants were subject to stimulus a priori. Bryman & Bell (2015) advocate that it is the most frequently used method for quantitative strategies. Self-completion questionnaires are also favorable in collecting data otherwise difficult to observe, such as consumer attitudes (Bhattacherjee, 2012). Furthermore, administration of a larger sample size is facilitated and potential data collection biases, e.g. interviewer variability, are mitigated through such questionnaires (Bryman & Bell 2015).

3.2. Preparatory Work

Two preparatory studies and a pilot test were conducted to aid the construction of the main study. The purpose of the first preparatory study was to determine customer expectations of the level of chatbot competence to have a benchmark of what level the signal should aim to convey. After a credible competence level had been determined, the perceived chatbot competence was tested to assess the effectiveness of the manipulation. Lastly, a pilot test was conducted to ensure comprehensibility of the questionnaire prior to proceeding with the main study.

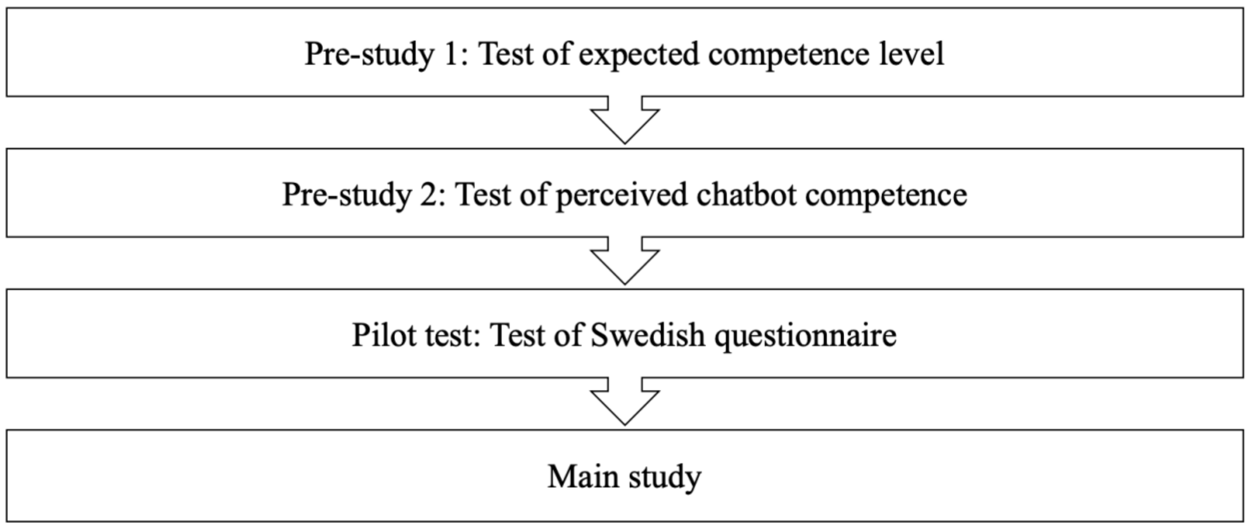

Figure 2. *An overview of the preparatory work process*

3.2.1. Stimuli Development

Designing the stimuli consisted of three components that were developed iteratively. These components are; 1) chatbot interface, 2) chatbot design and 3) chatbot competence signal. The process of composing the components is detailed below. The final stimuli are presented in appendix 1.

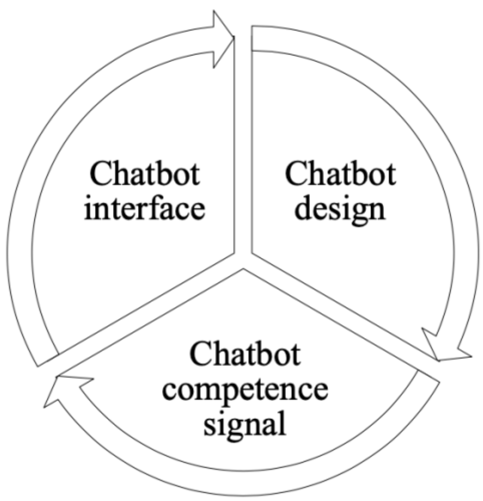

Figure 3. *A graphic representation of the stimuli development process*

3.2.1.1. Chatbot Interface

The first consideration was of the chatbot interface within which the empirical investigation of the second-order disclosure of the chatbot would be displayed. Several options were considered in order to find an optimal chatbot interface for this study, namely; 1) collaboration with a company providing an existing chatbot, 2) programming of a new chatbot and 3) creating a non-interactive proxy. Although a collaboration with a company would have been optimal, it was not feasible within the timeline of this study. In order to determine the best solution, a reflection was done on the purpose of the study, namely; to explore whether a variant of the second-order disclosure can affect humans' resulting attitudes as compared to first-order disclosure. The objective of this study was to create an introductory framing message and to measure the effect thereof on customer perceptions of chatbot competence. In doing so, it was deemed crucial to isolate the effect of the manipulation and to avoid spillover effects of the noise stemming from, for example, an uncontrolled conversation or aspects related to the functionality of the chatbot. Any noise not controlled for could potentially compromise the isolation of variables. Therefore, creating a non-interactive proxy was deemed to be the most viable solution for the chatbot interface used in the experiment.

3.2.1.2. Chatbot Design

Given that a non-interactive proxy was chosen as the interface for the experiment, a main consideration was to ensure a realistic and credible design of the proxy in order to establish ecological validity and to be able to attribute any changes in attitudes solely to the stimuli rather than faults in the interface. The process started exploratively by initially browsing approximately 20 webpages providing chatbots and chatting with existing chatbots in order to familiarize the authors with their linguistics and design to provide guidance for the proxy design. As customer service chatbot design is quite standardized and past studies testing chatbots, mentioned above, used such standardized interfaces, deviating from such designs would have added additional noise potentially causing changes in attitudes of customers due to deviations from the norm and lack of familiarity.

The vast majority of the existing chatbots found through the explorative process had been given names, either human-like, brand related or in several cases, a hybrid of both. Therefore, it was natural to also name the chatbot used for this study. The name Kim was chosen to avoid any spillover effects from using existing names used by well-known companies. Kim was thought to be fairly gender and ethnicity neutral and, thus, an appropriate choice in order to prevent any biases among the study participants.

The exploratory browsing of chatbots also indicated the frequent use of avatar images with varying levels of anthropomorphistic cues. As discussed under section 1.2, the majority of prior research on chatbots has investigated such anthropomorphistic cues in chatbots (Ciechanowski et al., 2019; Gong & Nass, 2007; Ishowo-Oloko et al., 2019; Lee & See, 2004; Luo et al., 2019; Mandell et al., 2017; Wiese et al., 2019; Weise & Weis, 2020; Weis & Wiese, 2017; Yamada et al., 2013). However, to avoid any uncanny feelings due to the cognitive dissonance resulting from the combination of chatbot text and the avatar design, the chatbot profile picture was kept simple, without any attempt of animation (Ciechanowski et al. 2019; Gong & Nass, 2007). This allowed for an isolation of the effect of variations in text while controlling for cognitive dissonance resulting from any perceived mismatch with the avatar.

Blue and grey were chosen as thematic colors for the chatbot after a consultation with a graphic designer (N. Kapo, phone interview, February 21, 2020). The blue color was selected because it is often perceived as a signal of trustworthiness and loyalty. It is, for example, often used in trust-requiring industries, such as banking and insurance. The grey color was chosen for its alleged neutrality and legibility. For the layout, the so called unjustified text (i.e. text starting from the left side with equal word-spacing and no hyphenation) was used for all text, because this alternative is the preferred layout for screen based texts (Wilson & Corlett, 2005).

In order to add a didactic element in the display and to reinforce the provided text-based information, an illustration was added. Illustrations are regarded to have an additive function, enhancing recall of the textual material (Levie & Lentz, 1982). Following the argument of (Wilson & Corlett, 2005) that a bar chart is “the simplest kind of graphical representation” used to facilitate understanding, a simple illustration of a bar chart was included in conjunction with the text signaling competence, with the aim to create an enhanced and uniform interpretation of the stimuli.

3.2.1.3. Chatbot Competence Signal

As defined in the theoretical framework, the trusting belief of relevance is the perception of the chatbot’s competence, i.e. the ability of the chatbot to do what the customer needs (McKnight et al., 2002). In the context of customer service in banking, the chatbot must be able to solve the customers’ inquiries efficiently and reliably (Chung, Ko, Joung & Kim, 2018; Yen & Chiang, 2020). Furthermore, persuasive communication ought to primarily focus on factualness, i.e. objective verifiable descriptions and information about features of the chatbot (Corritore et al., 2003; Fogg et al., 2001; Folstad et al., 2018; Holbrook, 1978; Lee et al., 2000). Hence, the chatbot competence signal included the chatbot’s ability to fulfill a customer request accurately and efficiently. A percentage rate of correctly solved tasks was deemed to be an effective way to display such information, inspired by the thesis supervisor.

The next consideration was the chosen percentage for the success rate information. A factual signal must be difficult to replicate by incompetent chatbots in order for the signal to be credible (Spence, 1973). Thus, the evidence of fulfilling a customer request accurately and efficiently must be strong enough so that an incompetent chatbot is not be able to achieve the same level. An adequately high percentage rate was tested through the first preparatory study.

