Bachelor Thesis

Engagement over Excellence – The Effects of Message Interactivity on the Perception of Customer Service Chatbots

Professor Dr. Ossama Elshiewy

Professor Dr. Augustin Süßmair

Submitted by: 12.05.2021

Völtzke, Christoph
Matriculation number: 3033352
Theodor-Storm Straße 42
24211 Preetz
christoph.voeltzke@stud.leuphana.de

Abstract

Chatbots are frequently replacing human agents in customer service by offering time- and cost-saving opportunities. They automate a wide range of tasks and provide an almost human-like interaction. However, existing chatbots often fall short of customer expectations, leading to miscommunications and a negative customer experience. This study addresses these issues by investigating how the *Message Interactivity* and the T*ask Type* influence psychological and desirable company-related outcomes in a *Human-Computer Interaction* (HCI). A 2 (high *Message Interactivity* vs. low *Message Interactivity*) x 2 (complaint vs. information search) between-subjects experiment (*N*=271) was conducted. The results indicate that both *Message Interactivity* and the *Task Type* influence the perceived human-likeness of a chatbot. Moreover, *Social Presence* and *Perceived Contingency* mediate the effect of *Message Interactivity* on company-related outcomes like customer satisfaction and behavioral intentions towards a website. Theoretical implications for research on *Social Cues* and practical implications for chatbot usage and design in customer service are discussed.

Words Abstract: 154
Words Text (excluding Abstract, Appendix, References, Tables, and Figures): 10.405

Table of Contents

List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
ANOVA	Analysis of Variances
CA	Conversational Agent
CASA	Computers Are Social Actors
CI	Confidence Interval
CL	Computer-like
DCA	Disembodied Conversational Agent
ECA	Embodied Conversational Agent
EFA	Exploratory Factor Analysis
HCI	Human-Computer Interaction
HL	Human-like
LLCI	Lower Level of the Confidence Interval
MI	Message Interactivity
NFHI	Need for Human Interaction
PC	Perceived Contingency
PCA	Principal Component Analysis
ULCI	Upper Level of the Confidence Interval
SP	Social Presence
TT	Task Type

List of Figures

List of Tables

1. Engagement over Excellence – The Effects of Message Interactivity on the Perception of Customer Service Chatbots

New technologies have entered our private life. Technologies like Apple's Siri and Amazon's Alexa support users' daily activities (Maedche et al., 2016). As customers spend more time in digital environments, businesses follow the trend of technological advancements by using non-human agents like chatbots to enhance the customer experience (Chung et al., 2018). Conversational agents (CA) are defined as software-based systems designed to interact with humans using natural language (McTear et al., 2016). Especially in customer service, due to the technological advances in artificial intelligence (AI) over the last decade, service chatbots have become the preferred option to obtain customer support (Larivière et al., 2017). Service chatbots shape the customer experience in a dynamic interaction by solving customer problems, handling complaints, and encouraging customers to purchase (Chung et al., 2018). Excellent service delivery is often viewed as a critical advantage and a key factor for the company's success, while disappointing customer service threatens customer loyalty and revenue growth (Gnewuch et al., 2017). To meet the customer's expectations of a fast, convenient, and personal service, organizations are using chatbots as a 24/7 channel for customer service and, at the same time, reducing the number of service employees (Gnewuch et al., 2017). Despite the considerable potential of a cost-effective solution for customer service, many CA's could not live up to their promises. Customers appear to have unsatisfactory experiences with AI-based CA's (Adam et al., 2020). In particular, by considering chatbots' artificial and generic conversation style, they tend to be short on humanness (Seeger et al., 2017). In this sense, service chatbots need to display human characteristics to make their interactions equivalent to human employees (Larivière et al., 2017). Previous studies identified different design elements – called *Social Cues* – for chatbots which can induce anthropomorphism and make the Human-Computer Interaction (HCI) appear more human-like (Feine et al., 2019). Anthropomorphism is the transfer of human characteristics to non-human entities to elicit favorable perceptions from the recipient (Epley et al., 2007). Service chatbots using *Social Cues* as design elements can avoid the lack of humanness and increase the service encounter quality to further enhance the customer experience (Larivière et al., 2017).

As service chatbots mainly use text messages to interact with a customer, verbal design elements play a crucial role in the perception of human-like characteristics. A *Social Cue* of human-like verbal communication is the contingency in responses (Go & Sundar, 2019). The ability to provide messages related to previous statements makes the chatbot appear human-like as it mimics the contingency usually found in interactions between humans (Rafaeli, 1988). In the literature, this *Social Cue* is labeled as *Message Interactivity* (Sundar, 2012). Several studies found that *Message Interactivity* can be used in web-based interfaces to elicit a sense of back and forth in the interaction, leading to positive attitudes and behavioral intentions towards the website that features the system (Go & Sundar, 2019).

Current researchers and practitioners have limited information about how a chatbots' human-like design can benefit customer service. Therefore, this study addresses this issue and contribute to the existing literature on *Message Interactivity* with the following research question:

RQ$_1$: How does the level of *Message Interactivity* in a customer service chatbot affect users' perception of the chatbot and the company?

Secondly, this study investigates how different tasks performed by a service chatbot influence the perception of psychological and company-related outcomes. These insights about *Task Types* are critical for companies as the chatbots' abilities to perform various tasks increases due to recent technological advancements (Hoyer et al., 2020). Regarding the perception of different *Task Types*, the *Theory of Anthropomorphism* (Epley et al., 2007) states that special motivational forces lead customers to engage with chatbots in a human-like way when the task has specific characteristics. First, humans anthropomorphize non-human interaction partners when the task requires human sense-making, like giving an apology (Sociality Motivation). Second, humans show a higher motivation to anthropomorphize non-human objects when there is a need to understand and control a situation (Effectance Motivation). Accordingly, this study seeks to determine whether different tasks in customer service influence the perception of the chatbot and the company.

RQ$_2$: How do tasks differentiating in their degree of humanness performed by a customer service chatbot affect users' perception of the chatbot and the company?

This study investigates the effect of *Message Interactivity* in a service encounter, while previous studies focused on different domains of *HCI* (Bellur &

Sundar, 2017; Go & Sundar, 2019; Liu & Sundar, 2018). Moreover, this thesis provides new insights for chatbot design through the combination of *Message Interactivity* and *Task Type*. This study works with a scenario where participants put themselves in a customers' position who interacts with a service chatbot of a fictitious web-shop. The participants are randomly assigned to one of four groups depending on the *Task Type* and the level of *Message Interactivity*. Following this, the participants fill out a questionnaire about their experiences with the interaction and the chatbot.

This thesis is structured as followed. First, the theoretical foundations and current research in chatbot design, customer service, and *Social Cues* are introduced. On this basis, hypotheses and a research model for evaluating this study are developed. Finally, the methodology and the empirically collected data are presented, followed by interpreting the results and explaining implications for practice and future research.

2. Theoretical Framework

2.1. Chatbots and Social Response Theory

CA's are software-based systems designed to interact with humans using natural language (McTear et al., 2016). Recently, organizations are especially interested in using CA's to help customers find important information about goods and services and perform routine tasks (Larivière et al., 2017; Maedche et al., 2016). CA's need to be differentiated by their mode of communication. They can be distinguished in either text- or voice-based CA's (Feine et al., 2019; Seeger et al., 2021).

Text-based CA's - often called chatbots - are increasingly implemented on messaging platforms like Facebook or e-commerce websites (Araujo, 2018). In contrast, voice-based CA's are usually integrated into mobile phones or other physical devices like Apple's Siri or Amazon's Echo Dot (Maedche et al., 2016). CA's can be further differentiated in embodied- (ECA) and disembodied CA's (DCA). ECA's usually have forms like a 3D avatar that can interact with humans through body gestures, facial expressions, and human speech. ECA's are primarily used in domains like health care and education (Feine et al., 2019). On the other hand, DCA's have either no visual representation or a static profile image and cannot communicate with users based on physical actions (Seeger et al., 2021).

This study focuses on text-based-DCA's (i.e., chatbots) as they are mainly used in customer service encounters (Larivière et al., 2017). They can sense and share various verbal and non-verbal characteristics through text messages that are generally associated with humans. Chatbots try to mimic human service agents to avoid the lack of humanness in a *HCI* and increase the service encounter quality (Larivière et al., 2017). As a result of the transfer of human characteristics to non-human entities, users respond socially to them (Bleier et al., 2019; Gnewuch et al., 2018; Go & Sundar, 2019).

In various studies, this phenomenon is explained with the widely accepted *Social Response Theory* (Nass et al., 1994). This theory builds on the *Computers Are Social Actors* (CASA) paradigm, offering evidence on how humans apply social rules to anthropomorphic chatbots (Araujo, 2018; Go & Sundar, 2019). Following this paradigm, humans are evolutionary biased and tend to react automatically and subconsciously to the *Social Cues* used by chatbots, no matter how rudimentary these cues are (Nass & Moon, 2000). In this study, *Social Cues* are defined as cues that trigger a social reaction towards the emitter of the cue (Nass & Moon, 2000). Previous studies further indicate that human characteristics in a service chatbot can positively influence different psychological and company-related outcomes, like perceptions of a *Social Presence* (Araujo, 2018) or user satisfaction with a CA (Verhagen et al., 2014).

2.2. Chatbots and their Role in Service Systems

A key concern for service providers is to balance service efficiency and service quality. Self-service through chatbots is becoming an increasingly powerful tool for brand marketers to deal with this challenge and to increase efficiency and enhance customer satisfaction, and repurchase intentions (Huang & Rust, 2013). Additionally, chatbots can standardize service delivery and provide cost-effective and comprehensive customer service 24/7. Consequently, more than 50% of global businesses are either already using chatbots or are planning to do so (Sands et al., 2020). Service chatbots' primary functions are to interact with customers to solve their problems, handling complaints, and encouraging them to purchase (Chung et al., 2018). The experience provided by these chatbots is perceived to be better than static delivery of information like a list of frequently asked questions. Additionally, CA's tend to replace human agents or telephone-based call support as they offer similar services (Gnewuch et al., 2017). However, this has resulted in new challenges as chatbots often fall short of consumers' expectations. Chatbots often fail to understand user input, resulting in customer skepticism and a negative customer experience (Sheehan et al., 2020). This forces practitioners to consider chatbot designs that can create a comparable experience to a human service agent. Moreover, previous research has shown that, while it is easy to transfer human language to *HCI's*, there are notable differences in the content and quality of these conversations (Adam et al., 2020). Therefore, it is essential to understand how the service chatbot's design impacts behavioral and attitudinal intentions towards a company.

2.3. Message Interactivity and Contingency

Feine et al. (2019) proposed a taxonomy of the established *Social Cues* to offer a comprehensive classification of the different *Social Cue's* characteristics. This taxonomy comprises *Social Cues* in four categories (i.e., verbal, visual, auditory, and invisible cues). As online marketers use text-based disembodied CA's to provide fast and personalized feedback to customer questions, verbal cues play a vital role in the chatbot's perception as a human-like employee (Araujo, 2018). Verbal cues refer to all *Social Cues* created by words, including what is said and how it is said (Feine et al., 2019). A key characteristic of human-like verbal communication is the contingency in responses (Go & Sundar, 2019). In other words, the chatbot's messages are related to the previous content of the conversation. This kind of interaction can make the chatbot appear human-like as it mimics the contingency usually found in interactions between humans (Rafaeli, 1988). In the literature, contingency in responses is labeled *Message Interactivity* (Sundar, 2012). It is defined as the dependency of current messages upon prior messages and past actions (Bellur & Sundar, 2017).

Previous conceptualizations of *Message Interactivity* (Song & Zinkhan, 2008; Sundar et al., 2003) highlighted the function of contingency in web-based interactions and further demonstrated how an online agent's message interactivity enhances the customer experience. Moreover, several studies (Sundar, 2012; Wise et al., 2006) found that designing *Message Interactivity* into a media interface leads to a sense of back-and-forth and interconnected conversations. These aspects of personalization and responsiveness are critical aspects of interactivity that foster positive attitudes and behavioral intentions to the message provider and the website that features the system (Araujo, 2018). Go, and Sundar (2019) recently operationalized *Message Interactivity* as a *Social Cue* in a live chatting situation, showing that interactivity in messages enhances attitudes and behavioral intentions to return to a website. This study extends the research on *Message Interactivity*, particularly to the domain of service chatbots, and tests whether this specific *Social Cue* can influence company-related outcomes. It is expected that higher levels of *Message Interactivity* in a *HCI* positively influence desirable company-related outcomes like behavioral intentions towards a website and customer satisfaction.

H_1. Higher levels of *Message Interactivity* will lead to more positive company-related outcomes like higher customer satisfaction and higher behavioral intentions towards a website.

In addition to company-related outcomes, the perception of *Social Cues* in a *HCI* can lead to different psychological effects. Especially in web-based service encounters, verbal cues like *Message Interactivity* can facilitate a feeling of interacting with another human and letting the conversation appear more contingent. The feeling of sensing another human's presence is widely known as the concept of *Social Presence*. The concept of *Social Presence* was initially defined as the "degree of salience of the other person in a mediated communication and the consequent salience of their interpersonal interactions" (Short et al., 1976, p.65). Recent definitions describe it as the perception of a *Social Presence* despite the lack of actual human contact (Gefen & Straub, 2003). This study argues that the perception of anthropomorphism in a *HCI* can be explained by the *Social Presence* felt during the interaction. Further research on *Social Presence* states that consumers tend to think that they are in an actual conversation with a human, which makes them less aware of the technology (Araujo, 2018). Several studies found that (Diederich et al., 2020; Gnewuch et al., 2018) the availability of *Social Cues* on websites (Cyr et al., 2009) or recommendation agents (Qiu & Benbasat, 2009) encourages the perception of a *Social Presence*. Additionally, Sundar et al. (2015) proposed that a higher degree of *Message Interactivity* in a chatting situation with a non-human agent increases the feeling of the other's presence even without the physical attendance. Therefore, this study expects that higher levels of *Message Interactivity* of a customer service chatbot will lead to increased perception of *Social Presence*.

H_{2a}. Higher levels of *Message Interactivity* will lead to increased feelings of *Social Presence*.

Another way to indicate the human-likeness of a chatbot regarding *Message Interactivity* is the users' perception of contingent messages. *Perceived Contingency* is defined as the degree to which the users get a personal reaction to their active input (Sundar, 2012). In other words, users are more confident and satisfied during a live-chat interaction if the messages of the chatbot fit their exclusive needs. Several studies demonstrated that users perceive the interaction as a human-like dialogue when the chatbot refers to content in the past or gives personalized answers, which are features of *Message Interactivity* (Bellur & Sundar, 2017). By receiving more contingent messages, users feel that the chatbot has a human-like voice which is a core characteristic of human-to-human communication (Go & Sundar, 2019). Therefore, users tend to anthropomorphize chatbots when they perceive a higher degree of contingent messages. This study proposes that higher levels of *Message Interactivity* heighten the *Perceived Contingency* in the messages of a service chatbot.

H_{2b}. Higher levels of *Message Interactivity* will lead to higher *Perceived Contingency* in the messages of a service chatbot.

Moreover, the two psychological outcomes serve as critical mediators of attitudinal and behavioral outcomes. Several studies already indicated that psychological effects like the perception of a *Social Presence* and the contingency in messages positively impact desired chatbot characteristics, such as trustworthiness (Diederich et al., 2020), perceived competency (Araujo, 2018), or authenticity (Wuenderlich & Paluch, 2017).

