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Conveying chatbot personality through conversational cues in social media messages

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ABSTRACT

A perceived personality of a chatbot or conversational agent is mainly conveyed by the way they communicate verbally. In this online vignette study (N = 168) we examined the possibility of conveying personality in short social-media-like messages by adding simple conversational cues. Social-oriented and responsive conversational cues, as well as their combination had distinct effects on the perceived personalities of the chatbots. Social-oriented cues had a clear effect on most OCEAN personality traits, warmth, and anthropomorphism, while responsive cues only affected neuroticism. In combination, effects of social-oriented cues were countered by responsive cues, but not for all personality traits. Competence and trust were not affected by any of the used conversational cues. The findings show that very few conversational cues are sufficient to convey distinct personalities in short messages.

1. Introduction

While chatbots in the wild sometimes seem rather dull, a few can appear more empathic, quirky, cynic, or extraverted. Obviously, this is based on the way they write, but how much is necessary to convey a distinct personality? In this study, we examine the use of conversational cues to form conversational styles, to convey distinct personalities of social bots in very short messages, as common in most forms of social media.

1.1. Review of relevant scholarship

There are several terms for technologies or systems that can autonomously engage in natural language communication, such as conversational agents, chatbots, or social bots. Broadly, these are defined as at least partially autonomous (ro)bots with a quasi-communication, language-based interface (Hepp, 2020; Bartneck & Forlizzi, 2004). Whether conversational bots are considered a form of AI depends primarily on whether the system was created through machine learning or manually. On the front end, this distinction does not matter to users unless the bot is continuously evolving during its use.

Starting with ELIZA in 1966 (Weizenbaum, 1966) and with ChatGPT rising, conversational bots are today prevalent in a variety of practical scenarios. Most can answer simple questions and maneuver dialogue trees, but there are also bots that serve in more complex areas in customer service (Gnewuch et al., 2018), education (Chocarro et al., 2021), or work settings (Blut et al., 2021; Lewandowski et.al., 2021).

Almost all research on conversational agents and social robots refers to the Computers Are Social Actors (CASA) paradigm (Nass et al., 1994) and the media equation theory (Reeves & Nass, 1996), which basically state that people generally respond to and interact with computers, machines, and robots socially, as if they were social actors. It is known, that very simple social cues presented via Computer Screen are sufficient to elicit social responses from users (Moon, 2000; Nass & Moon, 2000).

Aside from this, reviews highlight a noticeable lack of established fundamental models or theories that can serve as a joint foundation for the field. Thus, there is a wide and inconsistent use of different variables that are not always uniformly defined, labeled, or operationalized (Rapp et al., 2021). This is, for instance, the case for personality measures.

1.1.1. Personality as a variable

Personality is a concept to organize and process information about social partners, to understand and predict their behavior (Dryer, 1999). With computers, machines, and systems being treated as social partners (Nass et al., 1994; Nass et al., 1995; Reeves & Nass, 1996) this concept of personality likely functions similarly in interactions with conversational

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agents.

There is some indication, that robot personality is rated less expressed than human personality (Woods et al., 2005). However, when it comes to robots and virtual agents, the term "personality" is used quite liberally. While most studies refer to human personality models, especially the OCEAN or Big-Five model (Goldberg, 1990; John, 1990; McCrae & Costa, 1985), some studies use different variables, sometimes under the same name, or blur the lines with variants of anthropomorphism or perceived humanness (Esterwood & Robert, 2020). Additionally, in studies referring to the OCEAN model, often only Extraversion is examined (Ahmad et al., 2021, 2022; Robert et al., 2020).

It is important to keep in mind, that "(ro)bot personality" is mapped onto the systems by humans. There is no phenomenological personality within the technology, only an interpretation of their appearance and behavior by humans. It is in theory of course possible to simulate human-like personality by programming equivalent cognitive, emotional, and behavioral processes, leading to, for example, a certain level of extraversion, conscientiousness, or neuroticism. Personality trait models are particularly suitable to construct a personality for technical devices, as they represent personality in form of numerical scores (Vinciarelli & Mohammadi, 2014). There have been attempts to design frameworks based on the OCEAN model to design technical scripts for conversational agents (Egges et al., 2004; Rosenthal & Congdon, 2012; Sansonnet & Bouchet, 2014). Sansonnet and Bouchet (2014) criticized that most attempts lack "coverage", since only a few psychological phenomena were considered, and "comprehensiveness", since experts like psychologists were not involved in the design process.

While most machines, systems or technical devices were usually not designed with some form of inert personality, they are still being attributed a personality. This perceived personality, which is projected onto the systems, can still be useful for prediction, although the mechanisms might be different to human personality.

1.1.2. Cues to personality

Personality of bots can be conveyed through different kinds of social cues (Feine et al., 2019; Nass & Moon, 2000; Dryer, 1999). These can be within different areas like physical appearance of a robot or virtual avatar (Hwang, et al., 2013; Ogawa et al., 2009), stance and motion behavior (Isbister & Nass, 2000; Lee et al., 2006), auditive signals and speech parameters (Lee et al., 2006; Lee & Nass, 2003; Nass & Lee, 2001; Tay et al., 2014), and conversational style (Dryer, 1999; Ahmad et al., 2021; Völkel et al., 2022; Shumanov & Johnson, 2021; Neff et al., 2010; Ruane et al., 2021; Völkel & Kaya, 2021; Urakami et al., 2019). For text-based conversational bots, the latter is of course the one to focus on.

Feine et al. (2019) derived four categories of social cues from a literature review: verbal, visual, auditory, and invisible. Under the verbal category they differentiated two subcategories: content included cues, which refer to what is being said (e.g. small talk, joke, refer to past), and style included cues, which describe how something is being said (e.g. formality, sentence complexity, strength of language). Both variants can be communicated through text and are therefore relevant for conversational bots.

In a literature review Ahmad et al. (2022) collected 148 verbal, para-verbal, and behavioral cues, that were demonstrated to affect different dimensions of the OCEAN model perceived in conversational bots directly. Vice versa, there are approaches that convert the OCEAN traits to conversational agent traits equivalents, to derive fitting behavior (Lessio & Morris, 2020).