Furthermore, companies are perceived to be more competent when information with numerical precision is used in marketing stimuli, e.g. 5367 as opposed to 5000 (Dehaene & Mehler, 1992; Xie & Kronrod, 2012). Precise numbers are seen as more credible and scientific but only if the customer perceives the number to be believable (Xie & Kronrod, 2012). Therefore, the numbers used in the stimuli were inspired by the findings from the first preparatory study and the believability and efficiency of the signal were investigated in the second preparatory study.

Consequently, the theoretical framework combined with findings from the first preparatory study (discussed in section 3.2.2.), resulted in the following competence signal being tested in the main study; '*92% of inquiries solved directly in the chat - based on 5367 cases*', where 92% was the mean result from the first preparatory study and 5367 was an arbitrary precise number, tested for believability in the second pre-study. Since the signal must be credible and convincing to have an effect (Boateng, 2019; Spence, 1973), a successful manipulation shown through statistically significant differences in perceived competence is believed to imply that the signal fulfills such criteria.

3.2.2. Pre-Study 1: Testing Customer Competence Expectations

3.2.2.1. Purpose of Study

The purpose of the first preparatory study was two-fold; 1) to determine if the theoretical definition of competence in this study aligns with real-life associations and, 2) to gain an understanding regarding customers' expectations of chatbot competence in order to create an appropriate level of competence to signal. The study was inspired by Kuhnert, Ragni & Lindner's (2017) study which investigated the gap between human's current attitudes and their ideal expectations of robots to understand how the gap can be closed and expectations of people towards the technology be met.

The respondents in the preparatory study were asked to state the percentage of cases that their customer service chatbot in the banking industry should be able to solve, in order to gain an understanding of their expectations of desired competence levels. The question was presented as a graphic slider, where the respondent could select the rate of success from 0-100%. In the second part, the respondents received an open-ended question inquiring about their definition of chatbot competence.

3.2.2.2. Result & Conclusion

A convenience sample of 78 people participated in a survey distributed on social media channels via the authors' personal networks. The sample consisted of Swedish nationals and the average age of the sample was 29. The average mean of the responses related to the desired success rate of customer service chatbot was 92%. The respondents' definition of competence was largely in line with theory, as efficiency, reliability, security and the ability to solve customer service problems were the main components defined in the preparatory study.

3.2.3. Pre-Study 2: Testing Perceived Chatbot Competence

3.2.3.1. Purpose of Study

The purpose of the second preparatory study was to assess the assumption that the competence signal would have an effect on the participants' evaluation of the chatbot's perceived competence attributes. The intention was to test whether or not the stimuli was working as intended, i.e. if the stimuli would statistically significantly produce a difference in perceived competence between the treatment and control groups. A ten-point five-item semantic scale adopted from Bartneck et al. (2007) was used to collect responses, see section 3.4.3.7. for detailed measure information.

3.2.3.2. Result & Conclusion

The initial sample included 103 respondents recruited from the online crowdsourcing marketplace platform Mechanical Turk (MTurk). The sample was not delimited to Swedish bank account holders as such delimitations are not possible on the platform. Participants were randomly divided into either treatment or control groups, henceforth referred to as signaling and non-signaling, respectively.

To increase the data quality, two attention checks, so called trap questions, were included and participants who failed to answer those questions correctly were omitted from the final analysis (Jones, House & Gao, 2015). Filtering for failed checks left 25 respondents in the signaling group and 16 in the non-signaling group. Preceding tests confirmed that assumptions for normal distribution and homogeneity of variance were satisfied. Although a vast number of respondents were excluded in the analysis due to inattentiveness, Hauser and Schwarz (2016) argue that research has shown that the platform provides equally or more attentive participants than college subject pool students.

An independent samples t-test was performed to test the success of the manipulation. The t-test showed a significant difference in the perceived competence of the chatbot ($t(39) = 2.55$, $p = 0.008$) between the signaling condition ($M = 8.26$, $SD = 1.31$) and the non-signaling condition ($M = 6.95$, $SD = 1.98$, one-tailed). The Hedge's test indicated that the magnitude of the between-group differences had a large effect (0.815) (Hedges, 1981; Pallant, 2013).

The results suggested that the stimuli had successfully managed to manipulate the participants to perceive the chatbot as more competent, which was the intention of the signal. In order for the signal to be effective it had to be credible, appropriate, costly and most importantly properly understood by the receiver (Boateng, 2019; Mavlanova et al., 2016; Spence, 1973, p.359). Since the signal produced the desired outcome, the aforementioned prerequisites were therefore assumed to be fulfilled.

Before proceeding to the main study, the authors wanted to confirm that the manipulation would produce a tendency aligned with the proposed theoretical framework and consequently the main effect was measured, i.e. the effect of signaling chatbot competence on chatbot attitude. The t-test could confirm a significant difference in the attitude towards the chatbot ($t(39) = 1.83$, $p = .038$) between the signaling condition ($M = 8.09$, $SD = 2.21$) and the non-signaling condition ($M = 6.81$, $SD = 2.16$, one-tailed). The Hedge's test indicated that the strength of the association was moderate (0.585) (Hedges, 1981; Pallant, 2013). These results suggested that participants who were exposed to the competence signal also had a more positive attitude towards the chatbot, in comparison to the participants who were not exposed to the signal.

Conclusively, in connection with the established theoretical framework, the information deemed to be needed to proceed to the subsequent step in the preparations had been obtained.

3.3. Pilot Testing in Swedish

The last step of finalizing the preparatory work necessitated translating the questionnaire from English to Swedish. Subsequently, a qualitative pilot test in which 10 native Swedish speakers evaluated the final questionnaire was conducted in order to ensure comprehensibility. The main objective was to assure no idiomatic errors had occurred during the translation process, securing the preservation of the meaning of the measures (Hackett, 2019, p. 79). As advocated by Wilson and Corlett (2005), the participants for the evaluation trial were chosen to provide wide ability and age-ranges. Heterogeneity in regard to age, sex and socioeconomic background was also premiered since it resembled the variety in the main study sample. All respondents were asked to give verbal feedback on the survey as they completed it. This allowed for recording of their initial reactions towards the information. As a result of the procedure, one adjustment relating to a measure as well as minor changes in the introduction message were deemed adequate. Lastly, the data collection company (Norstat) provided feedback on the instructions and alterations were made accordingly prior to distribution.

3.4. Main Study

3.4.1. Sampling

In order to enable generalizability and validity of results, it is important to use a representative sample (Bryman & Bell, 2015; Svenning, 2003). The goal was to use a sample representative of a Swedish bank customer, meaning that a broad representation was desirable. Albeit the context may differ, an assumption is made that the vast majority of customers are exposed to communication with customer service at one point in time or another. Rather than focusing solely on customers with the habit of using chatbots for such services, the purpose was to detect effects significant for customers in general regardless of their current preferences for customer service agents.

Reflecting on the delimitation of the study to the bank sector, the likelihood of managing a bank account and/or related bank services was taken into consideration to the extent that it was deemed necessary for the respondent to be somewhat familiar with the aforementioned. A relevant factor presumably determining familiarity included age, since there is a lower age limit for opening a bank account (https://www.konsumenternas.se/spara/fakta/spara-till-barn). Thus, the final selection included Swedish customers above 18 years of age. However, no further demographic delimitations were deemed necessary since bank services are widely used among the whole Swedish population.

The sample consisted of 1000 respondents with the mean age of 43.96 years and equal gender distribution (men = 49,5%; women = 50,0%; other = 0,5%). The main survey was distributed through the data collection company Norstat and was launched between 16th - 23rd of April 2020. The collaboration facilitated unbiased sampling distribution representative of the relevant population due to Norstat's wide-reaching network. All respondents were randomly selected from Norstat's database based on adequate fit with the target population. Through their data tools, the survey was distributed online with both a mobile friendly and computer/tablet version. Since the study was delimited to only Sweden's population the survey was distributed only in Sweden.

3.4.2. Questionnaire

The questionnaire consisted of seven main questions with closed answers, four demographic questions as well as a manipulation and attention check. Closed answers were chosen to facilitate comparability of results (Bryman & Bell, 2015; Hackett, 2019). Since the population of interest was consumers in Sweden, the questionnaire was conducted in the native language to avoid idiomatic errors. All participants received identical questionnaires except for the stimuli differences between treatment and control group. See Appendix 1 for the full questionnaire.

To increase the attention of the respondents and avoid unnecessary noise, the intention was to avoid a lengthy questionnaire while still ensuring all relevant variables were included (Hauser, Ellsworth & Gonzalez, 2018; Söderlund, 2005, p.25). In addition, the order of the questions was considered important. Each question creates a psychological process for the respondent and spillover effects from previous questions may influence subsequent answers, i.e. it becomes harder to distinguish the accuracy of the result of each measure as the survey proceeds (Schwarz & Strack, 1991; Söderlund, 2005). The degree of measure importance therefore determined the order in which the question was asked, leading with the most important dependent variables (Malhotra, 2010).

The aforementioned argument is also relevant for the order chosen for the manipulation and attention checks. Manipulation checks are becoming increasingly important to assess the effectiveness of the stimuli since many experiments nowadays are conducted remotely on a computer without direct control (Baumeister, Vohs & Funder, 2007). To effectively measure the manipulation success without influencing other measures, the check is often conducted after measuring dependent variables. However, moving the manipulation check towards the end of the survey may compromise the validity of the measure as attention dwindles towards the end (Hauser et al., 2018). The manipulation check was therefore placed directly after the most crucial dependent variables.