In particular, prior research shows that the perception of a *Social Presence* increases the perceived human-likeness of a chatbot (Schuetzler et al., 2020). Moreover, studies suggest that as *Social Presence* increases, humans sense an improved relationship, leading to a more positive customer experience in terms of trust and expertise (Gefen & Straub, 2003; Verhagen et al., 2014). This effect of *HCI* research also appeared in customer service settings, with *Social Presence* positively enhancing customer satisfaction and intentions to purchase online (Araujo, 2018). Go, and Sundar (2019) showed that *Social Presence* mediates the relationship between *Message Interactivity* and behavioral and attitudinal outcomes. Therefore, *Social Presence* is an eligible outcome to measure the mediating effect of *Message Interactivity* on desirable company-related outcomes like customer satisfaction and behavioral intentions towards a website. This study proposes that heightened perception of a *Social Presence* while interacting with a service chatbot leads to more positive behavioral and attitudinal intentions.

H_{3a}. *Social Presence* will positively mediate the effect of *Message Interactivity* on company-related outcomes.

The same effect applies to the *Perceived Contingency* of chatbot answers. Sundar et al. (2016) showed that *Message Interactivity* in a live chat fosters positive attitudes and enhances behavioral intentions to return to a website through *Perceived Contingency*. Moreover, Burgoon et al. (2015) proposed that contingency within messages is a critical factor of interactivity. They stated that the *Perceived Contingency* impacts users perceived involvement, mutuality, and individuation in the interaction. Last, several studies (Bellur & Sundar, 2017; Go & Sundar, 2019) have shown that *Perceived Contingency* mediates the effect of *Message Interactivity* on behavioral and attitudinal intentions. Concluding, this study assumes that *Perceived Contingency* will mediate the effect of *Message Interactivity* on desirable company-related outcomes like customer satisfaction and behavioral intentions towards a website.

H_{3b}. *Perceived Contingency* will positively mediate the effect of *Message Interactivity* on company-related outcomes.

2.4. Chatbot Tasks in Service Encounters

New technologies like self-service through chatbots have changed the way customers engage with a company offering efficient, cost-effective, and comprehensive customer service. Primarily in customer service, the technological advancements in AI raised the number and complexity of tasks service chatbots can perform (Hoyer et al., 2020). However, there is no established literature on how different tasks performed by a service chatbot influence the perception of psychological and company-related outcomes. Recent studies on chatbot design suggest that a task can appear more human-like than others (Seeger et al., 2021). The underlying *Theory of Anthropomorphism* (Epley et al., 2007) states that special motivational forces lead customers to engage with chatbots in a human-like way when the task has specific characteristics. The psychological theory contains two relevant motivational forces that explain why humans respond socially to non-human agents. First, humans need to be socially related to a non-human interaction partner (Sociality Motivation). Secondly, humans need to understand and control the task to anthropomorphize non-human objects (Effectance Motivation) (Seeger et al., 2021).

Sociality Motivation is stimulated by tasks that fulfill humans' need for social connectedness to others. Previous examples in *HCI* show that this need is fulfilled for users seeking advice on health issues. This specific task requires *Social Cues* like empathic feedback, which is why users are used to interacting with other humans (e.g., physician, therapist). As users expect a human-like response, they anthropomorphize the executing chatbot who performs the task hitherto performed by a human agent (Krämer et al., 2018). Subsequently, a task appears more human-like when the technologies substitute human experts, or the users expect that humans usually perform the task (Lankton et al., 2015; Seeger et al., 2021). In line with this, scholars expect that customers interacting with a service agent are anthropomorphizing the chatbot depending on the task's human-likeness (Seeger et al., 2021; Song & Zinkhan, 2008). For example, customers making a complaint in a service encounter expect a human-like response from the service agent like an apology. In contrast, answering simple questions in a frequently asked question format does not trigger human relatedness (Seeger et al., 2021).

Effectance Motivation is stimulated by tasks that offer incentives to accurately understand or predict the behavior (Epley et al., 2007). Previous research has shown that Effectance Motivation is stimulated when a non-human interaction partner performs an unpredictable task (Rilling et al., 2008) or a task that requires human-like sense-making. For example, if customers make a complaint, they might believe that a chatbot cannot react accurately to their needs. By anthropomorphizing the chatbot, customers become confident to talk to the chatbot about more human-like topics. Accordingly, users incentivize more *human-like task*s performed by a chatbot as users feel that anthropomorphizing the chatbot will produce meaningful interactions (Seeger et al., 2021).

If humans do not feel confident and in control of a *human-like task*, they might feel intimidated as they do not know how to interact with the chatbot (Norman, 1994). In contrast, *computer-like tasks* lack the need for humans to anthropomorphize them. The missing Effectance Motivation results from the task's generic style and missing human sense-making (Seeger et al., 2021).

Several studies support both motivational factors. They show that higher Sociality and Effectance Motivation lead to higher perceptions of anthropomorphism in a specific task context (Epley et al., 2008; Mar, 2011). However, the number of studies investigating *Task Types* in *HCI's* is limited. For example, Song and Zinkhan (2008) operationalized the *Task Type* in a service encounter of a web-shop as an information search task and a complaint task. Their findings indicate that the complaint task elicited more personalization and interactivity than the information search task in a customer service encounter. Most recently, Seeger et al. (2021) investigated the influence of different chatbot tasks on perceived anthropomorphism. They found that *human-like tasks* enhance the perception of anthropomorphism positively. The researchers further posit that tasks can differentiate along a continuum ranging from *human-like* to *computer-like tasks*.

This study follows this classification as it is the only one established in the *HCI* context. Overall, this study expects more *human-like tasks* in customer service to positively influence the perception of *Social Presence* and *Perceived Contingency* compared to a *computer-like task* in customer service.

$H_{4a,b}$. Chatbots that perform *human-like tasks* elicit higher levels of (a) *Social Presence* and (b) *Perceived Contingency* than chatbots that perform *computer-like tasks*.

Moreover, previous research showed interaction effects between *Message Interactivity* and other *Social Cues* like a human profile picture in *HCI's* (Go & Sundar, 2019). However, it is uncertain how the *Task Type* and *Message Interactivity* interact. Regarding the assumptions of Effectance Motivation, humans need to feel confident and in control of the situation when engaging with a chatbot performing a *human-like task* (Epley et al., 2007). This study assumes that users feel intimidated when the chatbot performs a *human-like task* but lacks other *Social Cues*. In this case, users do not know how to interact with the chatbot and therefore perceive the company less positively (Norman, 1994). Concluding, this study expects participants in the low *Message Interactivity* and *computer-like task* condition to have a more positive perception of the company than participants in the low *Message Interactivity* and *human-like task* condition. This effect will be reversed in the high *Message Interactivity* condition as the *Task Type* is consistent with the chatbot's level of human-like behavior.

H$_5$. The performed task will moderate the effect of *Message Interactivity* on company-related outcomes.

2.5. The Role of the Individuals Need for Human Interaction

Several studies have examined the importance of users' *Need for Human Interaction* (NFHI) in customer service encounters (Ashfaq et al., 2020; Sheehan et al., 2020). The degree of *NFHI* is a crucial determinant for predicting attitudes and adoption intent towards self-service technologies like customer service chatbots (Dabholkar & Bagozzi, 2002). The concept is defined as the desire for human contact by the consumer during a service experience (Dabholkar, 1996). Kokkinou and Cranage (2015) found that for participants who had to choose between self-service technology and a service employee, the individual's *NFHI* is lower for participants who have chosen self-service technology. Further studies connect the high *NFHI* with hedonic behaviors, indicating that these consumers derive a positive advantage from intimate relationships in service delivery (Lee & Lyu, 2016).

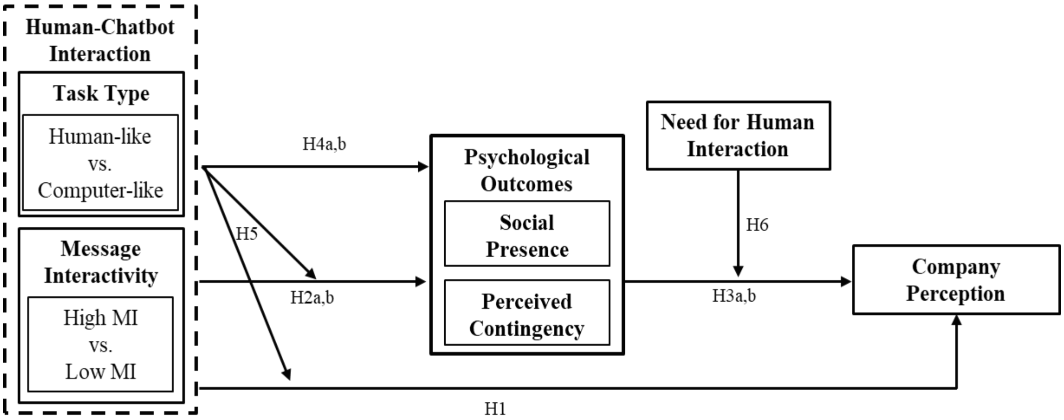
On the other hand, customers with a low *NFHI* would prefer technical solutions in service encounters over a service employee. Individuals low in *NFHI* perceive *HCI's* as more comfortable, more reliable, and easier to use (Dabholkar & Bagozzi, 2002). Recently, Sheenan et al. (2020) investigated if a chatbot that triggers human-like perceptions is enough to satisfy the customers' *NFHI*. The findings indicate that consumers who enjoy engaging with a human service agent (high *NFHI*) often enjoy interacting with a human-like chatbot, as well. Therefore, this study tests if *Message Interactivity* and a *human-like task* are sufficient to create enough humanness in a service chatbot to stimulate the participants' *NFHI*.

H$_6$. The *Need for Human Interaction* moderates the relationship between the mediators (*Perceived Contingency, Social Presence*) and company-related outcomes.

For a summary of the proposed hypotheses, see the research model in Figure 1.

Figure 1

Research Model and Hypotheses



Note. MI = Message Interactivity; H = Hypothesis. (Source: Own illustration).

3. Research methodology

3.1. Experimental Design

A 2 (low level of *Message Interactivity* vs. high level of *Message Interactivity*) x 2 (*computer-like task* vs. *human-like task*) between-subjects factorial design was conducted to explore the research questions and test the hypotheses. *Message Interactivity* is manipulated as the level of contingency and personalization in the chatbot's responses towards the customer. *Task Type* was operationalized as an information search task (i.e., computer-like) and a complaint task (i.e., human-like) and tested in an initial pre-test. Previous studies suggest that the complaint task elicits more human-likeness through personalization and interactivity than the information search task in a customer service encounter (Song & Zinkhan, 2008). This study created dialogues for each of the four conditions, characterized by different levels of *Message Interactivity* (low *Message Interactivity* vs. high *Message Interactivity*) and *Task Type* (complaint vs. information search) (see Table 1).

This study used a vignette technique featuring the presented chatbot conversation in an online experiment. Vignettes are defined as short descriptions of actual objects or situations used to influence participant's beliefs, attitudes, and judgments for the presented vignette scenarios (Atzmüller & Steiner, 2010). This technique has been used in several studies on chatbot design to simulate an actual *HCI* (Robert et al., 2009). Recently, Seeger et al. (2021) tested vignettes in a *HCI* by presenting simulated text-based interactions to participants and conducted attitudes and behavioral intentions towards a CA afterward.

Table 1

Summary of Experimental Conditions

TT \ MI	High Message Interactivity	Low Message Interactivity
Information Search	Group 1 (High MI + Complaint) (n=68)	Group 2 (Low MI + Complaint) (n=64)
Complaint	Group 3 (High MI + Search) (n=71)	Group 4 (Low MI + Search) (n=68)

Note. N=271. Conditions depending on the level of Message Interactivity and Task Type. TT = Task Type; MI = Message Interactivity.

3.2. Procedure

This online experiment worked with a scenario in which the participants are instructed to put themselves in the position of a customer looking for a digital camera in a fictitious web-shop called "*DigitalWorld."* Before the participants were instructed to read the conversation, they were asked to fill out a pre-test questionnaire including measures for the control variables and moderator variables. After this, they received general information about CA's and their use in customer service. Next, the participants received information regarding the initial situation and the particular task which needed to be solved. Detailed information about the manipulation of the independent variables is described in the following chapters. Then, the chatbot was introduced as the web-shop's customer service, and participants were instructed to read the conversation. The general content of the dialogue involved a customer who intended to send a digital camera as a birthday gift to a friend in Switzerland. The interaction displayed a back-and-forth of messages between the customer and the chatbot. The customer tried to gain information about shipment details regarding the particular task. The chatbot delivers appropriate answers to the customer's questions, and at the end of the conversation, the chatbot provides a solution for the customer. Afterward, participants were instructed to indicate their impressions of the chatbot and the interaction in a post-experiment questionnaire.

The questionnaire was created via the *Qualtrics* platform and included the *HCI* and the questions regarding the participant's attitudes and impressions (see Appendix A). The general content of the questionnaire was the same in all conditions.

The manipulation occurred only in the assignments for the particular task and the conversation itself. This study used digital cameras as the target product as several studies already used this product in customer service settings. For digital cameras, individuals are likely to need assistance from a CA due to the product's complexity and the involvement associated with it (Go & Sundar, 2019). The scenario of purchasing a gift for a friend was further adapted from previous studies to avoid personal preferences for the purchased product (Song & Zinkhan, 2008). For the full conversations, see Appendix B.

3.3. Manipulation of Message Interactivity

The first manipulated independent variable is *Message Interactivity*, which is operationalized in a low *Message Interactivity* condition and a high *Message Interactivity* condition. This study omitted other *Social Cues* associated with human-like behavior to prevent confounding results. For this reason, the chatbot had no auditory *Social Cues* like a voice (Bickmore et al., 2010), no visual *Social Cues* like a human profile picture (Go & Sundar, 2019), and also no invisible *Social Cues* like delayed response times (Gnewuch et al., 2018). Besides, the verbal *Social Cues* were limited to cues directly related to *Message Interactivity*. Especially verbal *Social Cues* associated with a human identity like a human name or self-referencing pronouns like "I" or "me" were avoided as they refer to other cues than *Message Interactivity*.

The effect of *Message Interactivity* was tested with two conditions differentiating in the presence or absence of specific *Social Cues*. This study followed the taxonomy established by Feine et al. (2019)[1] to select related verbal *Social Cues*. In the low interactivity conditions, participants engaged in a simple back-and-forth message exchange. This exchange included the participants asking questions and the chatbot delivering a suitable answer depending on the participants' request. These appropriate responses took the form of brief suggestions that included basic information about shipment details of the web-shop. Therefore, the low *Message Interactivity* conditions did not feature any specific *Social Cue*.

Several *Social Cues* were used in the high *Message Interactivity* conditions, which did not vary between the different *Task Types*. The answers provided by the chatbot in this message exchange included the following *Social Cues* (see

[1] Social Cue Design KIT: https://design.chatbotresearch.com/.

Table 2 for a summary of the used *Social Cues*). At the beginning of the conversation, the chatbot welcomed the customer (e.g., "Hello. Welcome to DigitalWorld."), which is a sign of recognition and increases user engagement (Cafaro et al., 2016). Next, the chatbot expressed content from the past by delivering tailored and personalized responses to the customer's questions (e.g., "Of course we can send the digital camera to the address in Switzerland."). Remembering customer's personal information conveys that the chatbot's messages and recommendations are contingent and interactive (Bellur & Sundar, 2017). However, this cue can also be referred to as Conversational Skill (Feine et al., 2019). Another added *Social Cue* is the chatbot sharing the same opinion with the customer (e.g., "Giving a digital camera as a gift is a great idea."). This type of *Social Cue* expresses a reaction to past messages and impacts the chatbot's engagement and believability (Li et al., 2017). The last used *Social Cue* involved the chatbot thanking the customer for the time spent (e.g., "Thank you for your time. Goodbye!"). By thanking the customer and wishing farewell, the chatbot indicates that it can remember the conversation and is perceived as part of a relationship (Bickmore & Picard, 2005).

