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ExtraBot vs IntroBot: The Influence of Linguistic Cues on Communication Satisfaction

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Completed Research

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Abstract

Conversational agents (CA) have emerged as a new type of dialogue systems, able to simulate human conversation. However, research suggests that current CAs fail to provide convincing interactions due to a lack of satisficing communication with users. To address this problem, we propose the idea of a personality adaptive CA that could enhance communication satisfaction during a user's interaction experience. As personality differences manifest themselves in language cues, we investigate in an experiment, whether linguistic styles have an influence regarding a user's communication satisfaction, when interacting with a CA. The results show that users perceive greater satisfaction when communicating with an extraverted CA (ExtraBot) than with an introverted CA (IntroBot). The outcomes of our study highlight that different linguistic styles can influence the course of the conversation and determine whether the user is satisfied with the communication and sees any value in the interaction with the CA.

Keywords

Conversational Agents, Personality, Language, Chatbots, Big Five

Introduction

Communicating with robots and virtual agents in “human” language is no longer just considered a realm of science fiction. In fact, the ability to conduct dialogues between humans and machines in natural language has immensely improved recently to technological progress in the field of artificial intelligence (AI)(Mallios and Bourbakis 2016). The desire to communicate with computers in natural language evolved naturally in the past years, due to the fact that almost every facet of people’s lives is affected by social technologies, directly or indirectly (Guzman 2018; Shawar and Atwell 2007). Communication specifically is about the meaning people derive in and through their interactions with machines, and one way of facilitating such interaction is by allowing users to express their wishes and queries by typing and speaking (Guzman 2018). Defined as “dialogue systems often endowed with ‘humanlike’ behavior” (Vassallo et al. 2010, p. 357), conversational agents (CA) have emerged as a new type of human-computer interaction (HCI) systems (Mallios and Bourbakis 2016). Communicating in spoken or written form (e.g. chatbots or virtual assistants), the driver behind the development of CAs is to simulate human conversation (Shawar and Atwell 2007). The majority of today’s CA applications provide assistant functionalities, such as sending messages, creating calendar entries or asking for the weather forecast and not only have been integrated in personal smartphones, but have also been incorporated in many organizations and companies specifically for customer service (Knijnenburg and Willemsen 2016). Due to these and a variety of other possible applications, the design and implementation of CAs and especially its communication abilities have been central to Information Systems (IS) research in the last few years (Grudin and Jacques 2019; McTear et al. 2016). However, natural language conversations are not linear but rather multi-threaded, unlike scripted dialogue trees (Grudin and Jacques 2019). Thus, providing the machine with the ability to converse with humans in a natural and for the user satisficing way, is to this day one of the fundamental challenges in AI (McTear et al. 2016; Turing 1950).

Reports from both industry and research suggest that current CAs fail to provide convincing and engaging interactions (Gnewuch et al. 2017; Schuetzler et al. 2014). Insufficient interaction during the phase of transaction in e-commerce for instance, led to a lack of service satisfaction and a high number of purchase cancellations, that often turned into customer frustration (Knijnenburg and Willemsen 2016; Robra-Bissantz 2018; Shawar and Atwell 2007). Grönroos (1982) states that the manner in which a provider behaves and communicates with the customer within a service encounter, is crucial for the customer's perception of the service. Both the provider and the customer actively participate in a dialogue process during a service encounter, and it is here where creation or destruction of value can take place (Mustelier-Puig et al. 2018). Robra-Bissantz (2018) proceeds on the assumption, that an increased quality during interaction can lead to an enhanced value in use and communication satisfaction and thus to an improved service satisfaction. Transferring this concept to HCI and an e-commerce context, where CAs handle communication with customers via natural language to assist them during the sales process for instance, can be particularly challenging, if the interaction does not meet the individual's requirements. Another context, in which CAs have the potential to play an increasingly important role is in health and medical care, supporting consumers with mental health challenges, or assisting patients and elderly individuals in their living environments (Laranjo et al. 2018). A lack of communication satisfaction, however, can also lead to frustration, since language is a primary tool to understand patients' experiences and express therapeutic interventions (Laranjo et al. 2018). This rises the question, whether language and specifically certain styles of language have an influence on the perceived communication satisfaction of the user.

