Social Influence in Customer-Robot Interactions

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Abstract

This paper focuses on social influence in customer-robot interactions. Drawing on social impact theory and the computers-are-social-actors (CASA) paradigm, we argue that customers' reluctance to provide information to a service robot decreases when other customers exhibit high information disclosure. The effect of demonstrated information disclosure on customers' reluctance to provide information is enhanced by the application of social norms. The results also show that social influence is stronger in customer-robot interactions than in customer-employee interactions. This article demonstrates the potential of social influence to reduce reluctance towards service robots, which has both theoretical and managerial implications. We extend existing research on the imitation of robot behavior with the imitation of user behavior, and discuss the ethical implications of customers mindlessly following other customers in customer-robot interactions.

Keywords: CASA Paradigm, Ethics, Information Disclosure, Service Robots, Social Impact Theory, Social Norms

Introduction

Service robots are expected to have significant implications for customers, businesses and society (Wirtz et al., 2018), for example in restaurants, retail, hospitality or healthcare (Mende et al., 2019). The emergence of service robots is changing the nature of service and the frontline experience for customers (van Doorn et al., 2017). This development can be a great opportunity, with many potential benefits (van Pinxteren et al., 2020). For example, service robots can take over the role of employees, thereby reducing the workload and increasing the speed of task execution (Harriott et al., 2011). Nevertheless, in a large survey of EU citizens from 27 countries on the topic of robot acceptance, 86 % of the participants said they had never used a robot in any context (Turja & Oksanen, 2019). One possible explanation could be that customers are reluctant to engage with service robots, so there is a need to reduce barriers to adoption (van Pinxteren et al., 2020).

Customers may be reluctant towards service robots for a variety of reasons: Some customers are reluctant to change and stick to their routines (Del Giudice et al., 2022), others may fear making mistakes while interacting with the robot (Pantano et al., 2022), or worry that their information will not be adequately protected (Pagallo, 2013). In this paper, we argue that social influence can reduce customer reluctance. Social influence is a process by which people determine the successful experience of their social group in using an innovation before deciding to adopt it (Lee et al., 2011). In the case of reluctance towards service robots, people would like to predict possible outcomes of an interaction with a service robot (Del Giudice et al., 2022). Social influence can reduce the uncertainty when communicating with service robots as these social cues trigger the application of social scripts (Fink, 2012; Lin et al., 2021). When other customers are willing to share information, it can signal to the focal customer that the environment is safe and trustworthy (Wu et al., 2012). Thus, the goal of this paper is to provide evidence that the reluctance to provide information in customer-robot interactions is affected by social influence.

In many service settings, the presence of other customers can have a profound impact on the customer experience of the focal customer (Brocato et al., 2012). In this paper, we define the other customer as the customer who is in the service facility simultaneously with the focal customer (Brocato et al., 2012). These two customers do not need to interact, but the focal customer observes the other customer (Brocato et al., 2012). In a commercial context, customers influence each other through interpersonal encounters or indirectly as part of the environment (Martin, 1996). The influence of other customers is then manifested through perceptions based on observed characteristics (Brocato et al., 2012). We focus on the level of demonstrated information disclosure by other customers during a service encounter as an observed characteristic and examine its effect on a focal customer's reluctance to provide information in both customer-robot interactions and customer-employee interactions. We ask: *How is a focal customer's reluctance to provide information to a service representative affected by other customers' demonstrated information disclosure?*

Previous research has examined the effect of social influence on customer behavior, for example in marketing (e.g., Acqusiti et al., 2012), but research on social influence in the context of customer-robot interactions is scarce. We address this issue. Positioned within Information Systems (IS) research, our paper examines the moderating effect of the type of service representative on social influence. Customer-robot interactions differ from customer-employee interactions in that service robots induce greater customer discomfort, leading to compensatory responses (Mende et al., 2019). The differences between humans and robots are a key issue, so the focus of this paper is on the differences towards service robots.

To ensure a common understanding, we define service robots as "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p. 909). The example of the Chat GPT, "the world's most advanced chatbot" (Rudolph et al., 2023, p. 1), shows that the technology is now very advanced and that there is a general curiosity. Compared to chatbots without a human interface, physically embodied service robots have the additional advantage of generating an automated social presence through their embodiment (van Doorn et al., 2017). In the service encounter, service robots simulate human appearance and are likely to reflect humans closely in face-to-face service encounters (Wirtz et al., 2018).

