Original Article

Just Like a Human? An Experimental Study on University Students' Perceptions of Warmth and Benevolence Towards Chatbots

Eileen Plagge and Regina Jucks

Institute of Psychology for Education, University of Münster, Germany

Abstract: Human–computer interaction has advanced significantly with the emergence of OpenAI's ChatGPT. However, it's unclear whether users perceive these chatbots to have positive human qualities. Using a 2 × 2 experimental design, university students evaluated the perceived warmth and benevolence of a chatbot, whereby we altered the description of the chatbot across experimental groups. Specifically, we altered its description according to Asch's (1946) concept of warmth, where we varied it to have traits suggesting high or low kindness, and we also varied the language used in the chatbot description (technical vs. anthropomorphic). We hypothesized that describing the chatbot using anthropomorphic (humanlike language) vs. technical language would increase its perceived warmth and benevolence and that descriptions highlighting kindness would enhance the chatbot's perceived warmth. Results revealed that kindness-related descriptions of the chatbot significantly affected its perceived warmth and benevolence, whereas differences in anthropomorphic or technical language did not. The role of personality traits in shaping AI perceptions is discussed.

Keywords: Chatbots, anthropomorphism, warmth, benevolence, artificial intelligence

Generative AI in the University Context

Since the launch of ChatGPT in November 2022, artificial intelligence has rapidly permeated various aspects of daily life. Modern AI systems exhibit communication styles that closely resemble human interactions. These anthropomorphic tendencies in language use can influence cognitive perceptions on multiple levels (Chi et al., 2024; Jia et al., 2024). Anthropomorphism refers to the attribution of human characteristics, intentions, or emotions to non-human entities, including technological systems (Nicolas & Agnieszka, 2021; Waytz et al., 2010). This psychological mechanism facilitates social understanding and interaction by allowing individuals to apply familiar human schemas to complex, non-human agents. Notably, factors such as benevolence may significantly impact user experiences (Holtgraves et al., 2007; Janssen et al., 2021; Jucks et al., 2018), while fundamental human traits, such as perceived warmth (Asch, 1946), could shape interactions with and assessments of AI technologies.

As AI models become more humanlike (Kasneci et al., 2023; Mei et al., 2024), a crucial question arises: how do these attributes manifest in user interactions, particularly in higher education? Addressing this question matters because such attributes may influence teaching and learning (Essel et al., 2022; Harris-Watson et al., 2023; Polyportis & Pahos, 2024). A deeper understanding of the communication mechanisms underlying AI interactions can enable both students and educators to utilize these technologies more effectively (Kim & Sundar, 2012; Konya-Baumbach et al., 2023; Linnemann & Jucks, 2016; Sundar, 2008). Given the continuous presence and growing integration of chatbots in academic settings, it is imperative to explore the patterns of interaction and communication with these systems. (Kasneci et al., 2023; Polyportis & Pahos, 2024; Wang et al., 2025).

In light of ongoing developments, universities are challenged to define ethical AI usage while identifying chatbot features that meaningfully support student learning in higher education (Debets et al., 2025; Gruenhagen et al., 2024). Focusing on students as the primary research population is necessary due to their unique role as frequent users and critical evaluators of AI in educational contexts. Unlike other demographic groups, students regularly engage with AI-powered technologies for learning, research, and assessment purposes, making them particularly susceptible to the cognitive and social effects of anthropomorphic AI communication (Deng et al., 2025; Jucks et al., 2018; Polyportis & Pahos, 2024). Moreover, the impact of perceived warmth and benevolence in AI interactions is especially relevant in academic settings, where these factors may influence learning processes (Baig & Yadegaridehkordi, 2024; Deng et al., 2025; Polyportis & Pahos, 2024). Since students continuously adapt to new digital tools within structured educational environments, analyzing their interactions with AI provides valuable insights into how these technologies shape cognitive and social dynamics in higher education (Baig & Yadegaridehkordi, 2024; Kasneci et al., 2023; Polyportis & Pahos, 2024).

Framing Machines as People: The Influence of Anthropomorphic Cues in Human-Computer Interaction (HCI)

One innovative element in the study of HCI is the perception of chatbots as social agents (Konya-Baumbach et al., 2023). This identification of chatbots as social entities enhances the likelihood that users will interact with them based on the same social norms and expectations they apply to human counterparts (e.g., Kim & Sundar 2012). Anthropomorphic signals, provided through both visual and verbal cues, can significantly shape social perceptions, thus accentuating the "humanity" of chatbots (Hamilton et al., 2024; J. Kim, 2010; Salah et al., 2024; Sundar, 2008).

In particular, the studies by Konya-Baumbach et al. (2023) and Salah et al. (2024) show that anthropomorphic features – especially linguistic framing – might increase perceived social presence. Kim and Sundar (2012) further investigated whether anthropomorphism necessarily involves an explicit belief in the computer's humanlike qualities and discovered that this often happens subconsciously, indicating the presence of automatic cognitive heuristics. Heuristics are mental shortcuts that play a crucial role in shaping quick judgments. They are instrumental in interpreting social cues and forming first impressions (Schwarz et al., 1991). Related attribution biases also shape responses: people even assign responsibility to a social robot for pre-programmed behavior, consistent with the fundamental attribution error (Horstmann & Krämer, 2022).

Recognizing the significance of these mechanisms in human cognition highlights their potential utility in designing and developing AI communication tools. One of the most influential mechanisms in heuristic person perception was introduced by Asch in 1946.

Central Personality Traits as Defined by Asch (1946)

Person perception plays a pivotal role in the way we collect, organize, and interpret information about others, significantly shaping our social interactions and decision-making processes. Asch's seminal work in 1946 delved into these dynamics. In his study, participants were presented with lists of adjectives describing a person. Asch (1946) pinpointed traits like "warm" or "cold" as central, noting that they had a disproportionate impact on the formation of overall impressions, unlike peripheral traits such as "polite" or "rude".

Asch (1946) characterized "warm" as indicative of friendliness, kindness, and approachability, qualities associated with good nature and generosity. On the other hand, "cold" was associated with unfriendliness, rudeness, and emotional distance, suggesting a person's indifference to others' feelings. In his experiments, Asch (1946) sought to explore how these central traits influenced perceptions of other personality characteristics and the general impression formed. The findings revealed that the trait "warm" led to more positive overall impressions than other adjectives.

This experiment demonstrates that central traits like "warm" and "cold" not only affect specific trait perceptions but also color the entire perception of one's character, creating a coherent overall impression. Asch (1946) concluded that overall impressions are not mere aggregations of traits but are integratively influenced by central traits. He emphasized that personality impressions are holistically formed, not through a simple tally of traits.

In the context of warmth and chatbots, Cai et al. (2024) and Hernandez and Chekili (2024) argue that warmth also plays a dominant role in human–chatbot interactions. While in certain situations other factors, such as perceived competence, should become more important (e.g., in healthcare; McKee et al., 2023; Wang et al., 2025) – particularly for achieving long-term goals – fostering warmth, even briefly, as a social attribute in chatbot development remains crucial for maximizing interaction satisfaction, user engagement, chatbot preference, and trust.

Building Trust in Communication and the Influence of Benevolence in Humans and Computers

Hendriks et al. (2015) introduced the Muenster Epistemic Trustworthiness Inventory, which incorporates the concept of benevolence, defined as the anticipation that others hold positive intentions and act kindly. They argued that perceptions of benevolence are influenced by the nature of interactions and the information exchanged, positing that a perceived benevolent individual is more likely to be trusted, thereby fostering positive and cooperative interactions.

In this context of communication and trust, researchers in HCI have become interested in how users perceive (and, thus, trust and communicate with) chatbots. Linnemann and Jucks (2016) reported that chatbots exhibiting humanlike behaviors are viewed more favorably, implying that emulating human interactions can elevate user satisfaction and acceptance. Similarly, research by Brummernhenrich et al. (2025) and Jucks et al. (2018) have indicated that chatbots perceived as polite are associated with higher assessments of benevolence. Moreover, research by Huiyang and Min (2022) and Linnemann and Jucks (2018) highlighted that in terms of trustworthiness, people generally prefer humans over computerized interlocutors.