1.1.3. Effects of personality

In general, implementing personality in conversational agents can have a positive effect on the user experience in terms of greater communication satisfaction or general preference. This was found especially for a less formal personality implemented (Ahmad et al., 2021; Mehra, 2021; Ruane et al., 2021; Zhou et al., 2019; Natarajan & Gombolay, 2020). However, the preferred personality of an agent seems to be context dependent (Zhou et al., 2019). For example, expressions of empathy were preferred in a health counseling bot (Liu & Sundar, 2018). Furthermore, users seem to prefer agents with a similar personality to their own (Dryer, 1999; Moon & Nass, 1996; Lee et al., 2006; Tapus et al., 2008; Shumanov & Johnson, 2021; Smestad & Volden, 2019; Völkel & Kaya, 2021; Woods et al., 2005), which fits the similarity attraction paradigm in interpersonal relationships (Byrne, 1971). It should be noted that most of those studies with conversational agents focus on extraversion only.

1.1.4. Conversational styles

The use of certain sets of conversational cues can be understood as a conversational style. Conversational bots are sometimes categorized into task-oriented vs. social-oriented based on their conversational style, which is usually linked to their purpose (Chattamaran et al., 2019; Xiao et al., 2020). As discussed, every conversational bot has a social component and social interaction is in most cases a part of their task. So, there is need for research to examine how and in what way bots should converse and how "social" they should be, to be most effective in accomplishing their tasks.

There is no consistent way social-oriented communication is operationalized in conversational bots. Different approaches apply a social-oriented communication style as an informal communication style (Chattamaran et al., 2019; Cicco et al., 2020; Goetz & Kiesler, 2002; Jiang et al., 2023; Mehra, 2021; Zhou et al., 2019), as small talk (Ai et al., 2010; Cassell, 2003; Cicco et al., 2020; Kim et al., 2021; Silvervarg et al., 2011), by using emoticons and pictures (Cicco et al., 2020), by expressing sympathy (Liu & Sundar, 2018; Urakami et al., 2019) or by looking for common ground (Bickmore & Cassell, 2001).

Xiao et al. (2020) designed an "active listening" conversational bot by making use of the techniques paraphrasing, verbalizing emotions, summarizing, and encouraging. They found those bots to be more engaging and eliciting higher quality user responses.

While these previous works are not very consistent in how social-oriented communication is operationalized, the concept of a rather informal, playful, empathic, sympathetic, and emotional communication can be surmised.

Aside from social-orientation, responsiveness is another important parameter of a conversational style for conversational bots. Responsiveness (also described as e. g. message-interactivity or back-channeling in other works) refers to a bot acknowledging and referring to what has been said. In its minimal form this begins with simple interjections that communicate awareness to what has been said. It can further be repeating key words and ultimately creates a thread or contingency in longer conversations (Go & Sundar, 2019; Jiang et al., 2023; Sundar et al., 2016; Lee et al., 2020). In computer science, responsiveness sometimes simply refers to reaction time, which is certainly a part of the construct, and those technical aspects have been shown to affect personality, more specifically conscientiousness (Holtgraves et al., 2007).

From this literature background, we derived social-oriented and responsive communication techniques and determined appropriate conversational cues for operationalization of conversational styles. We ordered the techniques in terms of complexity, starting with those, which can be operationalized by using simple words, to those, that demand more sophisticated consideration of the comment for which the response was created (Table 1). Obviously, variants and mixtures are also possible, which we also applied in this study.

1.1.5. Additional social perception variables

Aside from personality, additional outcome variables related to social perception can help create a more complete picture on how bots are perceived.

Warmth, competence, and discomfort. Warmth and competence are established as the prior two socio-cognitive variables that are used to evaluate others within the stereotype content model (Fiske et al., 2002).

Table 1
Conversational cues for social-oriented and responsive communication.

Conversational Style	Technique	Complexity	Conversational Cue Examples	
			German	English (untested)
Social-oriented communication	Exclamatory Feedback	very low	Wow!, Oh nein!, Auf jeden Fall!, Toll!, Was?!, Wahnsinn!, Super!	Oh no!, Definitely!, Great!, Amazing!
	Verbalizing emotions	low	Schade., Das ist traurig, Das freut mich, Das ist toll, Das tut mir leid	That's too bad, That's sad, I'm glad, That's great, I'm sorry to hear that
	Encouraging & Reassuring	medium	Ich verstehe, Da ist was dran, (Das) stimmt!	I see, That's right,
	Looking for common ground	medium	Würdest du da zustimmen? Da stimme ich zu Was meinst du? (Das) Ich finde auch … Das sehen viele so.	Would you agree? I agree What do you think? This is how many see it
Responsive Communication	Basic interjections	very low	Wirklich?, Aha, Ok, Mhm, Mh …	Really?,
	Repetition of user's utterances	low	Ich mag Schnee.→ "Du magst Schnee?"	I like snow.→ „You do like snow?"
	Paraphrasing/ Summarizing	high	Du meinst also …	So you are saying that …
	Infering completing information	very high	Adding (relevant) information to user statements	Adding (relevant) information to user statements

With artificial beings such as bots, "discomfort" was added in the Robotic Social Attributes Scale (RoSAS) to account for the underlying ambiguity (Carpinella et al., 2017). Warmth and competence have now shown to be prominent dimensions in the perception of different artificial intelligence systems (McKee et al., 2023). There, Virtual Assistants capable of verbal conversation scored higher in warmth and competence than other AI systems. However, research in Warmth and Competence to date has focused on robots (Christoforakos et al., 2021) and instrumentalization was mostly done via non-verbal cues, even with virtual agents (Nguyen et al., 2015). When choosing AI systems, perceived warmth may take precedence over perceived competence (Gilad et al., 2021), but context and task might play a role, just as with personality (Zhou et al., 2019).