The Anthropomorphic Robot Database (Phillips et al., 2018) shows that there are a variety of service robots with different functions, appearances, and effects. For our study, we use an android robot. The appearance of android robots is designed to be a perfect copy of a human body. An android robot is "an artificial system designed with the ultimate goal of being indistinguishable from humans in its external appearance and behavior" (MacDorman & Ishiguro, 2006, p. 289). We chose an android robot because it can evoke uncanny feelings during the service encounter, thus fostering reluctance (Mori et al., 2012; Rosenthal-von der Pütten & Krämer, 2015). Android robots differ from humanoid robots in that humanoid robots have extremities such as arms, legs, and a head (Mori et al., 2012), but still have a mechanical appearance (Ferrari et al., 2016). Previous studies on social influence have used humanoid robots, for example in a behavioral economic game (Zanatto et al., 2020), or in a litter picking task (Maeda et al., 2021). Our study differs from these studies by using an android robot. Humanoid robots also encounter customer information reluctance (Stock-Homburg & Hannig, 2020). However, it is particularly interesting for companies to study the effect of social influence on information reluctance towards android robots, as a more human-like robot increases perceived service value (Belanche et al., 2021). At the same time, uncanny valley theory suggests that "a person's response to a humanlike robot would abruptly shift from empathy to revulsion as it approached, but failed to attain, a lifelike appearance" (Mori et al., 2012, p. 98), which is particularly true for android robots (Ferrari et al., 2016).

In general, customers are uncertain when communicating with service robots (Lin et al., 2021). In this case, the demonstrated behavior may provide a model to follow, allowing the focal customer to replicate the actions of other customers who have faced a similar situation (Albrecht et al., 2017). This effect may differ between customer-robot interactions and customer-employee interactions, as customers are more familiar with their roles in human service encounters (Giebelhausen et al., 2014). We ask: *Does the effect of the demonstrated information disclosure on customer information reluctance differ between customer-robot interactions and customer-employee interactions?*

In addition, we examine whether the effect of demonstrated information disclosure on customer reluctance to provide information in customer-robot interactions is strengthened by the application of social norms. Social norms can be understood as "rules of action shared by people in a given society or group; they define what is considered normal and acceptable behavior for the members of that group" (Cislaghi & Heise, 2020, p. 409). Social norms guide or constrain behavior without the force of law (Cialdini & Trost, 1998). The difference between social influence and social norms is that social influence arises from observed experiences, whereas social norms refer to expectations of normal and acceptable behavior. Social influence describes psychological principles that exert various effects on people's attitudes and behaviors through the actual, imagined, or implied presence of other people (Stibe & Cugelman, 2019). The observed experiences may also exert their effects on attitudes and behaviors through, for example, social learning, social comparison, or social cooperation (Stibe & Cugelman, 2019). It is therefore necessary to consider social norms separately.

In customer-robot interactions, research has examined whether robots themselves should follow social norms. Several studies support the idea that in order to interact and collaborate with humans in a natural and friendly way, a robot should try to manifest behaviors that conform to the same social norms as humans (Carlucci et al., 2015). We now consider the reverse perspective and ask whether customers also apply social norms when interacting with service robots and whether this influences information reluctance. When customers are confronted with a certain level of demonstrated information disclosure by other customers, this may trigger thoughts about social norms. We ask: *How does the application of social norms affect the effect of demonstrated information disclosure on customer information reluctance in customer-robot interactions?*

This paper adds scientific value in several important ways. From a managerial perspective, understanding the importance of social influence in customer-robot interactions can help companies reduce customer reluctance to service robots and thus increase their use. The degree of customer information reluctance is an important issue for companies as the provision of information by customers increases the possibilities of service personalization (Riemer & Totz, 2003), which in turn drives service quality (Zeithaml et al., 2000). We demonstrate the potential of social influence, and point out how companies can benefit from it to generate more effective customer-robot interactions. In this context, we also show that the incorporation of social norms is an important factor. In addition, we highlight the ethical issues that arise when customers mindlessly follow others in their behavior towards service robots.

From a theoretical perspective, we extend the understanding of social impact theory with insights from robotics research, and show how social impact theory and the CASA paradigm are related. We provide important insights into how observing other customers can improve the use of service robots in the marketplace. While existing research focuses on imitating robot behavior (Kim & Phillips, 2021), we highlight the importance of imitating user behavior, or in our case, customer behavior. Using the customer's reluctance to provide information as an example, we show how customers plan to imitate the behavior of other customers in customer-robot interactions.

Theoretical Background

CASA Paradigm

Our research is based on the computer-are-social-actors (CASA) paradigm and social impact theory. The CASA paradigm helps to understand the use of social scripts in customer-robot interactions. According to the CASA paradigm, users mindlessly apply social rules and expectations to computers and use social scripts from human-human interaction in human-computer interaction (Nass & Moon, 2000). This paradigm can also be applied to customer-robot interactions. In customer-robot interactions, the extent to which social scripts are used depends on the physical presence of the robot and can be triggered by social cues that remind users of human attributes (Kim & Sundar, 2012; Nass et al., 1995). These social cues also include observed capabilities of verbal communication (Fink, 2012).