Rationale of the Current Study

In the current context of human communication with chatbots becoming widespread, we are curious about the extent to which *modern chatbots* can be perceived as "warm", in the sense of Asch (1946), and what mechanisms might make this possible. Traditional social heuristics that characterize human interactions can potentially be transferred to AI systems because of humans' tendency to anthropomorphize. As such, users might also attribute characteristics such as "warmth" or "empathy" to technological entities, especially as modern AI systems are able to mimic human qualities almost perfectly (Mei et al., 2024).

Underlying these heuristics could be a shift in people's mental models of chatbots: compared with earlier cohorts, today's users often hold multiple, differentiated models of systems such as ChatGPT and Gemini (Wang et al., 2025). Dialogue analyses have shown that conversational behavior is often guided by a human-oriented mental model, even when participants explicitly reject the chatbot as a social partner. It has further been suggested that future studies should experimentally examine how varying levels of social cues, the chatbots' general language (anthropomorphic or keyword-based), introduction text, and framing might influence users' mental models (Ordemann et al., 2021; Wang et al., 2025).

Studying these dynamics in students is especially important because they are high-frequency users in higher-education settings; their evolving mental models are likely to mediate the future learning conditions in higher education.

A fundamental difference of modern chatbots lies in the fact that they do not rely solely on predefined templates or response patterns. Traditional chatbots often operate within narrow domains and are limited in their functionality – for example, repeatedly referring to the same pieces of information or being unable to switch between topics (Liu, 2024; Ordemann et al., 2021). A traditional chatbot might be designed specifically for automotive customer service, while another may only process product returns. In contrast, modern models use probabilistic algorithms and advanced language modeling techniques to respond in a more flexible and context-sensitive manner (Wang et al., 2025).

This means that modern chatbots can respond across a wide range of topics and rephrase their answers in more humanlike ways, allowing for seemingly more dynamic and natural interactions (Chen et al., 2024; Mei et al., 2024). Communication with such systems more closely resembles human-to-human interaction, where responses are unpredictable and context-dependent – similarly to what users now experience with chatbots like OpenAI's ChatGPT (Wang et al., 2025).

In our study, we described the chatbot as accurate, creative, and context-aware to reflect modern capabilities – similar to OpenAI's ChatGPT. This framing aligns with recent calls to embed *pedagogical intelligence* into conversational agents – prioritizing instructional fit over surface humanlikeness (Díaz & Nussbaum, 2024).

Previous "description-only" chatbot studies were largely conducted when users' mental models involved narrow, domain-specific systems. Our study addresses this gap by testing whether perceptions change when participants *envision a modern, broadly capable* system such as ChatGPT. In doing so, we extend work on anthropomorphism and human–computer interaction by arguing that stimulus features can substantially shape the activation of social heuristics. Crucially, the ex-ante description of a chatbot is itself likely to prime particular mental models and thereby trigger heuristic processing – even before any actual interaction occurs.

Following this line of argumentation, we assumed that if users perceive a chatbot as benevolent, this perception could also influence their expectations of their own behavior during interactions. Specifically, when users believe that a chatbot acts in their best interests, they may show greater willingness to engage actively and trust it with personal information. This assumption is grounded in social exchange theory (Blau, 1964), which posits that positive expectations foster cooperative behavior through anticipating how an interaction partner – human or AI-based – should behave. Recent empirical findings support this view by demonstrating that perceived warmth enhances the acceptance of AI systems as team members, promoting more positive reflections on interactions and increased openness to collaboration (Harris-Watson et al., 2023).

This openness to collaboration with AI-based systems is especially relevant in educational contexts, where productive interactions and trustful relationships between learners and educational technologies are essential. Specifically, in higher education, chatbots are increasingly being deployed as virtual tutors or feedback generators (Essel et al., 2022; Lin et al., 2025). Given that AI has become a firmly established component of academic environments – and will likely remain central to education – it is crucial for universities not only to address associated risks, which evolve rapidly with technological progress, but also to actively equip students with the skills required to successfully navigate and thrive in the AI-supported future job market. In this context, understanding students' mental models of chatbots becomes particularly important: The way learners perceive and conceptualize AI tutors influences their interaction patterns, expectations, and ultimately the educational outcomes derived from these interactions. Therefore, examining and shaping these mental models can support more effective, meaningful, and productive integration of chatbot technology into educational practice.

Instead of comparing an older chatbot with a newer version, we specifically investigated whether the perception of the modern chatbot changes when it is described as either more humanlike or more technical. Central to our inquiry was the question of whether the advanced conversational capabilities typical of contemporary AI systems lead to different perceptions and mental models based solely on framing and heuristics. Participants knew the chatbot was artificial. Yet modern agents often mimic human interaction so closely that distinguishing them from humans can be difficult (Mei et al., 2024).

This ambiguity provided a theoretically intriguing context to explore potential conflicts between explicit knowledge of a chatbot's artificiality and heuristic-based processing – commonly articulated as, "if it speaks like a human, I respond as if it were a human". More concretely, we sought to determine whether explicit awareness of interacting with a machine reduces the likelihood of participants applying social heuristics, or whether the specific framing of the chatbot (humanlike vs. technical) influences heuristic application. Furthermore, we considered whether the inherent human need to seek warmth in interactions (Williams & Bargh, 2008) – manifested in questions like, "Who am I interacting with, and is this entity well-intentioned towards me?" – also interacts with heuristic processes.

We conceptualize our experimental manipulations as framing cues that are expected to activate social heuristics. Specifically, the anthropomorphic versus technical description of the chatbot and the presence versus absence of kindness cues should influence how participants apply interpersonal judgment processes to a non-human agent. This process can be summarized as:

framing cues → activation of social heuristics → attribution of interpersonal traits (warmth, benevolence)

Consistent with this pathway, recent evidence shows that attributing "mind" versus "experience" to AI agents differentially shapes trust and advice-taking, underscoring the role of trait inferences in downstream judgments (Colombatto et al., 2025; Jang et al., 2025).

Specifically, we hypothesized that an anthropomorphic description of the chatbot would lead to higher perceived warmth compared to a technical description (H1a). In addition, we expected that cues in the description indicating that the chatbot had a kind personality would lead to higher perceived warmth compared to descriptions that lacked these cues (H1b). Furthermore, we expected that the effect of kindness cues in the chatbot's description would increase the perception of warmth in both the anthropomorphic and the technical descriptions. However, we hypothesized that this effect would be stronger in the anthropomorphic description compared to the technical description (H1c).

Similarly, we expected that an anthropomorphic description of the chatbot would lead to higher perceived benevolence compared to a technical description (H2a). Furthermore, we expected that cues in the chatbot's description indicating a kind personality would lead to a higher perception of benevolence compared to descriptions without such cues (H2b). In addition, we expected an interaction, in that the effect of kindness cues in the chatbot's description would increase the perception of benevolence in both the anthropomorphic and the technical descriptions. We expected this effect to be more pronounced in the anthropomorphic description than in the technical description. (H2c).

Lastly, we hypothesized that cues indicating a kind chatbot personality would function as a central personality trait (H3). We expected that participants would rate the adjective "warmhearted" more positively than other adjectives (H3a). Additionally, we anticipated that participants would consistently choose positive adjectives when presented with opposing adjective pairs describing the personality (H3b).

Methods

The design with all used material, scales with items, manipulation checks, hypotheses, and analyses can be found on https://osf.io/jnrfq/overview.

Participants

The sample consists exclusively of current students. A higher education degree was defined to include a B.Sc./B.A. degree, allowing participants to be enrolled either in a master's program or in a completely different field of study. Additionally, a Prolific screener was used to ensure that only currently enrolled students could access the study. However, these data rely on self-reports and cannot be independently verified.

