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Published online: 23 May 2023.

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Weizi Liu ⓘ, Kun Xu ⓘ, and Mike Z. Yao

ABSTRACT

Chatbots provide functional and social support in various contexts. They are often designed with humanlike features. This study examines how chatbots' assigned names (humanlike vs. neutral vs. machinelike) and communication contexts (functional vs. social) influence users' willingness to disclose personal information. We conducted a 3×2 "between-subjects" online experiment with random assignments of 299 participants. The results showed that a functional communication context elicited greater participants' willingness to disclose information, but the impact of chatbot names was not significant. These findings provide an extended understanding of the Computers Are Social Actors paradigm and may inspire the exploration of conditional effects in privacy research. The practical implications for context-aware designs are discussed.

Introduction

Chatbots are computer programs that interact with users using natural language (Miner et al., 2016). They are pervasive and versatile personal confidants in various contexts, including e-commerce, healthcare, and education (Følstad & Brandtzæg, 2017). As information exchange between humans and machines is becoming more seamless, natural, and akin to interpersonal communication compared with conventional computer interfaces (Guzman & Lewis, 2020), chatbots that prompt and collect user information to provide personalized services make privacy concerns and information disclosure prominent issues (Ischen et al., 2019). Moreover, humanlike design features (e.g., human names, gender, voices) embedded in chatbots mimic human communicators, making human-chatbot interaction increasingly social and interpersonal (Xu & Liao, 2020). Scholars are concerned with how such design features and the application contexts of machines alter human-machine dynamics, resulting in different user perceptions and responses (Araujo, 2018; Waytz et al., 2014). There is a crucial agenda on issues surrounding transparent artificial intelligence (AI),

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user trust, and privacy decision-making in human-machine communication (HMC) (Lankton et al., 2015).

Self-disclosure, defined as the act of revealing personal information, thoughts, or feelings to others (Altman & Taylor, 1973), was originally studied in interpersonal communication for relational goals. In technology-mediated environments, users may disclose personal information to systems and devices in exchange for services, such as transactions and personalization (e.g., Dinev & Hart, 2006; Metzger, 2006). Existing studies in HMC have examined privacy concerns and trust-related attitudes in response to certain chatbot designs (Ischen et al., 2019; Waytz et al., 2014); however, few have focused on information disclosure, particularly across aforementioned application contexts (e.g., e-commerce, healthcare, etc.). In this study, we explore how chatbot names, a common design feature of the technology, and communication contexts might affect user self-disclosure.

Effects of naming conventions in HMC

The Computers Are Social Actors (CASA) paradigm posits an automatic tendency for humans to respond to computers socially (Nass et al., 1994). It suggests that certain humanlike technological features, sometimes referred to as social cues (e.g., human names, voices, personas, and gestures) can trigger social responses beyond functional human-computer interactions. Social cues embedded in machine interfaces can remind users of interpersonal communications, leading them to apply interpersonal norms to HMC (Nass & Moon, 2000). Recent research has provided updated explanations of technology users' responses to social cues, emphasizing unique human-media social scripts (Gambino et al., 2020). Name is a commonly found social cue in AI product design. Naming involves "key elements of identification and personhood." (Palsson, 2014, p. 618). Psychology research suggests that names significantly affect people's evaluations of intelligence, popularity, and competence (Young et al., 1993). When naming products, technology companies often provide detailed reasons and background stories to instill social meanings and brand values. For example, Amazon's agent "Alexa" was inspired by the Library of Alexandria as a symbol of knowledge (Ard, 2021); Google chose a more generic name ("Google assistant") because they "think of this as building each user their own individual Google" (Statt, 2016); some names such as "iRobot Roomba" are more machinelike. With a particular interest in name labels, this study considered a ground-up approach to selectively examine how humanlike, neutral, and machinelike names signal different social identities and influence disclosure as an important type of social response in HMC.

