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The media inequality: Comparing the initial human-human and human-AI social interactions

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ABSTRACT

As human-machine communication has yet to become prevalent, the rules of interactions between human and intelligent machines need to be explored. This study aims to investigate a specific question: During human users' initial interactions with artificial intelligence, would they reveal their personality traits and communicative attributes differently from human-human interactions? A sample of 245 participants was recruited to view six targets' twelve conversation transcripts on a social media platform: Half with a chatbot Microsoft's Little Ice, and half with human friends. The findings suggested that when the targets interacted with Little Ice, they demonstrated different personality traits and communication attributes from interacting with humans. Specifically, users tended to be more open, more agreeable, more extroverted, more conscientious and self-disclosing when interacting with humans than with AI. The findings not only echo Mischel's cognitive-affective processing system model but also complement the Computers Are Social Actors Paradigm. Theoretical implications were discussed.

1. Introduction

Since Alan Turing proposed the famous question “Can machines think?” in 1950, the emergence of intelligent machines has been witnessed in the past several decades. In the same year, Norbert Wiener envisioned the popularity of interactions between humans and machines and machines and machines (Wiener, 1988). While the idea of machine-machine communication has been testified with 61.5% of traffic on the web being non-human (Kelion, 2013), human-machine communication has yet to become prevalent.

Gunkel (2012) proposed that a paradigm shift from computer-mediated communication (CMC) to human-machine communication (HMC) is needed to address the issues associated with communicating with intelligent machines, autonomous decision making systems, and smart devices. Unlike previous generations of machines with few signs of intelligence, those intelligent machines now not only function as a channel of communication process, but also play an active role in participating in communicative interactions.

One of the most representative forms of those intelligent machines is robots. Robots have been adopted in restaurants, shopping malls, and hospitals. For instance, telepresence robot SAM can work as a nurse assistant to check on senior patients' physical status (Ackerman, 2016). Anderson (2016) observed that the Kirobi Mini robot from Japan could promote people's emotional responses to babies. In addition to the physically embodied robots, online chatbots have also been widely used. Franceschi-Bicchierai (2016) found that a Twitter chatbot in Argentina could trick people into believing its human identity. Today as people have a growing chance of interacting with these digital interlocutors, studying how people initiate and engage in a conversation with machines would lead us to understand our reactions and attitudes towards machines.

Comparing the initial human-machine communication and human-human communication would bring benefits to our interpretation of any potential boundary between humans and machines. Although previous research on media equation has suggested that humans treat media as social actors (Nass & Moon, 2000; Reeves & Nass, 1996), whether media users apply the same level of social responses to media as to humans remains to be explored. The current study on the comparisons between human-human communication and human-machine communication would thus contribute to the theoretical framework of media equation.

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In addition, engineers and designers could customize their products based on users' personalities in human-machine communication. For example, research has suggested that agreeableness could help reduce interpersonal distance between humans and robots (Takayama & Pantofaru, 2009). In order to improve the user experience of human-machine communication, designers could embed different types of personalities in machines or applications based on users' needs and social responses. Thus, examining the personalities people reveal in human-machine communication would have both theoretical and practical implications.

Overall, this study aims to investigate a specific question: During human users' initial interactions with artificial intelligence (AI), would they reveal their personality traits and communicative attributes differently from human-human interactions? Based on a review of two theoretical frameworks, hypotheses are proposed and tested by an exploratory study.

2. Literature review

2.1. Human-machine communication

The role machines play in communication process has changed rapidly in recent years. In the past few decades, the scholarship of CMC has viewed machines as a mere channel of information transmission. For instance, a typical question that CMC scholars investigate is whether technological affordances cut off the socio-emotional quality of communication online (Walther, Van Der Heide, Ramirez, Burgoon, & Peña, 2015). However, HMC researchers have interrogated a series of different questions, “What are the boundaries between human and machine? What communicative practices or precepts must be drawn, redrawn or reconsidered to explore these increasingly, or always-already technologized relationships?” (McDowell & Gunkel, 2016, p. 2). As Sundar, Jia, Waddell, and Huang (2015) pointed out, CMC concerns the shortcomings of machine in comparison with face-to-face interaction, whereas HMC is actually attributed to the shortcomings of human mind.