Across the different tasks and levels of *Message Interactivity*, the same number of messages are exchanged. Moreover, both *Task Types* are related to the same topic and included similar details to avoid confounding effects. See Figure 2 for a comparison between the low *Message Interactivity* condition and the high *Message Interactivity* condition.

Table 2

Summary of Social Cues regarding Message Interactivity

	Description and Example Phrase
Greeting and Farewell	The CA expresses a word of welcome or marks someone's departure. "Hello. Welcome to DigitalWorld."
Express Content from Past/ Conversational Skill	The CA refers to content from the past. CA gives a response that is tailored to the message provided by the user. "Of course we can send the digital camera to the address in Switzerland."
Opinion Conformity	The CA shares the same opinion as the user. "Giving a digital camera as a gift is a great idea."
Thanking	The CA expresses thankfulness to the user. "Thank you for your time. Goodbye!"

Figure 2

Experimental Stimuli - High and Low Message Interactivity Condition

Note. The first page of computer-generated stimuli used in the main experiment. Computer-like task condition with high (left) vs. low (right) Message Interactivity. (Source: Own illustration).

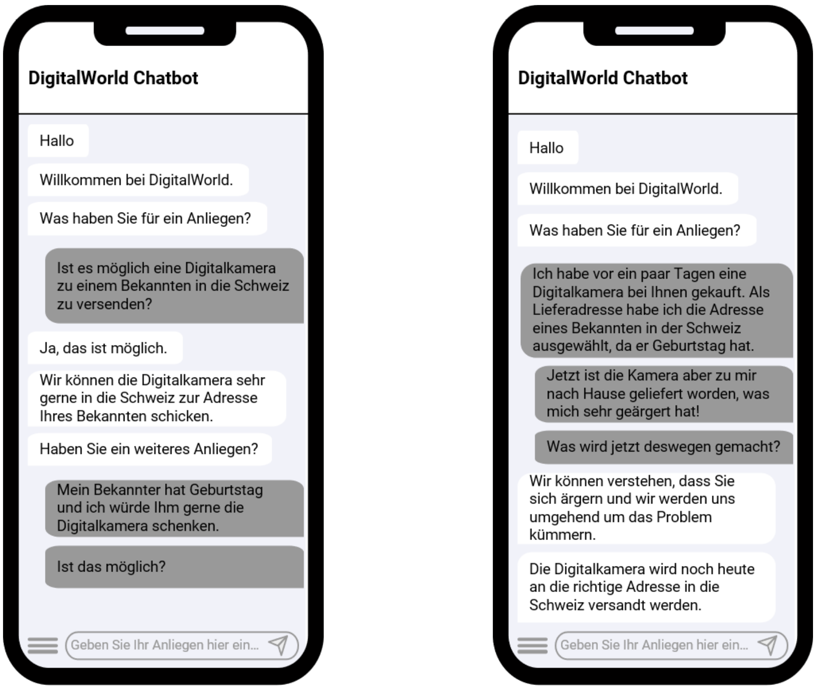
3.4. Manipulation of the Task Type

This study operationalized the *Task Type* as a *computer-like task* and a *human-like task*. This classification was adopted from previous research on tasks in *HCI's* (Seeger et al., 2021; Song & Zinkhan, 2008). These studies suggest that a complaint task in customer service is considered a more *human-like task* than an information search task as it requires human sense-making like an apology. Moreover, a complaint task elicits more personalization and interactivity than an information search task in a customer service encounter. In contrast, humans answering questions about payment details is regarded as a *computer-like task* that does not trigger human relatedness. This study adopted these findings to the experimental context and had several participants evaluate different scenarios in a qualitative pretest. Finally, the *computer-like task* was operationalized in a question-and-answer format where the customer seeks information about shipping details. The customer had several questions about the package's shipment, which were answered by the chatbot directly and appropriately. Due to the question-and-answer format, the chatbot answers are considered independent of each other, so no prior knowledge is required to answer the customer's separate questions.

The *human-like task* was operationalized in a complaint scenario. The scenario stated a mistake with the shipment of a package. The chatbot had to react to the customer's inconvenience and solve the delivery problems. The complaint scenario should trigger participants' need for social connectedness (Seeger et al., 2021). Like the *computer-like task* conditions, the chatbot answers are considered independent of each other. Both *Task Types* used a scenario where the customer wants to send a digital camera as a birthday gift to a friend in Switzerland. Besides, both tasks ended with the confirmation of delivery to Switzerland. The web-shop had the same delivery modalities across all conditions. In addition, the two tasks had the same number of message exchanges and the same beginning and end. See Figure 3 for a comparison between the *computer-like task* and the *human-like task*.

Figure 3

Experimental Stimuli - Human-Like Task and Computer-Like Task



Note. The first page of computer-generated stimuli used in the main experiment. High Message Interactivity conditions with the computer-like task (left) vs. human-like task (right). (Source: Own illustration).

3.5. Measures

All of the following measures in the questionnaire were adapted from previous studies in the *HCI* context (Gefen & Straub, 2003). Most of the items were assessed using a 7-point Likert scale ranging from "*Strongly disagree*" (1) to "*Strongly agree*" (7). The scales were first assessed in their original language and then translated into German and further adapted for the context of this research. For a detailed assignment of the items to the individual constructs, see Appendix C. This study adopted the five-item scale for *Social Presence* (*M*=2.81, *SD*=1.55, Cronbach's α=.94) from Gefen and Straub (2003) as the first psychological outcome. *Perceived Contingency,* as the second psychological outcome, was assessed in this study via four items (*M*=4.79, *SD*=1.56, Cronbach's α=.87) modified from Sundar et al. (2015), who assessed the scale with eleven items. The first company-related outcome was measured via the two-item scale *Behavioral Intention* towards a website (*M*=4.50, *SD*=1.41, Cronbach's α=.65) adapted from Hu and Sundar (2010). *Customer Satisfaction* was adapted via the three-item scale (*M*=5.08, *SD*=1.39, Cronbach's α=.86) from Bettencourt (1997). The moderator variable *NFHI* (*M*=4.77, *SD*=1.39, Cronbach's α=.76) was measured with a four-item scale adapted from Sheenan et al. (2020). Accordingly, only the two-item scale for *Behavioral Intention*s (Cronbach's α=.65) violated Cronbach's alpha assumptions (α>.7) (Nunnally, 1994).

This study also measured two control variables. *Conversational Agents Usage* (*M*=2,51, *SD*=1.90) was assessed from Adam et al. (2020) with one item on a seven-point scale ranging from never to daily. *Product Involvement* for camera equipment (*M*=2.34, *SD*=1.38, Cronbach's α=.89) was adapted from Zaichkowsky (1985) with three items. The control variables indicated moderately low *Product Involvement* and *Conversational Agent Usage* of the participants. Both scales were excluded from further analyses. Lastly, two manipulation checks were included in the experiment to ascertain that the manipulations were noticeable and successful. The manipulation check for *Message Interactivity* (*M*=4.76, *SD*=1.50, Cronbach's α=.83) was assessed from Bellur and Sundar (2017) with four items. The manipulation check for the *Task Type* (*M*=3.89, *SD*=1.71) was adapted from Seeger et al. (2021), with one item ranging from computer-like to human-like. Besides, demographic information (age, gender, and education) was collected for further analysis.

3.6. Sample

The data for the main study of this thesis was collected in February 2021 through an online questionnaire shared via SurveyCircle, SonaSystems, myStudy Blackboard, and WhatsApp. This study conducted an a priori power analysis for an "ANOVA: Fixed effects, special, main effects, and interaction" via G*Power software (Faul et al., 2007). For the sample size design, a medium effect was specified as relevant for the content (f=0.25 or Ω^2=0.06). The significance level is 5%, and the test strength to detect a medium effect if it exists is set at 80%. Due to the 2x2 design, there are four conditions with one degree of freedom for both main and interaction effects. Therefore, the sample size should be at least 128 participants. Finally, 292 participants participated in the study, randomly assigned within the questionnaire to one of the four experimental conditions. Before starting the analysis, the data was cleaned. Excluding criteria were incomplete questionnaires n=7 and participants who finished the questionnaire too fast, as it was critical to read the conversation between the customer and the chatbot carefully. The cut-off criterium for "too-fast" depended on the time needed to finish the questionnaire. The "rusher" group was identified through a gap between the "rusher group" and the normal distribution. The cut-off was set at 120 seconds, excluding n=14 participants from the study.

After data exclusion, N=271 participants were considered for data analysis. The average age of the subjects was 26 years (M=26.24, SD=7.43). The largest age group is the 18-25-year-olds with n=172 participants, followed by the 26-39-year-olds with n=84 subjects. The age groups 40-49 years included n=3, and participants over the age of 50 years included n=11 participants. There were n=83 male participants, n=182 were female, n=2 were diverse, while n=4 did not specify their gender. For most participants, the highest level of education is the Abitur/Fachabitur n=163 followed by a university degree n=96, and n=10 had completed professional training.

3.7. Statistical Methods

SPSS 26 statistical software was employed for data analysis. Statistical procedures such as variance and factor analyses were applied as part of the analysis. The SPSS extension Process v3.5 by Hayes (2017) was utilized for the moderation and mediation analysis. The statistical procedures used for the various analyses are explicitly named in the results section.

4. Results

This study investigates the influence of *Message Interactivity* and the *Task Type* on company-related perceptions in a *HCI*. Hypotheses of the research model described above will be evaluated in the following section (see Figure 1). Before proceeding with the analyses of the hypotheses, the validity of the constructs was checked as there were concerns with the *Behavioral Intention* scale violating Cronbach's alpha assumptions. Analyses showed that discriminant validity requirements were also unsatisfying for the *Behavioral Intention* and *Customer Satisfaction* scales (Fornell & Larcker, 1981) (see Appendix D). An exploratory factor analysis (EFA) was conducted to show the constructs loadings of the two scales (Appendix E). An EFA was decisive to ensure sufficient validity even though this study is based on a confirmatory model. This study performed a Principal Component Analysis (PCA) to extract the most important independent factors. The Kaiser–Meyer–Olkin measure of sampling adequacy was .827, representing a relatively good factor analysis. Bartlett's test of Sphericity was significant ($p<.001$), indicating that correlations between items were sufficiently large for performing a PCA. Only factors with eigenvalues ≥ 1 were considered (Cliff, 1988; Guttman, 1954). The scree-plot yielded empirical justification for retaining only one factor with an eigenvalue exceeding 1, which accounted for 67.46 % of the total variance. As a result, the two company-related outcomes were combined to a single variable named *Company Perception* (M=4.85, SD=1.29, Cronbach's α=.89). This study dropped one of the items of the original *Behavioral Intention* scale to improve Cronbach's alpha. After rejecting the item, *Company Perception* consisted of a four-item scale including *Customer Satisfaction* and *Behavioral Intentions* to return to the website. The information gained through the EFA showed that the internal validity of the scale improved after combining the scales. This further indicates that the exploratory model has a better fit than the assumed confirmatory model.

Besides, this study checked whether the measures of the dependent variables have resulted from a symmetrical distribution. A symmetrical distribution indicates if the mean value is a good predictor of the dependent variable. The analyses showed that for most conditions, the mean value was a good predictor. Only the high *Message Interactivity* condition in the *computer-like task* for the *Social Presence* scale showed a multimodal distribution. Tests for homogeneity of variances were not conducted due to the assessment via rating scales. Other prerequisites for a normal distribution of the residuals were neglected as well. This study persists on the high robustness of the procedures performed and the condition sizes $n>30$.

4.1. Manipulation Check – Independent Variables

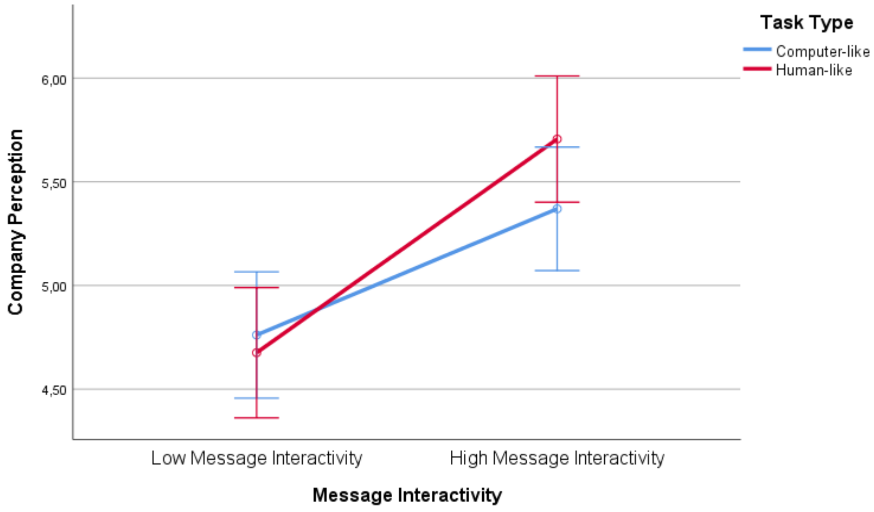
This study conducted two one-way analyses of variances (ANOVA) to test if the manipulations of the independent variables were successful. The manipulation check for *Message Interactivity* showed that participants in the high *Message Interactivity* conditions perceived significantly higher levels of back-and-forth interaction (M=5.41, SD=1.22) than those in the low *Message Interactivity* conditions (M=4.08, SD=1.47) $F(1, 269)=65.68$, $p<.001$. The manipulation of the *Task Type* showed that participants in the *human-like task* conditions significantly perceived the task as more human-like (M=4.20, SD=1.68) than those in the *computer-like task* conditions (M=3.58, SD=1.68) $F(1, 269)=9.20$, p=.003. Therefore, both manipulations of the independent variables were successful, and further analyses to examine the hypotheses were permitted.

4.2. Main Effect Analysis – Company Perception

A two-way between-subjects ANOVA was conducted to determine the effects of *Message Interactivity* (low, high) and the *Task Type* (human-like, computer-like) on the *Company Perception* (see Figure 4). The results showed that *Message Interactivity* directly affected the *Company Perception* $F(1, 267)=27.91$, $p<.001$, $\eta 2$=.095. Moreover, participants in the high *Message Interactivity* conditions (M=5.53, SD=1.18) perceived the company as more favorable than participants in the low *Message Interactivity* conditions (M=4.71, SD=1.36). See Table 3 for the means and standard deviations across conditions and independent variables. Therefore, hypothesis H_1 was supported. The effect size is f=0.32, which corresponds to a medium effect, according to Cohen (1988). As expected, there was no significant effect of the *Task Type* on *Company Perception* $F(1, 267)=0.65$, p=.42, $\eta 2$=.002.

Figure 4

The Company Perception across Different Levels of Message Interactivity and Task Type



Note. Company Perception is shown for participants in the low and high Message Interactivity condition and the computer-like and human-like task. Error bars indicate standard error. (Source: Own illustration).

Table 3

Means and Standard Deviations across Conditions and Independent Variables

		Company Perception	
MI	TT	*M*	*SD*
Low MI	CL	4.76	1.28
	HL	4.67	1.44
	Total	4.71	1.36
High MI	CL	5.36	1.27
	HL	5.70	1.06
	Total	5.53	1.18
Total	CL	5.07	1.31
	HL	5.20	1.36
	Total	5.13	1.33

Note. N=271, Low Message Interactivity (n=132); High Message Interactivity (n=139); Human-like Task (n=132); Computer-like Task (n=139). MI = Message Interactivity; CL = Computer-like; HL = Human-like.