To ascertain the necessary sample size, we conducted a power analysis using G*Power software (Faul et al., 2009). This analysis indicated that at least 280 participants were required to observe a small to medium effect size (f = 0.25), considering standard significance (α = .05) and power levels ($1 - \beta$ = .95) in psychological studies. Participants were sourced through the Prolific Academic recruitment platform. To accommodate potential exclusions, we initially enlisted approximately 10% additional participants, totaling 308 participants. After applying exclusion criteria, we obtained a final sample of 307 participants. One participant was excluded due to a false declaration of age. Reasons for exclusion included lack of consent to use data, failure to correctly respond to an attention check, technical difficulties, obviously incorrect information, and insufficient survey completion time.

Demographically, the sample included 42.3% female students, 56.4% male students, 1.0% diverse students, and 0.3% who chose not to disclose their gender. The average age was 25 years (SD = 4.32), with ages ranging from 18 to 44. Educational backgrounds varied, with 45.3% holding a university degree, 50.8% possessing a higher education entrance qualification, 3.9% having a secondary school qualification or having completed vocational training; all participants had some educational degree. Participants were compensated approximately €5.98 for their time, with the survey taking an average of 7 min and 3 s to complete. All participants were fluent in German and resided in Germany during the survey period. The percentage of native speakers was 82.7%, and 17.3% of participants had been speaking German for more than two years. The study was executed online using EFS Survey, and all instructions and questionnaires were presented in German.

Design and Materials

The research employed a 2 × 2 factorial design, with independent variables including the type of language used to describe the chatbot (anthropomorphic vs. technical) and the presence of kindness cues in the chatbot's description (presence vs. absence). For illustration, see Figure 1.

Participants were provided with a description of a prototype chatbot used in a university setting. The manipulation involved varying the description of the chatbot: one group of participants received a description that imbued the chatbot with humanlike qualities, while the other group encountered a description that emphasized the chatbot's technical attributes. For instance, the humanlike description read, "Ellie was specially trained to answer questions about degree programs, organizational processes, and technical content," whereas the technical condition stated, "E.L.L.I.E. was specially modeled to answer questions about degree programs, organizational processes, and technical content." This is just one example; in total, 49 words in the chatbot description (overall 246 words) were varied between the humanlike and technical conditions.

Additionally, the descriptions differed based on whether they included cues that the chatbot had kind personality traits. One group of participants read a description that included kindness cues, such as "Ellie is friendly and is characterized by her empathetic, warm, and trustworthy personality. Her primary goal is to be supportive and to assist users with their concerns effectively and compassionately." The other group was given a description without such kindness cues. We further ensured that the kindness manipulation differed between the anthropomorphic and technical descriptions. We additionally ensured that the kindness manipulation was not confounded with humanness manipulation.

Compare the anthropomorphic and kind condition:

> "*Ellie's responses* are generated based on *inferences*, which rely on *her own assumptions*. She behaves in a *warmhearted and compassionate manner*.",

to the technical and kind condition:

> "*E.L.L.I.E's outputs* are generated by *algorithms*, which rely on *probabilities*. She answers in a *warmhearted and compassionate manner*." The different chatbot descriptions indicate that, despite incorporating personality traits, a technical description was still maintained.

The survey software randomly assigned the participants to the conditions, resulting in 74 people in Condition 1, 75 people in Condition 2, 77 people in Condition 3, and 81 people in Condition 4. Groups did not differ in terms of age (F(2, 303) = 0.36, p = .78), gender (χ^2(9) = 6.46, p = .69), highest educational attainment (χ^2(12) = 8.07, p = .78), current degree course (χ^2(21) = 12.4, p = .93), current semester (χ^2(57) = 39.9, p = .96), and experience with generative AI (χ^2(15) = 12.3, p = .66).

Procedure

Initially, participants read a welcome text and were informed about the study's theme and duration. This was followed by information on voluntary participation, data handling, and data protection. To continue, students had to consent. Subsequently, a page collected demographic data, such as age, gender, native language, current semester, degree program, highest professional qualification, and experience with speech-generating AI.

Participants were then given a brief description of a chatbot prototype intended for academic advising at a university. The text varied depending on participants' randomized assignment to one of four conditions. After that, different scales measured perceived warmth and benevolence. Immediately after that, students could make comments on further points they wanted to mention regarding the use of chatbots in their studies. Upon completion of the

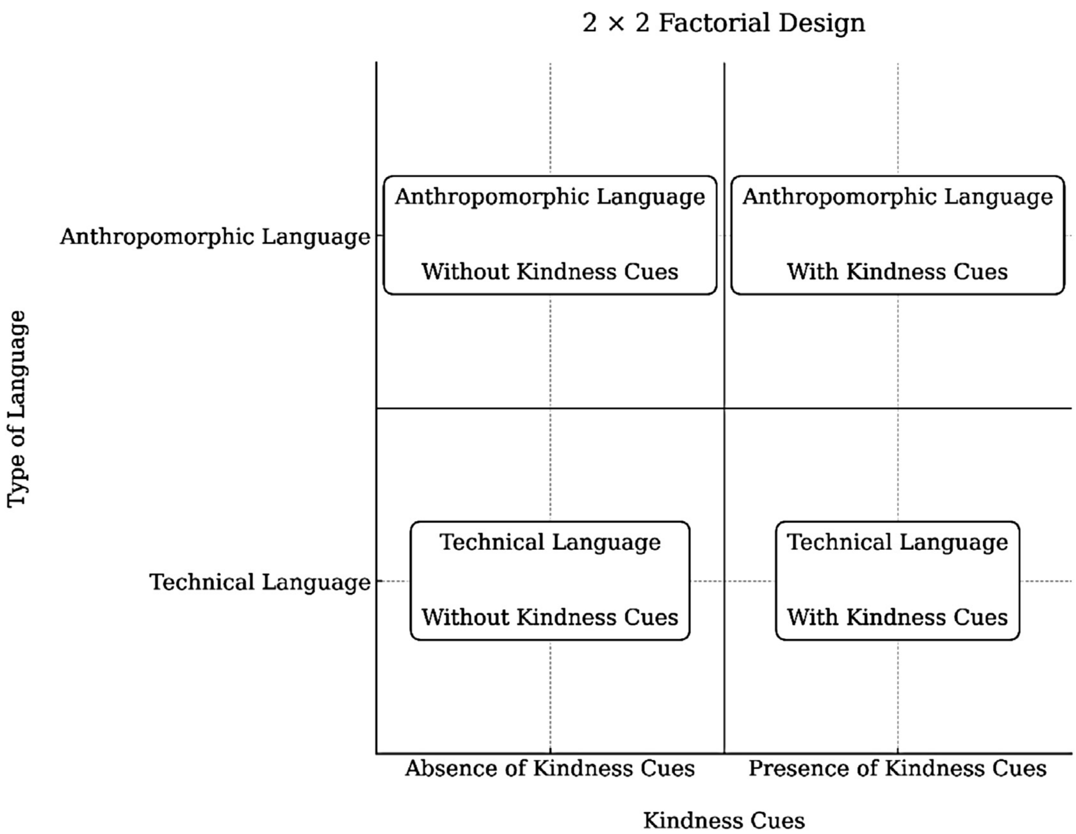


Figure 1. Conceptualization of our study design. Values and interaction effects are not illustrated.

questionnaire, students were debriefed about the study's specific objectives and were compensated with €5.98.

Dependent Measures

Warmth and benevolence are theoretically distinguished in literature. However, some item content overlaps between the scales. It is therefore possible that both measures partly capture the same underlying social-perception factor (see Discussion).

Perceived Warmth

To evaluate perceived warmth, we utilized a scale developed by Fiske et al. (2002) consisting of five items rated on a 7-point Likert scale ranging from exactly the opposite: 7 = *strongly agree*, 1 = *strongly disagree*. Questions probed participants' perceptions of the chatbot's friendliness, benevolence, trustworthiness, warmth, and sincerity in its interactions. Internal consistency was high, with Cronbach's alpha = .85.