Further, the respondents' attentiveness normally fluctuates throughout the questionnaire (Hauser et al., 2018). Participants could therefore in practicality stay attentive during a check, but not during a crucial measure. To solve this potential problem, the attention check was carried out in direct conjunction to the most important variables.

All questions were recorded on a ten-point semantic or Likert scale. An even-number scale was chosen to prevent respondents from choosing a middle option due to laziness (Malhotra, 2010). The majority of questions were constructed and probed on multi-item scales. Questions deemed 'easy' to answer included fewer items, whereas complex constructs, e.g. trust, in accordance with Berntson et al. (2016), needed additional items for the construct to be fully captured. The complexity of the question was therefore considered in the final item choice.

To facilitate understanding, all negative scale items (e.g. dislike) were placed on the left-hand side of the scale and positive items (e.g. like) were placed on the right hand (Malhotra, 2010; Söderlund, 2005). Previous research has shown that the order of the answers presented can impact the probability of choosing a specific answer. Answers presented first tend to be selected more frequently (Söderlund, 2005). To further mitigate potential response biases the orders of all items were randomized in the survey (Malhotra, 2010).

3.4.3. Measures

According to Söderlund (2005) a measure construct is twofold: the question asked (item stem) and the response alternative (item leaf). Both play a key role in the success of a study since choices regarding formulating measures can alter the results. The items should capture and reflect the construct in question (Berntson et al., 2016; Bryman & Bell, 2015; Söderlund, 2005). For this reason, all measures employed in this study were chosen with careful consideration and the vast majority of the measures used were established measures previously used in other similar research contexts. However, not all constructs and contextual factors of the study scope were considered to be adequately captured by existing measures and consequently a few measures were adapted when necessary. In particular this involved altering the item stem, while still applying established item leaves.

A comparison with existing measures was made in which small tweaks were applied by e.g. incorporating 'chatbot' rather than 'robot'. Adapting a measure demands careful consideration (Berntson et al., 2016; Hackett, 2019; Söderlund, 2005). Although completely new measures were not made, the few alterations made still followed recommendations suggested by Hackett (2019) and Söderlund (2005). The steps undertaken included, but were not limited to, an iterative process of formulation and reformulation of questions aiming to; 1) use linguistics understood by everyone, 2) only include one question at time and minimize word count, 3) avoid leading questions and 4) allow for uniform interpretation. Further, all items were tested both qualitatively, by conducting 'speak as you read' tests to capture spontaneous feedback, and quantitatively in the preparatory work.

3.4.3.1. Chatbot Attitude

This measure was chosen to test the respondents' overall attitude towards the chatbot. The measure was adapted from Holbrook and Batra (1987). This scale has been widely adopted in various research contexts measuring attitudes (Söderlund, 2005, p. 143), which makes it appropriate also in this study, despite the slightly different context from the original. Hitherto, negative attitudes toward bots has been the predominant measure (e.g. Bartneck, Suzuki, Kanda & Nomura, 2007), however a delimitation to negative attitudes was not deemed adequate for the purpose of this study since a broader understanding of general attitudes is needed. The respondents were asked the question: "What is your overall view of the chatbot?". Responses were recorded on a semantic ten-point three-item scale including "dislike - like", "bad - good" and "disadvantageous - advantageous" ($\alpha = 0.920$).

3.4.3.2. Trust

Trust was measured by adapting McKnight's (2011) 26-item trust scale where respondents were asked to rate the statements presented to them. The 26 items were narrowed down to include the item leaves adequately corresponding to the definition of trust used in this study, since it is important to use measures that reflect construct definitions (Berntson et al., 2016). Additionally, by excluding irrelevant items the response time could be shortened. The eight items included in the final scale were; "I think this chatbot system is reliable", "I think this chatbot is capable in meeting my needs", "I think this chatbot delivers good work", "I think this chatbot is credible", "I am convinced that this chatbot can work alone, without assistance of people", "I have faith in the skills of this chatbot" and "I trust this chatbot completely". All items were presented on a ten-point Likert scale ranging from "strongly disagree" to "strongly agree". The items were averaged into an index, Cronbach's $\alpha = 0.960$.

3.4.3.3. Intention To Use Chatbot

Chatbot usage intention was measured by adapting Wang et al.'s (2007) scale including the items "I would be willing to use this chatbot for customer service" and "The likelihood that I would use this chatbot for customer service is very high". All responses were recorded on a ten-point Likert scale (strongly disagree - strongly agree). The items were weighted into an index (Pearson's corr. = 0.919, sig. < 0.001).

3.4.3.4. Brand Liking

Brand liking was measured to capture potential spillover effects from chatbot attitude to the overall brand. It was measured through the question: "What is your opinion regarding the bank providing the chatbot?". All responses were recorded on a ten-point three-item semantic scale including "dislike - like", "bad - good" and "disadvantageous - advantageous" (Holbrook & Batra, 1987) ($\alpha = 0.977$).

3.4.3.5. Previous Chatbot Attitude

Similarly to ‘chatbot attitude’, the measure for previous chatbot attitude was adapted from Holbrook and Batra (1987) to ensure measure consistency. Respondents answered the question: “How would you describe your previous experiences with chatbots?”. Answers were recorded on a ten-point three-item semantic scale including “dislike - like”, “bad - good” and “unpleasant - pleasant” ($\alpha = 0.952$).

3.4.3.6. Anthropomorphism

This measure was included as a control variable to assure statistically non-significant differences between treatment and control group to isolate the effect of the manipulation. Perceived anthropomorphism was measured on a ten-point four-item semantic scale including the following items: “fake - natural”, ”machinelike - humanlike”, “unconscious - conscious” and “artificial - lifelike” (Bartneck et al., 2009). The items were averaged into an index ($\alpha = 0.910$).

3.4.3.7. Manipulation Check

To ensure that the stimuli had the desired effect, a manipulation check was performed. Although this had been confirmed in the second preparatory study, the questionnaire had been translated subsequently. Hence, the check was considered necessary for validating the effect also for the main study as an additional precaution. The success of the manipulation was tested through the statement: “Please rate the chatbot on the following features”. Responses were recorded on a ten-point five-item semantic scale including the items “unintelligent - intelligent”, “incompetent - competent”, “ignorant - knowledgeable” and “irresponsible - responsible” (Bartneck et al., 2009). The items were averaged into an index ($\alpha = 0.923$).

3.4.3.8. Background Variables

As mentioned in the theoretical framework, background variables may be of importance when investigating beliefs and the study context should determine which such factors are of relevance

(Ajzen, 2005, p. 134). To account for personal and social background factors, general demographic questions were asked. These included age, gender, income and educational level and were part of Norstat's standardized set of demographic questions.

Furthermore, the informative background variable of interest was deemed to be previous chatbot experience, in order to capture the respondents' previous habits of interaction with chatbots and thus their current familiarity with the technology. Respondents answered the question: "How familiar are you with interacting with chatbots? This includes both text and voice-based chatbots". All responses were recorded on a ten-point Likert scale with the options "not familiar at all - extremely familiar". The measure was based on recommendations in accordance with Söderlund (2005) and Hackett (2019).

3.4.4. Analytical Tools, Tests & Assumptions

The data from the main study was delivered by Norstat in a SAV. format and preparatory studies were exported from Qualtrics. All results were subsequently analyzed in the statistical tool SPSS, version 26, together with the add-on program Hayes PROCESS for SPSS, version 3.5. The data collection was conducted in collaboration with Norstat, and consequently the sample size was a result of discussions aiming to match resources and requisites. Although the statistical power of the sample could arguably be improved through an increase in sample size, 1000 participants are still considered enough to provide data quality (Bryman & Bell, 2015, p. 199). A large sample cannot guarantee precision; however, sample errors decrease as a consequence of an increase in sample size. Bryman and Bell (2015) argue that the sharp increase in precision of a sample becomes less pronounced around a sample size of 1000, which further motivated the authors' choice.

An attention check was included in the survey in order to increase statistical power (Oppenheimer, Meyvis & Davidenko, 2009). Jones, House and Gao (2015) argue that participants who fail to answer the attention check are also more likely to stay inattentive throughout the whole survey. By omitting such responses, the quality of the data should increase.

A significance level of 0.05 was chosen for all statistical analyses. A higher significance level increases the risk of type I error and decreases the probability of type II error. As the number of 0.05 is frequently applied as a critical significance level it was deemed appropriate also for this study (Janssens, Wijnen, De Pelsmacker & Van Kenhove, 2008, p. 49; Pallant, 2013, p. 250).

Independent sample t-tests were performed to test the hypotheses and establish any significant mean differences between treatment and control group. Levene's test for homogeneity of variance as well as Kolmogorov-Smirnov test for normality preceded the testing. The effect size was tested through Hedges g calculation. Bivariate and multiple regression analyses were carried out to establish possible effects of the independent variables on the dependent variables in the proposed theoretical framework. Assumptions for multicollinearity, outliers, normality, linearity and homoscedasticity were controlled for.

3.5. Data Quality

A common concern in quantitative research is the data quality in regard to the measurement reliability, validity and replicability (Bryman & Bell, 2015, p. 174). The three issues are addressed below, primarily focusing on the aspects of reliability and validity.