Anthropomorphism. Anthropomorphism describes the effect of perceiving a computer, robot, or agent (or any object) as human-like in a more or less specific way (Fink, 2012). This has been examined both as a design approach and as an outcome. Anthropomorphism is especially well considered in Human-Robot-Interaction (Blut et al., 2021) where physical appearance, behavior, and non-verbal communication often take precedence over verbal conversational cues. Generally, many factors including user features are affecting anthropomorphism, and anthropomorphism itself is affecting several functional and relational outcomes (Blut et al., 2021; Dubois-Sage et al., 2023; Kim & Im, 2023). For example, it has been shown that the anthropomorphism of a service chatbot increases the intention to use it, especially among people who have a high need for human interaction (Sheehan et al., 2020). The literature on anthropomorphism and specifically verbal communication (such as chatbots), however, is rather small, although verbal communication is mostly recognized as one dimension of anthropomorphism (Blut et al., 2021; Li & Suh, 2021). Concerning personality, it has been shown, that adding personality in any way to conversational agents (or robots) increases the perceived humanness or anthropomorphism (Ahmad et al., 2021). It is likely, that vice versa designing bots with anthropomorphic features might have unintended effects, resulting from changes in their perceived personality.

Trust – Trust in Automated Systems. Trust in systems seems to be very similar to trust between humans (Jian et al., 2000), but is more strongly related to function- and performance-based factors (Corritore et al., 2003). In social situations, this might be different, but still depends on the impression that the system is being helpful and doing a good job, which increases trust in the system (Følstad et al., 2018). Anthropomorphism, and thus possibly a perceived personality, can be counterproductive as more human-like features can lead to lower trust (Stower et al., 2021). Trust has already been found to be associated with a social-oriented communication style as well as perceived responsiveness (two-way interactivity) (Chattamaran et al., 2019).

1.2. Hypothesis, aims, and objectives

Based on literature review, two different styles of communication were identified, that would likely influence personality attribution and the chosen outcomes. Social-oriented communication (SO) attempts to establish a relationship besides purely task-oriented communication. It does so by using exclamatory feedback, verbalizing emotions, encouraging, and looking for common ground. All these types of cues were used to operationalize social-oriented responses.

Responsive Communication (RESP) refers to what has been said and emphasizes understanding of the subject matter. This can be done through basic interjections, repetition, paraphrasing, and inferring completing information. To operationalize responsive communication, a summarizing question referring to the statement was added at the beginning of the response.

To operationalize combined social-oriented and responsive communication, all cues from both conditions were applied in each vignette.

In this study we operationalized social-oriented and responsive communication styles by using equivalent conversational cues and measured their effects on personality and other social perception variables. We assumed that very few conversational cues within short messages or comments in a social media like setting can be sufficient to convey distinct personalities.

As primary hypotheses it was assumed, that in short social media like comments conversational cues of the different communication styles (H1) social-oriented, (H2) responsive and the (H3) combination of both would convey different personalities and affect differences in multiple personality traits, as well as the outcome variables warmth, competence, discomfort, trust, and anthropomorphism.

2. Method

2.1. Participants

Participants were recruited by notice, social media, and online platforms between March and June 2022. As an incentive, participants were informed that 25c would be donated to a beneficial organization against cybermobbing amongst children and teenagers for each legitimate participant. After the survey a total of 50€ was donated, according to the final sample size plus the outliers and rounded up for good measure.

Only participants, that finished the complete online experiment were considered. Missing data was not possible as all items had to be answered to proceed. Unfinished attempts were removed. Participants that failed the attention check among the items were removed. Data was checked for multivariate outliers using a robust variant of the Mahalanobis distance, removing 15 participants (Leys et al., 2018). Instead of the suggested subsample size of h = 3n/4 (0.75), which produced highly variable results at different iterations, a subsample size of h = 9n/10 (0.90) was found to provide better and reliable results.

The final data set consisted of 168 participants (91 female, 77 male; age = 16–69, mean = 31.9, median = 29, sd = 10.7; Fig. 1). Participants were also asked, if they had encountered bots before (yes: 93, no: 75), and how negative or positive they evaluate their experience with bots on a bipolar 7 points likert scale, which was neutral for most participants (mean: 3.95, sd: 1.04). Participants were distributed a bit unevenly over the four experimental groups (NONE: n = 37; SO: n = 59; RESP: n = 38; SORESP: n = 34).

2.2. Sample size & power

G*Power Software (version 3.1.9.7; Faul et al., 2007) was used to determine an adequate sample size for the two-factorial MANOVA design. As there were no suggestions for a fitting effect size, we assumed an effect size between low and medium of cohens f2 = 0.0625. As common, an estimated power of 0.8 was selected. Four groups resulted from the 2 × 2 factorial design and there were originally 16 response variables (five Big5-Personality factors, Anthropomorphism, Trust, Warmth, Competence, and Discomfort, plus six Cattell-Personality factors that were excluded from the analysis due to unacceptable reliability). Based on these parameters, the software suggested a total sample size of 172. It would have been 140 for 10 variables without the Cattel variables.

2.3. Conditions and design

The study was a two-factorial 2 × 2 between-subject experimental manipulation with participants randomly assigned to one of four groups. The experiment was constructed according to the recommendations for an Experimental Vignette Methodology (Aguinis & Bradley, 2014). The two factors were the two different communication styles Social-Oriented (SO) and Responsive (RESP) communication, resulting in the four conditions: NONE (no social-orientated communication cues and no responsive communication cues), SO (social-orientated communication cues but no responsive communication cues), RESP (no social-orientated communication cues but responsive communication cues) and SORESP (social-orientated communication cues and responsive communication cues).

After instruction, participants were randomly assigned to one of four groups by formr software. For each group a vignette consisting of 9 statement-response pairs were constructed (Table 2) and presented in the visual style of “Twitter” (Fig. 2). The statement-parts were the same for each group. The corresponding responses consisted of a fitting comment to which different conversational cues for each group were added. Each participant was only presented one of the four kinds of communication styles. The 9 statement-response pairs were presented in a random order for each participant. Conversational cues were identified from literature and applied as described above (Table 1).

Participants were instructed that the experiment was about “social bots” that can be active in Online Social Networks. Participants would be shown examples of responses written by a social bot to posted statements. In fact, the statements and responses were constructed manually. Participants were then asked to rate the bot based on the various items that followed. Participants were not informed that there were different groups or in which one they were.