Additionally, we assessed warmth as a central personality trait using a ranking scale by Asch (1946), where participants were presented with seven adjectives: intelligent, skillful, industrious, warm, determined, practical, and cautious. Participants indicated the extent to which the chatbot possessed each characteristic. The measurement was carried out on a 7-point Likert scale, with the possible answers ranging from 1 = *does not apply at all* to 7 = *applies completely*. Furthermore, Asch's (1946) trait-pair choice list was used, asking participants to select adjectives that best matched their perceptions of the chatbot on a bipolar 7-point Likert scale, including pairs such as generous vs. ungenerous, shrewd vs. wise, and happy vs. unhappy.

Perceived Benevolence

To measure perceived benevolence, we used the METI (Hendriks et al., 2015). Four items address the anticipation that others hold positive intentions and act kindly on a bipolar 7-point Likert scale. Participants evaluated the chatbot's communication behavior across dimensions such as considerate vs. inconsiderate, ethical vs. unethical, responsible vs. irresponsible, and moral vs. immoral. Internal consistency was acceptable, with Cronbach's alpha = .78.

Results

Manipulation Checks

No participants were excluded from the analysis, as removing participants based on manipulation checks could introduce selection effects, distort effect sizes, and reduce the generalizability of the findings (Kotzian et al., 2020).

Perceived Interlocutor

Of the 307 participants, 250 (81.43%) accurately recalled the type of description (technical vs. anthropomorphic) used for the chatbot, with 150 (60%) recalling the technical description and 100 (40%) recalling the humanlike description. These results indicate that the manipulation (varying the chatbot description) was more effective in the technical group than in the humanlike group.

Perceived Kindness

The data indicate that out of 307 participants, 203 (66%) accurately recalled the type of description (with vs. without kindness cues) used for the chatbot. Among these 203 participants, 135 (67%) were in the kindness-cues condition, and 67 (33%) were in the no-kindness-cues condition. This suggests that participants exposed to kindness cues were more likely to remember the chatbot's description, indicating that kindness cues may enhance recall or attention.

Table 1. Descriptive statistics for the variable perceived warmth

Kindness cues	Description of the Chatbot	*M*	*SD*
Absent	Anthropomorph	4.93	0.75
	Technical	4.78	0.92
Present	Anthropomorph	5.54	0.94
	Technical	5.54	1.06

Table 2. Descriptive statistics for the variable perceived benevolence

Kindness cues	Description of the Chatbot	*M*	*SD*
Absent	Anthropomorph	4.29	0.78
	Technical	4.54	0.91
Present	Anthropomorph	4.89	0.90
	Technical	4.87	0.78

Results Regarding Perceived Warmth (H1)

A two-way ANOVA was conducted to examine the effects of the chatbot's description (anthropomorphic vs. technical) and the presence or non-presence of kindness cues on perceived warmth. For hypothesis 1a, which stated that an anthropomorphic description of the chatbot would lead to higher perceived warmth compared to a technical description, the results did not show a significant main effect, $F(1, 303) = 0.48$, $p = .49$. This indicates that there was no difference in perceived warmth between the anthropomorphic and technical descriptions.

For hypothesis 1b, which proposed that cues indicating a kind personality in the chatbot's description would lead to a stronger perception of warmth compared to when such cues were not provided, the results showed a significant main effect, $F(1, 303) = 41.39$, $p < .001$, $\eta^2 = 0.12$. This means that the presence of kindness cues significantly increased the perceived warmth of the chatbot.

Our interaction hypothesis 1c stated that the effect of the kindness cues in the chatbot's description would result in an even stronger perception of warmth in both the anthropomorphic and technical descriptions, but in the anthropomorphic condition, even stronger. The analysis did not reveal a significant interaction effect, $F(1, 303) = 0.49$, $p = .49$. This indicates that the effect of kindness cues on perceived warmth was consistent across both types of chatbot descriptions. Table 1 shows the descriptive statistics.

Results Regarding Perceived Benevolence (H2)

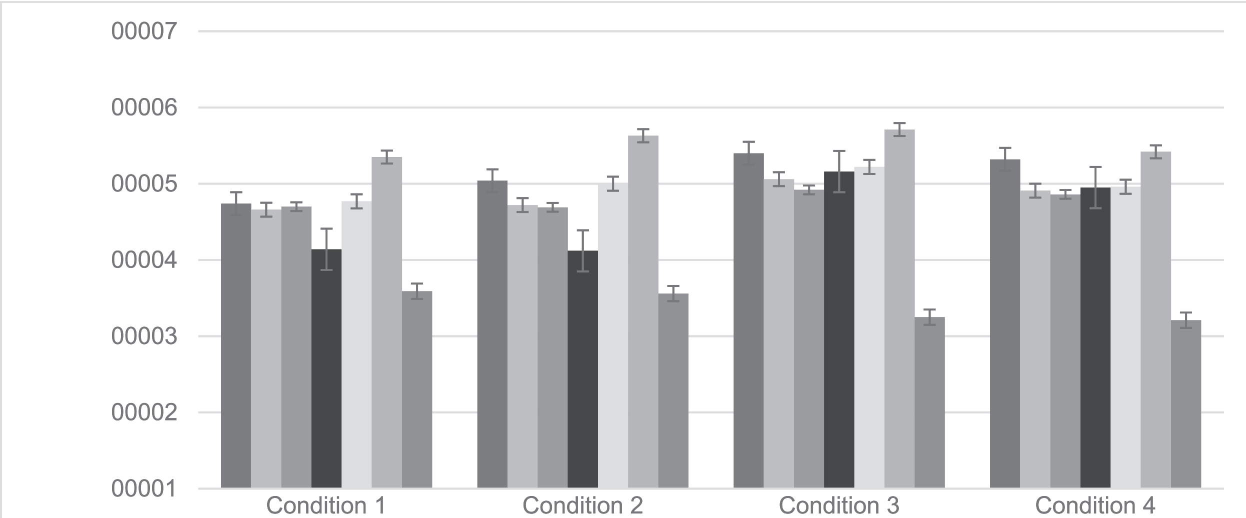
Hypothesis 2a examined whether an anthropomorphic description of the chatbot would lead to higher perceived benevolence compared to a technical description. The results indicated no significant main effect of description type on perceived benevolence, $F(1, 303) = 1.41$, $p = .24$. The anthropomorphic description did not significantly influence participants' perceptions in this regard.

In contrast, hypothesis 2b proposed that including cues of a kind personality in the chatbot's description would enhance the perception of benevolence compared to descriptions without such cues. This hypothesis was supported by the data, revealing a significant main effect of kindness on perceived benevolence, $F(1, 303) = 22.94$, $p < .001$, $\eta^2 = 0.07$. Participants who received descriptions with kindness cues perceived the chatbot as more benevolent.

Hypothesis 2c explored the possibility of an interaction effect between the description type and kindness cues, suggesting that kindness cues might amplify the perception of benevolence in both anthropomorphic and technical descriptions, but in the anthropomorphic condition, even stronger. The analysis did not find a significant interaction effect, $F(1, 303) = 2.01$, $p = .16$. The combination of anthropomorphic descriptions and kindness cues did not produce a stronger effect on perceived benevolence than either factor alone. Table 2 shows the descriptive statistics.

Results Regarding Central Personality Traits Based on Asch's (1946) Classic Experiment: Adjective Ranking (H3a)

We hypothesized that the cues indicating a kind personality would function as a central personality trait, leading participants to rate the adjective "warm" more positively than other adjectives. This hypothesis, however, was rejected, as the adjective "warm" did not receive significantly higher ratings in any condition, as shown in Figure 2. Nonetheless, a clear distinction was observed in the kindness conditions



	Condition 1	Condition 2	Condition 3	Condition 4
intelligent	4.74	5.04	5.40	5.32
skillful	4.66	4.72	5.06	4.91
industrious	4.70	4.69	4.92	4.86
warm	4.14	4.12	5.16	4.95
determined	4.77	5.00	5.22	4.96
practical	5.35	5.63	5.71	5.42
cautious	3.59	3.56	3.25	3.21

Figure 2. Mean values of the adjectives ranking, categorized by conditions. Condition 1 = anthropomorphic + no kindness; Condition 2 = technical + no kindness; Condition 3 = anthropomorphic + kindness; Condition 4 = technical + kindness. N = 307.