HMC is an ongoing sense-making process between human and machine (Guzman, 2016). In this communication process, how human interlocutors interpret their digital interlocutors and therefore behave accordingly becomes interesting. Will humans treat machines equally as they do to other humans in social interactions, as suggested by the media equation scholars? Or as other researchers posit (e.g., Fischer, Foth, Rohlfing, & Wrede, 2011), they react to machines differently from humans due to the change of interlocutors' nature? We will review the literature from both sides.

2.2. The computers are social actors paradigm

Nass and his colleagues were among the pioneers in investigating how humans treat machines in HMC processes. In the 1990s, they proposed the Computers Are Social Actors Paradigm (CASA) (Nass, Fogg, & Moon, 1996; Nass, Steuer, & Tauber, 1994). The CASA paradigm was based on a series of evidence from experiments on human computer interactions. Specifically, Reeves and Nass (1996) selected findings from social science research and replicated the role of humans with computers or televisions. Reeves and Nass (1996) proposed the media equation theory, suggesting that people treat computers and televisions like real people.

Nass and his colleagues have demonstrated that computer users apply politeness to computers (Nass et al., 1994). Nass et al. (1994) found that when a computer asked participants to evaluate its own performance, users tended to have a more positive attitude toward the computer. However, when a second computer asked participants to evaluate the performance of the first computer they interacted with, users did not show politeness and tended to be more critical of the first computer.

Users also perceive computers to have gender characteristics. Participants reported a computer with a male voice to be more credible and dominant (Nass, Moon, & Green, 1997). A computer with a female voice is seen as having more knowledge about love and relationships, while a computer with a male voice is perceived to be more knowledgeable about technical issues (Nass et al., 1997). Computers' voices can also manifest personalities. Nass and Lee (2001) manipulated the speech rate, volume level, fundamental frequency, and pitch range of computers' voices. They found that introverted participants would like to interact with a computer that has introverted voice, while extroverted participants preferred to talk with an extroverted computer (Nass & Lee, 2001).

This tradition of research is not limited to computers. Nass and Moon (2000) tested users' responses to televisions. They assigned some of the participants to one condition where they were asked to watch two different televisions showing news and entertainment respectively. In the other condition, participants watched news and entertainment on the same television. Nass and Moon (2000) found that the participants in the first condition believed that the two televisions were specialists. They were more informative, serious, and featured better quality. Comparatively, the participants in the second condition believed that the television was a generalist and provided less information and lower quality. Nass and Moon's (2000) research suggests that individuals not only perceive computers as social actors, but also televisions as social actors.

The CASA paradigm not only explained users' perception of machines, but also tested the social interactions between humans and machines. Nass and Moon (2000) found that users applied social norms in conversation with machines. Specifically, users were more likely to disclose private information when computers follow human conversations rules such as gradually shifting from one topic to another. In addition, when computers showed high reciprocity, users were more likely to do self-disclosure (Nass & Moon, 2000).

More recently, the CASA paradigm has been applied to user-chatbot interaction. Edwards, Edwards, Spence, and Shelton (2014) compared Twitter users' perception of chatbots' accounts and human's accounts. Results suggested that users could not differentiate twitter bots from human users. Twitter bots were perceived to be credible, attractive, and efficient in communication as much as humans.

In explaining the CASA paradigm, Nass and Moon (2000) proposed that individuals have not fully evolved to differentiate mediated experience from non-mediated experience. Nass and Moon (2000) argued that individuals are likely to focus on social cues and neglect the asocial characteristics of the entities. These social cues can easily trigger certain social expectations and rules, which lead individuals to use simple scripts that have been applied in the past social interaction.