2.4. Measures and covariates

2.4.1. Personality measures – Ten-Item Personality Inventory (TIPI) – Big Five

To measure perceived personality of the bots, the Big Five personality dimensions Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness were measured using the “Ten-Item Personality Inventory” (Gosling et al., 2003). The TIPI consists of 10 items (α = 0.71), with two items for each dimension Neuroticism (α = 0.61), Extraversion (α = 0.59), Openness (α = 0.68), Agreeableness (α = 0.40), and Conscientiousness (α = 0.69), one of which inversed. Each item consisted of two adjectives associated with the factor and was headed by the sentence “I see the bot as …”. The items were rated on a 7-point Likert scale and are conceptually bipolar with each trait having two opposite expressions. The center represents no strong expression in either direction.

2.4.2. Robotic Social Attributes Scale (RoSAS)

To measure the dimensions of the Stereotype Content Model (Fiske et al., 2002) the “Robotic Social Attributes Scale” (α = 0.83) was used

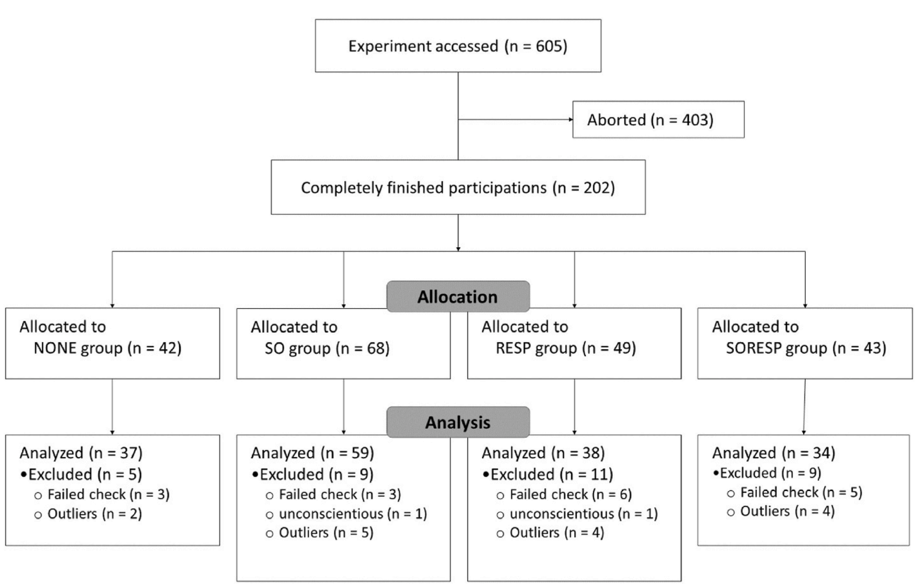

Fig. 1. CONSORT flowchart of participants.

Table 2
Presentation of the concept of vignette construction (example).

Part	Cue Version	German version used in experiment	English translation (not used in the experiment)
Statement		Meine neue Grafikkarte macht dieses unerträgliche Geräusch! Es macht mich wahnsinnig! Ich halte es nicht mehr aus. Warum? Ich will nicht mehr …	My new graphics card is making this unbearable noise! It's driving me crazy! I can't stand it anymore. Why? I don't want any more …
Response	No cues	Unter hoher Belastung entsteht bei manchen Grafikkarten sogenanntes Spulenfiepen, dass nicht schädlich ist, sich aber ungesund anhört.	Under high load, some graphics cards produce so-called coil whine, which is not harmful but sounds unhealthy.
	Social-oriented cues	**Oh nein! Das tut mir leid.** Unter hoher Belastung entsteht bei manchen Grafikkarten sogenanntes Spulenfiepen, dass nicht schädlich ist, sich aber ungesund anhört.	**Oh no! I'm sorry to hear that.** Under high load, some graphics cards produce so-called coil whine, which is not harmful but sounds unhealthy.
	Responsive cues	**Deine Grafikkarte macht ein unerträgliches Geräusch?** Unter hoher Belastung entsteht bei manchen Grafikkarten sogenanntes Spulenfiepen, dass nicht schädlich ist, sich aber ungesund anhört.	**Your graphics card is making an unbearable noise?** Under high load, some graphics cards produce so-called coil whine, which is not harmful but sounds unhealthy.
	Social-oriented and responsive cues	**Deine Grafikkarte macht ein unerträgliches Geräusch? Oh nein! Das tut mir leid.** Unter hoher Belastung entsteht bei manchen Grafikkarten sogenanntes Spulenfiepen, dass nicht schädlich ist, sich aber ungesund anhört.	**Your graphics card is making an unbearable noise? Oh no! I'm sorry to hear that.** Under high load, some graphics cards produce so-called coil beeping, which is not harmful but sounds unhealthy.

(RoSAS, Carpinella et al., 2017), which measures Discomfort ($\alpha = 0.84$) additionally to Warmth ($\alpha = 0.81$) and Competence ($\alpha = 0.81$) with 6 items each. Only 3 items were used for each dimension. For each of these three dimensions each of three adjectives were rated on a 7-point Likert scale following the question "How much do the following terms apply to the responding bot?".

2.4.3. *Godspeed Inventory – anthropomorphism*

To measure Anthropomorphism the corresponding 4 items ($\alpha = 0.84$) from the "Godspeed Inventory" were used (Bartneck et al., 2009). The fifth item was left out, as it refers to movement (of a robot). The items were measured on a 7-point semantic differential. The official german translation was used. The instructions for these items were: "Using the scales, please mark which term is more applicable to the responding bot:".

2.4.4. *Scale of Trust in Automated Systems (TAS)*

To measure Trust in the bots the "Scale of Trust in automated systems" was used (Jian, et al., 2000). We used 6 of 12 items to keep the questionnaire short ($\alpha = 0.82$). Participant rated short statements on a 7-point Likert scale for each item. The instructions for these items were: "How true are the following statements about the responding bot?".

2.4.5. *Covariates*

To describe the sample, Gender, Age, and Education Level were measured. Additionally, it was asked, if there were "prior experiences with social bots" (yes/no) and how prior experiences with social bots are rated (7-point scale, "very negative" to "very positive"). Gender, Age and quality of experience were included in a MANCOVA, to rule out those influences. All covariates were measured at the end of the survey.

2.5. *Data collection*

The experiment was conducted online using the formr survey framework (Arslan et al., 2020). All data was collected via survey questions with rating scales as described above. All data analyses were conducted using RStudio (R Core Team, 2022; RStudio Team, 2022).