(Condition 3 + 4) compared to the no-kindness conditions (Condition 1 + 2), where the presence of kindness cues resulted in higher evaluations, $F(1, 303) = 5.86$, $p < .008$, $\eta^2 = 0.02$. Particularly, the adjective "warm" increased the most from the no-kindness to the kindness condition ($M_{\text{Diff}} = 0.93$, $p < .001$, 95% CI [0.57, 1.29]). This significant difference in mean values was not observed for any other adjective.

Results Regarding Central Personality Traits Based on Asch's (1946) Classic Experiment: Trait-Pair Choice Adjectives (H3b)

Additionally, we hypothesized that participants in the kindness condition (compared to those in the no-kindness condition) would consistently rate the positive adjective higher on bipolar adjective scales describing personality traits (e.g., happy–unhappy). This hypothesis was confirmed, $F(1, 303) = 14.61$, $p < .001$, $\eta^2 = 0.05$. When the chatbot was described as kind, the score increased to the positive pole, independent of whether the chatbot was portrayed in technical or humanlike terms; for visualization, see Figure 3.

Discussion

In our study, we surveyed students on their perceptions of a hypothetical chatbot for academic advising, based on a provided description of the chatbot. We manipulated whether the chatbot was described in a more technical or humanlike manner and with or without cues indicating a kind personality. The aim was to investigate whether students apply human cognitive processes and heuristics (e.g., Schwarz et al., 1991; Topolinski & Strack, 2015) to clearly non-human entities. Of particular interest in this context was the concept of the central personality trait of "warmth" as introduced by Asch (1946). According to Asch (1946), traits such as warmth serve as overarching personality traits in person perception, often overshadowing other attributes. Additionally, we examined the influence of these manipulations on perceived benevolence, which plays a crucial role in the development of epistemic trust (Hendriks et al., 2015).

Our hypotheses were partially supported; however, some of our assumptions did not yield significant results, which contradicts our initial expectations. Contrary to our expectations, we found no significant effect of describing the chatbot's use of humanlike vs. technical language on students' perceptions. There were no main effects on

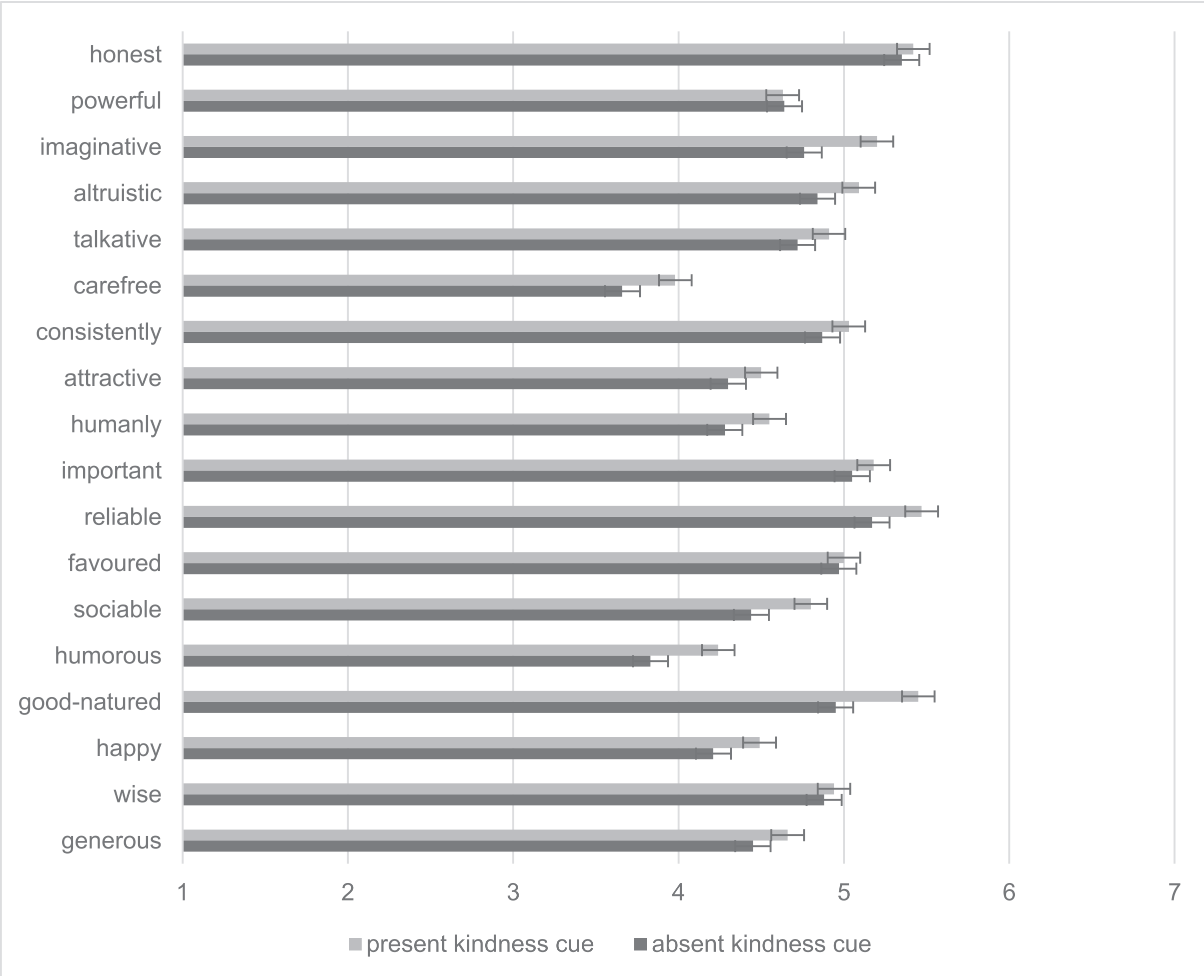


Figure 3. Mean values of the adjective scores, categorized by conditions with vs. without kindness. Error indicators are standard errors. N = 307.

perceived warmth (H1a) or benevolence (H2a). This outcome was surprising, as the literature provides robust evidence that humanized computers and AI systems are typically rated more positively across various dimensions than purely technical ones (e.g., Brummernhenrich et al., 2025; Duffau & Fox Tree, 2024; Holtgraves et al., 2007; Huiyang & Min, 2022; Jucks et al., 2018; Linnemann & Jucks, 2016).

Our findings suggest that while previous research has highlighted the positive perception of humanlike behaviors in chatbots, the present study did not replicate these effects in terms of perceived warmth and benevolence. To put this into context, the results of the studies mentioned above were obtained before large language models were widely accessible to the public, which limits their comparability to the present experiment. The discrepancy indicates that anthropomorphism effects are context-dependent and warrant closer analysis of interactional moderators. This context dependency aligns with findings by Yanit et al. (2023): when AI performs highly hedonic rather than low-hedonic tasks, perceived humanlikeness and warmth decrease, which in turn reduces support for the AI. Our academic advising scenario is clearly utilitarian; as a result, superficial anthropomorphic cues may be less effective, which could explain the absence of main effects.

Hamilton et al. (2024) found that interacting with a device does not automatically activate mental models of natural social interactions. Instead, participants' confidence in their own knowledge varied depending on the degree of humanness conveyed by the device. Those who interacted with a machine-like voice agent reported lower cognitive self-esteem compared to those who engaged with a socially oriented voice agent. This finding suggests that people apply specific interaction scripts for media rather than universally treating technology as social. Moreover, several variables – such as computing experience, digital literacy, and immersion – moderate search-induced cognitive overconfidence, highlighting the complexity of how individuals interact with and evaluate digital agents. Similarly, Guzman (2019) and Horstmann et al. (2021) suggest that voice-based digital agents are complex technologies with multiple "layers" of humanlikeness, further supporting the idea that the perception of humanness, or perceived agency in AI-driven interactions, is multifaceted and influenced by various factors. Konya-Baumbach et al. (2023) also highlight that anthropomorphic design alone does not automatically lead to positive user reactions. Rather, the crucial factor is whether this design also increases the social presence of the chatbot - only then do anthropomorphic features have a positive effect on trust, satisfaction, and intentions.