Social Impact Theory

Social impact theory provides a general model of social influence processes (Latané, 1981). Social impact theory refers to the effect of others on an individual (Latané, 1981). More specifically, an individual's intention or behavior can be influenced by the behavior of others (Daliri et al., 2014). According to the theory, the impact on the individual is determined by the strength, the immediacy, and the number of others in the specific situation (Latané, 1981). Even though an action may not be acknowledged by the individual, social influence puts pressure on the individual to act in accordance with social norms (Man et al., 2019).

Literature Review

Social Influence in Customer-Robot Interactions

In customer-robot interactions, social influence has been studied in terms of imitation of robot behavior. For example, some studies have demonstrated children's tendency to imitate robot behavior through observation (Kim & Phillips, 2021). In one study, children were more likely to imitate the robot's intended actions when the robot made eye contact with another adult than when it did not (Itakura et al., 2008). In another study, children showed less imitation of a robot model than of a human model, a phenomenon referred to as the robot deficit (Sommer et al., 2021). The few studies of social influence in customer-robot interactions that have targeted adult participants have yielded inconsistent results (Kim & Phillips, 2021). In one study, adult participants tended to imitate robot behavior in a behavioral economic game when the service robot appeared to be good at earning monetary gains (Zanatto et al., 2020). In another study, adult participants did not show more willingness to pick up litter after watching a service robot pick up litter (Maeda et al., 2021). Instead, people seemed to feel less guilty about littering when they watched a robot cleaning up than in the case when they watched a human cleaner (Maeda et al., 2021).

The primary goal of the previous studies has been to test whether human behavior can be influenced by robot behavior. Thus, the focus of the existing literature is on the imitation of robot behavior. We argue that social influence in customer-robot interactions can also occur through imitation of user behavior. In this case, other human users serve as a model for the customer-robot interactions, e.g. for the reluctance to provide information.

Information Reluctance in Customer-Robot Interactions

Information reluctance in customer-robot interaction is understood as the restraint in the disclosure of any personal information that a customer wants to communicate to a service robot. For many customers, a service robot is still an unknown communication partner (Turja & Oksanen, 2019). This creates behavioral uncertainty for customers when communicating with service robots (Lin et al., 2021). In a field experiment, hotel guests were reluctant to talk to the service robot, preferring to interact via a touchscreen (Pinillos et al., 2016). One study indicated a tendency to share negative and neutral personal content with a service robot (Uchida et al., 2017). Another study found no actual differences in content, but users perceived that they shared more information with humans than with service robots (Laban et al., 2020). Also, the duration was longer when users disclosed to a human service representative than to a service robot (Laban et al., 2021).

A field experiment in the workplace revealed a privacy paradox towards service robots: despite increasing privacy concerns, the reluctance to provide information decreased (Stock-Homburg & Hannig, 2020). Overall, human likeness matters: Embodied service robots were able to collect more information from users than a disembodied system (Tonkin et al., 2017). Android robots elicited more animation and variation in verbal and non-verbal forms of expressions from customers than humanoid robots (Stock-Homburg et al., 2020). Our paper builds on these studies of information reluctance toward service robots from the perspective of social influence, which to our knowledge has not been studied before.

Social Influence and Information Reluctance

The effect of social influence on the reluctance to provide information has been studied in non-robot contexts. For example, in a questionnaire titled "Test your ethics" in the online version of the New York Times, participants' information reluctance was influenced by signals about the information reluctance of others: Respondents were more willing to provide sensitive information when they were told that previous respondents had provided sensitive information (Acquisti et al., 2012). The provision of sensitive information is based on the lemming effect. The lemming effect shows the propensity of individuals to be easily influenced and follow the behavior of close people in an automatic way even when the behavior is dangerous (Snyman et al., 2017; Starke et al., 2014).

Further studies in the context of social networking sites (Cheung et al., 2015) and mobile applications (Kroschke & Steiner, 2017) have shown that social influence can reduce the reluctance to provide information. More recently, ChatGPT can serve as an example of how to overcome the reluctance towards AI by demonstrating the behavior of other users (Rudolph et al., 2023, p. 1). Texts and chat examples from ChatGPT have been published and distributed in print and online media around the world (e.g., The Guardian, 2020), which has led to the chatbot being tried out not only by specialists but also by the general public. As a result, many people now use ChatGPT normally in their everyday lives, for example to optimize texts or answer questions (Rudolph et al., 2023).

