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Unpacking the black box: Examining the (de)Gender categorization effect in human-machine communication

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ABSTRACT

Although studies have explored the gender categorization effect in both face-to-face and mediated communication environments in relation to the use of gender-linked language, whether the effect still holds in the context of human-machine communication (HMC) remains unknown. To examine this question, in this study, we asked 245 participants to assign gender categories to targets after viewing transcripts of the targets' conversations with a chatbot and a human interlocutor. The results showed that the participants had a better-than-chance probability (68.98%) of correctly guessing the gender of the target based on the target-human conversation transcripts. However, the predictive power of the language cues decreased sharply to a less-than-chance level (42.86%) based on target-chatbot conversation transcripts. We also examined the roles that social media use and demographics played in the gender categorization processes in both computer-mediated communication and HMC contexts. Although far from conclusive, our results suggested that there were significant differences between the styles of conversation in the target-chatbot and target-human interlocutor transcripts. These findings imply that people use different approaches when communicating with human and non-human interlocutors.

1. Introduction

In face-to-face communication, people rely on social cues to form impressions and make judgments of others (Berger & Calabrese, 1975). These social cues become prominently useful in computer-mediated environments (Walther, 1996). In particular, gender cues are the primary information that communicators seek to obtain in mediated environments (Turkle, 1995), such that people assign gender categories to others to avoid communication uncertainty and predict the mental and physical status of others (Infante, Rancer, & Womack, 1997). Based on the perceived gendered cues, conversation styles, and topics, communicators can speculate on the gender of others in both face-to-face contexts and mediated contexts (Herring, 1994; Witmer & Katzman, 1997; Wolfinger & Rabow, 1997; Yates, 1997). These cues can help people manage their conversations and build interpersonal relationships in face-to-face and computer-mediated communication (CMC) contexts.

Although users in CMC contexts can make gender categorizations based on gendered cues, their communication approaches may change when facing a digital interlocutor. With the rise of human-machine communication (HMC), users can now interact with a variety of chatbots including Twitter bots, Microsoft Cortana, and automated robots in online forums (Gehl, 2014; Neff & Nagy, 2016). A chatbot is “a machine conversation system [that] interacts with human users via natural conversational language” (Shawar & Atwell, 2005, p. 489). The unique perceived identity of a chatbot as a conversation partner is expected to underpin a new information process, expectations of the partner, and effects different from human-human interaction (Ho, Hancock, & Miner, 2018). Therefore, people who are less experienced in communicating with machines including chatbots may feel more uncertain, less confident, and less comfortable than those who are more experienced in human-machine communication (Edwards, Edwards, Spence, & Westerman, 2016; Hill, Ford, & Farreras, 2015).

Although gender categorization can help users reduce the ambiguity when communicating in CMC contexts, it is unknown whether media users apply the same approaches in HMC contexts. Therefore, in this study, we aim to extend the CMC research on gender categorization to HMC. Specifically, we examine whether and how communicators apply gender categorization when communicating with chatbots and how gender categorization in HMC may differ from that in CMC.

We base our research on previous inconsistent findings on media equation theory. Media equation theory suggests that people interact with media technologies as if they were social actors (Reeves & Nass, 1996). According to media equation, users should apply the same

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communication approaches in HMC as in interpersonal communication. However, other researchers have argued that individuals' social reactions to media technologies are contingent on the communication contexts, individual differences, and the nature of the digital interlocutor (Crawford, 1995; Duffy & Zawieska, 2012; Fischer, Foth, Rohfling, & Wrede, 2011). Hence, to gain a better understanding of how users interact with digital interlocutors, we compare the perceived gender of communicators when conversing with a chatbot and a human interlocutor. If the communicators apply the same communication approaches in both communication modes, their perceived gender characteristics and communication patterns should be similar. Thus, in the following sections, we review the gender categorization effect in CMC contexts, discuss how human language presents gendered cues, review the gender stereotypes in HMC, and examine gender as a schematic category.

2. Literature review

2.1. Gender categorization in CMC

Gender and geographic location are the first two things that communicators seek to know in a CMC environment (Cornetto & Novak, 2006; Turkle, 1995). Knowing communication partners' gender can reduce uncertainty in communication and help better understand others' messages and actions. Despite the importance of identifying communication partners' gender, cues related to gender information may be blocked in CMC contexts. For example, early CMC scholars focused on the influence of lack of social context cues. Kiesler, Siegel, and McGuire (1984) argued that lack of social responses and unpredictable messages from other communication partners would increase the difficulty to coordinate and comprehend messages. Due to lack of social cues, social influence may be perceived as more equal in CMC. Kiesler et al. (1984) further suggested that groups in CMC contexts would take longer to reach consensus and users would exchange fewer comments within limited time compared to face-to-face communication. Though lack of social cues might lead to more disinhibited behavior, Novak (2003) argued that in CMC contexts, cue-lean media would reduce the importance of social norms and led users to pay more attention to the content of the messages instead of the source of the messages.