In contrast, our findings related to kind personality cues in the chatbot description were notably more robust. The results indicate that these cues serve as a central personality trait: When the chatbot was described with kindness cues, its perceived warmth (H1b) and perceived benevolence (H2b) were positively affected. This was evidenced by significant effects on relevant scales and the trait-pair choice task (H3b). Although the analyses of adjective rankings (H3a) were not significant, they also showed a clear tendency toward an influence of kindness cues on perceived warmth.

Lastly, we found no significant interaction effects for the anthropomorphic factor (H2c) or the kind description factor (H1c).

How can these results be explained? First, it is intriguing and important for current research to observe that Asch's (1946) assumption of a central personality trait can also apply to chatbot descriptions. It seems that participants are subconsciously "looking for warmth" in the chatbot. This suggests an inherent tendency to seek familiarity and connection, even when interacting with non-human entities. This might be explained by the fact that in conditions 1 and 2, where no kindness cues were present, the mean values for perceived warmth were still relatively high, albeit lower than in the conditions with the kindness cue (Condition 1: M = 4.93, Condition 2: M = 4.78 on a 7-point Likert scale). It is possible that the mere fact that a chatbot operates through humanlike language unconsciously prompts users to seek warmth in their interactions.

To further investigate this potential phenomenon and to avoid possible priming effects caused by the question format, we aim to pay closer attention to this issue in our future research and assess perceived warmth using an alternative measurement approach.

However, why did the anthropomorphizing description factor yield no significant results? This outcome is noteworthy from several perspectives, especially regarding the manipulation of chatbot descriptions. The anthropomorphizing manipulation occupied significantly more space in the description than the kindness manipulation. The kindness manipulation consisted of approximately 38 (15%) (kind + anthropomorphic condition) and 36 (14%) (kind + technical condition words, while the anthropomorphizing manipulation included 49 (19%) words in both conditions, with an average text length of 246 words. Additionally, the no-kindness condition was already relatively personalized, which might have reduced the impact of manipulation. Participants likely recognized that a chatbot is not human and relies on algorithms. Despite this awareness, participants still seemed to seek warmth. This paradox merits further study.

Descriptive data showed that students cared less about a chatbot having a name or being anthropomorphic (M = 3.35) than about using polite phrases when interacting with it (M = 4.80), suggesting that cognitive heuristics may operate implicitly despite low explicit relevance – similar to findings by Kim and Sundar (2012).

In discussing benevolence, similar assumptions can be made as with perceived warmth. The similarity of the results may be attributable to the high correlation between the two dependent variables (r = .51, p < .001). This is further discussed in the next chapter.

Limitations

The present study demonstrated a significant effect on the perceived warmth and benevolence of a chatbot. However, the generalizability of the findings is limited, as the sample consisted exclusively of university students, potentially introducing an education-specific bias.

Another methodological consideration concerns the lack of cultural contextualization. While it was not the aim of the study to systematically examine sociocultural differences, existing research indicates that perceptions of warmth and benevolence vary considerably between individualistic and collectivistic cultures (Liu et al., 2021). Cultural background factors could thus exert a moderating influence on how personality attributions in chatbots are processed. Future studies should therefore explicitly account for cultural variables and prior experience with AI systems in their research designs.

A further central theoretical limitation lies in the conceptual overlap between *warmth* and *benevolence*. Although both constructs are sometimes treated as distinct in the literature, they share core semantic and functional elements (Brambilla & Leach, 2014; Fiske et al., 2002; Hendriks et al., 2015; Leach et al., 2007). *Warmth* typically encompasses social attributes such as friendliness, empathy, and care, whereas *benevolence* is more normatively and morally connoted, emphasizing goodwill and trustworthiness. Despite these definitional nuances, there is currently no strong empirical evidence supporting a clear separation between the two – especially not from the perspective of lay users in everyday interactions (e.g., Goodwin et al., 2014; Harris-Watson et al., 2023).

This conceptual proximity leads to several methodological challenges. First, without clear discriminant validity, it is unclear which construct drives observed effects, limiting internal validity. Second, there is a risk of redundant operationalization, where seemingly different scales tap the same underlying dimension. Third, method artifacts can make scale differences look theoretically meaningful when they are not. Fourth, replicability suffers if subsequent studies rely on theoretically different but empirically indistinguishable constructs (Bringmann et al., 2022; Flake & Fried, 2020; Podsakoff et al., 2003).

Against this backdrop, it appears both theoretically and methodologically advisable for future research to focus exclusively on *warmth* as the primary construct. *Warmth* is not only more broadly theorized, but also supported by a well-established empirical measurement tradition (Asch, 1946; Fiske et al., 2002, 2007; Williams & Bargh, 2008). This strengthens theoretical coherence and enhances the comparability and cumulative potential of subsequent studies.

Nonetheless, our results consistently point to a robust effect of *warmth* on participants' perceptions of the chatbot – supporting Asch's (1946) notion that warmth represents a central dimension of social cognition (Fiske et al., 2007). This was evident not only in the ratings on the scale but also in the outcomes of both the ranking task and the trait-per-choice paradigm.

Implications and Future Directions

The initial question of whether an AI can be perceived as "warm", and, if so, how, can be partially answered based on the present findings. Our results demonstrate that students are indeed capable of perceiving a chatbot as warm – even when no real interaction takes place and the framing is provided solely through textual description. This suggests that people's tendency to anthropomorphize may operate largely at an implicit level, with halo effects emerging through heuristic processing.

Practically, this insight has relevance for educational settings, where chatbots are increasingly deployed as virtual tutors. Understanding how students' mental models influence their willingness to engage, trust, and collaborate with AI systems can inform the design of more effective educational technologies. Moreover, the finding that subtle kindness cues can significantly shape perceptions underscores the importance of intentional language design in AI communication (Hamilton et al., 2024).

The literature provides numerous indications that, generally speaking, a "humanized" communication style is often more effective than a technical one. Our findings suggest an important theoretical insight: perceptions of warmth and benevolence can emerge even in purely hypothetical interactions. Extending Asch's (1946) framework on warmth perception to modern AI systems underscores a critical dimension for future work: when evaluating anthropomorphic cues, researchers must account for the shifting baseline expectations that participants bring to the interaction. Moreover, it is needed to examine in detail how even subtle design differences influence heuristic processing. Crucially, the pre-interaction description of a chatbot may exert the same effects as the interaction itself: labels, role titles, and introductory text establish the initial mental model and shape selection, trust calibration, and goal inference before any message is exchanged. In higher education, where students choose whether to consult a "course assistant", a "tutor", or an "experimental tool", such framing can alter uptake, adherence to guidance, and perceptions of legitimacy and academic integrity. In short, description is not mere packaging – it is part of the intervention.

In conclusion, it appears that humans transfer this psychological phenomenon to interactions with non-human entities. This raises the question: from a human perspective, how much "humanity" is embedded in such a system? From a technical point of view, the answer is simple: it is a matter of data and programming. But on closer examination, the question remains – can an AI genuinely convey warmth, or are we merely seeing what we wish to perceive?

References

Asch, S. E. (1946). Forming impressions of personality. *The Journal of Abnormal and Social Psychology, 41*(3), 258–290. https://doi.org/10.1037/h0055756

Baig, M. I., & Yadegaridehkordi, E. (2024). ChatGPT in the higher education: A systematic literature review and research challenges. *International Journal of Educational Research, 127*, Article 102411. https://doi.org/10.1016/j.ijer.2024.102411

Blau, P. M. (1964). *Exchange and Power in Social Life*. Wiley.