Research on the influence of social norms on information reluctance is still in its infancy (Masur et al., 2023). Qualitative work has shown that Facebook users model their information reluctance both by observing the behavior of others and by referring to what they think others would find appropriate (Zillich & Müller, 2019). During the Covid-19 pandemic, social norms of keeping distance increased interactions with a chatbot through a higher perceived usefulness (Huang & Kao, 2021). In e-commerce, social norms were positively related with the intention to share brand-related information (Gvili & Levy, 2021). Since information reluctance is a contextual behavior, it is important to understand whether the relationship between social norms and information reluctance differs across communication channels (Masur et al., 2023).

Framework and Hypotheses of the Study

Study Framework

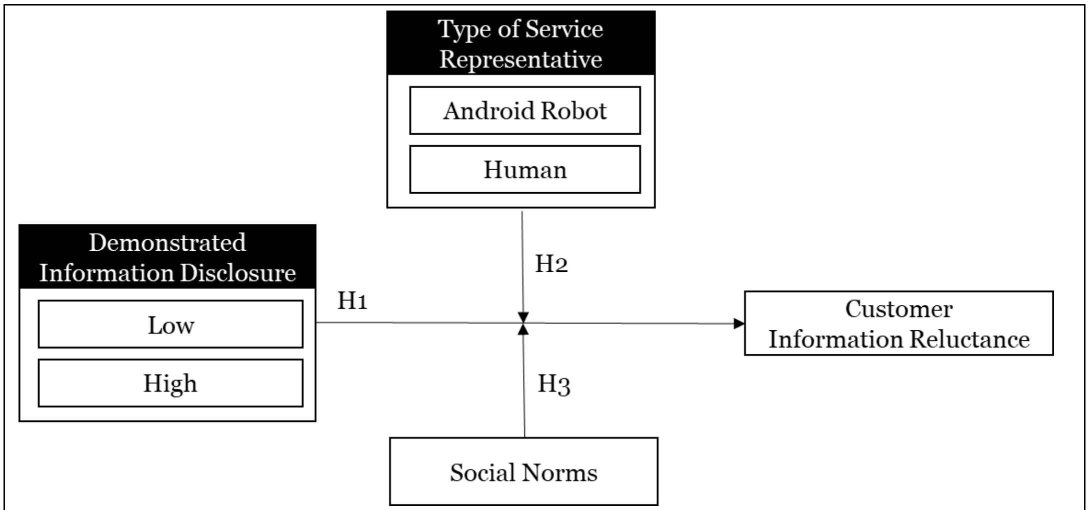

Figure 1. Framework of the Study

The framework of our study is depicted in Figure 1. The independent variable is demonstrated information disclosure. In our study, participants observed another customer demonstrating either a low or high level of information disclosure during an interaction with a service representative. This demonstrated information disclosure is supposed to affect customer information reluctance as the dependent variable.

In response to potential effects of contingency factors, we further examine moderating effects. We examine the type of service representative, comparing an android robot with a human service representative. Specifically, we examine whether the effect of demonstrated information disclosure on customer's information reluctance is stronger towards an android robot than towards a human service representative. We further examine social norms as a moderator. We argue that the relationship between demonstrated information disclosure and customer information reluctance is strengthened by the application of social norms. The development of the corresponding hypotheses is described in the following section.

Study Hypotheses

The first hypothesis is related to the main effect. Based on social impact theory, we argue that a focal customer's information reluctance towards the service representative is lower when another customer in the vicinity also discloses a lot of personal information. Customers adapt their behavior by observing other customers, as observation is a key learning activity in environments where learners can learn from models (Braaksma et al., 2002). In many retail service environments, social influence comes from another customer simultaneously occupying a store with a focal customer (Brocato et al., 2012). Customers form relationships with other customers, who may act as strangers, friends, or quasi-family members (Rosenbaum & Massiah, 2007), either through interpersonal encounters or indirectly by being part of the environment (Martin, 1996).

Of course it is also possible that customers focus only on the service representative and are more likely to provide their personal information when they observe the services they can receive. However, research has shown that a service customer's perceptions of other customers matter, and that these perceptions can explain variation in outcomes above and beyond that explained by the effects of perceptions of employee service quality (Brocato et al., 2012). Thus, customers' perceptions of other customers matter, and they manifest themselves based on observed characteristics (Brocato et al., 2012). We argue that information sharing is one such characteristic. If other customers are willing to share information, it may signal that the environment is safe and trustworthy (Wu et al., 2012), which may encourage the customer to share information as well. Therefore, we propose the following hypothesis:

Hypothesis H1: Customers will be less reluctant to provide information to a service representative when other customers around them also provide a lot of personal information.