Based on the CASA framework, researchers have tested the effects of labeling (e.g., color, nationality, and location) of a computer agent on users' social categorization (Eyssel & Kuchenbrandt, 2012; Reeves & Nass, 2002; Xu &

Lombard, 2017). They found that sharing the same cues with an agent led to users' group identification with the agent, more favorability, and greater anthropomorphism. Other research has examined how a chatbot's visual, identity, and conversational cues impact user disclosure (Ischen et al., 2019; Y. Kim & Sundar, 2012). Ischen et al. (2019) found that a chatbot with a human name, cartoon image, and casual language led to users' lower privacy concerns about information disclosure than those without these features. Following the CASA paradigm and based on findings from previous empirical studies, we hypothesize that a chatbot with a human name could induce more favorable responses from users, which includes more information disclosure than other naming options.

H1: The chatbot's humanlike name may elicit stronger user willingness to disclose personal information than a neutral or machinelike name.

Effects of communication contexts in HMC

Communication is context-based, while privacy is context-dependent (Acquisti et al., 2015). From a system design perspective, the theory of Contextual Integrity (Nissenbaum, 2004) discusses the privacy expectations and norms of information flows in specific contexts. Although privacy is a universal human need, privacy norms are not universal; one can feel comfortable sharing something in one context while considering the same information private in another. Situational factors heavily influence individual privacy management and self-disclosure (Masur, 2019). People's privacy preferences and decisions vary according to the context and type of conversation (Acquisti et al., 2015). Much research on HMC has investigated the effects of social cues in a particular scenario (Waytz et al., 2014; Y. Kim & Sundar, 2012); however, less is known about whether these effects may change in other contexts. The CASA paradigm discusses the tendencies of users' social responses; however, it offers a framework for users' social responses without distinguishing specific contexts.

By applying the notion of Contextual Integrity, we emphasize the effects of context in human-machine communication. The existing literature has focused on two general categories of contexts in human-chatbot interactions: functional-utilitarian and social-emotional (Brandtzaeg & Følstad, 2017; Yang & Lee, 2019). In these categories, chatbots are respectively designed for informational support (e.g., Brixey et al., 2017) and socio-emotional support (e.g., Y. C. Lee et al., 2020). While research on contextual differences in HMC has not been sufficiently systematic, existing studies offer hints. In interpersonal communication, Rhodes and Geller (1992) found that clients may open up more easily with researchers than with their therapists because the former relational context is more

professional and less intimate. In HMC, Cho et al. (2019) found that in a utilitarian context, participants perceived voice interaction as more efficient and evaluated VAs more positively than in a hedonic context. Sundar and Kim's (2019) research on machine heuristic suggested that users were more likely to disclose credit card information to a machine than to a human agent for flight reservations, emphasizing the reasoning for participants' faith in a machine's expertise and utilitarian nature. A more recent study suggested that users prefer functional AI (primarily for completing tasks) over social AI (primarily as a social companion) because functional AI is perceived as more useful (J. Kim et al., 2021). These findings indicate that people may be overall more accustomed to interacting with chatbots in functional contexts and may feel more comfortable with chatbots in functional roles. Therefore, we propose the following hypothesis:

H2: A chatbot designed for a functional context will elicit users' stronger willingness to disclose personal information than one designed for a social context.

Furthermore, we wonder whether different contexts could potentially alter the effects of social cues. As Darling (2015) suggested, some robots are designed to appear less social to be less threatening, whereas others are more desirable when they have more social characteristics. Moreover, Calo (2009) suggested that humanlike machines can trigger more user engagement, but they can also hinder intimate disclosures under certain circumstances. Therefore, a chatbot's label may differently affect disclosures according to the context. We speculate a context congruity issue: a chatbot with a humanlike name in a social context may increase disclosure willingness as supported by CASA; a machinelike name in a functional context may also increase disclosure willingness as supported by machine heuristics. When the name and the context are mismatched, the willingness to self-disclose decreases. Therefore, we raise the following exploratory research question:

RQ: Will the names of a chatbot interact with the communication context in affecting users' willingness to disclose personal information?

Method

Participants

With IRB approval, 381 adult participants were recruited from Amazon Mechanical Turk. Excluding 82 participants who failed the attention check,

the final sample size was 299 (198 males and 101 females). The participants' ages ranged from 21 to 65 years ($M = 34.6$, $SD = 9.38$). Informed consent was obtained from all participants.