Following the utopian promise of cue-lean media and the reasoning that gender cues might be blocked in CMC conversations, Novak (2003) found that participants were unable to correctly assign gender to their communication partners in text-based CMC environments. In a later study, Cornetto and Novak (2006) further found that participants were inaccurate in identifying partners' gender based on their online usernames. These empirical findings have shown the difficulty of perceiving others' gender in CMC environments.

While the impersonal communication perspective suggests that lack of social cues could lead to more disinhibited behavior (Kiesler et al., 1984; Siegel, Dubrovsky, Kiesler, & McGuire, 1986), social information processing theory suggests that users rely on whatever cues available to them to develop interpersonal relationships with others in CMC (Walther, Van Der Heide, Ramirez, Burgoon, & Pena, 2015; Walther & Parks, 2002). Specifically, Walther et al. (2015) argued that over time, CMC users can use the information such as usernames, profile pictures, descriptions, emoticons, and other individuated cues to form impression of others. In addition to the social information processing theory, the hyper-personal model of communication suggests that message senders can selectively present their desired information to the communication partners. Meanwhile, message receivers can read into these social cues and form ideal or exaggerated impression of these message senders (Walther, 2007; Walther et al., 2015). Compared to the social information processing theory which suggests that interpersonal relationships can also be achieved online, the hyper-personal model indicates that relational states can surpass rather than merely meet what is expected to occur in face-to-face communication settings (Walther et al., 2015). Based on these theories, though information about gender may be blocked in CMC, users may still assign others' gender based on the limited cues such as their communication partners' conversation styles, use of emoticons, and language.

2.2. Gendered language

As this study focuses on text-based communication with chatbots, language becomes an important social cue in reflecting communicators' personalities and gender. Language can provide insights into "how men and women approach their social worlds" (Newman, Groom, Handelman, & Pennebaker, 2008, p. 212). Following Lakoff's (1975) pioneering work on the use of language in social contexts, a large body of research has demonstrated the gender differences in language use. For example, Newman et al. (2008) used the Linguistic Inquiry and Word Count (LIWC) tool to analyze 14,000 text samples from 70 separate studies and detected gender differences in 35 word categories. In particular, they found that women referred more to psychological and social processes (e.g., emotions, sensations, friends, and family), while men used more words relating to the properties of objects and impersonal topics, such as finance and sports. Compared to women, men also used more articles (i.e., "a" and "the"), spatial words (e.g., "above" and "over"), and discussed financial and professional issues more than family and social life. Similarly, Mulac, Bradac, and Gibbons (2001) found that females used more hedging (e.g., "maybe" and "kind of"), tag questions (e.g., "isn't it?), longer sentences, intensive adjectives (e.g., "very much"), and references to emotions or feelings (e.g., "happy"), while males used more directives (e.g., "do it"), judgmental adjectives (e.g., "stupid"), and references to numbers. Other studies have shown that dominating and adversarial communication styles, such as interrupting the conversation and correcting wrong words, are often categorized as masculine, whereas hedging opinions, revealing thoughts or feelings, and using emoticons are more frequently associated with feminine styles of communication (Watson, 1997; Yates, 1997).

As males and females differ in language use, users can guess others' gender based on these language features. For instance, using a sample of 550 college students, Wolfinger and Rabow (1997) found that participants accurately identified the gender of the speakers in a drunk driving prevention test based on written conversation transcripts. Furthermore, automated text categorization techniques have been developed that can infer a writer's gender from formal written documents with up to 80% accuracy using the lexical and syntactic features of the language (Koppel, Argamon, & Shimoni, 2002).

In the context of CMC, language indicators can also be used to categorize the gender of others. Prior CMC research has demonstrated that males more frequently use assertive language, ask rhetorical questions, make sexual references, and challenge others, while females more frequently make justifications, use hedges, express emotions, and use supportive language (Herring & Martinson, 2004). Thus, users may assign gender to others based on these indicators. Savicki, Kelley, and Oesterreich (1999) found that readers could accurately tell the gender of others based on certain stylistic features including the use of adjectives, apologies, compliments, and insults. Herring and Martinson (2004) argued that users even made stereotyped responses based on their gender assignment in CMC. These studies suggest that users can use gendered language to postulate communication partners' gender.