Although mindlessness is viewed as one of the major reasons for people's social responses to computers, it has been challenged in previous literature. For example, Kanda, Miyashita, Osada, and Ishiguro (2008) found that participants responded to robots' greetings more slowly than to humans' greetings, indicating that participants experienced cognitive activities when responding to robots' behaviors. Fischer et al. (2011) found that participants laughed when responding to robots' greetings, indicating that they detected something unusual during their interaction with robots. These studies suggest that mindlessness may not account for humans' natural and social responses to robots. It is likely that people apply different communication strategies in human-machine communication. In addition, the work that challenged the explanatory power of mindlessness has centered on users' responses to robots' greetings. Little research has examined whether users' unnatural responses would be found in user-chatbot interaction. Furthermore, few researchers have focused on users' initial interaction with machines. There is a research gap in investigating the factors that lead to people's use of different communication strategies in human-machine communication. Thus in the current study, we attempt to examine users' initial interaction with chatbots from the perspective of their personalities and communication attributes. If users reveal different personalities and communication attributes in human-chatbot communication and human-human communication, researchers could find some potential explanations of users' unnatural responses to machines. The knowledge would also add complements to the CASA paradigm in terms of "when and why mindless behavior will occur" (Nass & Moon, 2000, p. 96).

2.3. The cognitive-affective processing system

While the promise of consistence across human-human interactions to human-machine interactions is held by the CASA scholars, social psychologists cast doubts over the psychological invariance that distinctively characterizes an individual across diverse situations (Mischel, 2004). For instance, a student who cheats on a quiz could be highly honest in other situations. Or an individual who are sociable in some events could remain rather shy in others. To solve the so-called "personality paradox", the cognitive-affective processing system (CAPS) was developed by Mischel and colleague (Mischel & Shoda, 1995; Shoda & Mischel, 1998, pp. 175–208).

According to the CAPS model, the personality system contains mental representations consisting of diverse cognitive-affective unites (CAUs). Those CAUs include individuals' core values, beliefs, memories, and so on. They are interconnected and organized, "guided by a stable network of cognitions and effects characteristic for that individual" (Mischel, 2004, p. 11). Individual differences lie in the accessibility of different CAUs. In diverse situations, different CAUs are activated to exhibit behavioral incoherence.

In interpersonal social interactions, individuals tend to obey certain social rules (Burgoon & Jones, 1976). A civil society requires individuals to be polite and sensitive to others' privilege; hence, one has to restrain himself/herself from deviant behaviors. For instance, being afraid of others' moral judgement, individuals will avoid self-disclosing information that contains morality-violating behavior. However, when encountering a nonjudgmental listener such as AI, one's fear of being judged would vanish. In that situation, different CAUs would be activated; he/she might perform baldly and therefore present different personality traits. In a similar vein, one's control over the interactions with a human interlocutor and a machine interlocutor may vary as well. Psychologists have long argued that the control over the events in one's life (including social interactions) demonstrates competence and superiority (Adler, 1930), as an individual constantly matches expectancy against perception in an effort to obtain optimum control (Kelly, 1955). Individuals are not identical in exerting control. For the same person, he/she may barely remain the same control level over all events. When interacting with a machine, some people may feel more confident and take more control over the interacting process while others may feel confused and even intimidated, and consequently implement less control.

It is notable that the CAPS model targets specifically at the inconsistence of personality across situations. Prior research has suggested that personalities could be linked to users' perception of robots (Takayama & Pantofaru, 2009). People with agreeableness would feel less distant from robots when they interact with them, while people with neuroticism would ask for more personal space when approaching robots (Takayama & Pantofaru, 2009).