When designing CAs to ensure better interaction, a large body of research suggests incorporating social behaviors (Feine et al. 2019; Gnewuch et al. 2017; Strohmann et al. 2019). In their taxonomy of social cues for CAs, Feine et al. (2019) identify verbal cues as one of four major categories, with verbal cues referring to all social cues that are created by words. In fact, forms of linguistic fingerprinting have been suggested in research for generations, as to some extent, the way people write and talk have been recognized as stamps of individual identity (Pennebaker and King 1999). Over the last decades, research in the field of psychology has demonstrated, that the words people use in everyday life reflect their personality, and the ways in which people use words is internally consistent, reliable over time, predictive of a wide range of behaviors and varies considerably from person to person (Boyd and Pennebaker 2017; Pennebaker 2011). Language, thus, is a fundamental dimension of personality, and unlike other standard personality markers, people do not need to complete questionnaires in order to provide useful personality data in the form of language (Boyd and Pennebaker 2017). These findings can be substantiated with one of the early HCI studies by Nass et al. (1995) and Moon and Nass (1996) who found, that depending on the strength of a computer's language, the expressed confidence level and the interaction order, participants were ascribing a certain personality to the computer. This implicates, that different personality dimensions have stylistic differences in language use that show even when describing the exact same content (Beukeboom et al. 2013). Linguistic styles also influence how conversations develop and what impression speakers leave (Beukeboom et al. 2013), which in turn has likely an influence on communication satisfaction. In order to address the problem of providing more value to a person's communication satisfaction during their interaction experience with an agent, our paper posits the following research question (RQ):

Do personality differences manifested in language use have an influence regarding a user's perceived communication satisfaction, when interacting with a CA?

Incorporating personality into a machine is receiving more emphasis as a crucial part of designing HCI (Kim et al. 2019). Previous studies have dealt with personality expressed via behavioral features (e.g. gestures, movements) and other verbal traits such as voice and emotions (Lee et al. 2019; Robert et al. 2020). However, while embodied physical action (EPA) robots can include a combination of several of these personality factors and therefore invoke strong emotional reactions that can lead individuals to project personalities onto them (Robert 2018; You and Robert 2018), CAs and specifically chatbots mainly express their personality through language. Consequently, text being one of the few channels of communication between chatbots and users, it is all the more important to study personality markers in language and their impact on the HCI quality. While most studies, especially in the field of affective computing, have applied sentiment analysis with adaptive responses to reduce user frustration during interactions (e.g. Diederich et al. 2019) our paper focuses on finding empirical support that the concept of a CA with personality adaptive responses influences a person's perceived communication satisfaction. Further, due to its importance ascribed in the field of human-human interaction (HHI), the majority of personality in HCI studies have particularly investigated the psychological opposites of extraversion and introversion (Robert 2018; Robert et al. 2020). Since the underlying components of extraversion have been well-established to date across various methodologies (Boyd and Pennebaker 2017; Mairesse et al. 2007), we base our experiment solely on these two contrasting personality dimensions and their identified language cues. We conducted an online experiment, simulating a pre-defined conversation between an extraverted personality adaptive CA (ExtraBot) and a fictional human and respectively an introverted personality adaptive CA (IntroBot) and a fictional person. Participants then had to complete a survey assessing the construct communication satisfaction (Hecht 1978) and had to indicate, which conversation they preferred. The results of the experiment provide design implications for personality expressions applicable for CAs as well as EPA robots.

Theoretical Foundations & Related Work

Personality & Language Cues

Personality is loosely defined as the construct that differentiates individuals from another but at the same time makes a human being's behavior, thoughts and feelings (relatively) consistent (Allport 1961). In order to measure an individual's personality, a widely used classification of personality – the Big Five model – has been applied in research (McCrae and John 1992). For a comprehensive assessment of individuals, the following five fundamental traits or dimensions have been defined and derived through factorial studies: Conscientiousness, Openness, Neuroticism, Agreeableness and Extraversion which refers to the extent to which people enjoy company and seek excitement and stimulation (Costa and McCrae 2008). A well accepted theory of psychology is that human language reflects the emotional state and personality, based on the frequency with which certain categories of words are used as well as the variations in word usage (Boyd and Pennebaker 2017; Golbeck et al. 2011; Yarkoni 2010). In fact, language use has been scientifically proven to be unique, relatively reliable over time and internally consistent, and as Boyd and Pennebaker (2017, p. 63) further state: „Language-based measures of personality can be useful for capturing/modeling lower-level personality processes that are more closely associated with important objective behavioral outcomes than traditional personality measures."