2.3. Gender categorization in HMC

The CMC literature above first indicates that in cue-lean media environments, correct assignment of gender can be a difficult task. Then it reviews the literature of the social information processing theory and the hyper-personal model of communication to discuss how communicators can present and rely on gendered cues to assign or identify the gender of their communication partners. However, it remains unknown whether communicators present the same communication patterns in the context of HMC. If communicators demonstrate similar gendered language and communication styles in interacting with chatbots and human interlocutors, they should be assigned same gender category by others. Media equation theory suggests that in the context of HMC, users naturally and socially respond to media technologies as social actors (Reeves & Nass, 1996). More specifically, users are sensitive to the social cues presented by media technologies, which can attract user's attention, remind users that they are communicating with other people, and trigger mindless social responses to media (Nass & Moon, 2000). Gender categorization is one of the social scripts that users apply to HMC. Nass, Moon, and Green (1997) found that when responding to computers, participants rated those with a male voice as more convincing and friendly. Male-voiced computers were also interpreted as being more competent and knowledgeable on mechanical topics, whereas female-voiced computers were thought to be more knowledgeable about relationships but less competent. In a study on the importance of the gender of voices in educational settings, Bracken and Lombard (2004) found that children who listened to praise from a computer with a female voice exhibited flattery effects. They also reported that the children were more confident and demonstrated a higher learning motivation after being praised by a female-voiced computer.

The abovementioned studies followed the assumptions of media equation theory and suggested that individuals treat computers that elicit human characteristics as if they were real people. However, a number of studies have produced findings that challenge these assumptions. For example, Amalberti, Carbonell, and Falzon (1993) found that users who believed that they were interacting with a computer tended to use a different conversational style than those who believed that they were interacting with a human operator. Kanda, Miyashita, Osada, Haikawa, and Ishiguro (2008) found that users sent their greetings more rapidly to their human communication partners than their robot partners. More recently, Mou and Xu (2017) found that when interacting with a Microsoft chatbot, users were more open, agreeable, extroverted, and conscientious than when interacting with people. Therefore, although media equation theory has been widely applied to HMC, the contrasting evidence found in these studies suggests that further research is needed on users' social responses to media technologies. Thus, in this study, we examine whether individuals treat chatbots like human communicators with respect to gender categorization. If individuals exhibit similar gender patterns when interacting with chatbots and humans, the findings of this study will serve as additional evidence in support of media equation theory. Therefore, we propose the following research question.

RQ1. Can individuals accurately perceive a target's gender based on the target's interaction transcripts with (a) a chatbot and (b) a human?

The media equation research has also investigated the relationship between users' media use experience and social responses to these media technologies. Following Nass and Moon's (2000) claim that no empirical evidence suggests that computer experts are immune to the social responses to computers, Johnson, Gadner, and Wiles (2004) found that experienced computer users reported higher levels of confidence and trust in a computer after being flattered by it. However, Nass, Lombard, Henriksen, and Steuer (1995) found no significant relationship between computer use experience and users' physical and psychological anthropocentrism of computers. Thus, there have been inconsistent findings on how media exposure influences users' social responses to technologies. Even less research has focused on how users' media use experience influences their gender assignment of other communicators. Thus, in this study, we apply a chatbot launched on a social media and investigate how people's media use experience affects their gender assignment process when they are exposed to human-chatbot conversations and human-human conversations.

Although people may assign gender stereotypes to digital interlocutors in the HMC context, their own gender may also influence their judgment of their communication partners. For example, Lee (2008) found that females were more likely to respond to flattery from a computer than males. Nass et al. (1995) also found that people's gender affected their acceptance of computers taking over social roles. More specifically, males were more tolerant than females in having computers serve as babysitters or judges. However, gender did not influence people's attitudes when it was suggested that computers serve as accountants, editors, or bank tellers. Based on the literature, gender appears to influence users' social attitudes toward computers in specific contexts. Thus in this study, we aim to understand how people's gender influences their gender assignment process when they are exposed to human-chatbot and human-human conversations. We propose the following research questions.

RQ2. How does participants' social media use experience predict the accuracy of perceiving a target's gender based on the target's interaction transcripts with (a) a chatbot and (b) a human?

RQ3. How does participants' gender predict the accuracy of perceiving a target's gender based on the target's interaction transcripts with (a) a chatbot and (b) a human?

2.4. Gender as a schematic category

In face-to-face communication, gender is one of the first cues that communicators notice and link to rich information (Skitka & Maslach, 1996). Bem (1981) argued that gender-based schematic processing resulted in gender categorization and yielded “a generalized readiness to process information on the basis of the sex-linked associations that constitute the gender schema” (p. 354). Due to the strong relationships between individual gender roles and gendered attitudes, beliefs, and behaviors, personality is commonly assumed to be gendered (Frable, 1989). For example, Ozanska-Ponikwia (2015) looked at the relationship between gender and personality traits in the context of second language use. The study suggested that women scored higher on extraversion, agreeableness, and openness, which further led to greater emotional expression in second language use, while men scored higher on emotional stability and regulation. In a meta-analytic study, Leaper and Ayres (2007) summarized the relationships between gender-linked language and the interpersonal dimensions of affiliation and assertiveness. Their findings suggest that men use more assertive language (i.e., the language used for influence), such as suggestion, criticism, and disagreement, than women. By comparison, women use more affiliative language to affirm their interpersonal relationships, such as supportive statements, agreement, and acknowledgement. Lengua and Stormshak (2000) also confirmed that femininity predicted higher levels of affiliation and avoidance.