On top of the relationship between personalities and interaction with robots, communicative attributes and personality traits are operationally intertwined, as personality has considerable influence on communicative behaviors. For instance, in McCrae and Costa's (1985) big five model of personality (i.e., openness, conscientiousness, agreeableness, extraversion and neuroticism), the level of extraversion is oftentimes reflected by the level of self-disclosure (Hollenbaugh & Ferris, 2014). Therefore, based on the CAPS model, when communicating with a machine, users' self-disclosing behavior should be different from when communicating with a human.

2.4. Study overview

In this study, we aim to compare the initial human-AI social interaction with initial human-human social interaction. In particular, we compare the personality traits and communication attributes reflected in human-AI interaction and in human-human interaction. We chose Little Ice, a chatbot developed by Microsoft as an example of AI. The choice was made based on two reasons. First, Microsoft launched Little Ice in China in 2014 and since then it has attracted over 90 millions of users to chat with it (Bingblog, 2016). Little Ice was specifically designed as a 17-year old girl with a lively and outgoing, sometimes naughty personality. This personality contributes to its popularity among users. Second, WeChat, a social network that combines features from Facebook and the mobile application WhatsApp, is currently one of the most popular social media platforms in the world, especially in China. On WeChat, any users can chat with Little Ice as with other human friends. Hence, we could compare one's interactions with Little Ice and with a human friend, while eliminating confounding factors associated with different platform use.

Based on the review of the abovementioned competing theories, we would argue that when conversing with Little Ice, human interlocutors would not remain mindless due to the novelty experience. The presumption of media equation theory is not fulfilled in this context. Hence, the personality traits and communication attributes exhibited in the HMC would be distinct from those in interpersonal communication, as predicted by the CAPS framework. In addition, the situation of introverted self-evaluation also sharply differs from HMC context. According to CAPS, it would be logical to expect differences between human users' self-rated traits and the traits exhibited in HMC.

Altogether, the following hypotheses are postulated:

H1a. The personality traits presented by human users in the initial social interaction with a chatbot are different from those presented in the initial social interaction with another human.

H1b. The personality traits presented by human users in the initial social interaction with a chatbot are different from the human users' self-rated personality traits.

H2a. Human users' self-disclosure level in the initial social interaction with a chatbot is different from that in the initial social interaction with another human.

H2b. The level of self-disclosure presented by human users in the initial social interaction with a chatbot is different from the human users' self-rated self-disclosure level.

H3a. Human users' level of control over the initial social interaction with a chatbot is different from that in the initial social interaction with another human.

H3b. The level of control over the initial social interaction with a chatbot presented by human users is different from the human users' self-rated level of control over social interactions.

3. Method

3.1. Procedure

Ten volunteers were recruited through snowball sampling to provide two copies of his/her conversation transcripts on WeChat: One with Little Ice and one with a normal human friend. Those ten volunteers are currently active WeChat users. By the time the conversation transcripts were collected, they had already initiated a chat with Little Ice and their friends on their own will. In other words, when they conversed with Little Ice and human friends, they had no idea of this study at all; so the conversations happened in natural settings. After removing four volunteers' conversation transcripts due to the length or incompleteness of a round of conversation, six volunteers' twelve conversation transcripts were used as the materials for later procedure. Notably, we particularly asked the volunteers to select a conversation transcript with a regular friend, not with a close friend or significant other. Moreover, only the transcripts of their first conversation with Little Ice and friend were retrieved to exclude the variance caused by relationship development. Since those volunteers are the targets of later analysis, we call them "targets" afterwards. Those targets were evaluated by 277 viewers on their personality and communication attributes. Meanwhile, each target filled out measures of their own personality traits and communication attributes.

3.2. Material and stimulus

Based on the targets' original conversation transcripts, three research assistants generated twelve copies of mock-up conversation transcripts after removing sensitive or identifiable information using the Photoshop software. In the name of privacy protection, all names and profile pictures were blocked (see an example of the transcript in Fig. 1).