The second hypothesis relates to the differences between android robots and human service representatives. For many customers, a service robot is still an unknown communication partner (Turja & Oksanen, 2019). Just the identity of the service representative being a service robot leads to people's different attitudes (Rosenthal-von der Pütten & Krämer, 2015). For example, humans are perceived differently from robots because they are self-aware and have metaphysical or transcendental characteristics such as having a soul or spirit, and most importantly, emotions (Rosenthal-von der Pütten & Krämer, 2015). This creates behavioral uncertainty for customers when communicating with service robots (Lin et al., 2021). When faced with uncertainty, customers may not have a clear idea of how to behave or what to do. In these situations, demonstrated behavior can be a valuable source of information and guidance (Zhang et al., 2019).

Based on the CASA paradigm, we argue that social cues, such as verbal communication (Fink, 2012), influence the degree of intended information reluctance in customer-robot interactions. Demonstrated verbal communication can provide a model for customers to follow, allowing them to replicate the actions of others who have faced similar situations (Albrecht et al., 2017). A challenge with social influence is that social influence does not always result in the correct or desired behavior (Zanatto et al., 2020). During interactions with a human service representative customers thus often apply their social scripts based on a range of past experiences (Giebelhausen et al., 2014). In this case, demonstrated behavior may be less necessary because customers are familiar with their roles during human service encounters. Therefore, we argue that the effect of demonstrated information disclosure on customer information reluctance is higher when customers interact with an android robot compared to a human service representative.

Hypothesis H2: The effect of demonstrated information disclosure on customer information reluctance will be higher when the service representative is an android robot (vs. a human service representative).

Based on social impact theory and the CASA paradigm, we argue that the application of social norms reinforces the effect of demonstrated information disclosure on customer's information reluctance in customer-robot interactions. In line with social impact theory, we argue that a customer confronted with a certain level of demonstrated information disclosure may come to view this level as normal and acceptable behavior in customer-robot interactions. The stronger this consideration, the stronger is the imitation of the behavior.

The CASA paradigm amplifies this effect in customer-robot interactions. When customers observe the verbal behavior of others, these social cues trigger the application of social scripts (Fink, 2012). The social cues can lead to a better understanding of the situation and indicate a possible behavior that might be normal and acceptable. Customers may gain insights and cues from the customer-robot interactions that they may not have been able to access otherwise. These insights may trigger thoughts about social norms. Formally, we argue:

Hypothesis H3: The effect of demonstrated information disclosure on customer information reluctance in customer-robot interactions is strengthened by the application of social norms.

Methodology

We conducted an online study on Amazon Mechanical Turk, and recruited participants who were United States residents, employed and had an approval rate of at least 95%. A total of 392 participants (50% female, Mage=38.82, SDage=11.27) completed the study and correctly answered the attention check questions.

The study consists of a 2x2 between-subjects design, with two different service representatives (android robot and human service representative) and different levels of demonstrated information disclosure by the other customer (low vs. high). The participants were confronted with videos of a retail setting. We chose a retail setting as service robots are already being used in retail settings (Mende et al., 2019), and sharing personal information in this setting may be sensitive (Ghoshal et al., 2020).

The android robot used for our study resembles a European woman. The android robot has a total of 49 degrees of freedom, twelve of which are in the face. The robot's exoskeleton is covered with a skin-like layer aimed to give it a more human-like appearance. Figure 2 shows photos of the two service representatives featured in the video.

Figure 2. Human service representative and android robot

The content of the retail video is about a customer who would like to refurnish his studio, and is being advised by the android robot or the human service representative in a furniture store. We asked the participants to imagine that the customer was a close friend of theirs, and that they were standing right next to them and listening to the interaction. We asked the participants to imagine the other customer as a close friend to ensure that the participants connected with the customer. This is a realistic scenario as customers who enter the service encounter with friends often do so because they use shopping as a way to gain companionship from their friends (Rosenbaum & Massiah, 2007).

The video was divided into three parts. The first part was an introduction. Participants saw one of the service representatives, either the android robot or the human service representative, interacting with the user. The type of the service representative remained the same in the subsequent parts. In the second part of the video, we manipulated the amount of personal information provided by the customer. Thus, the participants were either confronted with a situation of demonstrated customer behavior with low information disclosure, or with a situation of demonstrated customer behavior with high information disclosure. We then measured the application of social norms. The last part of the video showed the valediction of the service conversation. Afterwards, we measured the participants' reluctance to provide information to the service representative. All scales and items are listed in the appendix. Because social influence could also change customers' privacy concerns about sharing information, we also measured privacy concerns, but found no effect on information reluctance. Therefore, we did not include privacy concerns in further analyses.