Social psychologists have further used the assertiveness and affiliation dimensions to integrate the Big Five personality traits with the use of gendered language (DeYoung, Weisberg, Quilty, & Peterson, 2013; John, Naumann, & Soto, 2008). Specifically, assertive language use, which is often perceived as masculine, was found to be positively associated with extraversion, while affiliative language, which is often perceived as feminine, was positively associated with agreeableness. The studies above suggest that gender could be related to personality traits. It is possible that when people assign gender categories to their communication partners, they rely on their interpretation of the interlocutors' personality traits. Therefore, in this study, we seek to further understand how perceived personality traits is related to the assigned gender in both CMC and HMC contexts.

In addition to the relationship between personality traits and gender, researchers found that the gender schema effects were more robust for women than men because women tend to respond to gender salience more than men (Palomares, 2008; Reid, Keerie, & Palomares, 2003). For instance, women were found to use references to emotion (female-linked language) more than men when gender was strongly linked to a supportive prototype (female-linked prototype) (Palomares, 2008). Researchers have also found that women are consistently viewed as better decoders of limited information with respect to feeling empathy for others (Ambady, Hallahan, & Rosenthal, 1995). Considering that women are perceived to be more sensitive to gendered information, there could be a connection between people's gender and their gender assignment in both CMC and HMC contexts. Thus, based on the implications of previous studies, we propose the following research questions.

RQ4. How are a target's evaluated personality traits related to the assigned gender category?

RQ5. How is participants' gender related to the assigned gender category?

3. Method

3.1. Sample and procedures

In this study, we examined how communicators interacted with other people and the chatbot Little Ice on WeChat a social media platform. Little Ice, which was first launched by Microsoft in 2014 in China, was designed to resemble a sociable teenage girl who can communicate via texts, images, and animated emojis. The chatbot can tell jokes, share pictures, and recognize human faces (Bingblog, 2014). It has attracted over 200 million registered users in Asia (Linn, 2018). Little Ice has the average of 23 conversation turns per session with its users, compared to other chatbots that have on average only two conversation turns per session (Larson, 2016). Due to the success of simulating human language, Microsoft has launched different versions of Little Ice in Japan in 2015, in the U.S. in 2016, and in India in 2017 (Microsoft, 2018a). It has also talked with more than 100 million users in the U.S. (Microsoft, 2018b). On a variety of platforms, Little Ice can initiate conversation with humans and the conversation can last for 4 hours (Linn, 2018). On WeChat, users can chat with Little Ice just as they chat with their friends.

A total of 245 college student participants were recruited from a large public university in East China to read 12 conversation transcripts from six volunteers (hereafter referred to as the “targets”) on WeChat. Fox, Bukatko, Hallahan, and Crawford (2007) supported the validity of using conversation transcripts in a study on instant messaging. Three research assistants helped recruit the participants on campus, including in dorms, classrooms, and libraries. Of the 245 participants who provided valid and complete responses, 42.45% were male and 57.55% were female, and the average age was 20.46 years ($SD = 2.39$).

Of the six targets, three were male and three were females, and their ages ranged from 19 to 35 years. Two of the targets were working in industry and the rest were college students. All of them were active WeChat users and reported accessing WeChat multiple times each day. Each target had a conversation with Little Ice and another with a female interlocutor, to keep consistent with Little Ice's designated gender. Therefore, the gender combos were half male-female and half female-female. The six targets were recruited using a snowball sampling procedure. The conversation transcripts were collected after the targets had interacted with Little Ice and their human interlocutors spontaneously. In other words, the targets initiated their conversations on their own, not upon the researchers' request. After removing the targets' identifiable information (including names and profile pictures), the 12 conversation transcripts were used as the experiment stimuli (available upon request). We asked the targets to select the transcripts of their first conversation with Little Ice and a person on their social network to exclude confounding factors (e.g., familiarity and relational development). In order to avoid the influence of existent human relationship that was developed offline, we specifically asked the targets to choose their conversation partners whom they first got acquainted with on WeChat, e.g., someone they met in a WeChat conversational group with common interest. With the functions of “sharing business cards” and “forming conversational group,” WeChat can make introducing and connecting with new friends easy and efficient.

Each participant was assigned to read two transcripts and was asked to evaluate each target's personality traits and assign them a gender category. Unbeknownst to the participants, both transcripts were randomly selected from one of the six targets' transcript copies. Each copy represented the selected target's conversation with a human communication partner or with Little Ice.

3.2. Measures

A questionnaire was attached to each copy of the conversation transcript. The measure for personality traits was originally composed in English and was translated into Chinese before the questionnaire was administered.

Assigned gender category. The participants were asked to assign a gender category to the target using the question, “You believe that your conversation partner on the right side (the target) is A) male or B) female.” Based on the accuracy of the answers, the responses were coded as *(1) true* or *(0) false*.