Fig. 1. An example of the mock-up chatting screenshot of WeChat.

Among those six targets, three are males and three are females. Their age ranges from 19 to 35 years old. While four of them are college students, one works in a private corporate and one works in a major newspaper institute (see their profile detail in Table 1). Their conversations cover a variety of topics based on their identity and interest. For instance, a college female student talks about celebrities and selective courses at school. Another target, an entrepreneur, introduces his corporate. Those conversations seem natural and improvisational. By the time the targets conversed with their human friends, they either just met in virtual groups or were introduced by others in a professional setting or school environment. The conversation topics were included in Table 1.

3.3. Sample

Two hundred and seventy-seven participants (viewers) were recruited in a large public university in Eastern China to read the conversation transcripts and evaluate the targets. After removing sixteen who failed to provide a complete evaluation and another sixteen who were international students, 245 participants' responses were collected for later analysis. To ensure the same baseline, each of the participants was asked to read one of the six targets' two copies of conversation transcripts — one with Little Ice, one with a human friend — based on which they evaluated the targets' personality traits and communicative attributes. When the participants read the transcripts, they had no clue of the purpose of this study. Instead, they were told it was a study about self-presentation on social media in interpersonal communication contexts. Therefore, they were not aware that those two transcripts were from the same target, and one of the conversations happened between a human and a chatbot. Each target was evaluated by 38–43 randomly assigned participants.

Among the 245 viewers, 42.4% of them were males and the rest were females. Their age ranged from 18 to 44 years old. All of them were WeChat users.

3.4. Measure

The questionnaire was originally designed in English. So it was back-translated into Chinese before the questionnaire was administered. The question items in the targets' self-evaluation questionnaire and the viewers' questionnaire were identical, except the differences in sentence structure. For example, in the self-evaluation questionnaire, the direction was "How much do you agree with the following statements that describe yourself?" In contrast, in the viewers' questionnaire, the direction was "How much do you agree with the following statements that describe the target?"

3.4.1. Personality

McCord's (2002) five-factor personality scale was employed to measure personality traits. Although longer versions of measures were available, the 50-item version was used to control the length of the questionnaire. Ten items measured each of the five traits: openness, conscientiousness, agreeableness, extraversion and neuroticism. Specifically, examples of openness (to new experiences) include "have a vivid imagination" and "enjoy hearing new ideas." Examples of conscientiousness are "make plans and stick to them" and "am always prepared." Examples of agreeableness include "believe that others have good intentions" and "make people feel at ease." Examples of extraversion include "am skilled in handling social situations" and "know how to captivate people." Examples of neuroticism are "am not easily bothered by things (reverse coded)" and "feel comfortable with myself (reverse coded)." All the fifty items were measured on a 7-point Likert scale

Table 1
The profile detail of each target.

ID	Sex	Age	Profession	Self-rated personality traits	Self-rated level of self-disclosure	Self-rated level of control	Human friend and chatting topic
1	M	35	Entrepreneur	O = 5.60 N = 2.50 A = 5.60 E = 4.60 C = 5.20	6.00	4.00	A female introduced by a professional connection; introducing his corporate.
2	M	25	Journalist	O = 6.00 N = 4.20 A = 3.20 E = 4.10 C = 4.30	4.20	4.50	An unfamiliar female coworker; small talks associated with working setting.
3	M	24	College student	O = 4.30 N = 3.20 A = 4.60 E = 4.40 C = 4.30	4.90	3.83	Cannot tell the gender; small talks associated with the first impressions for each other.
4	F	19	College student	O = 5.60 N = 2.60 A = 5.40 E = 3.90 C = 5.00	5.40	4.00	Cannot tell the gender; on how to select courses on school's system.
5	F	19	College student	O = 5.17 N = 3.17 A = 5.00 E = 4.00 C = 4.00	5.12	4.30	A female student; on student union work.
6	F	20	College student	O = 4.90 N = 3.70 A = 4.80 E = 3.30 C = 5.10	4.44	5.17	A female student; on working on a project together.

from *(1) Strongly Disagree* to *(7) Strongly Agree*. The robustness of this scale has been testified by Cooper, Golden and Socha (2013). The reliability Cronbach's alphas for each factor were 0.78, 0.64, 0.61, 0.78, and 0.70 in that order.