4.3. Main Effect Analysis – Psychological Outcomes

Next, this study conducted several ANOVA's to measure the effect of *Message Interactivity* (low, high) and the *Task Type* (human-like, computer-like) on the two psychological outcomes (*Social Presence*, *Perceived Contingency*) (see Figure 5 and 6).

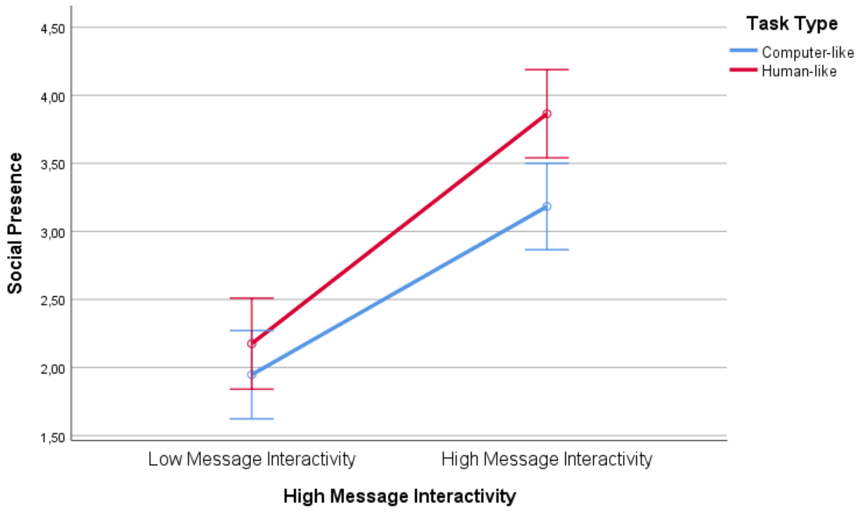
The results indicated that the level of *Message Interactivity* significantly affected *Perceived Contingency* $F(1, 267)=102.58$, $p<.001$, $\eta2=.278$, and *Social Presence* $F(1, 267)=78.59$, $p<.001$, $\eta2=.227$ (see Table 5). The analysis further showed that participants perceived higher contingency in the messages (M=5.57, SD=1.22) and a higher degree of *Social Presence* (M=3.51, SD=1.56) when they were in the high *Message Interactivity* conditions. In comparison, participants in the low *Message Interactivity* conditions perceived significantly lower contingency in the messages (M=3.95, SD=1.45) and a lower degree of *Social Presence* (M=2.05, SD=1.15).

Additionally, this study found a significant effect of the *Task Type* on *Perceived Contingency* $F(1, 267)=12.64$, $p<.001$, $\eta2=.045$ and *Social Presence* $F(1, 267)=7.59$, $p=.006$, $\eta2=.028$. The effect indicated that a *human-like task* enhances *Perceived Contingency* (M=5.08, SD=1.48) and the perceived *Social Presence* in the chatbot (M=3.04, SD=1.62). Participants in the *computer-like task* conditions perceived lower contingency (M=4.51, SD=1.59) and *Social Presence* (M=2.57, SD=1.45) than the participants in the *human-like task* conditions. See Table 4 for the means and standard deviations across conditions and independent variables.

Therefore, hypotheses $H_{2a,b}$, and $H_{4a,b}$ were supported. The effect sizes for the main effect of *Message Interactivity* on both *Perceived Contingency* (f=0.62) and *Social Presence* (f=0.54) are classified as strong according to Cohen (1988). The effect size for the main effect of the *Task Type* on both *Perceived Contingency* (f=0.21) and *Social Presence* (f=0.16) corresponds to a small effect (Cohen, 1988).

Figure 5

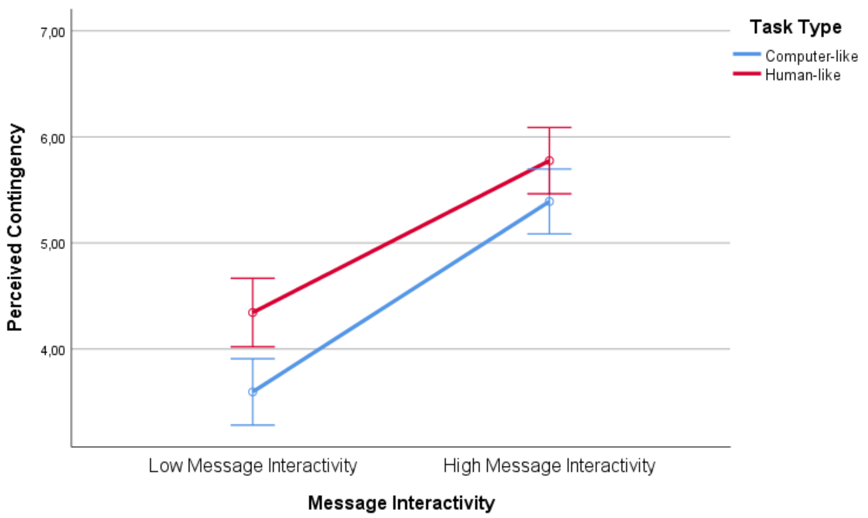
Perception of a Social Presence across Different Conditions



Note. Social Presence is shown for participants in the low and high Message Interactivity condition and for the computer-like and human-like task. Error bars indicate standard errors. (Source: Own illustration).

Figure 6

The Perception of Contingency across Different Conditions



Note. Perceived Contingency is shown for participants in the low and high Message Interactivity condition and for the computer-like and human-like task. Error bars indicate standard errors. (Source: Own illustration).

Table 4

Means and Standard Deviations across Conditions and Independent Variables

		Social Presence		*Perceived Contingency*	
MI	TT	*M*	*SD*	*M*	*SD*
Low MI	CL	1.94	1.12	3.59	1.32
	HL	2.17	1.17	4.34	1.48
	Total	2.05	1.15	3.95	1.45
High MI	CL	3.18	1.49	5.39	1.31
	HL	3.86	1.56	5.77	1.09
	Total	3.51	1.53	5.57	1.22
Total	CL	2.57	1.45	4.51	1.59
	HL	3.04	1.62	5.08	1.48
	Total	2.80	1.55	4.78	1.56

Note. N=271, Low Message Interactivity (n=132), High Message Interactivity (n=139), Human-like Task (n=132), Computer-like Task (n=139). MI = Message Interactivity; CL = Computer-like; HL = Human-like.

4.4. The Relevance of Perceived Contingency and Social Presence on Company Perception

The following analyses investigated the role of *Perceived Contingency* and *Social Presence* as mediators between *Message Interactivity* in a customer service chatbot and *Company Perception*s. Mediation analyses were conducted using the Hayes' PROCESS macro v. 3.5 (Hayes, 2017), which allows for the estimation of direct and indirect effects of the assessed mediators. Hayes PROCESS Model 4 with 5000 bootstrapped samples and a 95% confidence interval was used with *Message Interactivity* as the predictor (high *Message Interactivity* as 1, low *Message Interactivity* as 0), *Perceived Contingency* and *Social Presence* as mediators, and *Company Perceptions* as the dependent variable. This study conducted two simple mediation analyses. With *Perceived Contingency* and *Social Presence* being highly correlated $r_s(269)=.645$, $p<.001$, parallel mediation can lead to issues with collinearity, greater sampling variance, and reduced power (Hayes, 2017).

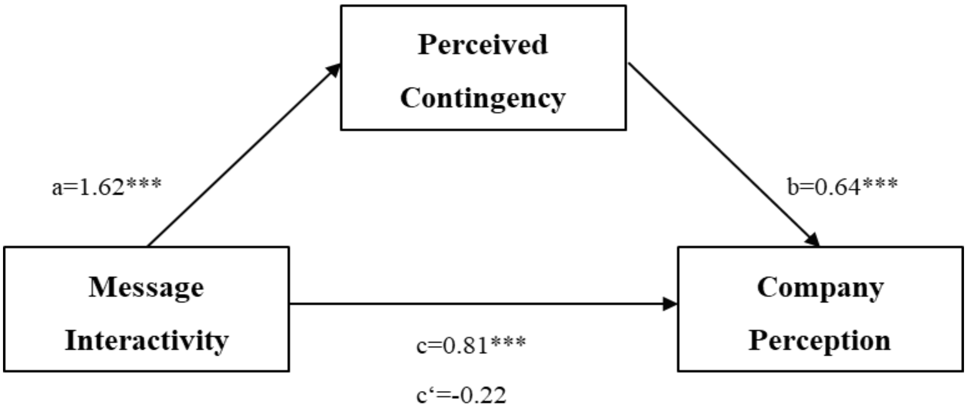
The first analysis showed that the level of *Message Interactivity* significantly predicts *Perceived Contingency* (b=1.62, se=0.16, t=9.96, p<.001). Additionally, *Perceived Contingency* had a significant effect on *Company Perception* (b=0.64, se=0.04, t=14.98, p<.001). This indicated an indirect effect through *Perceived Contingency* from *Message Interactivity* on *Company Perception* ab=1.04, se=0.14, *CI*[0.78; 1.33] (see illustrated model in Figure 7). The model accounted for 71% of the variance in *Company Perception*.

The second mediation analysis showed a significant effect of *Message Interactivity* on *Social Presence* (b=1.45, se=0.16, t=8.72, p<.001). The effect of *Social Presence* on *Company Perception* (b=0.44, se=0.04, t=9.00, p<001) was significant. This further showed an indirect effect from *Message Interactivity* on the company's perception with *Social Presence* as the mediator ab=0.65, se=0.10, *CI*[0.46;0.86] (see illustrated model in Figure 8). The model accounted for 55% of the variance in *Company Perception*. However, as the two mediators are highly correlated, they partly explain the same variance (Hayes, 2017).

The direct effect of *Message Interactivity* on *Company Perception* was not significant after adding *Perceived Contingency* as the mediator (b=-0.22, se=0.13, t=-1,70, p=.08). The same results were found in the second simple mediation after adding *Social Presence* as the mediator (b=0.16, se=0.15, t=1,05, p=.29). Therefore, the results indicate that both mediators fully mediate the effect of *Message Interactivity* and *Company Perception*, supporting hypotheses $H_{3a,b}$.

Figure 7

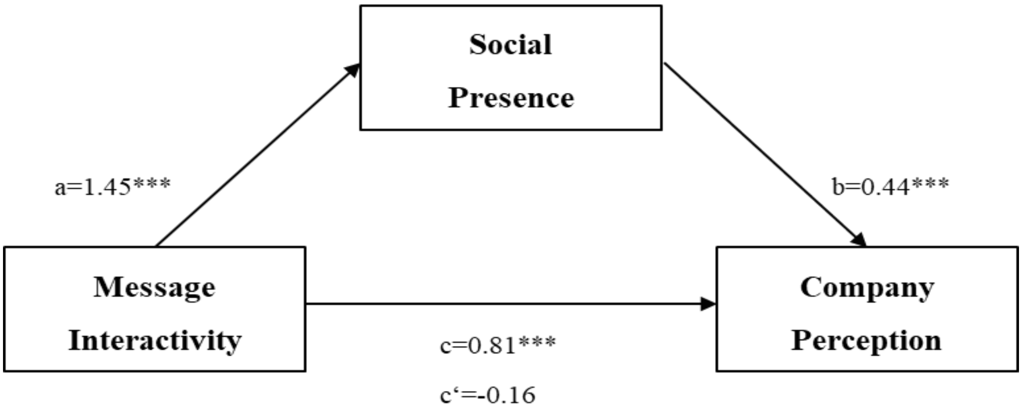
Mediation Analysis with Perceived Contingency as the Mediator



Note. ab= indirect effect, c’= direct effect, c = total effect. * p < .05, ** p < .01, *** p < .001. (Source: Own illustration).

Figure 8

Mediation Analysis with Social Presence as the Mediator



Note. ab= indirect effect, c'= direct effect, c = total effect. * *p* <.05, ** *p* < .01, *** *p* <.001. (Source: Own illustration).

4.5. Moderated Mediation of the Task Type

Next, this study tests the hypothesized moderated mediation whereby *the Task Type* moderates the effect of the path a and c'. Hayes PROCESS Model 8 with 5000 bootstrapped samples and a 95% confidence interval was used. Two separate moderated mediation analyses were conducted to account for each mediating variable and avoid issues with parallel mediation. *Task Type* is assessed as a dichotomous variable (*human-like task* as 1, *computer-like task* as 0). An index of moderated mediation was used to test the significance of the moderated mediation (Hayes, 2017). Significant effects are supported by the absence of zero within the confidence intervals.

The results indicated that the *Task Type* did not moderate the effect of *Message Interactivity* on *Social Presence* (*b*=0.45, *se*=0.33, *t*=1.37, *p*=.17). The interaction effect (*MI* x *TT*) on the c' path was also not significant (*b*=0.22, *se*=0.27, *t*=0.80, *p*=.43). Accordingly, the index of moderated mediation was not significant as the confidence interval spanned zero *Index of moderated mediation*=0.20, *CI*[-0.07;0.52]. The conditional indirect effects were significant and higher for participants in the *human-like task* condition *ab*=0.76, *CI*[0.50;1.06] than for participants in the *computer-like task* condition *ab*=0.55, *CI*[0.34;0.80].

Results of the second moderated mediation analysis indicated that the *Task Type* did not moderate the effect of *Message Interactivity* on *Perceived Contingency* (*b*=-0.36, *se*=0.32, *t*=-1.14, *p*=.26). Besides, the interaction term of the direct effect

(*MI* x *TT*) was significant, explaining 1,54% of the variance (b=0.66, se=0.22, t=2.95, p=.003). This effect was only significant in the *computer-like task* condition (b=-0.59, se=0.18, t=-3.42, p<.001), but not in the *human-like task* condition (b =0.67, se=0.23, t=2.95, p=.003).

However, the index of moderated mediation was not significant as the confidence interval spanned zero *Index of moderated mediation*=-0.23, *CI*[-0.62;0.18]. On the contrary to the first analysis, the conditional indirect effect was higher for participants in the *computer-like task* condition *ab*=1.15, *CI*[0.84;1.49] than for participants in the *human-like task* condition *ab*=0.92, *CI*[0.59;1.29]. The statistical results of the moderated mediation are shown in Table 5.

Consequently, the findings in this study do not support H_5 and indicate that the *Task Type* does not significantly influence the effect of *Message Interactivity* on *Company Perceptions*.

Table 5

Results of Moderated Mediation Analyses with Perceived Contingency and Social Presence as Mediators

Predictor	*b*	*p*	95% CI		Predictor	*b*	*p*	95% CI	
			LLCI	ULCI				LLCI	ULCI
			Outcome: *Social Presence*					Outcome: *Perceived Contingency*	
MI	1.24	<.001	0.78	1.68	MI	1.79	<.001	1.35	2.23
TT	0.23	.34	-0.24	0.69	TT	0.74	<.001	0.29	1.19
MI x TT	0.45	.17	-0.20	1.10	MI x TT	-0.36	.25	-0.99	0.26
			Outcome: *Company Perception*					Outcome: *Company Perception*	
MI	0.05	.79	-0.34	0.45	MI	-0.59	<.001	-0.94	-0.03
SP	0.45	<.001	0.35	0.55	PC	0.67	<.001	0.58	0.75
TT	-0.19	.34	-0.57	0.20	TT	-0.58	<.001	-0.91	-0.26
MI x TT	0.22	.43	-0.32	0.76	MI x TT	0.67	.003	0.22	1.10
Index of Moderated Mediation			Index BootSE 95% CI		Index of Moderated Mediation			Index BootSE 95% CI	
TT x MI	0.20		-0.07	0.52	TT x MI	-0.24		-0.66	0.19

Note. *N*= 271. LLCI = Lower level of the confidence interval, ULCI = Upper level of the confidence interval. MI = Message Interactivity; TT = Task Type; SP = Social Presence; PC = Perceived Contingency.