Personality traits. McCord's (2002) 50-item five-factor personality trait scale was adapted to measure the perceived personality traits. Ten items were used to measure each of the five traits: openness ($M = 3.87$, $SD = 0.52$, $\alpha = 0.79$), conscientiousness ($M = 3.80$, $SD = 0.53$, $\alpha = 0.64$), agreeableness ($M = 3.84$, $SD = 0.60$, $\alpha = 0.61$), extraversion ($M = 3.79$, $SD = 0.76$, $\alpha = 0.78$), and neuroticism ($M = 3.98$, $SD = 0.56$, $\alpha = 0.70$). The participants were asked to report their responses on a 7-point Likert-type scale ranging from *(1) Strongly Disagree* to *(7) Strongly Agree*. Examples of the questionnaire items include “This target has a vivid imagination” (openness), “This target makes plans and sticks to them” (conscientiousness), “This target believes that others have good intentions” (agreeableness), and “This target is not easily bothered by things (reverse coded)” (neuroticism).

Social media use experience. The participants' social media use experience was gauged by asking them to estimate how many hours they spent on various social media platforms each day (including on mobile devices) such as WeChat ($M = 2.46$, $SD = 2.26$), microblogs ($M = 0.89$, $SD = 1.21$), and QQ (another popular social media platform in China) ($M = 0.58$, $SD = 0.74$). The frequency of social media use was measured on a 7-point scale ranging from *(1) never or barely* to *(7) more than six times each day* ($M = 6.74$, $SD = 0.86$ for WeChat; $M = 4.13$, $SD = 2.18$ for microblogs; and $M = 3.72$, $SD = 2.33$ for QQ). Because the targets interacted with Little Ice and their friends on WeChat, we asked specifically about the use of WeChat. They were also asked to recall how many years they had used WeChat ($M = 2.77$, $SD = 1.26$).

Demographics. The participants' gender (male coded as 1 and female coded as 2) and age ($M = 20.46$, $SD = 2.39$) were also measured in the questionnaire. A total of 104 males (42.45%) and 141 females (57.55%) participated in the study.

3.3. Data analysis

SPSS (version 22) was used to examine the research questions. After data cleaning, Chi-square tests were used to answer RQ1, logistic regression analyses were used to answer RQ2 and RQ3, and bivariate correlation analyses were used to answer RQ4 and RQ5.

4. Results

RQ1 asked whether individuals could accurately perceive a target's gender based on the target's interaction transcripts with (a) a chatbot and (b) a human. We found that of the 245 participants, 42.86% ($n = 105$) assigned the targets to the correct gender category based on the target-Little Ice conversation transcripts, χ^2 (1, $N = 245$) = 5.00, $p < .05$. The correct rate improved to 68.98% ($n = 169$) based on the target-human conversation transcripts, χ^2 (1, $N = 245$) = 35.30, $p < .001$. A chi-square test indicated that there was a statistically significant difference between the correct gender categorization and making a guess based on the targets' interaction with chatbots and humans. The results suggested that the participants more accurately perceived a target's gender based on the target's communication with humans than with Little Ice.

RQ2 asked how a participant's social media use experience would predict the accuracy of perceiving a target's gender based on the target's interaction transcripts with (a) a chatbot and (b) a human. RQ3 asked how a participant's gender would predict the accuracy of perceiving a target's gender based on the target's interaction transcripts with (a) a chatbot and (b) a human. A binary logistic regression analysis suggested that among the various demographic and social media use factors, the years of WeChat use ($B = 0.39$, $SE = 0.19$, $p < .05$, Exp$(B) = 1.48$), daily microblogging use time ($B = -0.83$, $SE = 0.36$, $p < .05$, Exp$(B) = 0.44$), microblogging use frequency ($B = 0.53$, $SE = 0.18$, $p < .01$, Exp$(B) = 1.69$), and daily QQ use time ($B = 1.17$, $SE = 0.56$, $p < .05$, Exp$(B) = 3.22$) significantly predicted the participants' accurate identification of the target's gender based on the target-human conversation transcripts (Table 1). In other words, a one-year increase in WeChat use increased the odds of accurately assigning a gender category by 48%. A one-unit increase in microblogging use frequency and QQ use time increased the odds of accurately assigning a gender category by 69% and 222%, respectively. However, a one-unit increase in microblogging use time decreased the odds of accurately assigning a gender category by 56%. The participants' gender did not influence the accuracy of their selection of the targets' gender based on the target-human conversation transcripts (Table 1). Moreover, neither the participants' gender nor their social media use significantly predicted the accuracy of their selection of the targets' gender categories based on the target-Little Ice conversation transcripts (Table 2).