3.4.2. Self-disclosure

The level of self-disclosure was gauged by the scale developed by Miller, Berg, and Archer (1983). The participants were asked to indicate the degree to which they agree with the statements such as "People frequently tell me/this target about themselves." All the ten items were measured on a 7-point Likert scale from *(1) Strongly Disagree* to *(7) Strongly Agree*. The reliability Cronbach's alpha was 0.92.

3.4.3. Control over social interactions

The level of control over social interactions was measured by Shulman, Laursen, Kalman, and Karpovsky (1997) scale after removing two inapplicable items. The participants were asked to indicate the degree to which they agree with the statements such as "This target prefers/You prefer that everyone acts according to his/her/your decisions." All the six items were measured on a 7-point Likert scale from *(1) Strongly Disagree* to *(7) Strongly Agree*. The reliability Cronbach's alpha was 0.70.

3.4.4. Social media use

Targets' and viewers' social media use was gauged by asking them to indicate how much time they spend on various social media platforms each day (including social media on mobile devices) such as WeChat and microblogs. The frequency of social media use was measured on a 7-point scale from *(1) never or barely* to *(7) more than six times each day*. To gauge their use proficiency of WeChat, the participants were also asked to estimate the range of the number of their friends on WeChat, from *(1) less than 50* to *(7) more than 500*.

3.4.5. Demographics

The targets' and viewers' sex and age were also measured in the questionnaire. In particular, after reading each conversation transcript, the viewers were asked to guess the sex of the target. The responses were coded into (1) true or (0) false.

3.5. Manipulation check

Due to the use of the cover story, no real manipulation check was conducted. But based on the reaction of the viewers, they appeared not to have any doubt over the cover story. The most powerful demonstration of manipulation check was the results, which indicated a series of significant differences of ratings based on two different conversation transcripts (see below). Therefore, we concluded that the manipulation was successful.

4. Results

As the viewers spent more than 5 h ($M = 5.21$, $SD = 2.50$) online daily on average, they demonstrated a heavy use of the social media. They checked WeChat multiple times, and spent an average of 2.44 h ($SD = 2.27$) on WeChat each day. The average number of WeChat friends was over 300 ($M = 4.22$, $SD = 1.59$). The second most used social media platform was microblogging service, as the average daily use time was 0.87 h ($SD = 1.17$).

The means and standard deviations of self-rated levels of personality traits and communication attributes of each target were reported in Table 1.

H1-3 predicted significant differences (a) between the personality traits and communication attributes presented by human users in the initial social interaction with a chatbot and the initial social interaction with another human and (b) between those presented by human users in the initial social interaction with a chatbot and their self-rated ones. A series of paired *t*-test analyses were conducted (see Table 2). Notably, in testing H1-3, we combined the evaluations on those six targets together to save space. For the comparisons on each target, please see Appendix.