4.6. Moderated Moderated Mediation of the Need for Human Interaction

Last, the moderated moderated mediation model tests if the individual's *NFHI* will moderate the relationship between the mediating variables (*Perceived Contingency, Social Presence*) and the perception of the company (b path). *NFHI* is assessed as a dichotomous variable (high *NFHI* as 1, low *NFHI* as 0). Hayes PROCESS Model 21 with 5000 bootstrapped samples and a 95% confidence interval was utilized for analyses (Hayes, 2017). *Task Type* is included as the second moderator to account for all experimental conditions. The index of moderated moderated mediation was used to test the significance of the moderated moderated mediation (Hayes, 2017).

NFHI was not found to moderate the effect of *Message Interactivity* and *Company Perception* through the relationship of *Social Presence* and *Company Perception* (b=-0.05, se=0.09, t=-0.61, p=.54). Consequently, the index of moderated moderated mediation was not significant as the confidence interval spanned zero *Index of moderated moderated mediation*=-0.02, CI[-0.14;0.07]. The conditional indirect effect was strongest for participants in the *human-like task* condition and a low *NFHI ab*=0.81, *CI*[0.50;1.19] and weakest for participants in the *computer-like task* condition and a high *NFHI ab*=0.52, *CI*[0.32;0.74].

In the second analysis, *NFHI* was found to moderate the effect of *Message Interactivity* and *Company Perception* through the relationship of *Perceived Contingency* and *Company Perception* (b=-0.16, se=0.07, t=-2.16, p=.03). The index of moderated moderated mediation was still not significant as the confidence interval spanned zero *Index of moderated moderated mediation*=0.05, CI[-0.04;0.21]. In contrast to the analysis via *Social Presence*, the conditional indirect effect was strongest for participants in the *computer-like task* condition and a low *NFHI ab*=1.34, *CI*[0.94;1.75] and weakest for participants in the *human-like task* condition and a high *NFHI ab*=0.84, *CI*[0.52;1.20]. Additionally, the effect for participants in the *computer-like task* condition and a high *NFHI ab*=1.05, *CI*[0.75;1.38] and weakest for participants in the *human-like task* condition and a high *NFHI ab*=1.07, *CI*[0.67;1.50] was approximately the same. The statistical results of the moderated moderated mediation are shown in Table 6.

Consequently, the findings in this study do not support H_6. Therefore, suggesting that the participant's *NFHI* does not significantly influence the relationship between *Message Interactivity* and *Company Perception*.

Table 6

Results of Moderated Moderated Mediation Analyses with Perceived Contingency and Social Presence as Mediators

Predictor	*b*	*p*	95% CI		Predictor	*b*	*p*	95% CI	
			LLCI	ULCI				LLCI	ULCI
			Outcome: *Social Presence*					Outcome: *Perceived Contingency*	
MI	1.23	<.001	0.78	1.68	MI	1.79	<.001	1.35	2.20
TT	0.22	.33	-0.23	0.69	TT	0.74	<.001	0.29	1.19
MI x TT	0.45	.17	-0.19	1.10	MI x TT	-0.36	.25	-0.99	0.26
			Outcome: *Company Perception*					Outcome: *Company Perception*	
MI	0.15	.32	-0.15	0.45	MI	-0.25	.056	-0.51	.007
SP	0.48	<.001	0.32	0.63	PC	0.74	<.001	0.62	0.87
NFHI	-0.05	.85	-0.65	0.54	NFHI	0.45	.23	-0.29	1.19
SP x NFHI	-0.05	.54	-0.23	0.12	PC x NFHI	-0.16	.03	-0.30	-0.01
Index of Moderated Moderated Mediation			Index BootSE 95% CI		Index of Moderated Moderated Mediation			Index BootSE 95% CI	
TT x NFHI	-0.03		-0.14	0.06	TT x NFHI	0.06		-0.04	0.20

Note. *N*= 271. LLCI = Lower level of the confidence interval, ULCI = Upper level of the confidence interval. MI = Message Interactivity; TT = Task Type; SP = Social Presence; PC = Perceived Contingency; NFHI = Need for Human Interaction.

5. Discussion

This research aims to make theoretical as well as practical contributions. On the academic side, this study contributes to the research of text-based DCA's. This study mainly focuses on *Message Interactivity* as a common feature in customer service interactions. The goal is to broaden the existing literature on *Message Interactivity* in *HCI* by investigating the effect across different *Task Types*. Another contribution includes the systematic use of *Social Cues* in *HCI* research. This study works with the taxonomy introduced by Feine et al. (2019), which allows other researchers to track and reproduce this study. On the other hand, by following an empirical approach, this project gives practical implications on the design of customer service chatbots. Therefore, shedding light on deploying, using, and adapting customer service chatbots in practice.

The main findings of this study demonstrate that contingent messages of a chatbot in customer service positively influence psychological and desirable company-related outcomes. Participants in the high *Message Interactivity* conditions emphasized a higher degree of *Social Presence* and perceived higher contingency in the conversation than those in the low *Message Interactivity* conditions. This supports the assumption that a high level of interactive messages in a chatbot effectively makes the chatbot appear more human-like. These findings are in line with earlier research on *HCI* (Nass & Moon, 2000) and *Social Response Theory* (Nass et al., 1994). This study further shows that even the presence of minimal *Social Cues* like increased *Message Interactivity* in a chatbot can trigger stronger perceptions of *Social Presence* and substantially affect the perception of the chatbot. Consequently, this study supports the positive effect of anthropomorphic chatbot design on the perception of human-likeness. These findings further expand the *CASA* paradigm.

The next set of this study's findings also build on the *CASA* paradigm and investigates how contingent messages in a service chatbot influence the customer experience. The effect indicates that participants in the high *Message Interactivity* conditions have a more positive perception of the company than participants in the low *Message Interactivity* conditions. This positive perception of the company is indicated by higher customer satisfaction and a higher likelihood of returning to the company's website. This finding is in line with previous research (Araujo, 2018) and provides further evidence that chatbots, using verbal *Social Cues*, can positively affect the customer experience.

More importantly, the additional set of mediation analyses indicate that *Message Interactivity* influences participants' *Company Perception* via the two psychological outcomes (*Social Presence*, *Perceived Contingency*). The findings suggest that both *Perceived Contingency* and *Social Presence* fully mediate the effect of *Message Interactivity* on *Company Perception*. In other words, participants perceive the chatbot as more human-like regarding its ability to deliver contingent messages and, subsequently, evaluate the company more positively. These effects support previous findings, which also investigated the mediating effects of *Social Presence* and *Perceived Contingency* (Go & Sundar, 2019). Moreover, these findings provide additional evidence that human-like behavior in service chatbots is essential to gain a competitive advantage through excellent customer experience.

Another core contribution of this research is that *human-like task*s have a positive influence on the perception of the chatbot and the interaction. Participants in the *human-like task* conditions (complaint task) perceive a higher degree of *Social Presence* in the message exchange than participants in the *computer-like task* conditions (information search). The participants in the *human-like task* conditions also perceive the chatbot to deliver more contingent messages than participants in the *computer-like task* conditions. The results of this study are in line with the *Theory of Anthropomorphism* (Epley et al., 2008). They show that situational variables like specific tasks can influence human's motivation to anthropomorphize non-human interaction partners. As participants expect a human-like response, they anthropomorphize the service chatbot who helps them with their complaint even though it is not a human agent. Subsequently, a complaint task fulfilled by a service chatbot leads customers to be socially related to the chatbot (Sociality Motivation). Customers would also expect human-like sense-making like an apology, which can further anthropomorphize the chatbot (Effectance Motivation). In comparison, a simple information search task is not triggering human motivation to anthropomorphize a chatbot in customer service.

These findings also suggest that a *human-like task* performed by a CA is a *Social Cue*, which positively influences *Social Presence* and *Perceived Contingency* in a *HCI*. Therefore, the *Task Type* should be added to the established taxonomy (Feine et al., 2019). This work also helps to improve the distinction between human and non-human tasks performed by CA's and expands the existing literature by giving examples for typical tasks in customer service. Future researchers can further build on this knowledge and will be aware of the effects of different *Task Types* in *HCI's*.

This study also investigates the moderating influence of the *Task Type* on the relationship of *Message Interactivity* and *Company Perception* via the two psychological outcomes. However, the indices of moderated mediation were not significant, showing that the impact of the *Task Type* does not significantly affect the customer experience. Therefore, it can be inferred that distinct tasks in customer service, differentiating in their human-likeness, do not change the *Company Perception*. An explanation for the insignificant effects is the missing motivation of participants to anthropomorphize the interaction partner. According to the *Theory of Anthropomorphism* (Epley et al., 2008), humans need to be highly motivated to anthropomorphize a task. As the interaction was only presented on vignettes, the participants may not have felt the need to put themselves in the customer's position. Another explanation is that the moderating effect of the *Task Type* on the relationship of *Message Interactivity* and *Company Perception* is not strong enough. In particular, the influence of the *Task Type* on the psychological outcomes was significant, showing that the manipulation was successful. Subsequently, this study assumes that the effect of the *Task Type* on *Company Perception*s is not relevant but should be further tested with other *Social Cues*.

Finally, the moderation effect of the individual's *NFHI* on the relationship of *Message Interactivity* and *Company Perception* is investigated. This study is especially interested in the moderating effect of *NFHI* through the relationship of the mediating variables (*Social Presence*, *Perceived Contingency*) on *Company Perceptions* as the effect relies on the degree of perceived human contact. Indices of moderated moderated mediation were not significant, showing no moderating influence of *NFHI*. Mainly, the vignette technique limited this effect as the participants needed to put themselves in the customer's position. Participant's *NFHI* is an individual propensity that is hardly affected when participants do not experience the situation themselves. Future research should test this effect in an actual message exchange between participants and a chatbot. Another explanation regards the predicted moderating effect of the *Task Type*. According to the *Theory of Anthropomorphism* (Epley et al., 2008), humans might be intimidated if a *human-like task* lacks human-like traits. It could be assumed that the *Task Type* interfered with the predicted moderating effect of *NFHI* as it affects individuals with all levels of NFHI. Future research should investigate the effect of the individuals' *NFHI* on *Message Interactivity* in a separate experiment when controlling for the *Task Type*.

5.1. Implications for Practitioners

Besides the theoretical contributions, this study has several implications for practitioners on designing customer service chatbots. These contributions help platform providers and online marketers, especially those who consider employing AI-based CA's in customer service.

First, this study shows that even slightly noticeable design features like contingent messages can positively impact the users' perception of the chatbot and the company (Gnewuch et al., 2017). As suitable suggestions, this study recommends that AI-based CA's in customer service should send personalized messages, refer to the content expressed in the past, and convey an understanding of the content of the conversation (Bellur & Sundar, 2017; Sundar et al., 2016). To personalize messages, practitioners should call customers by their name and use personal details like the specific destination of an order. CA's in customer service should also express content from the past. Companies can use already stored information about the customer like order history or the specific destination of a customer. For example, suppose the fictitious customer of this study revisits the website, and the chatbot writes a message like "We hope you are still delighted with the digital camera you bought from us a few weeks ago. Do you want the next delivery to be sent to the same address in Switzerland again?". Another design feature of customer service CA's is to understand the content and emotional connectedness of a conversation. Even though this design feature needs a well-developed AI-based CA, companies can already implement template phrases like "We are sorry that you had a problem with your order." or "Thank you for your order. You have made an excellent choice.". If a company manages to engage with a customer in the described way, the customer's experience will likely be enhanced.

A second practical contribution gives new insights into the growing number of tasks CA's perform on various websites and platforms in businesses (Araujo, 2018; Feine et al., 2019). This study shows that *human-like task*s stimulate the perception of *Social Presence* and *Perceived Contingency*. However, this effect also occurs in *HCI's* in which designers intend to use no *Social Cues* at all. Therefore, practitioners should be aware of the possible undesired effects in cases where a computer-like interaction is preferred.

Nevertheless, the effect of the *Task Type* on the *Company Perception* is not as significant as the effect of contingent messages. Therefore, designers should consider CA's to handle various tasks in customer service and focus on designing them as engaging as possible. First, companies can save money and time by using chatbots rather than human assistants for *human-like task*s. Second, companies are still likely to maintain a positive customer experience as the CA's use an engaging and contingent communication style.

5.2. Limitations and Future Work

Several limitations must be considered when interpreting and discussing the results of this empirical study. One limitation results from the use of simulated interactions. On the one hand, the vignette technique is an established experimental procedure to study perceptions, attitudes, and judgments (Atzmüller & Steiner, 2010). On the other hand, vignettes cannot substitute an actual *HCI* and make it more difficult for participants to put themselves in the customer's position (Riedl et al., 2014). Therefore, future research should try to replicate this study with an actual *HCI*. Future investigations could be essential to review possible moderation effects of the *Task Type* and the individuals' *NFHI*, which were not found in this study.

A second limitation involves violating the confirmatory model as this study combined the *Customer Satisfaction* scale and the scale for *Behavioral Intentions*. The combination was assessed for several reasons discussed earlier, but the external validity of the two company-related outcomes (*Customer Satisfaction, Behavioral Intention*) is limited. Future research should investigate the effect of company-related consequences separately to gain as many insights about different outcomes as possible.

Another limitation results from the operationalization of the independent variables. The initial idea was to systematically conduct *Message Interactivity* only with *Social Cues* mentioned in the taxonomy of Feine et al. (2019) to improve the replicability. However, other *Social Cues* of *Message Interactivity* mentioned in previous studies investigating *Message Interactivity* (Bellur & Sundar, 2017; Go & Sundar, 2019) were omitted in this empirical study as they are not part of the taxonomy. Therefore, the effects of *Message Interactivity* are limited to the *Social Cues* assessed in this study, even though other features could improve the effect.

To overcome this concern, future researchers should focus on a universal taxonomy of *Social Cues* to further enhance the accessibility of insights regarding *HCI*.

Furthermore, a similar problem occurred for the operationalization of the *Task Type*. First, the investigated tasks are only two examples of possible tasks in customer service. As there is no classification of the human-likeness of tasks yet, no inference for other tasks can be assumed. Second, as mentioned earlier, the human-likeness of tasks might change over time, which shows the need that tasks need another categorization than human-like versus computer-like. Future researchers should tackle this issue and consider creating a classification, which defines characteristics of CA tasks.

One last limitation originates from the demographic distribution of the participants. 172 of the 271 participants are in the age group of 18-25 years, indicating a low average age of 26. Other socio-demographic factors also show an uneven distribution of the participants. A total of 259 participants have obtained the A-Level or have completed their university degrees. Thus, it can be noticed that there is no representative distribution of the German population in terms of both age and educational level. Future studies should achieve equal distribution in all age groups to make generally representative statements.