RQ4 asked how a target's evaluated personality traits would be related to the gender category assigned. A bivariate correlation analysis was conducted between the variables of assigned gender, the participant's gender, age, social media use experience, and personality traits. Based on the target-human conversation transcripts, the results suggested that perceived extraversion ($r = -0.27$, $p < .001$), openness ($r = -0.24$, $p < .001$), and neuroticism ($r = 0.29$, $p < .001$) were significantly correlated with assigned gender (male = 1, female = 2). That is, the participants were more likely to perceive those who were more extroverted, more open, and less neurotic in their conversations with humans as males than females (Table 3).

Table 1
Predicting the accuracy level of perceiving a target's gender based on target's interaction transcript with AI (RQ2a and RQ3a).

Predictor	B	S.E.	Wald	df	Sig	Exp(B)
Block 1						
Sex	-.09	.40	.06	1	.82	.91
Age	.02	.13	.02	1	.88	1.02
Block 2						
NetTime	.01	.11	.01	1	.92	1.01
WCTime	.12	.13	.78	1	.38	1.12
WCFreq	-.19	.35	.30	1	.59	.83
WCYear	-.05	.15	.11	1	.74	.95
WCFriend	-.21	.16	1.83	1	.18	.81
WBTime	.03	.25	.01	1	.92	1.03
WBFreq	-.05	.13	.17	1	.68	.95
QQTime	.03	.39	.01	1	.95	1.03
QQFreq	-.16	.14	1.31	1	.25	.85
Nagelkerke R Square = .17						

Note: B means unstandardized effect. S.E. means standard error. df means degree of freedom. Sig means significance level. Exp (B) means odds ratio.

Table 2
Predicting the accuracy level of perceiving a target's gender based on target's interaction transcript with a human (RQ2b & RQ3b).

Predictor	*B*	*S.E.*	*Wald*	*df*	*Sig*	Exp*(B)*
Block 1						
Sex	-.27	.51	.28	1	.60	.76
Age	.01	.16	.00	1	.96	1.01
Block 2						
NetTime	-.24	.14	2.76	1	.10	.79
WCTime	.18	.16	1.31	1	.25	1.20
WCFreq	-.39	.43	.84	1	.36	.68
WCYear	.39*	.19	4.38	1	.04	1.48
WCFriend	.05	.19	.07	1	.80	1.05
WBTime	-.83*	.36	5.37	1	.02	.44
WBFreq	.53***	.18	8.58	1	.00	1.69
QQTime	1.17*	.56	4.30	1	.04	3.22
QQFreq	-.32	.17	3.61	1	.06	.73
Nagelkerke R Square = .39						

Note: B means unstandardized effect. S.E. means standard error. df means degree of freedom. Sig means significance level. Exp (B) means odds ratio. * means p < .05, *** means p < .005.

The results of the correlation analysis also suggested that perceived openness ($r = 0.15$, $p < .05$) was correlated with the assigned gender in human-chatbot communication. This suggests that the participants were more likely to perceive those who were more open in their conversation with a chatbot as females than males (Table 4).

RQ5 asked how participants' gender was related to the gender category assigned. Bivariate correlation analyses showed that a participant's gender was neither significantly correlated with the assigned gender based on the target's interaction with Little Ice ($r = 0.11$, $p > .05$) nor with a human communicator ($r = 0.11$, $p > .05$).

5. Discussion

In this study, we investigated the gender categorization effect in HMC, as gender categorization can reflect individuals' communication approaches to interacting with both human and non-human agents. Specifically, the participants had a better-than-chance probability (68.98%) of correctly assigning the gender of a target based on the gender markers in the target's language in the CMC context (Mulac, 2006; Palomares, 2004). However, the predictive power of the targets' gendered language use decreased sharply to a less-than-chance level (42.86%) in the HMC context. Although far from being conclusive, our study revealed significant differences between the targets' conversation styles in target-chatbot interaction and target-human interaction. These results suggest that individuals use different communication approaches and present different communication patterns in interaction with human and non-human agents.

The participants were more likely to accurately perceive a target's gender based on the target's interaction with a human than with Little Ice. This finding implies that the participants were able to detect the language cues and assign the correct gender categories in a mediated environment. Although our results are inconsistent with some of previous CMC studies (Cornetto & Novak, 2006; Novak, 2003), our study corroborates the assumption of both social information processing theory and the hyper-personal model of communication (Walther, 1996; Walther et al., 2015) that users form impressions and develop interpersonal relations with others based on the cues available in the CMC context. These cues include but are not limited to the conversation style, hedges, length of sentences, adjectives, directives, and references (Herring & Martinson, 2004; Mulac, 2006).

Compared with their accuracy in assigning gender in the CMC context, the participants were unable to differentiate the gender of the

Table 3
The correlation coefficients between assigned gender category (female higher) and other variables based on target's interaction transcript with AI (RQ4 & RQ5).