In addition to a speaker's semantic content, utterances convey a great deal of information about the speaker, and one such type of information comprises cues to the speaker's personality traits (Mairesse et al. 2007). So even when the content of a message is the same, individuals express themselves verbally with their own distinctive styles, and both spoken language as well as written language is unique from person to person (Pennebaker and King 1999). Psychologists have documented the existence of such cues by discovering correlations between a range of linguistic variables and personality traits, across a wide range of linguistic levels (Mairesse et al. 2007). Of all Big Five traits, extraversion has specifically received the most attention from researchers, since the underlying components of extraversion have been well-established to date across various methodologies (Boyd and Pennebaker 2017; Mairesse et al. 2007). For example, speaker charisma has been shown to correlate strongly with extraversion (Mairesse et al. 2007). Extraverts also use more positive emotion words and show more agreements and compliments than introverts (Pennebaker and King 1999). Furthermore, relative to introverts, extraverts generally engage in more social activity, experience greater positive affect and well-being, and are reactive to external stimulation (Furnham 1990; Mairesse et al. 2007; Scherer 1979). Relative to their introverted counterparts, extraverts tend to talk more, with fewer pauses and hesitations, have shorter silences, a higher verbal output and a less formal language, while introverts use a broader vocabulary (Furnham 1990; Gill and Oberlander 2002; Pennebaker and King 1999; Scherer 1979). Extraverts also exert a more imprecise and "looser" style with reduced concreteness, whereas introverts exhibit a more analytic, careful, precise and focused style (Gill and Oberlander 2002). Research also showed that conversations between extraverts are more expansive and characterized by a wider range of topics whereas a conversation between two introverts are more serious and have a greater topic focus (i.e., discussing one topic in depth) (Furnham 1990). Table 1 shows a small overview of some of the identified language cues for extraversion and various production levels, based on studies by Scherer (1979), Furnham (1990), Pennebaker and King (1999), Gill and Oberlander (2002) and Mairesse et al. (2007).

Level	**Introvert**	**Extravert**
Conversational Behavior	Listen, less back-channel behavior	Initiate conversation, more back-channel behavior
Style	Formal	Informal
Syntax	Many nouns, adjectives, elaborated constructions, many words per sentence, many articles and negations	Many verbs, adverbs, pronouns (implicit), few words per sentence, few articles, few negations
Topic selection	Self-focused, problem talk, dissatisfaction, single topic, few semantic errors	Pleasure talk, agreement, compliment, many topics, many semantic errors
Speech	Slow speech rate, Many unfilled pauses, long response latency, quiet, low voice quality, low frequency variability	High speech rate, few unfilled pauses, short response latency, loud, high voice quality, high frequency variability
Lexicon	Rich, high diversity, many exclusive and inclusive words, few social words, few positive emotion words, many negative emotion words	Poor, low diversity, few exclusive and inclusive words, many social words, many positive emotion words, few negative emotion words

Table 1. Summary of Identified Language Cues for Extraversion

Personality in Human-Computer Interaction

Personality has been identified as one of the vital factors in understanding the quality and nature of HCI (Robert et al. 2020), but also as one of the key components when designing CAs (Strohmann et al. 2019). In their review of personality in human-robot interactions (HRI), Robert et al. (2020) divide their literature search into four thrust areas, including human personality in HRI and robot personality in HRI. Their resume coincides with findings from literature on HHI, that is that the majority of studies in both thrust areas investigated the personality dimension extraversion/introversion due to its importance ascribed in the field of HHI (Robert 2018; Robert et al. 2020). Robert et al. (2020, p. 10) continue, stating that "[g]enerally, most studies have assumed that human personality can be used to determine whether an individual would be more or less likely to interact with a robot and whether those interactions were likely to be enjoyable." In the framework of this paper, findings concerning machine personality are specifically of interest for us. Studies, such as Lohse et al. (2008) investigated whether people perceived distinctive characteristics of extraverted and introverted robots from each other, and Walters et al. (2011) studied whether people recognized differences between robots displaying either extravert or introvert characteristics (Robert et al. 2020). While these studies focus on EPA robots, we want to ascertain whether similar findings can be transferred to CAs that use *language* as an output. Focusing on chatbots, Smestad and Volden (2019) used an experimental study to investigate whether subjects could tell the difference between two chatbots that were designed based on different personality traits. However, the authors' conversation designs are not based on specific language cues derived from literature. One chatbot was considered to be agreeable, while the other one was described as mechanical and by the authors' definition as a chatbot with "no personality". To the best of our knowledge, we could not find any other previous work addressing personality-based language cues (and specifically extraversion) in connection with communication satisfaction during human-machine interaction. In addition, based on findings on extraversion mentioned earlier, we further want to investigate if personality differences manifested in language consequently lead to conversation preferences. Hence, we hypothesize as follows:

H: The ExtraBot achieves a higher perceived communication satisfaction than the IntroBot.

As it has been found that extraverts use more positive emotion words, show more agreements and compliments, and since it further has been shown that speaker charisma correlates strongly with extraversion (Mairesse et al. 2007), we argue that users perceive greater satisfaction when communicating with the ExtraBot, than with an introverted personality adaptive CA (IntroBot).

Method

Sample and Data Collection Procedure

In order to test our hypothesis, we conducted an online experiment that took place over the span of three months. We aimed to obtain a relatively large sample size of participants to ensure more reliable results and greater significance. We therefore chose to run our study through the crowdsourcing platform Mechanical Turk (mTurk). On Amazon.com's mTurk individuals perform small tasks such a surveys for micro payments (Downs et al. 2010). Another reason to use crowdsourcing for our study was to find diverse characteristics as well as native respectively advanced English speakers among a large pool of respondents. Since the experiment and more important the simulated conversations between the CA and the humans were conducted throughout in English - and language being a pivotal aspect of the hypothesis - it was necessary that only people whose first or second language is English, were participating – otherwise it would have biased the results. Although mTurk was the main source for collecting our data, we also recruited test persons via personal networks, who were not compensated for their participation. Of the total of 478 people participating in the study, we eliminated the data of 113 test persons who cancelled the experiment in advance. We also identified 56 invalid responses concerning our control question (i.e. entering a specific number, after having watched the conversations between the humans and the machine) and excluded these answers from our analysis. This reduced our sample size to 309 participants, out of which 206 are male, 101 female and 2 other. The age of the subjects ranged from 17 to 74 years (M = 32.9 years). 232 people indicated that English is their first language, while the remaining 77 speak English as their second language.

The test persons were first informed about the task and general procedure of the experiment via a link for a website especially created for the study. The website then randomly assigned participants to LimeSurvey (an online survey tool), where they either watched the conversation of the ExtraBot first (and IntroBot second) or vice versa. We chose a within-subject design, where the participants were exposed to both levels of treatment one after the other (Charness et al. 2012). This way we ensured that individual differences were not distorting the results, since every subject acted as their own control. This reduced the chance of confounding factors. The order of the two conditions was hence distributed randomly, and the dependent variable was measured after each condition by means of a subsequent survey. Every participant was provided with the exact same sets of information for the experiment (Dennis and Valacich 2001). The complete experiment took approximately 15 minutes per participant.

Conversational Agent Design

Our within-subject design was structured as follows: Prior to the actual experiment, we created two pre-defined dialogue structures using the conversational design tool Botsociety (2020), which allows visualizing and prototyping CAs. Subject of the dialogues are communications between the CA called Raffi and the humans Jamie and respectively Francis. While in the dialogue between Raffi and Jamie the CA is intended to take on an extraverted personality (ExtraBot), the CA in the Raffi-Francis conversation is aimed to be more introverted (IntroBot). In order to create and simulate a personality adaptive CA, we based our conversational designs on the previously mentioned language cues for extraversion and introversion (see Table 1). For instance, the ExtraBot uses a rather informal language (e.g. "what r u up to?", "...cause TGIF!"), compliments and uses many positive emotion words ("Sounds amazing!" "Have fun at the party!") and uses few words per sentence ("Nope. Locals as well.", "Told ya!"). The IntroBot on the other hand sticks to mainly two topics (travel and books) while chatting with Francis, and also has a rather rich vocabulary throughout the whole dialogue by using many words per sentence. Further, the IntroBot has fewer semantic errors ("At least it's Friday! How was your day?") and uses fewer emotional words compared to the ExtraBot. Although the leitmotiv in both conversations are similar, the ExtraBot talks about many topics in a short amount of time (weekend plans, music, travel, party).