Brambilla, M., & Leach, C. W. (2014). On the importance of being moral: The distinctive role of morality in social judgment. *Social Cognition, 32*(4), 397–408. https://doi.org/10.1521/soco.2014.32.4.397

Bringmann, L. F., Elmer, T., & Eronen, M. I. (2022). Back to basics: The importance of conceptual clarification in psychological science. *Current Directions in Psychological Science, 31*(4), 340–346. https://doi.org/10.1177/09637214221096485

Brummernhenrich, B., Paulus, C. L., & Jucks, R. (2025). Applying social cognition to feedback chatbots: Enhancing trustworthiness through politeness. *British Journal of Educational Technology*, bjet.13569. https://doi.org/10.1111/bjet.13569

Cai, N., Gao, S., & Yan, J. (2024). How the communication style of chatbots influences consumers' satisfaction, trust, and engagement in the context of service failure. *Humanities and Social Sciences Communications, 11*(2), Article 687. https://doi.org/10.1057/s41599-024-03212-0

Chen, J., Guo, F., Ren, Z., Li, M., & Ham, J. (2024). Effects of anthropomorphic design cues of chatbots on users' perception and visual behaviors. *International Journal of Human–Computer Interaction, 40*(14), 3636–3654. https://doi.org/10.1080/10447318.2023.2193514

Chi, R., Zhang, J., & Pan, M. (2024). The effect of anthropomorphic competence-warmth congruence of service robots on recommendation intention. *Current Psychology, 43*(7), 6570–6583. https://doi.org/10.1007/s12144-023-04825-5

Colombatto, C., Birch, J., & Fleming, S. M. (2025). The influence of mental state attributions on trust in large language models. *Communications Psychology, 3*(1), Article 84. https://doi.org/10.1038/s44271-025-00262-1

Debets, T., Banihashem, S. K., Joosten-Ten Brinke, D., Vos, T. E. J., Maillette de Buy Wenniger, G., & Camp, G. (2025). Chatbots in education: A systematic review of objectives, underlying technology and theory, evaluation criteria, and impacts. *Computers & Education, 234*, Article 105323. https://doi.org/10.1016/j.compedu.2025.105323

Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. *Computers & Education, 227*, Article 105224. https://doi.org/10.1016/j.compedu.2024.105224

Díaz, B., & Nussbaum, M. (2024). Artificial intelligence for teaching and learning in schools: The need for pedagogical intelligence. *Computers & Education, 217*, Article 105071. https://doi.org/10.1016/j.compedu.2024.105071

Duffau, E., & Fox Tree, J. E. (2024). Expecting politeness: Perceptions of voice assistant politeness. *Personal and Ubiquitous Computing, 28*(6), 907–929. https://doi.org/10.1007/s00779-024-01822-8

Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education, 19*(1), Article 57. https://doi.org/10.1186/s41239-022-00362-6

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fiske, S. T., Cuddy, A. J. C., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences, 11*(2), 77–83. https://doi.org/10.1016/j.tics.2006.11.005

Fiske, S. T., Cuddy, A. J. C., Glick, P., & Xu, J. (2002). A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of Personality and Social Psychology, 82*(6), 878–902. https://doi.org/10.1037/0022-3514.82.6.878

Flake, J. K., & Fried, E. I. (2020). Measurement schmeasurement: Questionable measurement practices and how to avoid them. *Advances in Methods and Practices in Psychological Science, 3*(4), 456–465. https://doi.org/10.1177/2515245920952393

Goodwin, G. P., Piazza, J., & Rozin, P. (2014). Moral character predominates in person perception and evaluation. *Journal of Personality and Social Psychology, 106*(1), 148–168. https://doi.org/10.1037/a0034726

Gruenhagen, J. H., Sinclair, P. M., Carroll, J.-A., Baker, P. R. A., Wilson, A., & Demant, D. (2024). The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. *Computers and Education: Artificial Intelligence, 7*, Article 100273. https://doi.org/10.1016/j.caeai.2024.100273

Guzman, A. L. (2019). Voices in and of the machine: Source orientation toward mobile virtual assistants. *Computers in Human Behavior, 90*, 343–350. https://doi.org/10.1016/j.chb.2018.08.009

Hamilton, K. A., Ward, A. F., & Yao, M. Z. (2024). Mind or machine? Conversational internet search moderates search-induced cognitive overconfidence. *Journal of Media Psychology*, 1864–1105. https://doi.org/10.1027/1864-1105/a000419

Harris-Watson, A. M., Larson, L. E., Lauharatanahirun, N., DeChurch, L. A., & Contractor, N. S. (2023). Social perception in human-AI teams: Warmth and competence predict receptivity to AI teammates. *Computers in Human Behavior, 145*, Article 107765. https://doi.org/10.1016/j.chb.2023.107765

Hendriks, F., Kienhues, D., & Bromme, R. (2015). Measuring laypeople's trust in experts in a digital age: The muenster epistemic trustworthiness inventory (METI). *PLoS One, 10*(10), Article e0139309. https://doi.org/10.1371/journal.pone.0139309

Hernandez, I., & Chekili, A. (2024). The silicon service spectrum: Warmth and competence explain people's preferences for AI assistants. *Frontiers in Social Psychology, 2*, Article 1396533. https://doi.org/10.3389/frsps.2024.1396533

Holtgraves, T. M., Ross, S. J., Weywadt, C. R., & Han, T. L. (2007). Perceiving artificial social agents. *Computers in Human Behavior, 23*(5), 2163–2174. https://doi.org/10.1016/j.chb.2006.02.017

Horstmann, A. C., Gratch, J., & Krämer, N. C. (2021). I just wanna blame somebody, not something! reactions to a computer agent giving negative feedback based on the instructions of a person. *International Journal of Human-Computer Studies, 154*, Article 102683. https://doi.org/10.1016/j.ijhcs.2021.102683

Horstmann, A. C., & Krämer, N. C. (2022). The fundamental attribution error in human-robot interaction: An experimental investigation on attributing responsibility to a social robot for its pre-programmed behavior. *International Journal of Social Robotics, 14*(5), 1137–1153. https://doi.org/10.1007/s12369-021-00856-9

Huiyang, S., & Min, W. (2022). Improving interaction experience through lexical convergence: The prosocial effect of lexical alignment in human-human and human-computer interactions. *International Journal of Human–Computer Interaction, 38*(1), 28–41. https://doi.org/10.1080/10447318.2021.1921367

Jang, J., Yang, S., & Kim, H. (2025). Simulating conversations with nature: The effects of an environment-anthropomorphic chatbot on climate attitudes and intentions. *Energy & Environment*, Article 0958305X251343056. https://doi.org/10.1177/0958305X251343056

Janssen, I., Hendriks, F., & Jucks, R. (2021). Face masks might protect you from COVID-19: The communication of scientific uncertainty by scientists versus politicians in the context of policy in the making. *Journal of Language and Social Psychology, 40*(5–6), 602–626. https://doi.org/10.1177/0261927X211044512

Jia, X., Zhao, X., Tao, W., & Ahn, S. (2024). From exclusion to connection: The role of anthropomorphic Chatbots in shaping customer responses post-social exclusion. *Journal of Internet Commerce, 23*(3), 205–232. https://doi.org/10.1080/15332861.2024.2375965

Jucks, R., Linnemann, G. A., & Brummernhenrich, B. (2018). Student evaluations of a (rude) spoken dialogue system insights from an experimental study. *Advances in Human-Computer Interaction, 2018*, 1–10. https://doi.org/10.1155/2018/8406187

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., . . . Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kim, J. (2010). Balancing uniqueness and assimilation in computer-mediated groups. *Computers in Human Behavior, 26*(4), 778–784. https://doi.org/10.1016/j.chb.2010.02.001

Kim, Y., & Sundar, S. S. (2012). Anthropomorphism of computers: Is it mindful or mindless? *Computers in Human Behavior, 28*(1), 241–250. https://doi.org/10.1016/j.chb.2011.09.006

Konya-Baumbach, E., Biller, M., & Von Janda, S. (2023). Someone out there? A study on the social presence of anthropomorphized chatbots. *Computers in Human Behavior, 139*, Article 107513. https://doi.org/10.1016/j.chb.2022.107513