2.6. *Data diagnostics*

Multivariate normality was checked using the multivariate Shapiro-Wilk normality test. Considering the 10 outcome variables data for all four groups deviated from multivariate normality (NONE: $W = 0.83$, $p < .001$; SO: $W = 0.91$, $p < .001$; RESP: $W = 0.89$, $p < .001$; SORESP: W

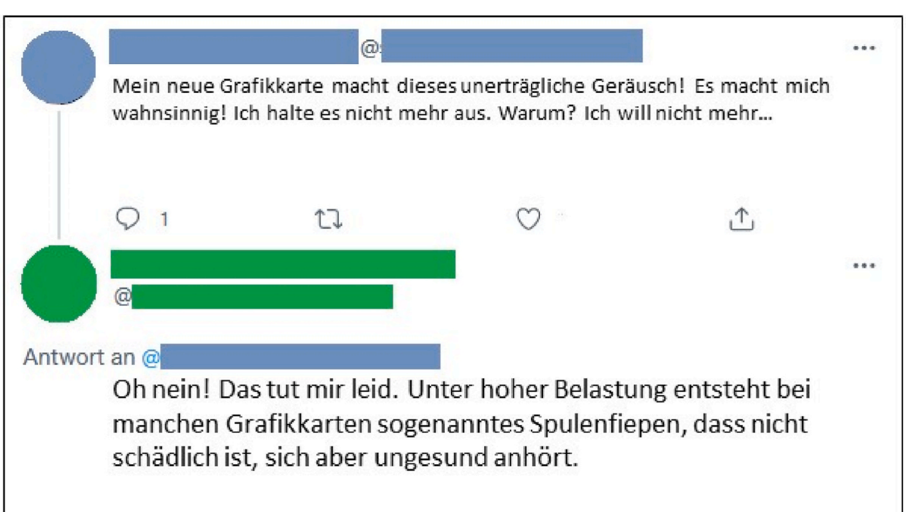

Fig. 2. Example for a statement-response pair vignette with social-oriented cues in the style of Twitter.

= 0.86, $p < .001$).

Variance homogeneity was tested using the distance-based test for homogeneity of multivariate dispersions (Anderson, 2006), which is robust even when there is no multivariate normality and groups are uneven. With the test being non-significant, homogeneity of covariance matrices could be assumed ($F(3,164) = 0.99$, $p = .40$).

There was no inacceptable multicollinearity. The intercorrelation matrix was checked for multicollinearity by checking if the determinant of the matrix ($p = .012$) was higher than $p = .00001$. Further no intercorrelation between the variables was higher than $r = 0.70$.

Scores were conducted as mean values of the associated items.

2.7. Analytic strategy

Considering the violation of assumptions and the imbalanced group sizes a Permutational Multivariate Analyses of Variance (PERMANOVA) was conducted (McArdle & Anderson, 2001) using the vegan package (v2.6-2; Oksanen et al., 2022). The results were followed up by linear discrimination analysis and univariate PERMANOVAs, followed with Bonferroni corrected pairwise t-tests, to explore crucial determinants.

3. Results

Only participants, that finished the complete online experiment were considered. Missing data was not possible as all items had to be answered to proceed. Unfinished attempts were removed. Participants that failed the attention check among the items were removed. Data was checked for multivariate outliers using a robust variant of the Mahalanobis distance, removing 15 participants (Leys et al., 2018). Instead of the suggested subsample size of $h = 3n/4$ (0.75), which produced highly variable results at different iterations, a subsample size of $h = 9n/10$ (0.90) was found to provide better and reliable results.

3.1. Statistics and data analysis

A Two-Way PERMANOVA showed overall significant differences between the four groups in personality and outcome variables ($F(3,167) = 8.24$, $p < .001$, $R^2 = 0.13$). Social-Oriented communication (SO; $F(1,167) = 15.59$, $p < .001$, $R^2 = 0.08$), Responsive communication (RESP; $F(1,167) = 6.40$, $p < .001$, $R^2 = 0.03$), and the combination of both (SORESP; $F(1,167) = 2.72$, $p < .05$, $R^2 = 0.01$) each showed significant influence on the personality and other outcome variables.

The PERMANOVA was followed up with a linear discriminant analysis (LDA), which revealed three discriminant functions. The first function (DF1) explained 77 % of the variance, the second (DF2) 17 %, and the third (DF3) only 7 %. The coefficients of the discriminant functions (Table 3) revealed that DF1 mainly differentiated by Warmth ($b = 0.75$), Extraversion ($b = 0.41$), and Trust ($b = -0.33$), DF2 differentiated by Agreeableness ($b = 0.76$), Competence ($b = 0.35$), and Openness ($b = -0.32$), and DF3 differentiated by Openness ($b = -0.81$), Neuroticism ($b = -0.63$), and Trust ($b = -0.54$). The discriminant function plot (Fig. 3) showed, that DF1 discriminated the groups with Social-Oriented communication from those without (SO/SORESP vs. NONE/RESP), while DF2 discriminated the groups with Responsive Communication from those without (RESP/SORESP vs. NONE/SO). DF3 barely discriminated the two groups with either social or responsive communication from those without or with both communication styles (SO/RESP vs. NONE/SORESP; Fig. 4). Using the discriminant functions found, 60.7 % of all cases could be correctly assigned to their actual group post hoc. (Table 4).

In Addition to the LDA, the PERMANOVA was followed up with univariate Two-Way PERMANOVAs, which were all significant aside from Competence and Trust (Table 5). Pairwise *t*-test with Bonferroni correction were conducted to examine group contrasts (Table 6). Mean values are visualized in Figs. 5 and 6.

Table 3
Discriminant Loadings of Personality Traits and other Outcomes.

Measures	Discriminant Functions		
	DF1 (77 %)	DF2 (17 %)	DF3 (7 %)
Big 5 (TIPI)			
Neuroticism	−.01	.13	−.63[(2)]
Extraversion	.41[(2)]	−.22	.17
Openness	−.07	−.32[(3)]	−.81[(1)]
Agreeableness	.27	.76[(1)]	−.14
Conscientiousness	−.17	.18	−.45
ROSAS			
Warmth	.75[(1)]	−.18	.35
Competence	−.14	.35[(2)]	.47
Discomfort	−.07	−.17	−.02
Godspeed Inventory			
Anthropomorphism	−.01	.14	.07
Robotic Social Attributes Scale			
Trust	−.33[(3)]	−.23	−.54[(3)]

Note. [(x)] = Rank of highest discriminant loadings per function.