Experiment design and procedures

The online experiment adopted a 3 (chatbot name) × 2 (communication context) between-subjects design. Participants were randomly assigned to one of six conditions. We manipulated the names and introductions of the chatbot and maintained the same aesthetic design and dialogue across the conditions. Based on the naming conventions in industry (e.g., "Alexa," "Google Assistant," "iRobot"), we manipulated the chatbot's names in the three conditions as (a) "Sam" – a unisex humanlike name ($n = 137$); (b) "Assistant No.1" – a generic name without explicit human or machine name cues ($n = 116$); (c) "Chatbot" – a machinelike name ($n = 128$). While "Sam" is more often used as a human name and "Chatbot" is a machine name, the name "assistant" does not inherently imply a specific entity. It only suggests the function or purpose of providing assistance, regardless of whether it is performed by a human, a machine, or a combination of both. These names consistently and repeatedly appeared in the instructions and the conversation scripts given to the participants. Communication contexts were manipulated by informing participants of the different design purposes. In the functional context, the chatbot was introduced to provide professional health advice. In the social context, the chatbot was introduced to provide companionship and social support.

Participants were told that the research team was developing a chatbot and invited to evaluate the user interface. They first read a screenshot of a sample conversation between a chatbot and a human user (see Figure A1). "The chatbot greeted the user and briefly introduced itself." After reading the conversation, participants were asked how willing they were to disclose their personal information if the chatbot needed it for a personalized service. The respondents indicated their willingness to disclose information by responding to a list of queries. The questionnaire also included an attention check question that asked participants to recall the name of the bot ("Sam," "Assistant No.1," "Chatbot," or "do not remember").

Dependent measures

To measure participants' willingness to disclose personal information to the chatbot, 20 items of personal information (e.g., age, address, height/weight, mental status, and personal life) were adapted from previous research on self-disclosure and online privacy (Joinson et al., 2008; Nass & Moon, 2000). Participants reported their willingness to disclose each item on an 11-point

scale (0 = extremely unwilling, 10 = extremely willing). They were asked, "Please indicate how willing you are to share this information (e.g., age) with Sam." Responses were added and averaged to form an index of their willingness to disclose ($M = 6.20$, $SD = 1.99$, $\alpha = .95$).

We also included perceived anthropomorphism of the chatbot with a five-item bi-polar scale (Ho & MacDorman, 2010) as an additional measure aside from the main analysis. The items were rated on a 11-point scale (e.g., 0 = Machinelike to 10 = Humanlike). The items were averaged into a composite score ($\alpha = .93$, $M = 6.35$, $SD = 2.24$).

Results

After verifying the statistical assumptions, a two-way ANCOVA was conducted to test the main and interaction effects of names and communication contexts on users' willingness to disclose information. As previous studies suggested that gender and age differences exist when people make privacy-related decisions (Kezer et al., 2016; Tifferet, 2019), we controlled participants' gender and age. The results revealed that there was no significant difference in willingness to disclose information among the three conditions (F [2, 291] = 0.08, $MSE = 0.31$, $p = .93$, $\eta^2 = .001$). Therefore, $H1$ was not supported. However, there was a significant difference in the willingness to disclose information between the two contexts (F [1, 291] = 6.08, $MSE = 23.95$, $p = .014$, $\eta^2 = .02$). The mean score for willingness to disclose information in the social context ($M = 5.91$, $SD = 2.07$) was significantly lower than that in the functional context ($M = 6.49$, $SD = 1.86$) (Figure A2). Therefore, $H2$ was supported. Moreover, there was no significant interaction effect between social cues and communication context (F [2, 291] = 0.15, $MSE = 0.57$, $p = .87$, $\eta^2 = .001$), which answered the research question.

Discussion

Differing from much of the existing research comparing human and machine agents (e.g., Laban et al., 2021; Sundar & Kim, 2019), this study focuses on the effects of different designs and interaction contingencies (i.e., name labels and communication contexts) of a chatbot. Studies have suggested that people's subjective perceptions of disclosures to artificial and human agents are often aligned with their objective disclosures (Laban et al., 2021), and our findings on participants' willingness to self-disclose information provide implications that help us understand the nuances in HMC, with a particular emphasis on contextual factors.