Results

Participants were able to understand the video clips. Overall, the participants rated the comprehensibility ($M=5.36$, $SD=1.33$), the sound quality ($M=5.02$, $SD=1.47$), and the image quality ($M=5.73$, $SD=1.14$) of the video clips in a satisfactory range on a 7-point Likert scale. The human service representative was perceived as more humanlike ($M=6.04$, $SD=1.16$) than the android robot ($M=3.57$, $SD=1.89$, $\Delta M=2.47$, $SE=.16$, $p<.001$). We also found that our manipulation of demonstrated information disclosure by the other customer elicited the intended effect, resulting in significant mean differences in perceived demonstrated information disclosure for both service representatives. Overall, demonstrated information disclosure was perceived to be higher in the high condition ($M=4.82$, $SD=1.21$) than in the low condition ($M=2.90$, $SD=1.83$, $\Delta M=1.92$, $SE=.16$, $p<.001$).

In hypothesis H1, we argued that customers will be less reluctant to provide information to a service representative when other customers also provide a lot of personal information. The results show a significant effect of demonstrated information disclosure on customer information reluctance. When the level of demonstrated information disclosure was low, customers indicated that they would be more reluctant to provide information to the service representative ($M=4.93$, $SD=1.92$) as to when the level of demonstrated information disclosure was high ($M=4.40$, $SD=1.70$, $\Delta M=.54$, $SE=.18$, $p<.01$). Thus, the results support hypothesis H1.

In hypothesis H2, we argued that the effect of demonstrated information disclosure on customers' information reluctance will be higher when the service representative is an android robot. Therefore, we compared the effect of demonstrated information disclosure on customers' information reluctance separately for both service representatives. Table 1 shows the results.

Type of Service Representative	Demonstrated Information Disclosure			
	Low	High		
	Mean (SD)	Mean (SD)	Δ Mean (SE)	p-Value
Android Robot	5.17 (1.98)	4.47 (1.79)	.70** (.26)	.01
Human	4.67 (1.84)	4.30 (1.59)	.36 (.26)	.17

Notes: Customer Information Reluctance, 7-point Likert-type scale with anchors from 1 ("totally disagree") to 7 ("totally agree"). n(Android) = (107|109); n(Human) = (94|82). SD=Standard Deviation; SE=Standard Error. **p<.01.

Table 1. T-Test Results Customer Information Reluctance

It can be seen that the effect of demonstrated information disclosure on customers' information reluctance is only significant for the android robot, not for the human service representative. Customers indicated that their reluctance to provide information to the android robot would be significantly reduced if the other customer demonstrated high information disclosure behavior in the customer-robot interaction. In addition, there was a significant mean difference between the measured customer information reluctance towards the android robot in the case of high demonstrated information disclosure ($M=4.47$ $SD=1.79$) and a hypothetical mean based on the mean difference in the human group ($M=4.81$, $\Delta M=-.34$, $p<.05$). Thus, the results support hypothesis H2.

In hypothesis H3, we proposed a moderating impact of the application of social norms on the relationship between demonstrated information disclosure and customer information reluctance in customer-robot interactions. To control for the hypothesized moderating influence, we used hierarchical regression analyses as a moderation analysis approach (Baron & Kenny, 1986) with customer information reluctance as the dependent variable. This involved z-standardizing the independent and moderating variables and then constructing the interaction term of interest (Jaccard et al., 1990).

To test the hypothesis, we used the data from the android robot group and included demonstrated information disclosure and social norms in the first regression model. Demonstrated information disclosure (ß=-.16, $p<.05$) and social norms (ß=-.17, $p<.05$) accounted for a significant amount of variance in customer information reluctance towards the android robot ($R^2=.05$, $F(2,174) = 4.06$, $p<.05$). In the second model, the interaction term between demonstrated information disclosure and social norms was added to the regression model, which accounted for a significant proportion of variance in customer information reluctance (Model 2: $\beta_{\text{Interaction}} = -.24$, $p < .01$, $\Delta R2 = .05$, $\Delta F(1, 173) = 10.26$, $p < .01$). The results indicate that the application of social norms moderates the effect of demonstrated information disclosure on customer information reluctance, supporting hypothesis H3.

The examination of the interaction plot illustrates the moderating influence of social norms on the relationship between demonstrated information disclosure and customer information reluctance in customer-robot interactions (Figure 3). Simple slopes were tested for low (-1 SD below the mean), moderate (mean), and high (+1 SD above the mean) levels of social norms. The simple slope test for low values of social norms showed no significant effect. The simple slope test for moderate values of social norms revealed a significant negative association between demonstrated information disclosure and customer information reluctance ($b = -.57$, $SE = .28$, $t = -2.06$, $p < .05$), as did the simple slope test for high values of social norms ($b = -1.47$, $SE = .39$, $t = -3.76$, $p < .001$).

Regarding the simple slope test for low values of social norms, it seems possible that for some sub-population, the social norms do not work. Therefore, we conducted supplemental analyses. We calculated a median split on social norms, but could not find any demographic differences in terms of age and gender between the group who applied more social norms, and the group who applied less social norms.