3.5.1. Reliability

Reliability is concerned with issues of consistency of measures (Bryman & Bell, 2015, p. 168). A low degree of reliability increases the risk of a type II error, meaning that incorrect conclusions may be drawn (Berntson et al., 2016, p. 69). To strengthen the reliability, primary data was collected as multi-item measures and all measures were indexed to new mean averaged variables (Berntson et al., 2016; Bryman & Bell, 2015, p. 168). To assess the internal reliability, Cronbach's alpha tests were performed for all measures, with an acceptance level of minimum 0.7 and for well-established measures 0.8 (Nunnally, 1978). Reviewing section 3.4.3., it is evident that all measures scored above the satisfactory level, assuring a high internal consistency.

Furthermore, the data collection provided limited risk for problems relating to inter-rater reliability. Such issues entail dealing with potential lack of consistency in decision-making based on subjective judgement by more than one rater (Bryman & bell, 2015, p. 169). Since the raw data was collected through self-reporting questionnaires with no observer prevalent, inter-rater inconsistency was arguably non-existent. Inconsistency was further limited by the data collection process, in which the raw data was automatically transferred from the survey tool to the statistical analytical program. Lastly, all measures were decided upon prior to the data collection; closed-ended questions measured on multi-point scales facilitated analysis without further need of data categorization.

Due to the temporal changeability of attitudes, the stability of the measures might be an issue. To ensure reliability in a measure, it should be measured during multiple occasions, by the same respondent (Söderlund, 2005, p. 138). The aim with this study is to examine how to alter attitudes, and thus any efforts hoping to maintain equivalent attitudes over time for the same respondent is of little relevance for the nature of the study. In addition, it was also not considered practically viable to conduct several measurements. As a consequence, the inability to execute multiple measurements might be a limitation of the reliability. It should, however, be noted that attitudes are longer-lasting mental states of readiness and an accumulation of salient beliefs formed over time, meaning they are a considerably stable concept (Bagozzi et al., 1999; Fishbein, 1963).

3.5.2. Validity

Validity refers to whether or not a measure truly measures the concept of interest (Bryman & Bell, 2015, p. 170). High reliability does not provide evidence for a sufficient validity and thus, both constructs deserve attention.

In this study, the proposed measures are parts of larger nomological networks based on established attitude theories. By applying and testing relationships that have previously been examined in research, the internal validity increases (Bryman & Bell, 2015, p.171). For example, many attitude theories claim that attitudes will affect intention (Söderlund, 2015, p. 155). This provides support for the existence of such links also in this study context. Further, the vast majority of all measures applied has been used extensively in prior research, indicating a high content validity. Small alterations were done to a few measures to fit the context of this study. Although these changes were considered minor, extensive work was carried out to ensure that the validity would not be compromised. Alterations were done in accordance with Söderlund (2005) and Hackett's (2019) recommendations on how to successfully construct measures, see section 3.4.3. for detailed explanation, and the measures were 'sanity checked' by the supervisor. Since the measures were translated from its original language to Swedish prior to distributing the main study, the face validity was further confirmed in a pilot study.

External validity refers to the extent that results from a study can be generalized beyond the specific research context for a particular study (Bryman & Bell, 2015, p. 51). The collaboration with Norstat facilitated sampling by providing access to a representative sample of a Swedish customer within the banking sector. Findings should therefore be generalizable to the whole population of investigation. The contextualization of the banking industry may create limitations to generalizations beyond the sector. Due to the nature of the industry, interactions within banking often require a higher degree of complexity and trust, compared to e.g. customer service interactions in retail (Boateng, 2019). Such differences may affect the relevance of applying findings extrapolated in this study in other industry-specific environments.

Limitations may also exist in terms of ecological validity. Ecological validity is concerned with the extent to which social scientific findings are applicable in people's real-life, natural settings (Bryman & Bell, 2015, p. 51). Since the participants were not provided with a real chatbot to interact with, only a framing message, it could be argued that the interaction was seemingly unnatural. To bridge this distance, emphasis was placed on producing a realistic chatbot interface and design, as well as delivering an introductory message encouraging the respondents' imagination and 'transporting' them into a realistic scenario.

3.5.3. Replicability

Replicability refers to the extent research can be reproduced successfully by others. A prerequisite is the need for clear documentation of procedures in order for others to replicate the findings (Bryman & Bell, 2015, p. 176). All procedures in this study have been systematically documented in detail, both theoretically, methodologically as well as empirically to facilitate replicability.

4. Results

In this section the results of the main study will be presented. Hypotheses will either be accepted or rejected and additional findings will be acknowledged. The exposure of the treatment and control group is referred to as signaling condition and the non-signaling condition respectively. The proposed conceptual framework is presented below as a reminder prior to testing the hypotheses, see figure 4.

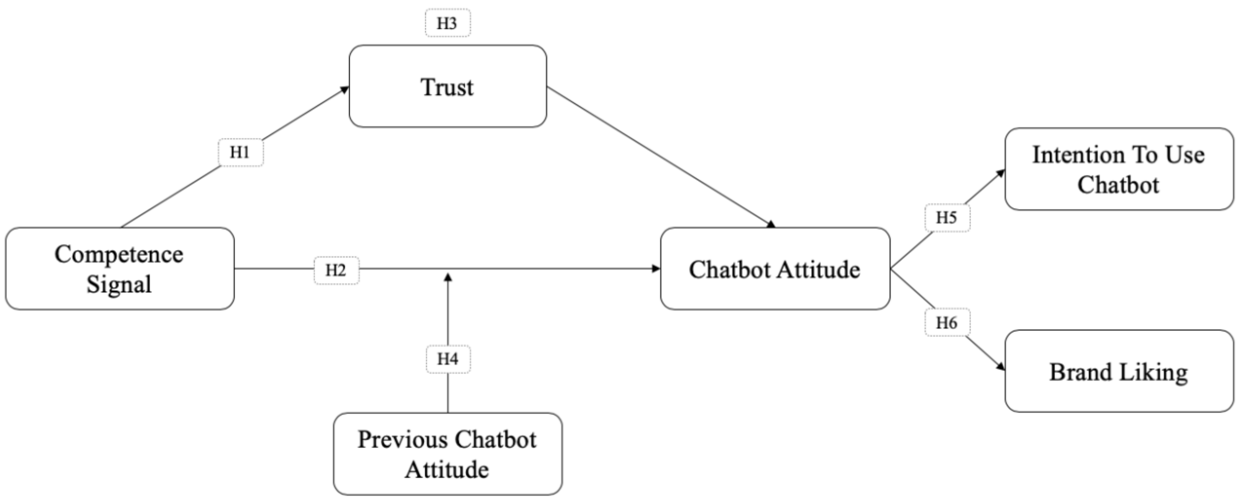

Figure 4. *Conceptual model of theoretical framework*

4.1. Attention & Manipulation check

All respondents who did not pass the attention check were omitted from the final analysis to enhance data quality (Jones, House & Gao, 2015). After such omissions, 908 of the initial 1000 respondents remained, corresponding to 91% of the total participants. Both conditions had an equal number of successful answers ($n_{signaling}$=454; $n_{nonsignaling}$=454), resulting in 908 observations in the final data set.

Surprisingly, the manipulation check did not manage to reproduce the results from the second preparatory study. The independent samples t-test showed no significant difference in the perceived competence of the chatbot (t(906) = -.17, p = .433) between the signaling condition (M = 5.07, SD = 2.00) and the non-signaling condition (M = 5.09, SD = 1.99, one-tailed). Hence, it was not possible to confirm that the respondents received the signal successfully, see table 2 below.

	Mean values		
	Signaling condition	Non-signaling condition	Difference
Perceived Chatbot Competence	5.07	5.09	-.022

Table 2. *Independent samples t-test results showing the perceived competence of the stimuli*

In the case that the non-statistically significant manipulation was a result of a fault in the measure itself, the authors' proceeded with the remainder of the tests as planned in order to do a thorough analysis of the data before drawing any conclusions.

4.2. Hypothesis Testing

4.2.1. Signaling Effect on Trust

To test the hypothesis that signaling chatbot competence would have a positive effect on trust, an independent samples t-test was performed, as suggested by Janssens et al. (2008). The test showed no significant difference in trust (t(906) = -.04, p = .484) between the signaling condition (M = 4.41, SD = 2.10) and the non-signaling condition (M = 4.42, SD = 2.07, one-tailed), see table 3. Thus, signaling competence was not associated with significantly higher or lower trust. No empirical evidence was therefore found to accept the first hypothesis.

	Mean values		
	Signaling condition	Non-signaling condition	Difference
Trust	4.41	4.42	-.006

Table 3. *Independent samples t-test results showing trust levels of the stimuli*

H1: Signaling chatbot competence has a positive effect on trust **NOT SUPPORTED**

4.2.2. Signaling Effect on Attitude

Signaling chatbot competence was hypothesized to induce a positive chatbot attitude. The between-group mean values were compared through an independent samples t-test, resulting in a non-statistically significant difference in chatbot attitude (t(906) = -.59, *p* =.277) between signaling condition (*M* = 5.20, *SD* = 2.29) and the non-signaling condition (M = 5.30, *SD* = 2.29, one-tailed), see table 4. These results suggest that signaling competence does not have a significant effect on chatbot attitude. Thus, hypothesis 2 was not supported.