Kotzian, P., Stoeber, T., Hoos, F., & Weissenberger, B. E. (2020). To be or not to be in the sample? On using manipulation checks in experimental accounting research. *Accounting Research Journal, 33*(3), 469–482. https://doi.org/10.1108/ARJ-06-2019-0128

Leach, C. W., Ellemers, N., & Barreto, M. (2007). Group virtue: The importance of morality (vs. competence and sociability) in the positive evaluation of in-groups. *Journal of Personality and Social Psychology, 93*(2), 234–249. https://doi.org/10.1037/0022-3514.93.2.234

Lin, J., Han, Z., Thomas, D. R., Gurung, A., Gupta, S., Aleven, V., & Koedinger, K. R. (2025). How can i get it right? Using GPT to rephrase incorrect trainee responses. *International Journal of Artificial Intelligence in Education, 35*(2), 482–508. https://doi.org/10.1007/s40593-024-00408-y

Linnemann, G. A., & Jucks, R. (2016). As in the question, so in the answer? Language style of human and machine speakers affects interlocutors' convergence on wordings. *Journal of Language and Social Psychology, 35*(6), 686–697. https://doi.org/10.1177/0261927X15625444

Linnemann, G. A., & Jucks, R. (2018). 'Can i trust the spoken dialogue system because it uses the same words as i do?' – Influence of lexically aligned spoken dialogue systems on trustworthiness and user satisfaction. *Interacting with Computers, 30*(3), 173–186. https://doi.org/10.1093/iwc/iwy005

Liu, J. (2024). ChatGPT: Perspectives from human–computer interaction and psychology. *Frontiers in Artificial Intelligence*, *7. https://doi.org/10.3389/frai.2024.1418869*

Liu, S. S., Shteynberg, G., Morris, M. W., Yang, Q., & Galinsky, A. D. (2021). How does collectivism affect social interactions? A test of two competing accounts. *Personality and Social Psychology Bulletin, 47*(3), 362–376. https://doi.org/10.1177/0146167220923230

McKee, K. R., Bai, X., & Fiske, S. T. (2023). Humans perceive warmth and competence in artificial intelligence. *iScience, 26*(8), Article 107256. https://doi.org/10.1016/j.isci.2023.107256

Mei, Q., Xie, Y., Yuan, W., & Jackson, M. O. (2024). A Turing test of whether AI chatbots are behaviorally similar to humans. *Proceedings of the National Academy of Sciences, 121*(9), Article e2313925121. https://doi.org/10.1073/pnas.2313925121

Nicolas, S., & Agnieszka, W. (2021). The personality of anthropomorphism: How the need for cognition and the need for closure define attitudes and anthropomorphic attributions toward robots. *Computers in Human Behavior, 122*, Article 106841. https://doi.org/10.1016/j.chb.2021.106841

Ordemann, S., Skjuve, M., Følstad, A., & Cato Alexander, B. (2021). Understanding how chatbots work: An exploratory study of mental models in customer service chatbots. *IADIS International Journal on WWW/INTERNET*, *19*(1). https://doi.org/10.33965/ijwi_202119102

Plagge, E., & Jucks, R. (2025, January 13). *Just like a human? An experimental study on University students' perceptions on chatbots* [Data, Materials]. https://doi.org/10.17605/OSF.IO/K46MF

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *The Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Polyportis, A., & Pahos, N. (2024). Understanding students' adoption of the ChatGPT chatbot in higher education: The role of anthropomorphism, trust, design novelty and institutional policy. *Behavior & Information Technology*, 1–22. https://doi.org/10.1080/0144929X.2024.2317364

Salah, M., Alhalbusi, H., Ismail, M. M., & Abdelfattah, F. (2024). Chatting with ChatGPT: Decoding the mind of Chatbot users and unveiling the intricate connections between user perception, trust and stereotype perception on self-esteem and psychological well-being. *Current Psychology, 43*(9), 7843–7858. https://doi.org/10.1007/s12144-023-04989-0

Schwarz, N., Bless, H., Strack, F., Klumpp, G., Rittenauer-Schatka, H., & Simons, A. (1991). Ease of retrieval as information: Another look at the availability heuristic. *Journal of Personality and Social Psychology, 61*(2), 195–202. https://doi.org/10.1037/0022-3514.61.2.195

Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. M. J. Metzger & A. J. Flanagin (Eds.), *Digital, Media, Youth, and Credibility* (pp. 72–100). https://doi.org/10.1162/dmal.9780262562324.073

Topolinski, S., & Strack, F. (2015). Heuristics in social cognition. In J. Wright (Ed.), *International Encyclopedia of the Social & Behavioral Sciences* (pp. 825–828). Elsevier.

Wang, B., Shibo, B. W., & Kafle, J. (2025). When ChatGPT speaks about health: Examining perceptions of warmth and competence toward AI as a health information source. *Journal of Health Communication, 0*, 1–11. https://doi.org/10.1080/10810730.2025.2540864

Wang, X., Wang, X., Park, S., & Yao, Y. (2025). Users' mental models of generative AI Chatbot ecosystems. *Proceedings of the 30th International Conference on Intelligent User Interfaces* (pp. 1016–1031). https://doi.org/10.1145/3708359.3712125

Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human? The stability and importance of individual differences in anthropomorphism. *Perspectives on Psychological Science, 5*(3), 219–232. https://doi.org/10.1177/1745691610369336

Williams, L. E., & Bargh, J. A. (2008). Experiencing physical warmth promotes interpersonal warmth. *Science, 322*(5901), 606–607. https://doi.org/10.1126/science.1162548

Yanit, M., Yanit, M., & Wan, F. (2023). Right agent, wrong level of hedonism: How high (vs low) hedonic values in AI-performed tasks lead to decreased perceptions of humanlikeness, warmth, and less consumer support. *Computers in Human Behavior, 147*, Article 107870. https://doi.org/10.1016/j.chb.2023.107870

History
Received January 6, 2025
Revision received August 22, 2025
Accepted September 8, 2025
Published online November 19, 2025

Acknowledgments
The authors are thankful to Celeste Brennecka for language editing.

Conflict of Interest
The authors have no relevant financial or non-financial interests to disclose.

Publication Ethics
This research was conducted in accordance with the guidelines of the ethics review board of the University of Münster Department of Psychology and Sports Sciences. No personally identifiable information was collected from the study participants.
Statement: "I hereby confirm that the Ethics Committee has no ethical objections to the above-mentioned project. The listed

revision notes were taken into account in a revised version of the ethics application, and this was sent back to the EC for review. The revised version of the application is decisive for the vote."

Authorship

Eileen Plagge, data collection, data analysis, manuscript–writing; Regina Jucks, Eileen Plagge manuscript – additional revisions, study conception, design, and preparation of study materials, final manuscript – reading and approval.

Open Science

The authors are willing to share their data, analytics methods, and study materials with other researchers. The material is available at a repository.

- Open Data: All analysis scripts and data are available on OSF: https://osf.io/jnrfq/ (Plagge & Jucks, 2025).
- Open Materials: All materials are available on OSF: https://osf.io/jnrfq/ (Plagge & Jucks, 2025).
- Preregistration: Due to a misunderstanding, the study was uploaded to OSF as a project prior to data collection, but was not formally preregistered.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript. Open access publication enabled by the University of Münster, Germany.

ORCID

Eileen Plagge
https://orcid.org/0009-0001-4769-7154
Regina Jucks
https://orcid.org/0000-0002-3980-4327

Eileen Plagge
Institute of Psychology for Education
University of Münster
Fliednerstraße 21
48149 Münster
Germany
eileen.plagge@uni-muenster.de

Eileen Plagge is a PhD student in Psychology at the University of Münster, Germany, researching communication and interaction with chatbots in higher education, with a focus on social psychological phenomena in the use of generative AI.

Regina Jucks has been a professor at the Institute of Psychology in Education and Instruction at the University of Münster since 2009, as well as being the director of the Centre for Higher Education. Her research focuses on communication, mediation and trust in digital educational settings.