6. Conclusion

Anthropomorphically designed CA's have become increasingly popular in various companies. They offer time- and cost-saving opportunities to automate different tasks while delivering the sense of human-like contact in the interaction. However, the capabilities of existing CA's are very limited in their human-likeness, which reminds customers that they are interacting with a chatbot, and thus a negative customer experience emerges. This study offers an efficient and straightforward way to avoid these potential adverse effects by showing the positive impact of *Message Interactivity* on psychological and desirable company-related outcomes. This study further gives new insights into the performance of different tasks by chatbots in a service encounter. Consequently, this empirical research extends prior knowledge of CA's in customer service and provides theoretical and practical recommendations for chatbot designers.

Appendix

Appendix A

Questionnaire of the Main Experiment

Beginn des Blocks: Einleitungstext

Q1 Liebe Teilnehmer/innen,

Vielen Dank, dass du dir Zeit nimmst, an meiner Umfrage teilzunehmen! Diese Befragung ist Teil meiner Bachelorarbeit an der Leuphana Universität Lüneburg und behandelt die Interaktion mit einem Chatbot. (Befragungsdauer: **max. 8 Minuten**).

Bitte beachten Sie folgende Hinweise:

- Beantworten Sie alle Fragen spontan.
- Es gibt keine richtigen oder falschen Angaben, nur Ihre persönliche Meinung zählt.
- Alle Daten werden vollständig anonym gespeichert und ausgewertet.

Bei Fragen oder Anmerkungen können Sie mich gerne per E-Mail kontaktieren: christoph.voeltzke@stud.leuphana.de

Vielen herzlichen Dank für Ihre Unterstützung!

Ende des Blocks: Einleitungstext

Beginn des Blocks: Einleitung

Q2 Der folgende Fragebogen besteht aus **zwei Abschnitten**. In beiden Abschnitten werden Themen zu virtuellen Assistenten behandelt.

Virtuelle Assistenten sind nicht-menschliche Dialogsysteme, die Anfragen von Benutzern beantworten und Aufgaben in privaten oder wirtschaftlichen Zusammenhängen erledigen können.

Virtuelle Assistenten sind beispielsweise **Sprachassistenten** wie Siri (Apple) und Alexa (Amazon) oder **Chatbots**, die mittels menschlicher Sprache oder in textbasierter Form mit einem Benutzer kommunizieren.

Im **ersten Abschnitt** werden Sie zur Nutzung von virtuellen Assistenten in verschiedenen Situationen sowie zu weiteren ausgewählten Themen befragt.

Im **zweiten Abschnitt** werden Sie den textbasierten Dialog eines Kunden mit einem Chatbot lesen. Anschließend sollen Sie Ihre Meinung und Ihre Einschätzung zu diesem Dialog in einer Reihe von Fragen wiedergeben.

Ende des Blocks: Einleitung

Beginn des Blocks: Moderator: NFHI

Q3 Die folgenden Aussagen sollen Ihre Meinung zu klassischen Aufgaben im Kundenservice erfassen. Beispielhafte Aufgaben des Kundenservices sind die Hilfe bei der Informationssuche oder die Problemlösung bei Reklamationen nach dem Kauf.

	Stimme überhaupt nicht zu (1)	(2)	(3)	(4)	(5)	(6)	Stimme voll und ganz zu (7)
Der menschliche Kontakt beim Kundenservice macht den Prozess für den Kunden angenehm. (1)	○	○	○	○	○	○	○
Ich interagiere gerne mit der Person, die den Service erbringt. (2)	○	○	○	○	○	○	○
Es stört mich, eine Maschine zu benutzen, wenn ich stattdessen mit einer Person sprechen könnte. (3)	○	○	○	○	○	○	○

Ende des Blocks: Moderator: NFHI

Beginn des Blocks: Covariates

Q4 Bitte geben Sie an, wie häufig Sie virtuelle Assistenten benutzen.

	Nie (1)	(2)	(3)	(4)	(5)	(6)	Täglich (7)
Wie oft nutzen Sie virtuelle Assistenten, wie Siri (Apple), Google Assistant (Google) oder Alexa (Amazon)? (1)	o	o	o	o	o	o	o

Q5 Vielen Dank! Der erste Abschnitt ist geschafft!

Ende des Blocks: Covariates

Beginn des Blocks: Einleitung Abschnitt 2

Q6
Nun folgt der zweite Abschnitt in der Sie die Interaktion zwischen einem Kunden und einem Chatbot lesen.

Ende des Blocks: Einleitung Abschnitt 2

Beginn des Blocks: High MI & HL

Q7 Bitte lesen Sie sich die Informationen zur folgenden Interaktion zwischen dem Kunden eines Webshops und einem Chatbot aufmerksam durch.

Stellen Sie sich vor, dass Sie vor ein paar Tagen eine Digitalkamera bei diesem Webshop erworben haben und nun Lieferschwierigkeiten aufgetreten sind, weshalb Sie sich bei dem Kundenservice beschweren.
Der Chatbot ist für den Kundenservice des Webshops **"DigitalWorld"** verantwortlich und unterstützt die Kunden dabei in Echtzeit.

Versetzen Sie sich in die **Lage des Kunden** (grau hinterlegte Nachrichten), der mit dem Chatbot des Webshops (weiß hinterlegte Nachrichten) interagiert.

In dieser Interaktion ist es die **Aufgabe des Chatbots**, dem Kunden bei einer **Beschwerde** wegen aufgetretener Lieferschwierigkeiten einer Bestellung zu helfen und eine Lösung für das Problem des Kunden bereitzustellen.

Q8 Conversation Picture 1: High MI & HL

Q9 Conversation Picture 2: High MI & HL

Q10 Conversation Picture 3: High MI & HL

Ende des Blocks: High Mi & human-like

Beginn des Blocks: Low MI + human-like

Q11 Bitte lesen Sie sich die Informationen zur folgenden Interaktion zwischen dem Kunden eines Webshops und einem Chatbot aufmerksam durch. Stellen Sie sich vor, dass Sie vor ein paar Tagen eine Digitalkamera bei diesem Webshop erworben haben und nun Lieferschwierigkeiten aufgetreten sind, weshalb Sie sich bei dem Kundenservice beschweren. Der Chatbot ist für den Kundenservice des Webshops **"DigitalWorld"** verantwortlich und unterstützt die Kunden dabei in Echtzeit. Versetzen Sie sich in die **Lage des Kunden** (grau hinterlegte Nachrichten), der mit dem Chatbot des Webshops (weiß hinterlegte Nachrichten) interagiert.
In dieser Interaktion ist es die **Aufgabe des Chatbots**, dem Kunden bei einer **Beschwerde** wegen aufgetretener Lieferschwierigkeiten einer Bestellung zu helfen und eine Lösung für das Problem des Kunden bereitzustellen.

Q12 Conversation Picture 1: Low MI & HL

Q13 Conversation Picture 2: Low MI & HL

Q14 Conversation Picture 1: Low MI & HL

Ende des Blocks: Low MI + human-like

Beginn des Blocks: High MI + computer-like

Q15 Bitte lesen Sie sich die Informationen zur folgenden Interaktion zwischen dem Kunden eines Webshops und einem Chatbot aufmerksam durch.

Stellen Sie sich vor, dass Sie ein Produkt aus dem Sortiment dieses Webshops erwerben wollen und sich bereits für eine Digitalkamera entschieden haben. Bevor Sie den Kauf abschließen, möchten Sie noch einige Fragen zu den Versandoptionen klären.
Der Chatbot ist für den Kundenservice des Webshops **"DigitalWorld"** verantwortlich und unterstützt die Kunden dabei in Echtzeit.

Versetzen Sie sich bitte in die **Lage des Kunden** (grau hinterlegte Nachrichten), der mit dem Chatbot des Webshops (weiß hinterlegte Nachrichten) interagiert.

In dieser Interaktion ist es die **Aufgabe des Chatbots**, den Kunden mit **Informationen** zu den vorhandenen Versandoptionen und den Liefermodalitäten des Webshops zu versorgen.

Q16 Conversation Picture 1: High MI & CL

Q17 Conversation Picture 2: High MI & CL

Q18 Conversation Picture 3: High MI & CL

Ende des Blocks: High MI + computer-like

Beginn des Blocks: Low MI + computer-like

Q19 Bitte lesen Sie sich die Informationen zur folgenden Interaktion zwischen dem Kunden eines Webshops und einem Chatbot aufmerksam durch.
Stellen Sie sich vor, dass Sie ein Produkt aus dem Sortiment dieses Webshops erwerben wollen und sich bereits für eine Digitalkamera entschieden haben. Bevor Sie den Kauf abschließen, möchten Sie noch einige Fragen zu den Versandoptionen klären.
Der Chatbot ist für den Kundenservice des Webshops **"DigitalWorld"** verantwortlich und unterstützt die Kunden dabei in Echtzeit.

Versetzen Sie sich bitte in die **Lage des Kunden** (grau hinterlegte Nachrichten), der mit dem Chatbot des Webshops (weiß hinterlegte Nachrichten) interagiert.

In dieser Interaktion ist es die **Aufgabe des Chatbots**, den Kunden mit **Informationen** zu den vorhandenen Versandoptionen und den Liefermodalitäten des Webshops zu versorgen.

Q20 Conversation Picture 1: Low MI & CL

Q21 Conversation Picture 2: Low MI & CL

Q22 Conversation Picture 3: Low MI & CL

Ende des Blocks: Low MI + computer-like

Beginn des Blocks: Einleitung Abschnitt 2.1

Q23 Es kommen jetzt noch einige Fragen zu der eben gelesenen Interaktion mit dem Chatbot und dann haben Sie es geschafft. Vielen Dank!

Ende des Blocks: Einleitung Abschnitt 2.1

Beginn des Blocks: Behavioral Intention

Q24 Bitte geben Sie an, welchen Eindruck Sie von der Webseite "DigitalWorld" hatten.

	Stimme überhaupt nicht zu (1)	(2)	(3)	(4)	(5)	(6)	Stimme voll und ganz zu (7)
Ich würde die Webseite DigitalWorld für die zukünftige Nutzung als Lesezeichen speichern. (1)	○	○	○	○	○	○	○
Ich würde die Webseite DigitalWorld in Zukunft wieder besuchen. (2)	○	○	○	○	○	○	○

Ende des Blocks: Behavioral Intention

Beginn des Blocks: Customer Satisfaction

Q25 Bitte geben Sie an, welchen Eindruck Sie von der Interaktion mit Chatbot hatten.

	Stimme überhaupt nicht zu (1)	(2)	(3)	(4)	(5)	(6)	Stimme voll und ganz zu (7)
Ich habe die Interaktion mit diesem Chatbot wirklich genossen. (1)	○	○	○	○	○	○	○
Ich bin mit der Chatbot-Interaktion zufrieden. (2)	○	○	○	○	○	○	○
Die Entscheidung, mit diesem Chatbot zu interagieren, war eine gute Entscheidung. (3)	○	○	○	○	○	○	○

Ende des Blocks: Customer Satisfaction

Beginn des Blocks: Perceived Contingency

Q26 Bitte geben Sie an, welchen Eindruck Sie von der Interaktion mit Chatbot hatten.

	Stimme überhaupt nicht zu (1)	(2)	(3)	(4)	(5)	(6)	Stimme voll und ganz zu (7)
Die Antworten des Chatbots berücksichtigten den Zusammenhang mit meinen früheren Eingaben. (1)	○	○	○	○	○	○	○
Ich hatte das Gefühl, dass der Chatbot meine Antworten sorgfältig registrierte und Feedback auf der Grundlage der von mir eingegebenen Informationen gab. (2)	○	○	○	○	○	○	○
Ich hatte das Gefühl, dass der Chatbot eine exklusive Antwort auf meine Aktionen gab. (3)	○	○	○	○	○	○	○
Die Antworten des Chatbots schienen miteinander verbunden zu sein. (4)	○	○	○	○	○	○	○

Ende des Blocks: Perceived Contingency

Beginn des Blocks: Soziale Präsenz

	Stimme über-haupt nicht zu (1)	(2)	(3)	(4)	(5)	(6)	Stimme voll und ganz zu (7)
...verspürte ich einen menschlichen Kontakt mit dem Chatbot. (1)	○	○	○	○	○	○	○
...fühlte ich eine persönliche Beziehung zum Chatbot. (2)	○	○	○	○	○	○	○
...hatte ich das Gefühl von Geselligkeit mit dem Chatbot. (3)	○	○	○	○	○	○	○
...konnte ich bei dem Chatbot menschliche Wärme verspüren. (4)	○	○	○	○	○	○	○
...spürte ich bei dem Chatbot eine menschliche Sensibilität. (5)	○	○	○	○	○	○	○

Q27 Basierend auf meinen Eindrücken...

Q28 Gleich geschafft!

Ende des Blocks: Soziale Präsenz

Beginn des Blocks: Manipulation Check - Task

Q29 Bitte schätzen sie ein, ob die durchgeführte Aufgabe eher menschenähnlich (normalerweise durch einen Menschen durchgeführt) oder eher computerähnlich (normalerweise von einem Computer durchgeführt) ist.

	sehr computerähnlich (1)	(2)	(3)	(4)	(5)	(6)	sehr menschenähnlich (7)
Die durchgeführte Aufgabe ist... (1)	○	○	○	○	○	○	○

Ende des Blocks: Manipulation Check - Task

Beginn des Blocks: Manipulation Checks: MI

Q30 Bitte geben sie an, wie die Interaktion mit dem Chatbot verlief.

	Stimme überhaupt nicht zu (1)	(2)	(3)	(4)	(5)	(6)	Stimme voll und ganz zu (7)
Der Chatbot erinnert sich an meine Antworten. (1)	○	○	○	○	○	○	○
Die Antworten des Chatbots standen im Zusammenhang mit meinen früheren Antworten. (2)	○	○	○	○	○	○	○
Der Chatbot gab einige intelligente Vorschläge, die auf meinen Antworten basierten. (3)	○	○	○	○	○	○	○

Ende des Blocks: Manipulation Checks: MI

Beginn des Blocks: Product Involvement

Q31 Bitte geben sie an, wie Sie folgende Aussagen einschätzen würden.

	Stimme überhaupt nicht zu (1)	(2)	(3)	(4)	(5)	(6)	Stimme voll und ganz zu (7)
Ich bin generell an Kameraequipment interessiert. (1)	○	○	○	○	○	○	○
Kamera-equipment ist für mich ein persönlich relevantes Thema. (2)	○	○	○	○	○	○	○
Ich suche aktiv nach Informationen über Kamera-equipment. (3)	○	○	○	○	○	○	○

Ende des Blocks: Product Involvement

Beginn des Blocks: Demografie

Q32 Vielen Dank! Sie haben alle Fragen beantwortet. Jetzt sollen Sie nur noch ein paar demografische Angaben machen.

Q33 In welchem Jahr sind Sie geboren?

____

Q34 Welches Geschlecht haben Sie?

○ Weiblich (1)

○ Männlich (2)

○ Divers (3)

○ Ich möchte keine Angabe machen (4)

Q35 Was ist ihr höchster Bildungsabschluss?