	Mean values		
	Signaling condition	Non-signaling condition	Difference
Chatbot Attitude	5.20	5.30	-.090

Table 4. *Independent samples t-test results showing chatbot attitude of the stimuli*

H2: Signaling chatbot competence has a positive effect on chatbot attitude **NOT SUPPORTED**

4.2.3. Trust as a Mediator

It was hypothesized that trust would mediate the effect of signaling competence on chatbot attitude. A mediation analysis using Hayes macro PROCESS for SPSS, model 4, was performed to test this hypothesis. The macro allows for testing though a linear regression framework using a bootstrapping sample (n = 5000) (Preacher & Hayes, 2008).

Prior to running the macro, preliminary analyses were performed to ensure that there was no violation of necessary assumptions. The analysis was unable to provide support for an indirect effect (95% CI [-.236, .221]) since the confidence intervals cross zero. In addition, a direct effect was not statistically significant due to confidence intervals once again crossing zero (95% CI [-.282, .111]). In accordance with Zhao et al. 2010, the failure in detecting neither a significant direct nor indirect effect indicates that no mediation or "no-effect" prevails. Thus, the result does not provide empirical support that trust mediates the effect of signaling competence on the chatbot attitude. Hence, hypothesis 3 was not supported.

H3: Trust will mediate the positive effect of signaling chatbot competence on chatbot attitude
NOT SUPPORTED

4.2.4. Previous Chatbot Attitudes as a Moderator

The hypothesized moderating effect of previous chatbot attitude on the relationship between signaling competence and chatbot attitude was tested using model 1 in Hayes PROCESS tool for SPSS, applying a bootstrapping for indirect effect (n = 5000). Signaling competence and previous chatbot attitude explained 50% of the variance in chatbot attitude, R^2 = .50, (F(3,904) = 305.852, *p* < .001). Non-significant results prevailed for the effect of signaling competence on chatbot attitude, β = -0.04, *t* = -.18, *p* = .858. Previous chatbot attitude significantly predicted chatbot attitude β = .715, *t* = 21.64, *p* < .001. These results suggest that overall previous attitude towards chatbots will affect the attitude towards this particular chatbot but signaling competence will not. However, no significant interaction effect was found β = -.00, *t* = -.15, *p* = .879. This indicates that prior chatbot attitude does not act as a moderator as hypothesized. Hypothesis 4 was therefore not supported.

H4: Previous chatbot attitude moderates the effect of signaling competence on chatbot attitude

NOT SUPPORTED

4.2.5. Signaling & Intention to Use Chatbot

In order to investigate if signaling chatbot competence has a positive effect on intention to use the chatbot, an independent samples t-test was conducted. The analysis did not show a significant difference (t(906) = -.22, p =.412) between the signaling condition (M = 4.57, SD = 2.76) and the non-signaling condition (M = 4.62, SD = 2.72, one-tailed). These results indicate that signaling competence does not significantly affect the intention to use the chatbot, see table 5. Thus, hypothesis 5 was not supported.

	Mean values		
	Signaling condition	Non-signaling condition	Difference
Intention To Use Chatbot	4.57	4.62	-.041

Table 5. *Independent samples t-test results showing intention to use chatbot level of the stimuli*

H5: Signaling chatbot competence has a positive effect on intention to use the chatbot

NOT SUPPORTED

4.2.6. Signaling & Brand liking

It was hypothesized that signaling competence would have a positive effect on brand liking. The independent samples t-test did not provide a significant difference in brand liking (t(906) = -.68,

p =.250) between the signaling condition (M = 4.59, SD = 2.26) and the non-signaling condition (M = 4.69, SD = 2.26). Therefore, the competence signal was not associated with a significantly higher or lower brand liking, see table 6. Hypothesis 6 was thus rejected.

	Mean values		
	Signaling condition	Non-signaling condition	Difference
Brand Liking	4.59	4.69	-.101

Table 6. *Independent samples t-test results showing intention to use chatbot level of the stimuli*

H6: Signaling chatbot competence has a positive effect on brand liking

NOT SUPPORTED

4.2.7. Additional Findings

With respect to the ambiguity in confirming the success of the manipulation, additional testing was excogitated.

An unsuccessful manipulation would not expect to produce significantly different between-groups mean values in accordance with proposed hypotheses, with the rationale that the respondents would not have been manipulated as intended and consequently no effect should arise. Since neither of the variables extrapolated significantly different mean values, the results indicated that the two conditions could potentially be merged for further analysis.

Although the results did not provide support that *signaling* competence would induce positive firm-level effects in line with the hypotheses, the effect of introducing and substituting the former with perceived chatbot competence in the proposed framework was examined through a set of regression analyses. Despite the failure of the signal, the sample still included the respondents' perceived chatbot competence, enabling an analysis of the relationship between perceived chatbot competence and the remaining variables, see figure 5 for modified proposed framework.

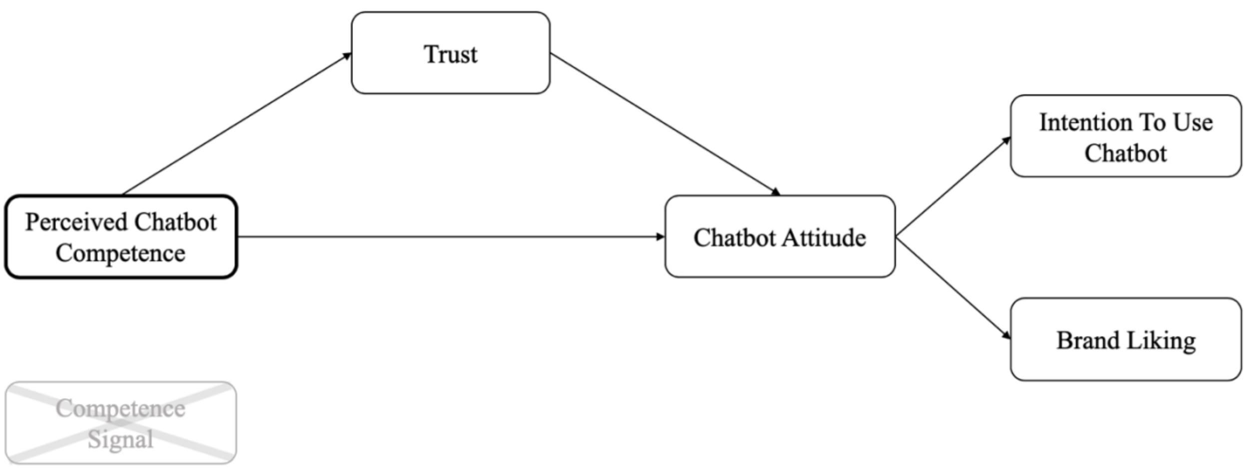

Figure 5. *Adjusted proposed theoretical framework*

In order to merge the treatment and control group, the effect of each independent variable on the dependent variable had to not significantly differ between the signaling and non-signaling condition. Hence, regression analyses including interaction variables were conducted for all model variables. All interactions were non-significant, as shown in table 7, indicating that the groups did not significantly differ from each other and consequently a merger of the signaling and non-signaling condition was plausible.

Dependent variable	Independent variable	Interaction coefficient	Sig.
Trust	Perceived Chatbot Competence	.069	.115
Chatbot Attitude	Perceived Chatbot Competence	.015	.784
Chatbot Attitude	Trust	-.007	.891
Intentions To Use Chatbot	Chatbot Attitude	.032	.553
Brand Liking	Chatbot Attitude	.048	.295

Table 7. *Overview of non-significant interactions between competence signaling and independent variables*

The additional findings resulting from the regression analyses of the merged groups are presented below.

4.2.7.1. Perceived Competence & Trust

A simple linear regression was calculated to predict the trust in the chatbot based on perceived competence of the chatbot. Perceived chatbot competence explained 60% of the variance in chatbot attitude, R^2 = .60, (F(1,906) = 1342.805, p < 0.001). Thus, perceived chatbot competence significantly predicts trust, β = .81, t = 36.64, p < 0.001. The results indicate that perceived competence of the chatbot has a positive effect on the trust in the chatbot.

4.2.7.2. Perceived Competence & Chatbot Attitude

In order to test if perceived chatbot competence has an effect on the chatbot attitude, a bivariate regression was performed. A significant regression equation was found (F(1,906) = 755.885, p < 0.001), with an R^2 = .46. Thus, perceived competence significantly predicts chatbot attitude, β =

.77, $t = 27.49$, $p < .001$. This suggests that the perceived competence of the chatbot predicts a higher attitude towards the chatbot.

4.2.7.3. Trust as a Mediator

To determine if trust acted as a mediator for perceived competence on chatbot attitude, Hayes PROCESS macro for SPSS was used (Hayes, 2013). The test allows for mediation testing though a linear regression framework and was performed with model 4 and a bootstrapping sample of 5000. Preliminary analyses were performed to ensure that there was no violation of necessary assumptions. The variable *perceived competence* was used as independent variable, *trust* was set as a mediator and *chatbot attitude* was used as dependent variable in the analysis. A significant indirect effect of .509 was retrieved from the bootstrap analysis (95% CI [.433, .588]). The results also provide support for a direct effect of .265 (95% CI [.189, .341]). The simple mediation analysis suggests that trust significantly mediates the effect of perceived chatbot competence on chatbot attitude. Thus, the perceived chatbot competence predicts a higher level of chatbot attitude, which is partially due to the sense of higher trust in the chatbot. Since both the direct effect and the indirect effect are significant and point in the same direction, the mediation is classified as complementary mediation (Zhao et al., 2010).