	Assigned Gender 1	Viewer Sex 2	Age 3	NetTime 4	WCTime 5	WCFreq 6	WCYear 7	WCFriend 8	WBTime 9	WBFreq 10	QQTime 11	QQFreq 12	E 13	O 14	N 15	A 16	C 17
1	–																
2	.11	–															
3	.03	-.21**	–														
4	-.08	.13	.03	–													
5	-.06	.12	-.02	.68***	–												
6	.08	.06	.02	.26***	.29***	–											
7	.10	.05	-.18**	-.16*	-.20**	-.03	–										
8	.04	-.04	.30***	-.02	.12	.29***	-.21**	–									
9	-.04	.14*	-.09	.57***	.48***	.17**	-.15*	-.03	–								
10	.01	.16*	-.13*	.32***	.23***	.27***	-.10	.11	.56***	–							
11	.02	-.02	-.12	.16*	-.01	-.13*	.18**	-.19**	.01	-.17**	–						
12	.01	-.05	-.20**	-.15*	-.27***	-.19**	.25***	-.11	-.23***	-.22**	.68***	–					
13	.04	.07	-.24***	-.13*	-.12$^{\#}$	-.08	.14*	-.09	-.09	-.08	.14*	.20**	–				
14	.15*	.08	.08	-.05	-.07	.06	-.10	.10	-.00	.12	-.14*	-.08	-.23***	–			
15	-.12	.01	-.13*	.13*	.09	-.00	.06	.01	.04	.06	.09	.08	.29***	-.37***	–		
16	-.07	.05	-.15*	-.09	-.03	-.04	.16*	.06	-.00	-.09	.11	.14*	.41***	-.35***	.22**	–	
17	.08	.09	-.21**	-.07	-.00	.00	.08	-.09	-.04	-.10	-.01	.05	.58***	-.28***	.24***	.30***	–

Note: E = extraversion; O = openness; N = neuroticism; A = agreeableness; C = conscientiousness. * means $p < .05$. ** means $p < .01$. *** means $p < .001$.

Table 4
The correlation coefficients between assigned gender category (female higher) and other variables based on target's interaction transcript with a human (RQ4 & RQ5).

	Assigned Gender 1	Viewer Sex 2	Age 3	NetTime 4	WCTime 5	WCFreq 6	WCYear 7	WCFriend 8	WBTime 9	WBFreq 10	QQTime 11	QQFreq 12	E 13	O 14	N 15	A 16	C 17
1	–																
2	.11	–															
3	.07	-.21**	–														
4	.12	.13	.03	–													
5	.19**	.12	-.02	.68***	–												
6	.14*	.06	.02	.26***	.29***	–											
7	-.05	.05	-.18**	-.16*	-.20**	-.03	–										
8	.04	-.04	.30***	-.02	.12	.29***	-.21**	–									
9	.07	.14*	-.09	.57***	.48***	.17**	-.15*	-.03	–								
10	.05	.16*	-.13*	.32***	.23***	.27***	-.10	.11	.56***	–							
11	-.11	-.02	-.12	.16*	-.01	-.13*	.18**	-.19**	.01	-.17**	–						
12	-.16*	-.05	-.20**	-.15*	-.27***	-.19**	.25***	-.11$^{\#}$	-.23***	-.22**	.68***	–					
13	-.27***	.01	.13*	.04	.03	.10	.01	.12$^{\#}$	.08	.04	.06	-.08	–				
14	-.24***	-.03	.12	.03	.07	.13*	.10	.16*	.06	.04	.06	-.04	.77***	–			
15	.29***	.04	-.09	.08	.05	.01	-.01	-.08	.03	.01	-.07	.03	-.69***	-.60***	–		
16	-.05	-.12	.25***	-.02	-.08	.03	.05	.06	-.04	-.05	-.06	-.10	.46***	.35***	-.41***	–	
17	-.08	.01	.16*	.06	.02	.09	-.01	.04	.02	-.02	-.02	-.14*	.61***	.46***	-.60***	.49***	–

Note: E = extraversion; O = openness; N = neuroticism; A = agreeableness; C = conscientiousness. * means $p < .05$. ** means $p < .01$. *** means $p < .001$.

targets in the HMC context. The differences between the accuracy levels in CMC and HMC challenge the media equation theory that users naturally respond to media technologies as social actors (Reeves & Nass, 1996). In line with other studies (Amalberti et al., 1993; Kanda et al., 2008), our findings suggest that users' social responses to media technologies vary with contexts and tasks. At least in their initial interaction with chatbots, users might have used a different style of communication than when they interacted with their human interlocutors, which would reduce the accuracy of their gender categorization.

We further examined how the participants' media consumption may have influenced their judgement. Our results suggest that the participants relied on their past social media use experience when assigning a gender category to the target based on the target-human conversation transcripts. We found that more experienced social media users were more likely to become well-trained detectors of gender. Although it is inconsistent with the previous finding that chat room use experience did not predict gender categorization (Cornetto & Novak, 2006), it is reasonable to speculate that experienced social media users have more skills in discerning the gender of their communication partners online. However, social media use experience did not appear to assist the participants in completing the same task based on the target-chatbot conversation transcripts. It may be because people experiment with different approaches and try different social principles in interpersonal communication when they first converse with non-human agents (Weil, 2017). In conjunction with Mou and Xu (2017) finding that users exhibit different personalities when conversing with a chatbot than with a human friend, the results of this study call for further examination of the differences between HMC, CMC, and interpersonal communication.