○ Kein Abschluss (1)

○ Abgeschlossene Berufsausbildung (2)

○ Abitur/Fachabitur (3)

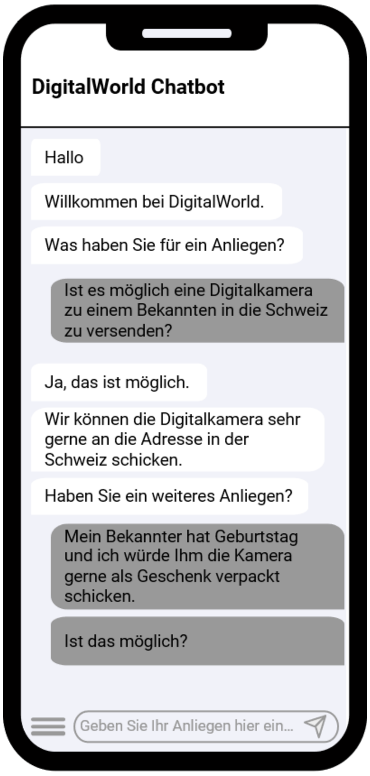
○ Hochschulabschluss (4)

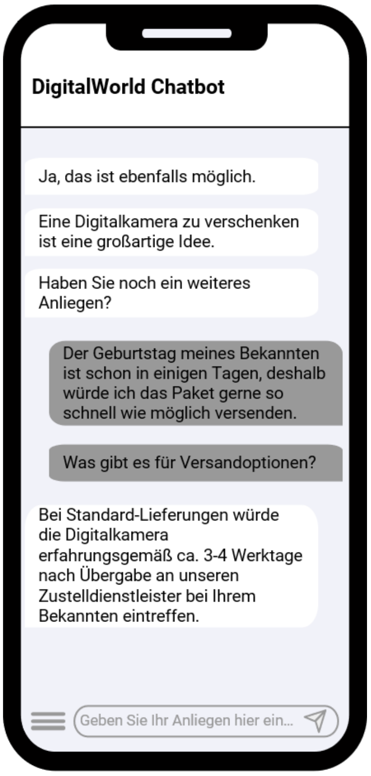
○ Sonstiges (5)

Ende des Blocks: Demografie

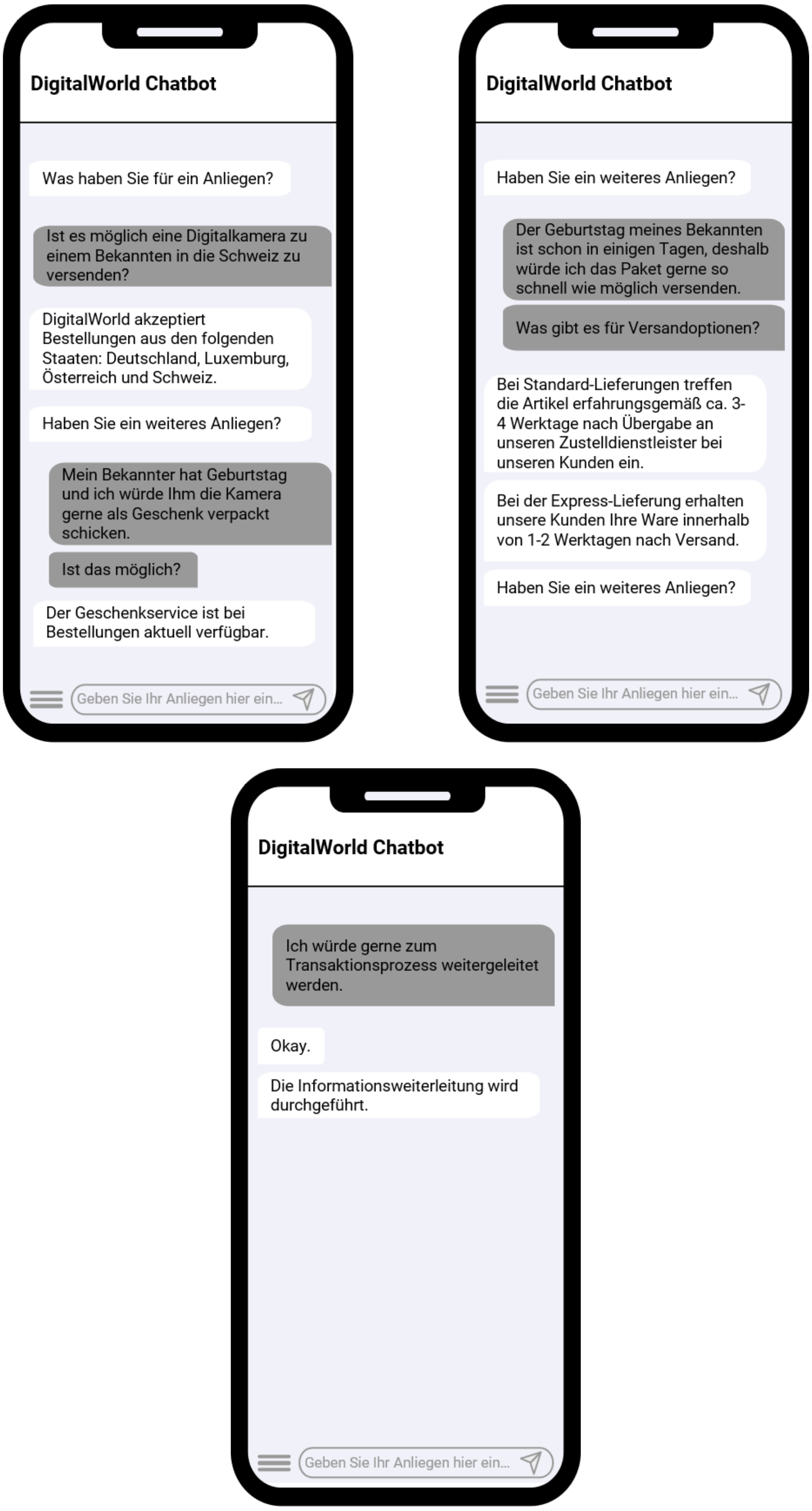
Appendix B

Screenshots of the Different Conditions

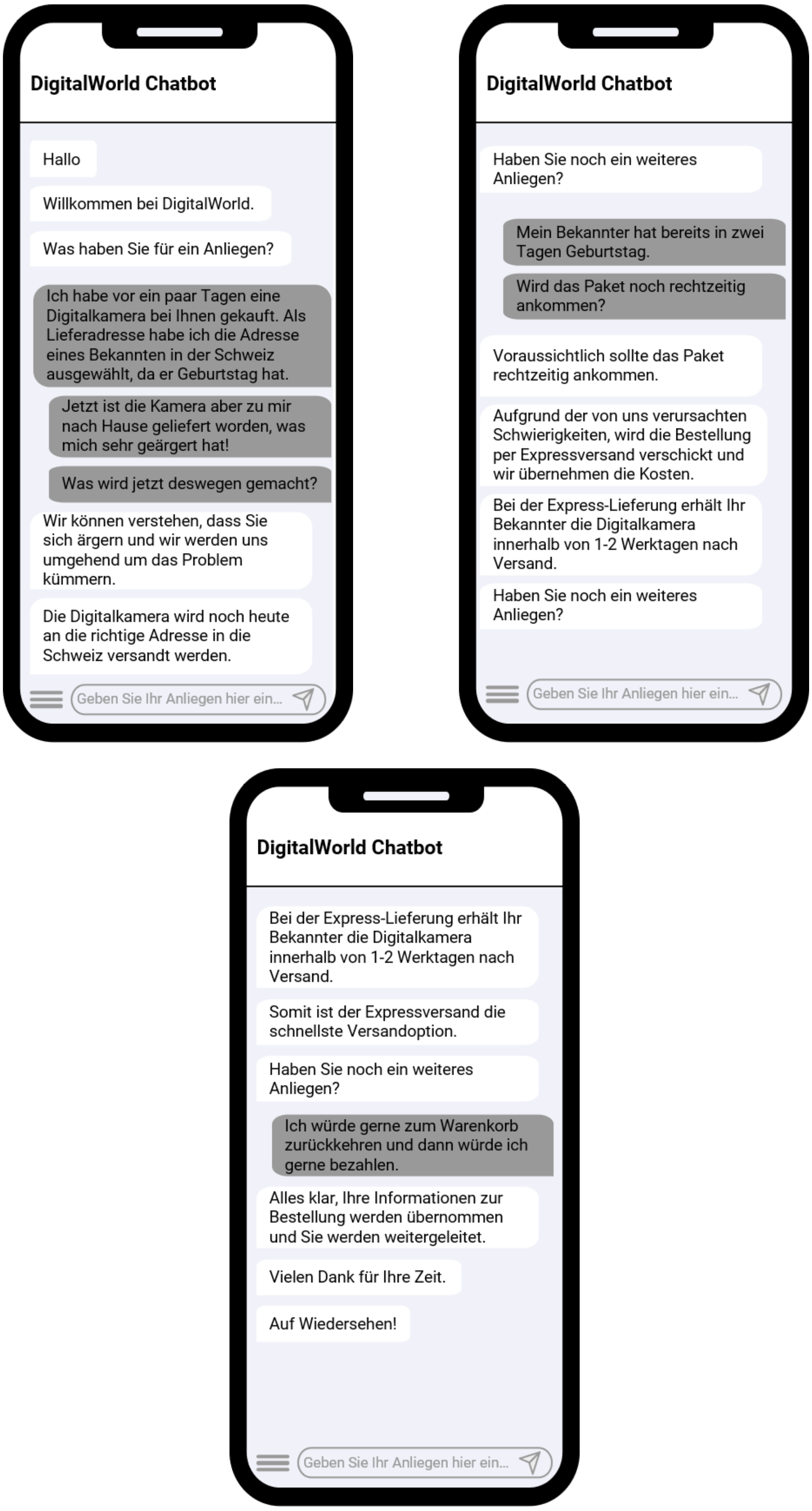




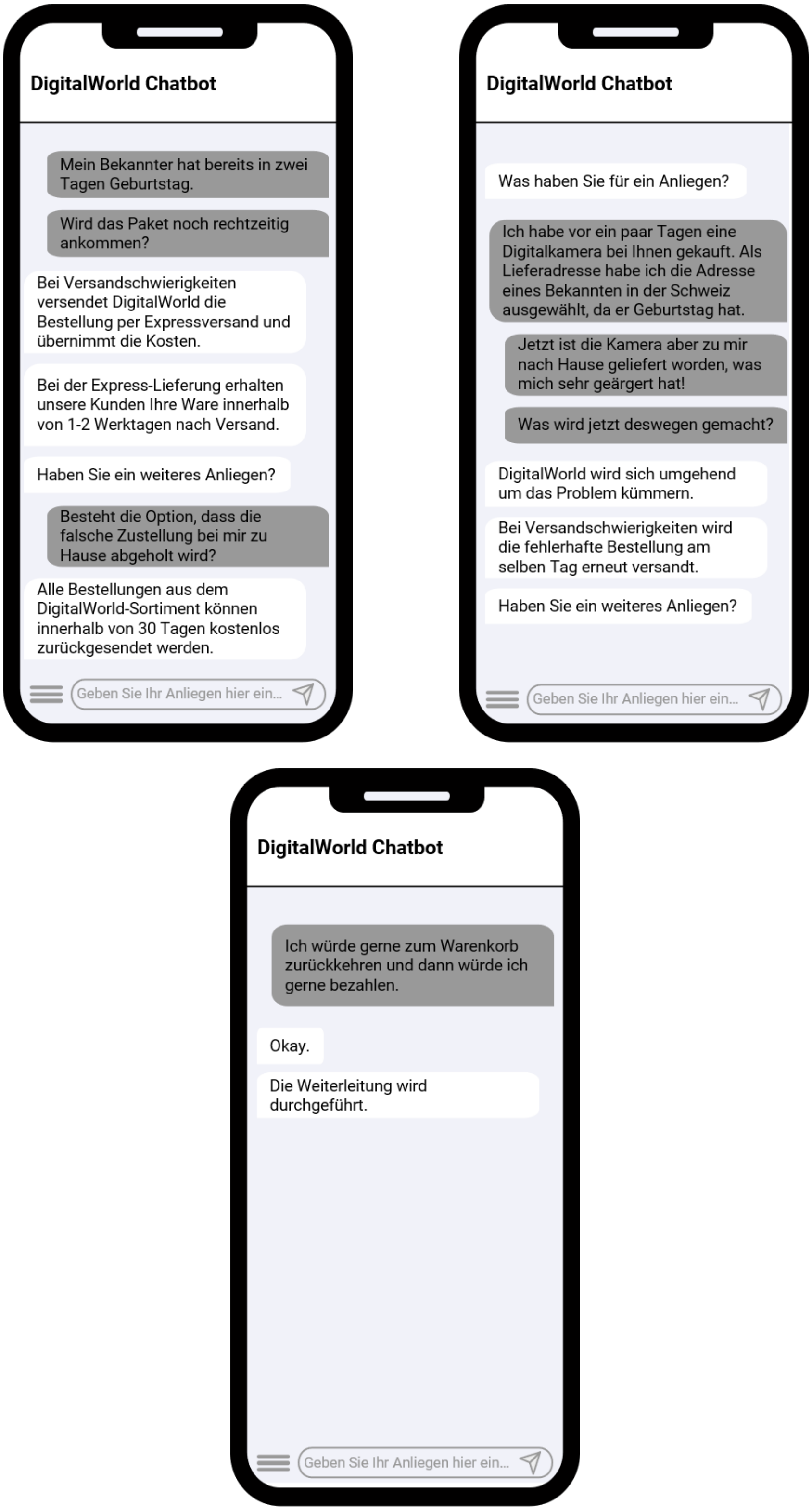
Note. High Message Interactivity & human-like task condition



Note. Low Message Interactivity & human-like task condition



Note. High Message Interactivity & computer-like task condition



Note. Low Message Interactivity & computer-like task condition

Appendix C

Measured Constructs

Constructs	Code	Item
Need for human interaction Sheenan et al. (2020) Cronbach's α=.76	Q3_1 (NFHI_1)	Der menschliche Kontakt beim Kundenservice macht den Prozess für den Kunden angenehm.
	Q3_2 (NFHI_2)	Ich interagiere gerne mit der Person, die den Service erbringt.
	Q3_3 (NFHI_3)	Es stört mich, eine Maschine zu benutzen, wenn ich stattdessen mit einer Person sprechen könnte.
CA Usage Adam et al. (2020)	Q4_1 (CAU_1)	Wie oft nutzen Sie virtuelle Assistenten, wie Siri (Apple), Google Assistant (Google) oder Alexa (Amazon)?
Behavioral Intention Hu et al. (2010) Cronbach's α=.65	Q24_1 (BI_1)	Ich würde die Webseite DigitalWorld für die zukünftige Nutzung als Lesezeichen speichern.
	Q24_2 (BI_2)	Ich würde die Webseite DigitalWorld in Zukunft wieder besuchen.
Customer Satisfaction Bettencourt (1997) Cronbach's α=.87	Q25_1 (CS_1)	Ich habe die Interaktion mit diesem Chatbot wirklich genossen.
	Q25_2 (CS_2)	Ich bin mit der Chatbot-Interaktion zufrieden.
	Q25_3 (CS_3)	Die Entscheidung, mit diesem Chatbot zu interagieren, war eine gute Entscheidung.
Company Perception (Own Scale) Cronbach's α=.89	Q24_2 (CP_1)	Ich würde die Webseite DigitalWorld in Zukunft wieder besuchen.
	Q25_1 (CP_2)	Ich habe die Interaktion mit diesem Chatbot wirklich genossen.
	Q25_2 (CP_3)	Ich bin mit der Chatbot-Interaktion zufrieden.
	Q25_3 (CP_4)	Die Entscheidung, mit diesem Chatbot zu interagieren, war eine gute Entscheidung.