The first hypothesis, which predicted a significant effect of the names assigned to chatbots, was not supported. This finding is incompatible with prior research on the effects of other social cues, such as gender,

nationality, and team membership, on computers (Eyssel & Kuchenbrandt, 2012; Reeves & Nass, 2002). One possible explanation is that our manipulation of names was not strong enough to affect participants' perceptions and decisions. Many participants failed the attention check, indicating that the minimal manipulation of names was easily neglected. Furthermore, Beattie et al. (2020) found that participants did not differentiate between human and chatbot message sources but rated emoji-featuring messages higher than verbal-only messages, regardless of the human or chatbot labels, indicating that ostensible cues matter less than other factors such as message quality in human-chatbot interactions. Another possible explanation is the users' lack of social presence and identification with the chatbot. In past literature, users' social responses have been categorized into first-degree responses (user identification of the social characteristics of technology such as social presence and perceived personalities) and second-degree responses (attitudinal and behavioral changes) (K. M. Lee et al., 2006). In this study, the effects of names may not have been sufficient to induce changes in the second-degree responses (i.e., disclosure decisions).

The main effect of the communication contexts was significant, meaning that given the same dialogue, interface, and information queries, users would rather disclose information to a functional tool than a social companion. Echoing Calo's (2009) research, this may occur because a socio-emotional context triggers more social pressure and privacy concerns. Another explanation can be that in a social context, participants may not expect a chatbot to fulfill their socio-emotional needs as in interpersonal relationships, especially in their initial encounter through sample conversation. According to the social penetration theory (Altman & Taylor, 1973), individuals' evaluation of relationship advancement is heavily dependent on the nature of perceived rewards and costs (Tang & Wang, 2012). Disclosing information to a functional chatbot compared to a social one may result in more concrete rewards. In the social context, if individuals have concerns over the progression of the claimed social-emotional relationship and rewards, they may express less disclosure willingness. Finally, another possibility is that users develop unique social scripts and apply them to media agents (Gambino et al., 2020). These unique social scripts are developed based on the social affordance of the media agents as well as the temporal and situational factors affecting users' relationships with media agents.

Our findings have theoretical implications for HMC research. Past research on the CASA paradigm has offered a broad framework that indicates the necessity of including the specifications of social cues, individual differences, and contextual factors (Lombard & Xu, 2021). This study not only examined naming conventions but also added context as an under-studied dimension to manifest increased nuances in HMC and provide novel insights. Researchers

should contextualize privacy and disclosure based on participants' communication goals in HMC. This requires the integration of theories and methods from both HMC and interpersonal communication. As we only distinguished social and functional contexts, more contextual factors, such as social rituals, cultural influences, and people's acceptance of social roles, may provide new guidelines for extending CASA.

Our findings inform context-aware designs in the domain of intimate HMC. Designing chatbots for social purposes requires more effort to build users' trust and sense of security than designing them for functional purposes. This study also advocates catering to implicit and explicit user needs regarding the role of chatbots, the nature of interactions, and the interplay between contexts and design features.

Limitations and future directions

The chatbot names tested in this study were selected empirically from existing conventions. The name "assistant," neither humanlike nor machinelike, may also imply a social role, which could be confounding. A deeper examination of the meanings of these names is required. Furthermore, our additional measure of perceived anthropomorphism did not yield significant differences among the three conditions, which suggested a weakness in the manipulation of names. Future studies should theoretically analyze these names, directly explore users' interpretations, and seek alternative manipulation methods to confirm their effects.

The effect size of the difference between functional and social contexts in user disclosure was relatively small, which indicated that contextual effects can be significant but subtle. This may have been caused by the experimental design as the context manipulation was not explicit. Participants may not have formed significantly different impressions of the chatbot based on its introduction. Future studies should seek alternative designs to retest the effect size.

Finally, instead of testing users' real self-disclosure behavior, this study only examined the effects of chatbots' names by displaying sample conversations and measuring users' willingness to self-disclose. It remains unknown whether name labels would have more salient and accumulated effects in real human-chatbot conversations. Future studies could utilize real conversations to examine these findings and explore whether participants' subjective disclosure intentions and objective behaviors are consistent.