We also examined whether gender stereotypical personality traits, as a gender-linked attribute, could provide a potential way of revealing how people assign gender categories. Based on the target-human transcripts, the targets who were perceived as extroverted were more likely to be male. This supports the finding that assertiveness and dominance were more likely to be interpreted as being representative of masculine language (Park et al., 2016). In their computational linguistic studies, Park et al. (2016) concluded that language used by self-identified females was warmer, more compassionate and polite, but colder, more hostile and impersonal by self-identified males based on a sample of over 15,000 Facebook users (significant effect size d ranged from 0.11 to 0.14). Moreover, the targets who were perceived as open and neurotic in CMC were also more likely to be identified as males. The result aligned with the finding that men are generally more open and extroverted, but refuted Costa, Terracciano and McCrae's (2001) finding that they are less neurotic. Comparatively, in the HMC context, openness was the only significant predictor of gender categorization, and the targets who were perceived as open were more likely to be assigned a female gender in the HMC context. This difference reinforces our theory that users present different personality traits in HMC and CMC (Mou and Xu, 2017).

It is notable that interpersonal communication approaches are highly contingent on contexts. Targets may have different motivations of initiating a conversion. Chatbots like Little Ice are generally designed to sustain broad conversations, but their ability to develop extended goal-directed in-depth discussion on a particular topic is rather limited (Hill et al., 2015). Moreover, the intrinsic novelty of chatbots and no fear of negative judgments by chatbots would also trigger users to test the limits of chatbots' conversational domain (Lucas, Gratch, King, & Morency, 2014). That is probably why researchers have identified salient differences in both the content and the quality of conversations between human-human and human-chatbot communication, including the greater use of profanity and less richness of vocabulary in human-chatbot conversations (Hill et al., 2015).

The characteristics of the chatbot system used in this study might also have confused the targets and forced them to converse in a different manner. Jia (2004) found that due to the absence of linguistic knowledge and the limited understanding of the users' input, the responses of chatbots did not follow the rules of interpersonal communication, which further induced people not to respond to the bots in a social manner. In her experiment designed to test whether the participants could distinguish between the chatbot ALICE and a human interlocutor, Jia (2004) found that most of the participants figured out that ALICE was not a real person after a brief interaction and soon gave up further communication. In our study with Little Ice, although Microsoft applied deep learning and big data techniques to better understand the semantic meanings of people's messages, the system lacked the capacity to fathom contexts and conventions, and the conversations thus tended to be shallow and temporary.

In both CMC and HMC contexts, we found that females were not more accurate in assigning gender categories, which contradicted the research finding that females tend to pay more attention to subtle gender-linked cues (Ambady et al., 1995). Inconsistent with self-schema theory, which posits that a person who is schematic in a particular area is an expert within that domain (Markus, Crane, Bernstein, & Saladi, 1982), neither males nor females showed a significant tendency to assign their corresponding gender categories in both CMC and HMC contexts. One possible reason is that both male and female participants in the study shared similar online use experiences, which diminished their gender advantages in detecting gendered cues.

Several limitations need to be considered when interpreting the results of this study. First, we did not code the language features to identify the gender markers. Instead, we relied on the overall impression of the participants. It is likely that biological males can have feminine conversational patterns and vice versa. As this study only aims to examine the assumptions of media equation through the gender categorization process, we did not include the connection between biological sex and socially constructed gender differences. Thus, future research may consider using language feature coding to fully understand the gender assignment process and further explore the relationship between one's social gender and biological sex. Second, the targets conversed with their friends or Little Ice in Mandarin Chinese, which is a less gender-marked language than many other languages such as German and French. Thus, we caution against generalizing the results to other languages. The lack of systematic cross-language research calls for further studies in this area. Third, we examined the conversation transcripts of only six targets. Thus, the conversations may not be representative of the typical conversations between humans and chatbots. Recruiting more targets and using more transcripts would provide larger samples and ensure greater variance in the messages. Besides, to increase the generalizability of the findings, we decided to use conversations from natural settings and did not control for the conversation topics. Potentially, their conversation topics could influence participants' perception of the targets' gender. Fourth, this study did not explore participants' psychological processing of chatbots. Thus, why participants treated chatbots differently from humans remained unknown. As researchers have been debating over mindlessness and anthropomorphism (Epley, Waytz, & Cacioppo, 2007; Kim & Sundar, 2012; Lee, 2010; Nass & Moon, 2000), future studies can further examine which psychological mechanism has more explanatory power of people's social responses to chatbots.

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