4. Discussion and conclusions

We examined the effects of using different conversational cues to convey distinct personalities in very short messages as common in most forms of social media on the Big Five personality traits and additional social perception variables warmth, competence, discomfort, anthropomorphism, and trust.

The study adds to the field of personality perception and general social perception of chatbots, other conversational agents and AI, or other technical system. Knowledge of how different personalities can be conveyed can be used to examine their effects in different contexts and with different goals in mind. Also, this study demonstrates, that focusing on one personality trait can be insufficient, when different personality variables are changed due to different conversational cues and their combination.

In this study especially our operationalization of social-oriented conversational cues was able to create a clear distinction. Responsive cues seemed to have less and, in combination with social-oriented cues, altering effects.

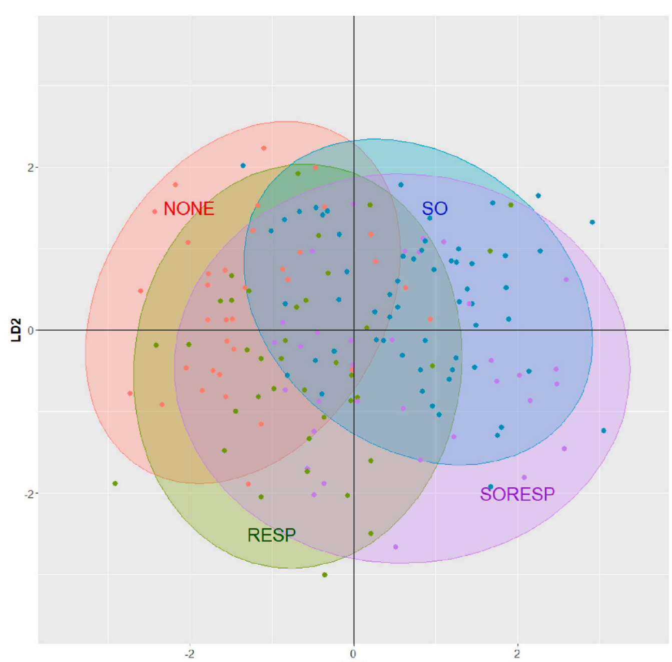

Fig. 3. Discriminant function plot LD1 and LD2.

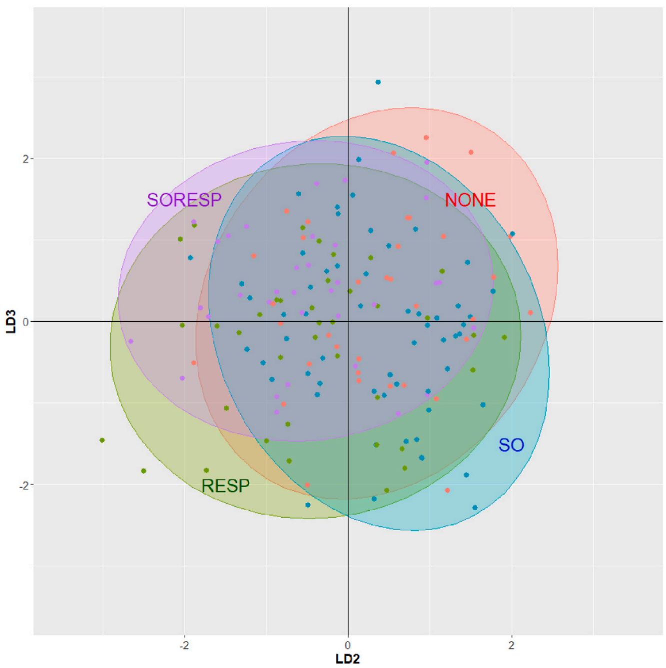

Fig. 4. Discriminant function plot LD2 and LD3.

Table 4
Post-hoc Prediction of participant groups by discriminant functions.

Actual Group	n	Predicted Groups by Discriminant Functions				Correct Prediction Rate
		NONE	SO	RESP	SORESP	
NONE	35	25	5	6	1	71.4 %
SO	61	6	43	3	7	70.5 %
RESP	38	9	6	21	2	55.3 %
SORESP	34	2	14	5	13	38.2 %
all	168	42	68	35	23	60.7 %

4.1. Support of original hypothesis

The primary hypothesis that the different communication styles with or without Social-oriented and Responsive communication cues would affect perceived personality traits, as well as warmth, competence, discomfort, anthropomorphism, and trust are supported by the overall PERMANOVA results. Both independent variables and the interaction were significant. The follow-up analyses offered further insights.

The linear discrimination analysis (LDA) shows that the different conversational styles were differentiated by different outcome variables. Those groups with social oriented conversational cues were mainly differentiated by higher Warmth and Extraversion. The groups with responsive conversational cues were mainly differentiated by higher Agreeableness and lower Openness. There was a third discriminant function, but its discriminative power was very low. Interestingly, discomfort and anthropomorphism had very low loadings in the LDA.

The follow-up univariate PERMANOVAs showed that, compared to the no-cue condition, with social-oriented cues all personality variables except conscientiousness were higher, as well as warmth and anthropomorphism. Responsive cues only increased neuroticism significantly. While responsive cues alone had little effect, in combination with social-oriented cues, openness and agreeableness were no longer affected. It seems like the responsive cues were countering the effect of social-oriented cues, but only on these two variables. Extraversion and warmth were not affected. Also, Conscientiousness was lower when both cues were used.

In the group-wise comparison, consistent with the LDA, warmth and extraversion were significantly different between the groups with and without social-oriented cues. Trust and competence were not significant in their univariate analysis, although they had relatively high loadings in the LDA.

In Conclusion: The different conversational cues and their combination affected the personality traits differently. Social-oriented cues had a clear effect on most personality traits, while responsive cues only affected neuroticism. In combination, effects of social-oriented cues were countered by responsive cues, but not for all personality traits! Competence and trust were not affected by any of the used conversational cues.