For the personality trait of openness, the self-rated level was the highest ($M = 5.27$, $SD = 0.54$), followed by the level rated on human-human interaction ($M = 4.10$, $SD = 0.66$). The level rated on human-AI interaction was the lowest ($M = 3.87$, $SD = 0.52$). There existed significant differences among those three evaluations: $t_{self\text{-}AI}(244) = 29.67$, $p < 0.001$; $t_{self\text{-}human}(244) = 20.28$, $p < 0.001$; and $t_{AI\text{-}human}(244) = -4.27$, $p < 0.001$. The trait of agreeableness followed the same pattern: the self-rated level was the highest ($M = 4.79$, $SD = 0.77$), followed by the level rated on human-human interaction ($M = 4.37$, $SD = 0.58$). The level rated on human-AI interaction was the lowest ($M = 3.84$, $SD = 0.60$). Those three evaluations were significant from each other: $t_{self\text{-}AI}(244) = 16.85$, $p < 0.001$; $t_{self\text{-}human}(244) = 6.29$, $p < 0.001$; and $t_{AI\text{-}human}(244) = -9.09$, $p < 0.001$. The trait of conscientiousness fell into the same category as well. The self-rated level was the highest ($M = 4.66$, $SD = 0.47$), followed by the level rated on human-human interaction ($M = 4.29$, $SD = 0.59$). The level rated on human-AI interaction was the lowest ($M = 3.80$, $SD = 0.53$). Those three evaluations were significant from each other: $t_{self\text{-}AI}(244) = 18.93$, $p < 0.001$; $t_{self\text{-}human}(244) = 7.25$, $p < 0.001$; and $t_{AI\text{-}human}(244) = -8.98$, $p < 0.001$.

Interestingly, the trait of neuroticism yielded an opposite pattern: the level rated on human-AI interaction was the highest ($M = 3.98$, $SD = 0.56$), followed by the level rated on human-human interaction ($M = 3.69$, $SD = 0.61$) and self-rated level ($M = 3.21$, $SD = 0.59$). Those three evaluations were significant from each other as well: $t_{\text{self-AI}}$ (244) = −14.62, $p < 0.001$; $t_{\text{self-human}}$ (244) = −9.56, $p < 0.001$; and $t_{\text{AI-human}}$ (244) = 5.36, $p < 0.001$. The trait of extraversion reflected a different pattern: the level rated on human-human interaction was the highest (M = 4.21, SD = 0.73), followed by self-rated level (M = 4.05, SD = 0.41); while the level rated on human-AI interaction was the lowest (M = 3.79, SD = 0.76). Those three evaluations were significant from each other as well: $t_{\text{self-AI}}$ (244) = 5.04, $p < 0.001$; $t_{\text{self-human}}$(244) = −3.47, $p < 0.001$; and $t_{\text{AI-human}}$(260) = −5.74, $p < 0.001$. Therefore, H1a and H1b were supported.

As for the self-disclosure level, the self-rated level was the highest (M = 5.01, SD = 0.66), followed by the level rated on human-human interaction (M = 4.03, SD = 0.98) and the level rated on human-AI interaction (M = 3.30, SD = 0.84). Significant differences existed between those three levels: $t_{\text{self-AI}}$ (244) = 24.53, $p < 0.001$; $t_{\text{self-human}}$ (244) = 12.70, $p < 0.001$; and $t_{\text{AI-human}}$ (260) = −7.67, $p < 0.001$. Hence, H2a and H2b were supported.

As for the level of control, the self-rated level was the highest (M = 4.30, SD = 0.49), followed by the level rated on human-human interaction (M = 4.10, SD = 0.81) and the level rated on human-AI interaction (M = 4.01, SD = 0.69). Significant differences existed between the self-rated level and other two levels: $t_{\text{self-AI}}$ (244) = 3.61, $p < 0.001$; $t_{\text{self-human}}$ (244) = 3.95, $p < 0.001$. But there was no significant difference between the latter two levels: $t_{\text{AI-human}}$ (244) = 1.31, n.s. Therefore, H3a was not supported; but H3b was supported.

5. Discussion

This study set out to detect the discrepancy between the initial social interaction between human and AI and that between humans. The findings suggested that when WeChat users interacted with Little Ice, they demonstrated different personality traits from interactions with humans. Specifically, users tended to be more open, more agreeable, more extroverted, more conscientious and self-disclosing when interacting with humans than with AI. In contrast, they also showed higher level of neuroticism with AI than with humans. In sum, human users demonstrated more socially desirable traits in communicating with humans than with AI. The only exception was the level of control over social interactions, as no significant difference was detected between conversing with humans and with AI.