Concerning the context of the conversations, we chose to not put the CA in a specific service encounter setting or the like, as this could have been a confounding factor. The idea behind this reasoning was to not distract the subjects by the service quality of the CA, but to merely focus on communication satisfaction by texting about day-to-day conversations. Raffi should be considered more as a "virtual" friend, who gives travel recommendations, but is detached from the thought that it is a chatbot of a certain company. We embedded the conversational designs as a video format in LimeSurvey. The videos lasted about 3 minutes, skipping was not allowed, and we added a control question at the end of the video. The only task that the participants had in this part of the experiment, was to put themselves in the shoes of Francis and Jamie and closely observe the conversations with Raffi the CA. The videos of the complete conversations can be watched at the following links: https://youtu.be/B1N7XwcdCE0, https://youtu.be/d26eKdHBKeQ. Figure 1 shows a snippet of the two conversations between the ExtraBot and Jamie (left) and the IntroBot and Francis (right).

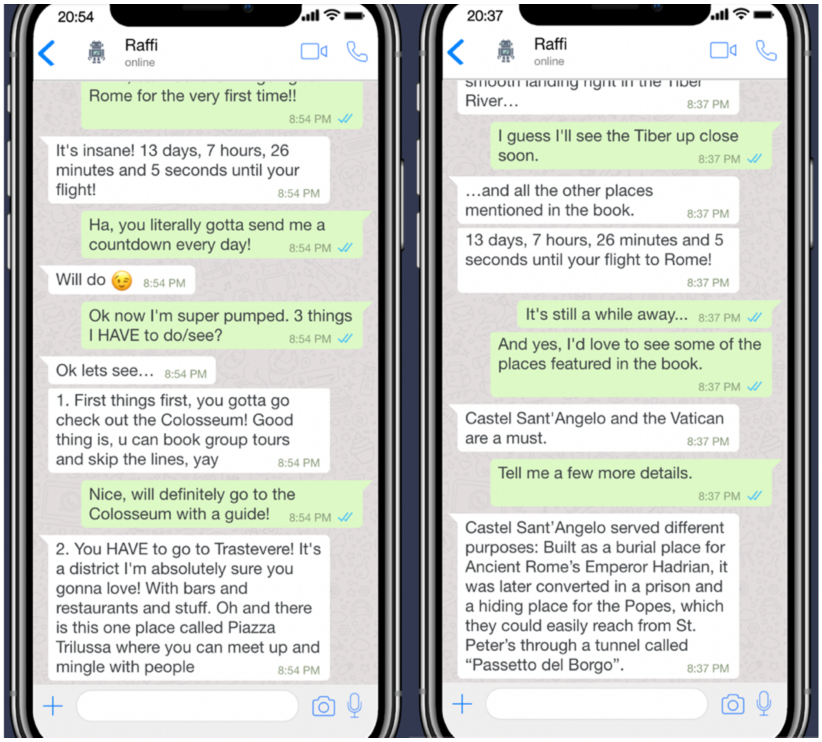

Figure 1. Mockups of the ExtraBot (left) and IntroBot (right) Conversation

In order to verify (to the best possible extent) that the language cues we used in our conversation designs reflect extraversion/introversion to a certain degree, we double checked the dialogues. First, we used the IBM Watson Personality Insights tool (2020). The personality mining service returns percentiles for the Big Five dimensions based on text that is being analyzed. In this context, percentiles are defined as scores that compare one person to a broader population (IBM Watson PI 2020). For the ExtraBot dialogue, we received a score of 83%, meaning that our ExtraBot is more extraverted than 83% of the people in the population. The IntroBot on the other hand, had a percentile of 36%, thus scoring low in extraversion (and high in introversion). Although Watson's PI service is in some instances criticized for being a black box, it did validate our conversation designs to be considered as extraverted respectively introverted language. Second, as part of our survey, we asked the participants to indicate the extent to which the attributes *sociable, talkative, active, impulsive, outgoing, shy, reticent, passive, deliberate, reserved* apply to the CAs (Back et al. 2009). While the first five items reflect high extraversion, the last five attributes stand for low extraversion (Back et al. 2009). The results showed on average, that the ExtraBot (M = 4.49) was indeed perceived as more extraverted than the IntroBot (M = 3.85).