4.2.7.4. Chatbot Attitude & Intention to Use Chatbot

The proposed framework also outlines the potential effect of perceived chatbot competence on the intention to use the chatbot. The simple linear regression retrieved a significant regression equation ($F(1,906) = 1104.527$, $p < 0.001$), with an $R^2 = .55$. Hence, chatbot attitude significantly predicts intention to use, $\beta = .89$, $t = 33.23$, $p < 0.001$.

4.2.7.5. Chatbot Attitude & Brand Liking

Lastly, the proposed relationship between chatbot attitude and brand liking was addressed in a bivariate regression. A significant regression equation was found ($F(1,906) = 973.203$, $p < 0.001$), with an $R^2 = .52$. Thus, chatbot attitude significantly predicts brand liking, $\beta = .71$, $t = 31.20$, $p < 0.001$. The results therefore suggest that the attitude towards the chatbot predicts a higher brand liking.

4.3. Summary of Hypotheses Testing

Summary of Hypotheses and Results

H1	Signaling chatbot competence has a positive effect on trust	**NOT SUPPORTED**
H2	Signaling chatbot competence has a positive effect on chatbot attitude	**NOT SUPPORTED**
H3	Trust will mediate the positive effect of signaling chatbot competence on chatbot attitude	**NOT SUPPORTED**
H4	Previous chatbot attitude moderates the effect of signaling competence on chatbot attitude	**NOT SUPPORTED**
H5	Signaling chatbot competence has a positive effect on intention to use the chatbot	**NOT SUPPORTED**
H6	Signaling chatbot competence has a positive effect on brand liking	**NOT SUPPORTED**
Additional finding	*Perceived Chatbot Competence* has a positive effect on *Trust*	
Additional finding	*Perceived Chatbot Competence* has a positive effect on *Chatbot Attitude*	

Additional finding	*Trust* mediates the effect of *Perceived Chatbot Competence* on *Chatbot Attitude*
Additional finding	*Chatbot Attitude* has a positive effect on *Intention To Use Chatbot*
Additional finding	*Chatbot Attitude* has a positive effect on *Brand Liking*

Table 8. *Summary of hypotheses and results*

Conclusively, although the results did not provide support that *signaling* competence would induce positive firm-level effects in line with the proposed hypotheses, when including perceived chatbot competence in the model as an independent variable substituting the signaling condition, the hypothesized relationships were supported.

5. Discussion

The final section below will discuss the results of the study from a theoretical perspective in relation to the research question as well as the potential implications resulting from the findings. Following the conclusion, limitations of the study and future research opportunities will be discussed.

5.1. Discussion & Critique of Results

The findings from the hypothesis testing indicated that none of the initial hypotheses were supported. There were non-significant statistical differences between the signaling and non-signaling conditions across the chosen variables in the study, including trust, chatbot attitude, intention to use the chatbot and brand liking. As all of the hypotheses were built on the notion that the competence signal would cause an effect on the dependent variables. The results indicate that either the reactions as a result of the signal were not adequately captured or that the signal itself was unsuccessful. To control for the former and increase the quality of the data, care was given to remove inattentive responses through an attention check (Jones, House & Gao, 2015). Furthermore, the placement of the manipulation check had been strategically placed in the middle of the questionnaire rather than the end to increase validity (Hauser et al., 2018). It is therefore likely that the fault was not in capturing the effect but instead in the success of the signal in the main study. In other words, the treatment group did not perceive the chatbot to be more competent as a result of the signal stimuli. This generates an interesting discussion on two accounts; why the signal was successful in the pre-study but not the main one and what potential aspects of the signal failed to elicit the desired effect.

The theoretical framework outlined a number of aspects that are important in generating a successful signal. The signal content should be factual and include information relating to expertise, efficiency and abilities to satisfy the utilitarian function of the trusting beliefs of customers (Corritore et al., 2003; Fogg et al., 2001; Folstad et al., 2018; Holbrook et al., 1978; Katz, 1960; McKnight et al., 2002; Lee et al., 2000). In terms of actually relaying the signal as a persuasive communication, it must be perceived to be credible by the customer by not being easily mimicked by incompetent agents (Spence, 1973). And most importantly, the signal must be received and properly understood by the customer for it to achieve the desired effect (Boateng, 2019; Mavlanova et al., 2016; Spence, 1973). Given the fact that the content was created through the first preparatory study with a Swedish sample in connection to established theory, the more reasonable assumption is that the signal was properly received or seen as credible by the pre-study audience but not by the sample in the main study.

Therefore, it is interesting to explore what potential factors could have affected the difference in audience receptiveness to the signal between the preparatory and main study samples. The primary inconsistency between the samples was the demographic distribution. The main study sample was constrained to Swedish nationals, whereas nationalities on MTurk were unconstrained. Although this is a limitation of the study, further discussed in section 5.5., it also contributes to the insight that there are background variables at play that have affected the competence perceptions resulting from the signal. Ajzen (2005) argued that background variables may, but do not necessarily, impact salient beliefs, which in turn drive attitudes. Study contexts are the determining factor for which such variables are of relevance (Ajzen, 2005). The discrepancy in findings between the pre-study and the main study, with demographic factors being the main separating aspect, indicate that social background factors, such as nationality may be of importance for the effectiveness of signals to customers.

Furthermore, the importance of background variables may also be noticeable within the main study itself. The study controlled for seemingly important variables such as age, gender, education and previous experiences with chatbots based on the importance of these in past studies. However, it is possible that other background variables such as e.g. technology literacy in the control group were higher leading to better perceived competence from the outset for this group. In such a case, even an efficient signal leading to higher perceived competence in the signaling condition would not result in significant differences from the non-signaling condition. More attention and room should potentially have been given for background variables to control for such effects.

Although the unsuccessful signal in the main study is a key limitation of the study, it also renders an important observation about the need for contextualized and adapted signals. The results of this study indicate that the Swedish population of the main study did not receive the signal effectively, and therefore, their salient beliefs were not impacted as no association was activated or considered as a result of the signal (Ajzen, 1975). However, the association was activated for the more international Mturk sample. Therefore, customization of signals and truly understanding what drives the salient beliefs of customers is important for companies to consider to succeed in implementing any signals and improve perceptions.

5.2. Discussion of Additional Findings

The additional findings are a result of replacing the unsuccessful competence signal variable with perceived competence to test whether the remaining variables have significant relationships when the signal itself is omitted. The results provide interesting insights into the overall mechanism for facilitating trust and attitudes towards chatbots specifically within the banking customer service context.

The authors recognize that by replacing the signaling independent variable with perceived competence of the chatbot, there is no randomized manipulation preceding the other dependent variables, making the causality chain more unclear. However, given the established chain of causality between these variables, such as attitude preceding intentions, in other studies and by common sense reasoning, the authors still infer that there is an evident effect of perceived competence on the other variables of interest (Bryman & Bell, 2015, p. 174).

5.2.1. The Central Role of Perceived Competence

Although the results did not provide support that *signaling* competence would induce positive effects, using perceived chatbot competence in the model as an independent variable supported the hypothesized relationships between the remainder of the variables. More specifically, the results indicated that perceived chatbot competence had a positive effect on trust and attitude levels. Such a finding is in line with past studies investigating trust in HCI, highlighting the central role of competence perceptions as a key variable (Corritore et al., 2003; Hancock et al., 2011; Schaefer, 2013; Ullman & Malle, 2018).

However, the past studies investigated these relationships in other contexts, such as, trust towards websites (Corritore et al., 2003) or robots (Hancock et al., 2011; Schaefer, 2013; Ullman & Malle, 2018). Furthermore, although some studies identify chatbots specifically, the focus of these studies has been the role of anthropomorphic dimensions on trust and the chatbots are not within the customer service context specifically (Ciechanowski et al, 2019; Fogg et al., 2001; Folstad et al., 2018; Toader et al., 2019). In turn, the few studies within chatbot customer service are not within the banking industry, with the exception of a few studies such as Boateng (2019). Finally, none of the studies mentioned include disclosure of the chatbot identity as a premise from the outset. Therefore, the finding of the inherent importance of perceived competence within the proposed model and context ties together findings from past disconnected studies to this new environment where disclosure is a norm for bank chatbots within the service encounter. The central role of perceived competence impacting trust and attitudes within this scope is therefore, a theoretical contribution of this study.

5.2.2. Trust As a Mediator

Having investigated the positive effects associated with perceived chatbot competence, the results further indicate that trust significantly mediates the effect of perceived chatbot competence on chatbot attitude. Partial mediation prevails, which indicates that the positive effect on attitude associated with the perceived competence is partly explained by the increase in trust levels. Other factors, not taken into account in this study, are also predicting the attitude towards the chatbot. This finding is in line with expectations resulting from the theoretical framework. Since attitudes are a summation of salient beliefs and competence perceptions are a foundation for trusting beliefs, it could be inferred, given the results, that some of the salient beliefs underlying attitude formation include the trusting beliefs. As a result, trust is an important mechanism when attempting to influence attitudes towards chatbots. Since part of the higher levels of chatbot attitude is explained by the increase in trust, it means that in order to achieve a more positive attitude towards the chatbot the aim of companies should also be to increase trust.

The central role of trust in the theoretical framework is thus highlighted. Trust has in previous research contexts been associated with intention to use a chatbot in the banking sector (Agariya & Singh, 2011; Angenu, Quansah & Okoe, 2015; Benamati & Serva, 2007; Boateng, 2019). However, this study contributes theoretically by introducing a means to achieve trust, namely through perceived competence, and by establishing the relationship between variables in a way that has not, to the authors' knowledge, been established previously for customer service chatbots in the banking industry.