Disclosure statement

Notes on contributors

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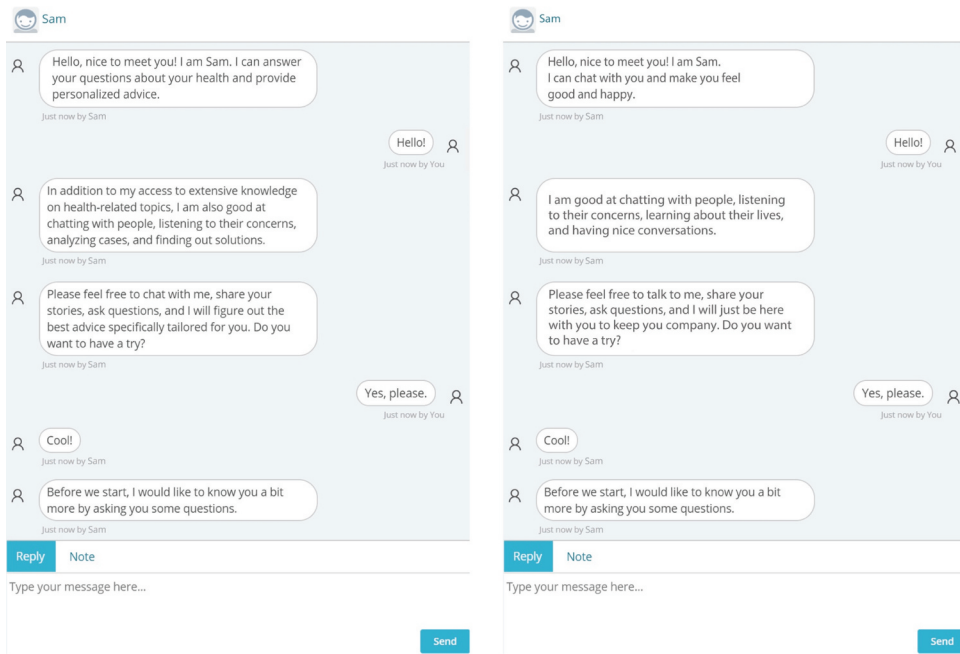
Appendix

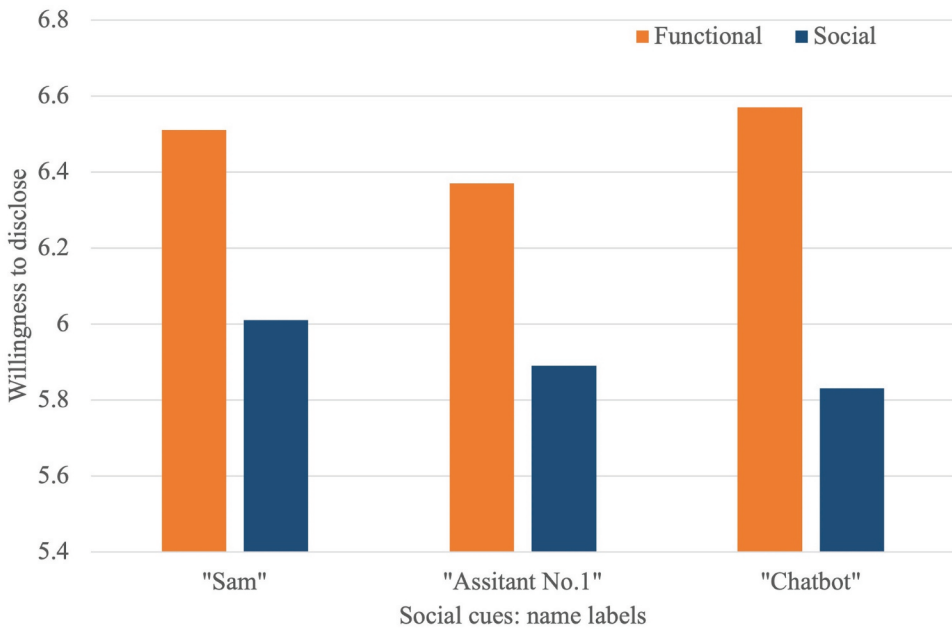**Figure A1.** Stimuli: Sample screenshots in the "Sam" condition in the functional/social context.

Figure A2. Willingness to disclose personal information in each condition.