Measures and Results

Following the video of the conversation, the participants completed a survey that included questions about the CA's attributes (see above), demographic questions (gender, age, language), an open question (*Which conversation did you personally prefer and why?*) and their perceived communication satisfaction (Hecht 1978). In order to measure, whether the subjects are more satisfied with the communication style of the ExtraBot or the IntroBot, we used the established measuring construct *communication satisfaction* by Hecht (1978). The inventory shows a high degree of reliability and validity when measuring communication satisfaction with "actual and recalled conversations with another perceived to be a friend, acquaintance, or stranger" (Hecht 1978, p. 253). Originally intended for HHI, we transferred this construct to a HCI context.

The construct consists of 19 items, and as suggested in the study, we used a 7-point Likert scale. However, we adapted the phrasing of the items accordingly to our CA. For example, we changed the wording of the original item "*The other person expressed a lot of interest in what I had to say*" to "*Raffi expressed a lot of interest in what I had to say*".

We analyzed the data by means of descriptive analysis and a Mann-Whitney-U test, as the data is non-normally distributed (the Shapiro-Wilk test of normality was used to investigate this assumption) and we used ordinal scales (Wu and Leung 2017). Prior to that, we computed Cronbach's alpha for the construct communication satisfaction to ensure the internal validity of our measure. With $\alpha = .90$ our construct with 19 items shows a high internal validity. All analyses were carried out using the statistical computing software RStudio (Version 1.2.5033). Table 3 provides an overview of the descriptive statistics, the Shapiro-Wilk normality tests and the Mann-Whitney-U test.

Communication satisfaction (n=309)						
$\text{Mean}_{\text{ExtraBot}}$	$\text{SD}_{\text{ExtraBot}}$	Shapiro-Wilk	$\text{Mean}_{\text{IntroBot}}$	$\text{SD}_{\text{IntroBot}}$	Shapiro-Wilk	Mann-Whitney-U
5.01	0.98	$W = .92$ $p < .01$	4.84	0.92	$W = .93$ $p < .01$	$W = 52890$ $p = .02$

Table 3. Results of the Experiment for the Construct Communication Satisfaction

The results (Table 3) show that the participants evaluated the communication satisfaction of the ExtraBot as higher ($M = 5.01$, $SD = 0.98$) than the communication satisfaction of the IntroBot ($M = 4.84$, $SD = 0.92$). The data further reveals that there is a significant difference between the perceived communication satisfaction by the participants. Thus, these findings support our hypothesis that the subjects were more satisfied with the communication of the ExtraBot than the IntroBot. These results were also confirmed by the open question *("Which conversation did you personally prefer and why?):* Out of the 309 participants, 189 preferred the ExtraBot's conversation, while 92 liked the conversation of the IntroBot more. 28 people could not decide, which conversation they preferred. Table 4 summarizes some of the participants' responses in terms of their preferences over conversation.

ExtraBot: Jamie & Raffi	**IntroBot: Francis & Raffi**	**Neutral**
"I preferred conversation 1. It was more fluent and knowledgeable and outgoing. In conversation about Dan Browns book at the beginning I felt little attention and sensibility from Raffi."	"I am not as social, outgoing, and "party happy" as Jamie. I'm more like Francis... bookish and reserved. I don't want the in your face enthusiasm and energy Raffi showed in the first conversation, and prefer the more sedate, subtly humorous Raffi of the second conversation."	"Both conversations were similar and Raffi reacted differently because Jamie and Francis acted different from each other. Both were fine."
"The first one was more natural for me. It seemed like a conversation I would have with a dear friend."	"Francis was better able to express his interests and Raffi listened and added to the conversation."	"I really didn't prefer one conversation over the other."
"Raffi seemed to pick up on the communication style of the human and adjust accordingly."	"I think Francis was more like me and therefore I enjoyed following the conversation a bit more."	"Both conversations were similar to me."
"I was much more like Jamie than Francis. It was easier to relate."	"The first conversation was way too over the top and aggressively social. The second one was much more calm and chill."	"I preferred both because they both felt like I was talking to a human and not an AI or robot."