5.2.3. Intention to Use Chatbot

The results show that the attitude towards the chatbot predicts the intention to use it, where a more favorable attitude will increase the willingness of interaction. Such links have been established before in other research contexts (e.g. Davis, 1989). Intention is an antecedent of the actual behavior (Ajzen, 1975), meaning that a favorable evaluation of the chatbot also indirectly leads to usage of the chatbot. Hence, the findings confirm that if efforts are spent on creating favorable attitudes among potential users, the spillover towards adoption comes naturally as intentions are often seen as conative components of attitude (Fishbein & Ajzen, 1975, p. 288). As such, the results substantiate the predictive validity of behavioral intentions, contributing theoretically to replication within a new setting.

5.2.4. Attitude Towards Brand

The findings suggest that an increase in attitude towards the chatbot will lead to a higher brand liking. To review, the definition of brand liking is "the customers' entire perception of a brand and its associations connected to it" (Keller, 2008). From a practical perspective the results mean that the positively evaluated perception of the chatbot will help form favorable associations towards the company. Hence, the chatbot has the capability of, to some extent, affecting company perception outcomes. Such a finding is not surprising and is in line much prior research (e.g. Söderlund & Rosengren, 2008) suggesting that the evaluation of the employee – in this case the chatbot – will evoke a direct associated evaluation of the company for which the employee works. Bitner et al. (1990) complement this argument by stating that the service agent of the company *is* in fact the company from the customers' point of view. The results in this study therefore contribute by confirming such findings, restating the importance of achieving a positive evaluation of the service agent. Contextualization of this study means that the dyadic relationship between the customer and the service encounter agent needs reformulation to not only consider human employees but also the increasingly prominent virtual agents.

5.3. Managerial & Practical Implications

5.3.1. Company Implications

As argued in section 2.2.1., until respect-based trust is viable, and given the fact that a positive attitude is a prerequisite for the intention and actual action to use a chatbot, calculative trust must be the starting point for establishing a form of trust. Since attitude precedes the intention to use the chatbot (Ajzen, 1975; Davis et al., 1989), and trust has been found to be a mediator for perceived competence on improved attitudes, trust should be an important focus of banks to reap the efficiency benefits of chatbots in their customer services. Current customer service online often provides various contact options, meaning that if trust is not improved, other contact means such as phone, email or visiting the office for routine tasks may still be utilized, reducing the reliance on chatbots.

This study's results highlight how difficult it is to effectively provide competence signals and that background factors may impact the receptiveness of customers to any presented communication. Therefore, truly understanding what drives the salient beliefs of customers is important to succeed in implementing any signals that successfully improve perceptions. The managerial implication of this is that companies must further test and trial how to convey competence while accounting for the possible variances within the customer base that can lead to the need for personalized and contextualized signals, as opposed to one standardized stimulus. Merely improving objective competence of chatbots will not automatically lead to efficiency gains if companies do not overcome the inhibition of negative perceptions. Only after such perceptions are updated will usage rates increase due to resulting behavior caused by increased intentions, making full efficiency through automation possible.

5.3.2. Employee Implications

Employees are also directly impacted by the customer's propensity to rely on a chatbot for customer service. The purpose of utilizing chatbots is to automate more routine inquiries and free up time for employees on more complex and personalized tasks that chatbots are not capable of handling (Kannan & Bernoff, 2019). If customers choose to not rely on chatbots due to mistrust towards them, then lead times for human agents will remain long and cluttered by routine tasks that add to their workload, leading to bottlenecks and inefficiencies. However, if chatbot usage rates increase, the role of the human customer agent in the service encounter will ultimately transform since humans will increasingly handle only challenging tasks and additionally act as potential supervisors of the automated agents. Because employees are the company essentially, any resulting changes to their work style and burden must be considered and provided for as chatbot implementation increases and becomes more prominent.

5.3.3. Customer Implications

From a customer perspective, the use of chatbots ought to improve customer service satisfaction and experience by significantly reducing lead times, being able to provide service 24/7 at much higher speeds and being able to provide contextualized recommendations through machine learning algorithms (Kannan & Bernoff, 2019). Therefore, lack of trust towards chatbots will hinder such gains and create cues for human customer agents, prohibiting those with more complex and urgent challenges from getting quicker service.

Furthermore, the topic covered in this study is especially relevant for customers as disclosure and transparency aim to create a safe, ethical and transparent HCI environment for consumers. Studies have shown that chatbots are indeed more efficient and can achieve e.g. higher sell rates if they remain opaque about their identity (Luo et al., 2019), yet this study has taken the position that customers have a right to know who they are interacting with regardless of effects on such findings. In line with Koehn's (2003) condition that companies operating online must be transparent, it is the authors' position that not disclosing chatbot identity merely for the sake of efficiency is a form of manipulation and incompatible with trust-building, as posited earlier. Therefore, this study has implications for the consumer by reducing the possibility of deceit online and creating a more transparent HCI environment for them. Effective second-order disclosure and signaling may also provide consumers with the evidence that they need to reduce information asymmetry and to make informed decisions relating to who they interact with online.

5.3.4. Brand Implications

The impact of trustworthiness evidence does not only affect the usage rates of chatbots and resulting efficiency but also directly impacts the company's brand. Positively evaluated stimuli messages contribute to a positive brand evaluation (Mitchell & Olson, 1981). As such, developing successfully positively evaluated evidence of competence is beneficial for both efficiency and brand improvement. Conversely, the opposite could be true where the reduced perceptions of chatbot competence resulting from disclosure without any additional signals could be coupled with worsened brand attitudes. Therefore, companies in countries where chatbot disclosure is becoming a standard must evaluate how they can attempt to improve attitudes to such disclosure in order to mitigate any negative effects on their brand as well.

5.4. Conclusion

The research question guiding this study was:

To what extent can a second-order disclosure induce positive customer attitudes and increase trust towards service encounter chatbots?

The purpose of this study was to explore whether a variant of second-order disclosure can affect humans' resulting attitudes, as compared to first-order disclosure, towards customer service chatbots within the banking industry specifically. To answer the research question; this study has been unable to provide support that second-order disclosure can induce positive attitudes and increase trust towards service encounter chatbots to any extent. However, the authors believe that the research question is still an important topic to investigate. Although the main study did not manage to create a successful variant of second-order disclosure, including the chatbot's identity as well as a competence signal, the findings showed that the theoretical relationships between the variables and perceived competence in the proposed model do hold. Therefore, the conclusion of the study is that a successful signal impacting perceived competence can potentially have the desired effect of improving attitudes and thus, contribute to solving the disclosure paradox. The inability of this study to create such a signal, despite some initial success in the pre-study, highlights the importance and complexity of the presented challenge. As chatbots must become more transparent and disclose their identities, yet such disclosure leads to negative attitudes, more forms of second-order disclosure must be explored to see if they have better success at overcoming the paradox.

The results of the study indicate the underlying importance of perceptions of consumers, especially related to competence. Although chatbots, algorithms, robots and other AI solutions can be objectively more competent, intelligent, effective and a multitude of other beneficial terms compared to human agents, their usefulness and realized benefits in practice are directly tied to how consumers perceive them. Companies aiming to utilize such technology must not forget the customer's role in HCI. Chatbots are treated in a largely social manner, implying that the interactions include complex psychological and relational elements, trumping the objective efficiency and competence of the technology.

5.5. Limitations

The most prominent limitation of the study is the evident inability to develop a successful manipulation, which in turn affected the ability to confidently form conclusions regarding the data as hypothesized. Since the manipulation check was passed in the pre-study, the authors believed it to be unnecessary to disrupt the flow and length of the main study by adding additional intrusive control measures and greater focus was placed on the dependent variables of interest (Hauser et al., 2018). However, such argumentation is only valid if the pilot test is run on very similar participants to the main study, which was not the case. Accessibility to unbiased sampling representative of the population of interest is an issue commonly dealt with by many researchers and especially students. As opposed to using MTurk as a pre-study sampling platform, it would have been beneficial to perform stimuli testing on participants similar to the target population, to more reliably investigate whether or not the manipulation would be successful. Unfortunately, accessibility to a representative target sample was the main limitation resulting in the choice of the authors. By including the sample from a different population, incorrect assumptions were inferred regarding the target population and consequently the benefits of having access to a large representative sample for the main study was offset. Due to time and resource constraint, redoing the experiment was not possible.

Another critique attributed to the study is that it entailed a scenario decoupled from a real-life chatbot usage setting. Perhaps a better option would have been to let participants fill out the questionnaire after an actual interaction. Due to the difficulty in partnering with existing banks to provide access to their chatbots for the task, or alternatively skilled coders to build a chatbot, the solution of designing a chatbot interface proxy was determined most the viable option considering time and resource constraints. In addition, an issue arising with potentially including a real interaction entailed managing the conversation and thus controlling for potential noise. By providing only a framing message it was believed to provide a noise-free environment with the possibility to clearly test the isolated effect of competence signaling. However, it is unclear whether the former acclaimed benefit would truly offset the benefit of natural real interaction in a research context. Lastly, an actual interaction could have also mitigated the possibility of the respondents not staying attentive throughout the experiment. Although this was to some extent controlled for with an attention check, an actual interactive scenario would likely have intensified the participants' engagement level.