4.2. Similarity of results and interpretation

To our knowledge there is no study so far that examined the effects of conversational cues on an entire personality profile of a Conversational Bot in social-media-like short messages. There is however data on how specific personality traits of conversational bots or robots are affected in different settings.

In our study, the clearest effects on personality were related to Extraversion and Agreeableness, which are also the two personality traits that are most examined in this field. In other works, colleagues were able to design conversational bots with higher Extraversion (Neff et al., 2010; Shumanov & Johnson, 2021; Tapus et al., 2008; Völkel et al., 2022), Agreeableness Völkel and Kaya (2021) or both (Ruane et al., 2021) by using only or predominantly conversational, verbal, or language cues.

The variables warmth and competence of the Stereotype Content Model (Fiske et al., 2002) have been considered in some studies

Table 5
Means, Standard Deviations, and univariate Two-Way PERMANOVAs for each Dependent Variable.

Measure	NONE		SO		RESP		SORESP		$F(3,167)$	R^2
	M	SD	M	SD	M	SD	M	SD		
Big 5 (TIPI)										
Neuroticism	1.76	0.60	2.29	0.96	2.34	1.00	2.60	1.02	4.91**	.08
Extraversion	2.74	1.04	3.95	1.16	3.41	1.01	4.26	1.29	11.38***	.17
Openness	2.86	1.10	3.97	1.26	3.58	1.12	3.51	1.44	5.81***	.10
Agreeableness	3.95	1.09	4.90	1.04	3.67	1.28	3.94	1.22	9.90***	.15
Conscientiousness	5.97	0.90	5.49	0.93	5.62	0.91	5.22	0.78	3.52*	.06
ROSAS										
Warmth	2.29	0.94	3.84	0.95	2.63	0.89	3.57	1.14	23.69***	.30
Competence	5.45	1.00	5.43	0.70	5.15	1.04	5.10	0.75	1.74n.s.	.03
Discomfort	3.57	1.35	3.06	1.19	3.93	1.45	3.90	1.35	3.37*	.06
Godspeed Inventory										
Anthropomorphism	2.76	1.30	3.58	1.25	2.85	1.03	3.18	1.25	3.96**	.07
Trust in Auto. Systems										
Trust	4.99	0.92	4.97	0.90	4.77	0.90	4.52	0.77	2.00n.s.	.04

Note. *p < .05. **p < .01. ***p<.001. ^{ns}p>.05.

Table 6
Univariate analysis of contrasts' Cohen's d with Bonferroni-corrected significance levels.

Measure	NO–SO	NO-RE	NO-SORE	SO-RE	SO-SORE	RE-SORE
Big 5 (TIPI)						
Neuroticism	.63*	.71*	1.02***			
Extraversion	1.08***		1.31***			.74**
Openness	.92***					
Agreeableness	.91***			−1.08***	−.87***	
Conscientiousness			−.89**			
ROSAS						
Warmth	1.64***		1.23***	−1,31***		.92***
Competence						
Discomfort				.67*	.67*	
Godspeed Inventory						
Anthropomorphism	.65**			−.63*		
Trust in Auto. Systems						
Trust						

Note. *p < .05. **p < .01. ***p < .001.

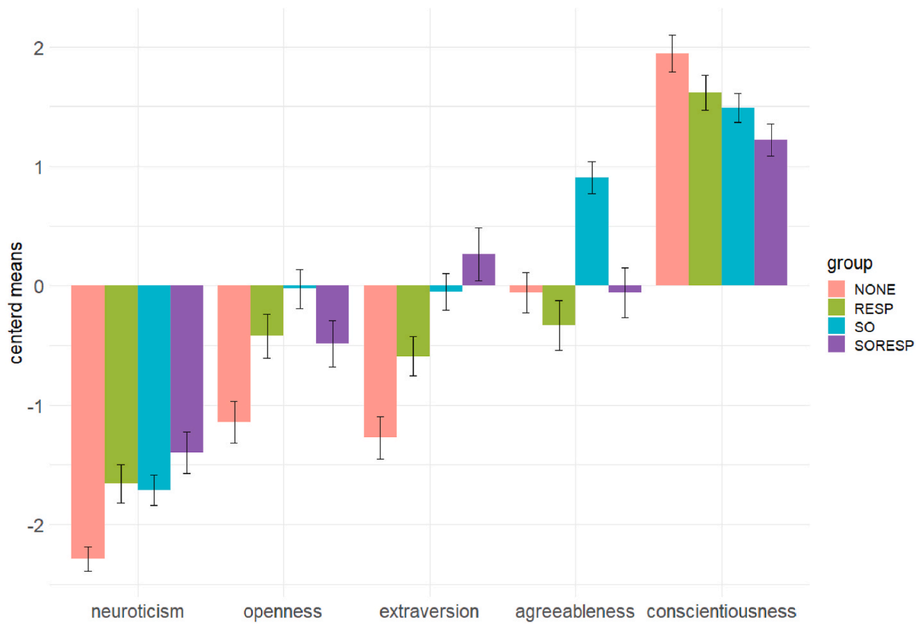

Fig. 5. Centered mean values of Big Five variables with Standard Errors.

concerning conversational bots or robots (McKee et al., 2023; Oliveira et al., 2019). The Robotic Social Attributes Scale (RoSAS; Carpinella et al., 2017) adds discomfort as an additional variable because of the potential uncanniness of artificial conversational partners.

In our study warmth was a dominant variable in differentiating the use of social-oriented conversational cues. Similar results were found by Kim et al. (2021), who found more favorable attitudes towards AI instructors that used social-oriented communication style than towards those using a functional style.

Competence and Trust correlated relatively high ($r = 0.64$, $p < .001$). This correlation fits the finding, that trust in interaction with technical systems is mainly based on functionality and performance (Corritore et al., 2003). Neither competence nor trust were affected by conversational cues. This is probably due to the fact, that the bots in our study design did not have a clear task in which they had to prove themselves competent and trustworthy. The responses just had to be appropriate, which they were by design. Sociality only has a positive effect on perceived competence and trust, when it fits the task (Jiang et al., 2023) and generally competence for AI systems is rated higher with greater autonomy of the system (McKee et al., 2023). Differences in personality alone have shown no effect on perceived intellect of a robotic assistant (Goetz & Kiesler, 2002). Considering the task- and context-sensitivity of conversational style or personality in bots, our manipulation might not have affected the perceived functionality in our scenario.