Constructs	Code	Item
Perceived Contingency Sundar et al. (2015) Cronbach's α=.88	Q26_1 (PC_1)	Die Antworten des Chatbots berücksichtigten den Zusammenhang mit meinen früheren Eingaben.
	Q26_2 (PC_2)	Ich hatte das Gefühl, dass der Chatbot meine Antworten sorgfältig registrierte und Feedback auf der Grundlage der von mir eingegebenen Informationen gab.
	Q26_3 (PC_3)	Ich hatte das Gefühl, dass der Chatbot eine exklusive Antwort auf meine Aktionen gab.
	Q26_4 (PC_4)	Die Antworten des Chatbots schienen miteinander verbunden zu sein.
Social Presence Gefen & Straub (2003) Cronbach's α=.94	Q27	Basierend auf meinen Eindrücken…
	Q27_1 (SP_1)	…verspürte ich einen menschlichen Kontakt mit dem Chatbot.
	Q27_2 (SP_2)	…fühlte ich eine persönliche Beziehung zum Chatbot.
	Q27_3 (SP_3)	…hatte ich das Gefühl von Geselligkeit mit dem Chatbot.
	Q27_4 (SP_4)	…konnte ich bei dem Chatbot menschliche Wärme verspüren.
	Q27_5 (SP_5)	…spürte ich bei dem Chatbot eine menschliche Sensibilität
Manipulation Check Task Type Seeger et al. (2021)	Q29	Bitte schätzen sie ein, ob die durchgeführte Aufgabe eher menschenähnlich (normalerweise durch einen Menschen durchgeführt) oder eher computerähnlich (normalerweise von einem Computer durchgeführt) ist.
	Q29_1 (MPTT_1)	Die durchgeführte Aufgabe ist...

Constructs	Code	Item
Manipulation Check Message Interactivity Bellur and Sundar (2017) Cronbach's α=.84	Q30_1 (MPMI_1)	Der Chatbot erinnert sich an meine Antworten.
	Q30_2 (MPMI_2)	Die Antworten des Chatbots standen im Zusammenhang mit meinen früheren Antworten.
	Q30_3 (MPMI_3)	Der Chatbot gab einige intelligente Vorschläge, die auf meinen Antworten basierten.
Product Involvement Zaichkowsky (1985) Cronbach's α=.90	Q31_1 (PI_1)	Ich bin generell an Kameraequipment interessiert.
	Q31_2 (PI_2)	Kameraequipment ist für mich ein persönlich relevantes Thema.
	Q31_3 (PI_3)	Ich suche aktiv nach Informationen über Kameraequipment.

Appendix D

Convergent and Discriminant Validity

Item	CS_1	CS_2	CS_3	BI_2	BI_1
CS_1	1	.646**	.648**	.625**	.496**
CS_2	.646**	1	.814**	.719**	.383**
CS_3	.648**	. 814**	1	.665**	.413**
BI_2	.625**	.719**	.665**	1	.497**
BI_1	.496**	.383**	.413**	.497**	1

Note. *N*=271, For further information about the items, see Appendix C. * *p* <.05, ** *p* <.01 (2-tailed).

Appendix E

Principal Component Analysis for Company-Related Outcomes

PCA Item	Factor loading
	1
Q25_1	.833
Q25_2	.884
Q25_3	.876
Q24_2	.860
Q24_1	.643

Note. *N* = 271. For further information about the items, see Appendix C.

References

Adam, M., Wessel, M. & Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *9*(2), 1-19. https://doi.org/10.1007/s12525-020-00414-7

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

Ashfaq, M., Yun, J., Yu, S. & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 1–40. https://doi.org/10.1016/j.tele.2020.101473

Atzmüller, C. & Steiner, P. M. (2010). Experimental vignette studies in survey research. *Methodology*, 6(3), 128-138. https://doi.org/10.1027/1614-2241/a000014

Bellur, S. & Sundar, S. S. (2017). Talking Health With a Machine: How Does Message Interactivity Affect Attitudes and Cognitions?. *Human Communication Research*, *43*(1), 25–43. https://doi.org/10.1111/hcre.12094

Bettencourt, L. A. (1997). Customer voluntary performance: Customers as partners in service delivery. *Journal of retailing*, 73(3), 383-406. https://doi.org/10.1016/S0022-4359(97)90024-5

Bickmore, T. W., Fernando, R., Ring, L. & Schulman, D. (2010). Empathic touch by relational agents. *IEEE Transactions on Affective Computing*, *1*(1), 60–71. https://doi.org/10.1109/T-AFFC.2010.4

Bickmore, T. W. & Picard, R. W. (2005). Establishing and maintaining long-term human-computer relationships. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *12*(2), 293–327. https://doi.org/10.1145/1067860.1067867

Bleier, A., Harmeling, C. M. & Palmatier, R. W. (2019). Creating Effective Online Customer Experiences. *Journal of Marketing*, *83*(2), 98–119. https://doi.org/10.1177/0022242918809930

Burgoon, J. K., Bonito, J. A., Bengtsson, B., Ramirez, A., Dunbar, N. E. & Miczo, N. (2015). Testing the Interactivity Model: Communication Processes, Partner Assessments, and the Quality of Collaborative Work. *Journal of management information systems*, *16*(3), 33–56. https://doi.org/10.1080/07421222.1999.11518255

Cafaro, A., Vilhjálmsson, H. H. & Bickmore, T. (2016). First Impressions in Human--Agent Virtual Encounters. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *23*(4), 1–40. https://doi.org/10.1145/2940325

Chung, M., Ko, E., Joung, H. & Kim, S. J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 117, 587–595. https://doi.org/10.1016/j.jbusres.2018.10.004

Cliff, N. (1988). The eigenvalues-greater-than-one rule and the reliability of components. *Psychological bulletin*, *103*(2), 276-279. https://doi.org/10.1037/0033-2909.103.2.276

Cyr, D., Head, M., Larios, H. & Pan, B. (2009). Exploring human images in website design: A multi-method approach. *MIS quarterly*, 539–566. https://doi.org/10.2307/20650308

Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: an investigation of alternative models of service quality. *International Journal of research in Marketing*, *13*(1), 29–51. https://doi.org/10.1016/0167-8116(95)00027-5

Dabholkar, P. A. & Bagozzi, R. P. (2002). An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. *Journal of the academy of marketing science*, *30*(3), 184–201. https://doi.org/10.1177%2F0092070302303001

Diederich, S., Brendel, A. B. & Kolbe, L. M. (2020). Designing Anthropomorphic Enterprise Conversational Agents. *Business & Information Systems Engineering*, *62*(3), 193–209. https://doi.org/10.1007/s12599-020-00639-y

Epley, N., Akalis, S., Waytz, A. & Cacioppo, J. T. (2008). Creating social connection through inferential reproduction: Loneliness and perceived agency in gadgets, gods, and greyhounds. *Psychological science*, *19*(2), 114–120. https://doi.org/10.1111/j.1467-9280.2008.02056.x

Epley, N., Waytz, A. & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological review*, *114*(4), 864–886. https://doi.org/10.1037/0033-295X.114.4.864

Faul, F., Erdfelder, E., Lang, A.-G. & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Feine, J., Gnewuch, U., Morana, S. & Maedche, A. (2019). A Taxonomy of Social Cues for Conversational Agents. *International Journal of Human-Computer Studies*, *132*, 138–161. https://doi.org/10.1016/j.ijhcs.2019.07.009

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: *Algebra and statistics*, *18*(3), 382-388. https://doi.org/10.1177%2F002224378101800313

Gefen, D. & Straub, D. (2003). Managing User Trust in B2C e-Services. *e-Service Journal*, *2*(2), 7-24. https://doi.org/10.2979/esj.2003.2.2.7

Gnewuch, U., Morana, S., Adam, M. & Maedche, A. (2018). Faster is not always better: Understanding the effect of dynamic response delays in human-chatbot interaction. *Proceedings of the 26th European Conference on Information Systems (ECIS),* Portsmouth, 23-28.

Gnewuch, U., Morana, S. & Maedche, A. (2017). Towards Designing Cooperative and Social Conversational Agents for Customer Service. *Proceedings of the 38th International Conference on Information Systems (ICIS),* Seoul, 1-13.

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

Guttman, L. (1954). Some necessary conditions for common-factor analysis. *Psychometrika*, *19*(2), 149–161. https://doi.org/10.1007/BF02289162

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications.

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K. & Shankar, V. (2020). Transforming the Customer Experience Through New Technologies. *Journal of Interactive Marketing*, *51*, 57–71. https://doi.org/10.1016/j.intmar.2020.04.001

Hu, Y., & Sundar, S. S. (2010). Effects of online health sources on credibility and behavioral intentions. *Communication Research*, 37(1), 105-132. https://doi.org/10.1177/0093650209351512

Kokkinou, A. & Cranage, D. A. (2015). Why wait? Impact of waiting lines on self-service technology use. *International Journal of Contemporary Hospitality Management*, *27*(6), 1181-1197. https://doi.org/10.1108/IJCHM-12-2013-0578

Krämer, N. C., Lucas, G., Schmitt, L. & Gratch, J. (2018). Social snacking with a virtual agent–On the interrelation of need to belong and effects of social responsiveness when interacting with artificial entities. *International Journal of Human-Computer Studies*, *109*, 112–121. https://doi.org/10.1016/j.ijhcs.2017.09.001

Lankton, N. K., McKnight, D. H. & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the Association for Information Systems*, *16*(10), 880-918. https://doi.org/10.17705/1jais.00411

Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., Wünderlich, N. V. & Keyser, A. de (2017). "Service Encounter 2.0": An investigation into the roles of technology, employees and customers. *Journal of Business Research*, *79*, 238–246. https://doi.org/10.1016/j.jbusres.2017.03.008

Lee, H.-J. & Lyu, J. (2016). Personal values as determinants of intentions to use self-service technology in retailing. *Computers in Human Behavior*, *60*, 322–332. https://doi.org/10.1016/j.chb.2016.02.051

Li, J., Zhou, M. X., Yang, H. & Mark, G. (2017). Confiding in and Listening to Virtual Agents: The effect of personality. *Proceedings of the 22nd International Conference on Intelligent User Interfaces,* Limassol, 275–286. https://doi.org/10.1145/3025171.3025206

Liu, B. & Sundar, S. S. (2018). Should Machines Express Sympathy and Empathy? Experiments with a Health Advice Chatbot. *Cyberpsychology, behavior and social networking*, *21*(10), 625–636. https://doi.org/10.1089/cyber.2018.0110

Maedche, A., Morana, S., Schacht, S., Werth, D. & Krumeich, J. (2016). Advanced user assistance systems. *Business & Information Systems Engineering*, *58*(5), 367–370. https://doi.org/ 10.1007/s12599-016-0444-2

Mar, R. A. (2011). The neural bases of social cognition and story comprehension. *Annual review of psychology*, *62*, 103–134. https://doi.org/10.1146/annurev-psych-120709-145406

McTear, M. F., Callejas, Z., & Griol, D. (2016). *The conversational interface*. Springer.

Nass, C. , Steuer, J. & Tauber, E. R. (1994). Computers are social actors. *Proceedings of the SIGCHI conference on Human factors in computing systems*, Boston, 72-78.

Nass, C. & Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *Journal of Social Issues*, *56*(1), 81–103. https://doi.org/10.1111/0022-4537.00153

Norman, D. A. (1994). How might people interact with agents. *Communications of the ACM*, *37*(7), 68–71. https://doi.org/10.1145/176789.176796

Nunnally, J. C. (1994). *Psychometric theory 3E*. Tata McGraw-Hill education.

Qiu, L. & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of management information systems*, *25*(4), 145–182. https://doi.org/10.2753/MIS0742-1222250405

Rafaeli, S. (1988). From new media to communication. *Sage annual review of communication research: Advancing communication science*, *16*, 110–134.

Rilling, J. K., Dagenais, J. E., Goldsmith, D. R., Glenn, A. L. & Pagnoni, G. (2008). Social cognitive neural networks during in-group and out-group interactions. *Neuroimage*, *41*(4), 1447–1461. https://doi.org/10.1016/j.neuroimage.2008.03.044

Robert, L. P., Denis, A. R. & Hung, Y.-T. C. (2009). Individual swift trust and knowledge-based trust in face-to-face and virtual team members. *Journal of management information systems*, *26*(2), 241–279. https://doi.org/10.2753/MIS0742-1222260210

Sands, S., Ferraro, C., Campbell, C., & Tsao, H. Y. (2020). Managing the human–chatbot divide: how service scripts influence service experience. *Journal of Service Management*, 715-734. https://doi.org/10.1108/JOSM-06-2019-0203

Schuetzler, R. M., Grimes, G. M. & Scott Giboney, J. (2020). The impact of chatbot conversational skill on engagement and perceived humanness. *Journal of management information systems*, *37*(3), 875–900. https://doi.org/10.1080/07421222.2020.1790204

Seeger, A. M., Pfeiffer, J., & Heinzl, A. (2017). When do we need a human? Anthropomorphic design and trustworthiness of conversational agents. *Proceedings of the Sixteenth Annual Pre-ICIS Workshop on HCI Research in MIS*, Seoul, 1-6.

Seeger, A. M., Pfeiffer, J., & Heinzl, A. (2021). Texting with human-like conversational agents: Designing for anthropomorphism. *Journal of the Association for Information Systems: JAIS*, tba.

Sheehan, B., Jin, H. S. & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research*, *115*, 14–24. https://doi.org/10.1016/j.jbusres.2020.04.030

Short, J., Williams, E. & Christie, B. (1976). *The social psychology of telecommunications*. John Wiley & Sons.

Song, J. H. & Zinkhan, G. M. (2008). Determinants of Perceived Web Site Interactivity. *Journal of Marketing*, *72*(2), 99–113. https://doi.org/10.1509/jmkg.72.2.99

Sundar, S. S. (2012). Social psychology of interactivity in human-website interaction. *Oxford handbook of internet psychology.* Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199561803.013.0007

Sundar, S. S., Bellur, S., Oh, J., Jia, H. & Kim, H.-S. (2016). Theoretical Importance of Contingency in Human-Computer Interaction. *Communication Research*, *43*(5), 595–625. https://doi.org/10.1177/0093650214534962

Sundar, S. S., Go, E., Kim, H. S., & Zhang, B. (2015). Communicating art, virtually! Psychological effects of technological affordances in a virtual museum. *International Journal of Human-Computer Interaction*, 31(6), 385-401. https://doi.org/10.1080/10447318.2015.1033912

Sundar, S. S., Kalyanaraman, S. & Brown, J. (2003). Explicating Web Site Interactivity. *Communication Research*, *30*(1), 30–59. https://doi.org/10.1177/0093650202239025

Verhagen, T., van Nes, J., Feldberg, F. & van Dolen, W. (2014). Virtual Customer Service Agents: Using Social Presence and Personalization to Shape Online Service Encounters. *Journal of Computer-Mediated Communication*, *19*(3), 529–545. https://doi.org/10.1111/jcc4.12066

Wise, K., Hamman, B. & Thorson, K. (2006). Moderation, Response Rate, and Message Interactivity: Features of Online Communities and Their Effects on Intent to Participate. *Journal of Computer-Mediated Communication*, *12*(1), 24–41. https://doi.org/10.1111/j.1083-6101.2006.00313.x

Wuenderlich, N. V. & Paluch, S. (2017). A nice and friendly chat with a bot: User perceptions of AI-based service agents. *ICIS 2017 Proceedings*, Seoul, 1-11.

Zaichkowsky, J. L. (1985). Familiarity: product use, involvement or expertise?. ACR North American Advances, 12(1), 296-299.

Affidavit

Hiermit versichere ich, dass

- die Arbeit selbstständig verfasst und keine anderen Hilfsmittel benutzt wurden,
- alle Stellen der Arbeit, die wörtlich oder sinngemäß aus anderen Quellen übernommen wurden, als solche kenntlich gemacht wurden,
- die Arbeit in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegt wurde.

Preetz, den 12.05.2021 C. Völtzke

Ort, Datum Christoph Völtzke