5.6. Future Research

Considering that the experiment in this study was not carried out successfully, any future research must firstly aim to find empirical support for an effect of signaling competence. Such a future study could be a replication of this study, with alterations to the stimuli, accounting for the limitations mentioned in section 5.5. For example, conversing with a real chatbot rather than reading a message might be a way to improve the study. If an effect of competence signaling prevails, it would also be useful to assess the robustness of such a signal, i.e. matching a competence signal with an objectively competent versus incompetent chatbot. Furthermore, future research could investigate what specific background factors may impact competence perceptions to gain a further understanding of the contexts in which signals can successfully act as strategic communication of chatbot characteristics.

Based on the delimitation to the banking industry, future attempts to solve the disclosure paradox could focus on other industries such as retail. Although this study identified capacity trust as a crucial component for banks specifically, other industries may benefit from investigating the relevance of trust and customer perceptions towards their chatbots as well. In addition, as the adoption of chatbots spreads, the effectiveness of other types of second-order disclosures should be examined. Such disclosures could, for example, include the use of second-order disclosures for high vs. low involvement engagements and goods vs services.

The possibilities of investigating potential means to overcome the disclosure paradox of chatbots in the service encounter are many and this is hopefully just the initiation of many future findings.

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6.1. Journals

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7. Appendix 1 – Main Study Questionnaire

Hur gammal är du?

\>>

Är du man eller kvinna?

- Man
- Kvinna
- Vill inte uppge/annat

\>>

Vilket postnummerområde bor du i?

Ange ditt postnummer, fem siffror, utan mellanslag (t.ex. 12345)

\>>

Hej,

Du kommer nu få ta del av en undersökning. Ditt deltagande är anonymt och svaren kommer ligga till grund för en akademisk uppsats.

Vi ber dig att noggrant läsa igenom scenariot på nästa sida och sedan besvara frågorna. Det finns inget rätt eller fel svar; vi är intresserade av din personliga åsikt.

Tack för din tid och ditt engagemang!

>>

Du är inne på en banks hemsida eftersom du är i behov av hjälp. Därför klickar du på “kontakta oss” i menyn. Du bestämmer dig för att använda bankens chattfunktion, vilken introduceras på följande sätt:

>>

Stimulus for treatment group, signaling competence

Du är inne på en banks hemsida eftersom du är i behov av hjälp. Därför klickar du på “kontakta oss” i menyn. Du bestämmer dig för att använda bankens chattfunktion, vilken introduceras på följande sätt:

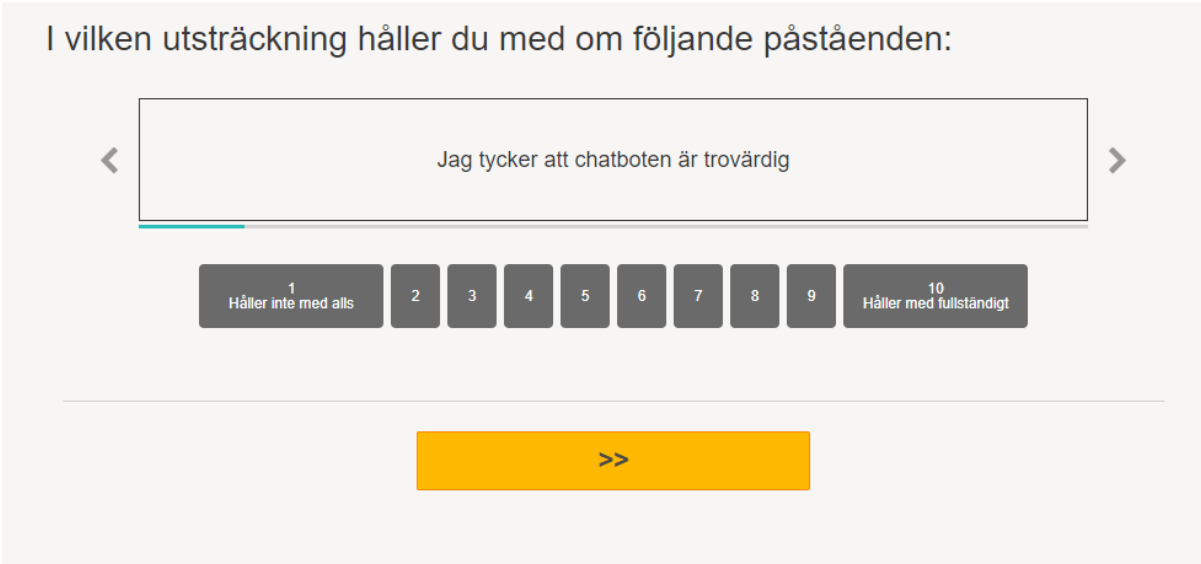
>>

Stimulus for control group, not signaling competence

Vad är din uppfattning om chatboten?

	1	2	3	4	5	6	7	8	9	10	
dålig	○	○	○	○	○	○	○	○	○	○	bra
ogillar	○	○	○	○	○	○	○	○	○	○	gillar
ofördelaktig	○	○	○	○	○	○	○	○	○	○	fördelaktig

>>


I vilken utsträckning håller du med om följande påståenden:
Jag tycker att chatboten är trovärdig
1
Håller inte med alls
2
3
4
5
6
7
8
9
10
Håller med fullständigt
>>


I vilken utsträckning håller du med om följande påståenden:
Jag har förtroende för chatbotens kompetens
1
Håller inte med alls
2
3
4
5
6
7
8
9
10
Håller med fullständigt
>>


I vilken utsträckning håller du med om följande påståenden:
Jag litar fullständigt på chatboten
1 Håller inte med alls
2
3
4
5
6
7
8
9
10 Håller med fullständigt
>>


I vilken utsträckning håller du med om följande påståenden:
Jag tror att chatboten gör ett bra jobb
1 Håller inte med alls
2
3
4
5
6
7
8
9
10 Håller med fullständigt
>>


I vilken utsträckning håller du med om följande påståenden:
Jag tror att chatboten är kapabel att tillgodose mitt behov
1 Håller inte med alls
2
3
4
5
6
7
8
9
10 Håller med fullständigt
>>


I vilken utsträckning håller du med om följande påståenden:
Denna fråga testar din uppmärksamhet, vänligen klicka i svarsalternativet “håller inte med alls”
1 Håller inte med alls
2
3
4
5
6
7
8
9
10 Håller med fullständigt
>>


I vilken utsträckning håller du med om följande påståenden:
Jag är övertygad om att chatboten kan arbeta ensam utan mänsklig assistans
1
Håller inte med alls
2
3
4
5
6
7
8
9
10
Håller med fullständigt
>>


I vilken utsträckning håller du med om följande påståenden:
Jag har tillit till teknologin bakom chatboten
1
Håller inte med alls
2
3
4
5
6
7
8
9
10
Håller med fullständigt
>>

I vilken utsträckning håller du med om följande påståenden:

Jag tycker att chatboten är pålitlig

1 Håller inte med alls	2	3	4	5	6	7	8	9	10 Håller med fullständigt

>>

Betygsätt chatboten enligt nedanstående egenskaper:

	1	2	3	4	5	6	7	8	9	10	
dum	○	○	○	○	○	○	○	○	○	○	förståndig
ansvarslös	○	○	○	○	○	○	○	○	○	○	ansvarstagande
okunnig	○	○	○	○	○	○	○	○	○	○	kunnig
ointelligent	○	○	○	○	○	○	○	○	○	○	intelligent
inkompetent	○	○	○	○	○	○	○	○	○	○	kompetent

>>

Hur väl stämmer följande påståenden in på dig?

	1 Håller inte med alls	2	3	4	5	6	7	8	9	10 Håller med fullständigt
Jag kan tänka mig att använda den här chatboten för kundservice										
Sannolikheten att jag skulle använda den här chatboten för kundservice är hög										

>>

Vad är din uppfattning om banken som tillhandahåller den här chatboten?

	1	2	3	4	5	6	7	8	9	10	
dålig											bra
ogillar											gillar
ofördelaktig											fördelaktig

>>

Betygsätt din uppfattning om chatboten enligt nedanstående egenskaper:

	1	2	3	4	5	6	7	8	9	10	
omedveten											medveten
onaturlig											naturlig
robotlik											mänsklig
konstgjord											levande

>>

Hur skulle du beskriva dina tidigare erfarenheter då du interagerat med chatbotar?

	1	2	3	4	5	6	7	8	9	10	
dåliga	○	○	○	○	○	○	○	○	○	○	bra
ogillar	○	○	○	○	○	○	○	○	○	○	gillar
oangenäma	○	○	○	○	○	○	○	○	○	○	angenäma

>>

Hur van är du att interagera med chatbotar? Detta gäller både text- och röstbaserade chatbotar.

1 Inte van alls	2	3	4	5	6	7	8	9	10 Väldigt van
○	○	○	○	○	○	○	○	○	○

>>

Vilken är din huvudsakliga sysselsättning just nu?

- ○ Anställd
- ○ Egen företagare
- ○ Student
- ○ Pensionär
- ○ Arbetssökande
- ○ Annat

>>

Hur stor är din månadsinkomst före skatt?

- 0-14 999 kr
- 15 000-21 999 kr
- 22 000-29 999 kr
- 30 000-39 999 kr
- 40 000-59 999 kr
- 60 000 kr eller mer
- Vill ej uppge

>>