Discomfort was only relevant between Social-Oriented and Responsive communication, with included responsive cues leading to increased discomfort. This might be due to the more repetitive and mechanical structure of the RESP items.

4.3. Limitations

This study was a bit of a shotgun approach implementing a lot of personality and social perception variables. Originally, even more variables were included in the experiment. Items for the 6 personality measures of Cattell's 16 PF were also measured during the experiment (Cattell & Mead, 2008). Unfortunately, except for one, reliabilities for those variables were beyond unacceptable ($\alpha < 0.50$). We did all analysis with and without this alternative personality measures and decided to leave them out, as the results did not differ but were much easier to discuss and communicate.

Reliabilities for the Big Five measure (TIPI) were better, but agreeableness was below the threshold with $\alpha = 0.40$. This might be an indication, that the common personality measures might not be the best fit for artificial conversational or social systems. There have been

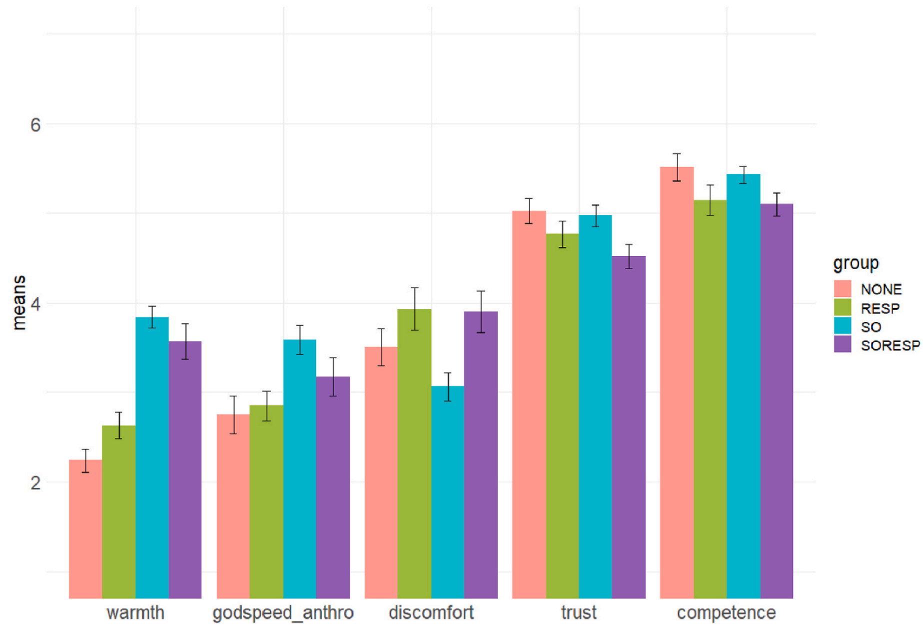

Fig. 6. Mean values of social perception variables with Standard Errors.

attempts to identify alternative personality models for conversational agents (Soonpipatskul et al., 2023; Völkel et al., 2020), which might be interesting to investigate further.

While we based our item design on the given literature, our derived operationalization for social-oriented and responsive cues can surely be refined further. For instance, the responsive items were in hindsight a bit repetitive in design, which might have induced a more mechanical impression of the bot and negatively affecting anthropomorphism and personality. Also, the baseline comments used in all conditions were always referring to the post, which was per definition already a form of responsiveness. More focused experiments can probably get better results here.

While there was no high multicollinearity, mediating and moderating effects are still possible. More precise experimental analyses are necessary to clarify this to help conduct a consistent model.

4.4. Generalizability and implications

This study was conducted in the context of a project to investigate the possibilities of using social bots in online social media to intervene against hate speech and for a better discussion culture. The aim was to gain a better understanding of how bots are perceived in short message format that is common in social media. Conversational style and use of words are obviously relevant and can affect perceived personality and social perception of social bots.

Apart from the described findings it is noteworthy that neuroticism was generally rated very low, and conscientiousness rated very high. Emotional Stability (low Neuroticism) and Conscientiousness are two things we would likely expect from a technical system. Accordingly, with all cues from both conversational styles added, Neuroticism increased, and Conscientiousness decreased.

In line with earlier findings this study confirms that suitable conversational cues can convey certain personalities, even in very short messages. The conversational cues used in this study have shown to be effective and can be used to affect certain traits. The results also demonstrate that interactions between different cues can lead to varying results and side effects. Given the design and sample of this study the findings should translate well into practical application and further studies on social perception of robots, agents, or technical systems.

However, among others, four additional aspects should be considered going on. Firstly, as this was a vignette study, it should be considered that participating in the social interaction with bots will likely affect the social perception. Of course, this demands a much different design. Secondly, we focused on the verbal modality alone, which fits for social media comments, but appearance of embodied conversational agents and robots brings additional variables into the mix (e. g. Belpaeme et al., 2018). Thirdly, it is well known that there are several in-person variables that influence the perception and acceptance of bots (e. g. Graaf & Ben Allouch, 2013). Especially the interaction between user personality and perceived bot-personality needs further research. And fourthly, context and field of application are important variables. In the wrong context, conversational cues can be distracting (e. g. Veletsianos, 2012) and counteract the desired effects.

Designing technical systems with sociability in mind is a form of usability that relates to the social mechanisms we are familiar with. It can contribute to acceptance, accessibility, and natural communication with devices. There are studies on this, but there is no coherent framework so far. As examples, responsive communication behavior can increase social desirability when answering “sensitive questions” (Schuetzler et al., 2018). Warmth and competence both have a positive effect on believability of a virtual agent (Demeure et al., 2011; Niewiadomski et al., 2010), which is a very important variable in the field of ai-based assistance systems. And a more assertive tone, which may be at odds with a social-oriented communication style, can increase the perceived competence and reliability of an assistance system (Calisto et al., 2023).

CASA as a theory is about 25 years old at this point and while a lot of research has been done in the field of social robotic, and social perception of technical systems, more elaborated models are noticeably missing.

CRediT authorship contribution statement

Holger Heppner: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Birte Schiffhauer:** Conceptualization, Funding acquisition, Project administration, Supervision. **Udo Seelmeyer:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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