Overall, the results show that in the case of higher demonstrated information disclosure, customers' reluctance to provide information towards the android robot decreases the more they apply social norms.

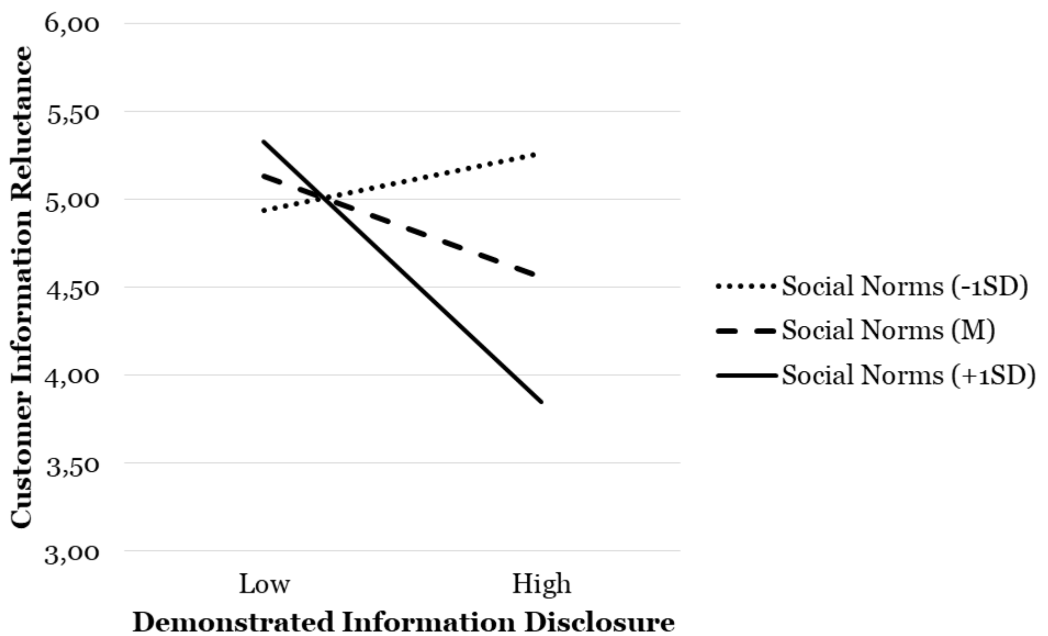

Figure 3. Interaction Plot: Moderating Effects of Social Norms

Discussion

The results provide interesting insights into the effect of social influence on customers' reluctance to provide information to service robots. In the service encounter, customers adjust their planned information reluctance according to what they have observed with other customers. This effect is stronger for android robots than for human service representatives, and it is strengthened by the application of social norms.

Just the identity of the service representative being a service robot instead of a human service representative seems to make customers more responsive to social influence. An exciting question is why social norms work in customer-robot interactions, and why their impact is larger when customers face service robots. Social influence may be particularly important when customers have limited knowledge (Lee et al., 2011). This is more likely to occur in customer-robot interactions than in human-employee interactions. In the context of limited knowledge, the importance of reflecting normal and acceptable behavior increases.

However, mindlessly following others is not without risk. Particularly with regard to children and the elderly, unanticipated risks and ethical issues must be considered in the context of service robots (Sharkey, 2008). A challenge of social influence in customer-robot interactions is that social influence may not always lead to the correct or desired behavior (Zanatto et al., 2020). Based on the lemming effect, customers can be easily influenced and automatically follow the behavior of other users even when the behavior is dangerous (Snyman et al., 2017; Starke et al., 2014). Our results show that one customer's behavior, in terms of demonstrated information disclosure, may be sufficient for a focal customer to plan to follow the behavior. In privacy-sensitive environments, mimicking another customer's information-sharing behavior may unknowingly compromise one's own privacy needs. As service robots can be equipped with innovative sensors and processors that enable more advanced observational capabilities, they could potentially be used for unsolicited data collection (Lutz & Tamò-Larrieux, 2020). Previous research also shows that privacy concerns do not prevent users from sharing information with service robots (Stock-Homburg & Hannig, 2020).

Beyond these privacy risks, there are other negative consequences: Following the social norms of others can limit innovation in customer-robot interactions. By simply copying what other customers do, customers may miss opportunities to learn about the full range of service robot capabilities and functionalities. As a result, customers may have false expectations about what service robots can do. In addition, following other customers may cause one's individual needs and preferences to fade. Each customer may have different needs or preferences when interacting with service robots (Moharana et al., 2019). Furthermore, if social norms in customer-robot interactions followed by certain groups are biased or discriminatory, then following these norms may lead to the same bias. These ethical issues must be considered in the context of social influence in customer-robot interactions.