Table 4. Extract of Participants' Responses to Their Preferred Conversation

Discussion

In our experiment setting, language cues of extraversion showed to be the independent variable that proved to be more suitable in achieving higher communication satisfaction, confirming our hypothesis. This could be due to the fact that the "looser" writing style of the ExtraBot was better received by the test persons than the somewhat more "serious" style of the IntroBot. Despite the results of this experiment, we however do not propose to only include extraverted language cues to enhance the interaction experience when designing a CA. Quite the contrary, in fact we strongly assume that the level of communication satisfaction is very much dependent upon the user's own personality. This idea corresponds with Hecht (1978, p. 263) pointing out that "one's own and other's predispositions [...] are important determinants of satisfaction when the other is perceived to be an acquaintance." Although not mentioned in the paper before, we have paid attention to give Jamie and Francis similar personality traits as their corresponding conversation partners. The participants' responses (see Table 4) seem to coincide with Hecht's statement: People who considered themselves more extraverted (e.g. *"I was much more like Jamie than Francis. It was easier to relate."*) were more satisfied with the ExtraBot, whereas the participants who considered themselves Introverts *("I think Francis was more like me and therefore I enjoyed following the conversation a bit more.")* chose the IntroBot. This implicates that humans prefer machines that have a similar personality to their own and thus speaks for the Law of Attraction, about which there are already numerous studies (Robert 2018; Robert et al. 2020).

The initial goal of our conducted experiment was to examine whether personality differences manifested in language use have an influence regarding a user's perceived communication satisfaction when interacting with a CA. The results of our experiment demonstrate that linguistic cues that are specific for a particular personality dimension a) have been noticed by the majority of the participants and b) have an influence on users' perceived communication satisfaction when having a conversation with a CA (since the majority of the subject preferred one Bot over the other). These findings are consistent with previous studies (e.g. Schuetzler et al. 2014) that the subjects significantly perceive adaptive responses via language. Our results further show that using personality-based language cues can impact the interaction quality and turn it into a valuable conversation for the user. The outcomes of this study also highlight the importance of personality adaptive CAs. Since every human being is unique in terms of their personality traits, the design of future CAs needs to be able to respond and adapt accordingly to a user's personality – and especially CAs that aim for extended conversations, such as in service encounters or therapeutic conversations in healthcare. One of the decisive reasons designing personality adaptive CAs with language cues is that implementing consistent patterns of reactions is much easier than immediate and unregulated responses (Lee et al. 2019). Different linguistic styles can influence the course of the conversation and ultimately determine whether the user (be it a customer or patient) is satisfied with the communication and sees any value in the interaction with the CA.

Conclusion

As a step towards designing and evaluating the value of personality adaptive CAs, we investigated in this paper, whether personality differences manifested in language use have an influence in regard to a user's communication satisfaction, when interacting with a CA. Based on findings of previous studies in the field of psychology as well as in HCI, we focused on the personality dimension extraversion/introversion and have put forward the hypothesis that users perceive greater satisfaction when communicating with an extraverted personality adaptive CA (ExtraBot), than with an introverted personality adaptive CA (IntroBot). We tested the hypothesis by conducting an online experiment in which subjects were asked to evaluate simulated conversations between the ExtraBot and a fictional person and the IntroBot and another fictional person. In the subsequent survey, the subjects answered questions on the construct communication satisfaction (Hecht 1978) and indicated their preferred dialogue. The results of the experiment showed that our hypothesis proved to be true: The extraverted personality adaptive CA achieved a higher perceived communication satisfaction than its introverted counterpart and its linguistic style of writing was preferred over the IntroBot's communication style by the majority of the participants. The outcomes of this experiment further demonstrate, that language cues that reflect a certain personality dimension should be taken into consideration when designing personality adaptive CAs, in order to enhance a user's communication satisfaction during their interaction experience. Further, the outcomes of the experiment provide design implications for personality expressions applicable for CAs as well as EPA robots. The concept of a personality adaptive CA could be put into use to the development of responsive services where interaction and particularly language-based communication plays an important role.

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