Then, social influence effects have a great potential for spreading customer-robot interactions. Our results show that when other customers share a lot of personal information with the service robot, customers feel more comfortable in planning to share their own personal information with the service robot. Following social norms strengthens this effect and can help customers become more familiar with the service robot and its intended use. Following these norms can help customers become less reluctant and feel more comfortable and confident when interacting with service robots. In addition, the social influence of other customers can create a sense of community among customers interacting with the same service robot. Following social norms can also help maintain the quality of the robot's function and performance. If most customers use service robots in a certain way, they can be designed and programmed accordingly, ensuring that the service robot works optimally and delivers the expected results.

Our study is limited in that the data include only US employees. Cultural factors may influence the responses to service robots (De Keyser & Kunz, 2022), as well as the application of social norms (Heinrichs et al., 2006). In addition, we asked about the willingness to disclose information in an online study. Further research could validate the behavior in a field study.

As to whether the results of the experiment can be generalized to real-world scenarios, social impact theory argues that social influence can be enhanced by immediacy (Latané, 1981). Immediacy is understood as closeness in space or time and the absence of intervening barriers or filters (Latané, 1981). Therefore, social influence could be even larger in real-world scenarios.

These limitations notwithstanding, we extend existing research on social influence in customer-robot interactions, which has focused on imitation of robot behavior (Kim & Phillips, 2021), with the perspective of imitation of user behavior. We extend the understanding of social influence theory with insights from robotics research and show how social influence theory and the CASA paradigm are related. Previous research has raised several research questions about service robots that still need to be discussed, such as how to overcome consumers' initial distrust of robots or how to effectively integrate service robots into teams (Wirtz et al., 2018). Here, we show that social influence can be a means to overcome the barriers associated with information reluctance and scale up customer-robot interactions.

From a managerial perspective, there are several ways companies can use social influence in customer-robot interactions. For example, companies can show customers how other customers interact with service robots. Companies can partner with influencers to promote their service robots and demonstrate how they can be used in innovative and useful ways. This can help increase visibility and credibility with potential customers. By highlighting use cases for or encouraging customers to follow the lead of other customers, companies can help ensure that customers provide information and have a positive and satisfying experience with service robots. In addition to retail, the effects of social influence on customer-robot interactions may be particularly effective in service domains where individuals are particularly skeptical of service robots, such as healthcare (Barrett et al., 2012; Caic et al., 2019). For example, observing another user being cared for by a service robot without complications and without the person experiencing negative consequences may reduce the observer's concerns about service robots and interacting with them.

While the use of humanoid robots in customer interactions has already been tested in the market (Mende et al., 2019), our results provide interesting insights into the implementation of android robots in customer interactions. It shows the potential for customers to be willing to share information once the ice has been broken. Then, android robots can fulfill their human-like potential. It seems that social influence can reduce uncanny feelings towards android robots. Our results show that the application of social norms enhances the effect of demonstrated information disclosure and can reduce users' reluctance towards android robots.

The study of social influence in customer-robot interactions is still in its infancy, which provides interesting research opportunities. Thus, research in this area remains promising and important.

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Appendix

Variables: Measures and Items

Demonstrated Information Disclosure (adapted from (Jiang et al., 2013) – α = .96

- In the particular experience, my close friend revealed a great amount of information about himself to the service representative.
- In the particular experience, my close friend gave out intimate information to the service representative.
- In the particular experience, my close friend shared a variety of information about himself to the service representative.
- In the particular experience, my close friend disclosed information openly to the service representative.
- In the particular experience, my close friend revealed very personal thoughts, feelings and experiences to the service representative.

7-point Likert-type scale with anchors from (1) totally disagree to (7) totally agree

Social Norms (adapted from (Stibe & Cugelman, 2019) – α = .70

- In this particular situation, I would have preferred to do what my friend did.
- In this particular situation, I would have preferred to act the way my friend was acting.
- In this particular situation, I would have followed behaviors that my friends did.
- In this particular situation, I wouldn't have like to do what my friends did. (r)
- In this particular situation, I wouldn't have copied the behaviors that my friend did. (r)

7-point Likert-type scale with anchors from (1) totally disagree to (7) totally agree

Customer Information Reluctance (adapted from (Jiang et al., 2013) – α = .96

- In the particular experience, I would reveal a great amount of information about myself to the service representative. (r)
- In the particular experience, I would give out intimate information to the service representative. (r)
- In the particular experience, I would share a variety of information about myself to the service representative. (r)
- In the particular experience, I would disclose information openly to the service representative. (r)
- In the particular experience, I would reveal very personal thoughts, feelings and experiences to the service representative. (r)

7-point Likert-type scale with anchors from (1) totally disagree to (7) totally agree

Note: (r) = reversed item.