The findings suggest that users apply different strategies to interact with AI from with humans. The results echo Mischel's CAPS model. When individuals encounter different types of interlocutors, various cognitive-affective unites will be activated. The activation further leads human users to present different personalities. As the CAPS provides a general framework to predict and explain the results, we need to delve into the more specific HMC frameworks.

The findings in this study may complement the CASA paradigm. Nass and Moon (2000) argued that users mindlessly apply social scripts from human-human interaction to human-computer interaction. Reeves and Nass (1996) further used evolutionary psychology to argue that computer users have not evolved enough to distinguish mediated environments from non-mediated environments. The finding in the current study may provide a different perspective of the narrative. If users are aware that they will interact with an AI that is supposed to act like real people, users will show less openness and less extraversion. It is consistent with the prior research finding that people who believed that they would interact with a robot would report lower perceived attractiveness than those who believed that they would interact with a person (Spence, Westerman, Edwards, & Edwards, 2014). Meanwhile, the naughty performances of Little Ice led users to react in a more neurotic way. On one hand, the findings corroborate previous studies in that mindlessness may not be explanatory in some contexts (Amalberti, Carbonell, & Falzon, 1993; Fischer et al., 2011; Kanda, Miyashita, Osada, Haikawa, & Ishiguro, 2008). On the other hand, it should be noted that users' mindless responses occur only when technologies show "enough cues to lead the person to categorize it as worthy of social responses" (Nass & Moon, 2000, p. 83). Thus, it is possible that Little Ice only demonstrated the social cues that evoke a certain degree of social responses but not enough to elicit the same level of responses to humans.

Among the five big personalities, users were perceived to have higher neuroticism in communicating with Little Ice. The result may corroborate Nass and Lee's (2001) finding that computers users preferred to interact with those that have similar personalities to them. As Little Ice was designed to be a naughty girl that can tell jokes, recite poetry, tell horror stories, and so on, users may prefer to respond to Little Ice in a more neurotic way. Meanwhile, the amalgam of AI's naughty personality and the multiple social functions might have led users to feel insecure and reluctant to disclose their information to AI.

In addition, Duffy and Zawieska's (2012) analysis of the different conditions where users suspend their disbelief in social robots could be a good reference to the results. Though Little Ice was endowed with different response mechanisms, the degree of bidirectionality and the strangeness in the conversation between humans and AI may determine how much users suspend their disbelief and build up their trust in the AI (Duffy & Zawieska, 2012). Despite the multiple social functions and designs of Little Ice, it is likely that human users can still tell that Little Ice's responses were not as natural as human conversation. Therefore, the low suspension of disbelief may inhibit users from demonstrating their personalities.

Going beyond the debate surrounding the media equation theory or CASA paradigm, the results of this study also shed light on general social relationships with machines. Based on a discourse analysis, Shechtman and Horowitz (2003) found that when participants believed that they were talking to a person instead of a computer, participants used more words and spent more time in conversation. More importantly, participants used statements about relationships (such as "Well, I definitely would be thankful to have you by my side in this situation.") in human-human

Table 2
Three types of evaluations by viewers on personality and communicative attributes.

Trait	Mean	SD	Comparison (all df = 244)
O_{self}	5.27	0.54	$t_{\text{self-AI}} = 29.67^{***}$
$O_{\text{w/AI}}$	3.87	0.52	$t_{\text{self-human}} = 20.28^{***}$
$O_{\text{w/human}}$	4.10	0.66	$t_{\text{AI-human}} = -4.27^{***}$
N_{self}	3.21	0.59	$t_{\text{self-AI}} = -14.62^{***}$
$N_{\text{w/AI}}$	3.98	0.56	$t_{\text{self-human}} = -9.56^{***}$
$N_{\text{w/human}}$	3.69	0.61	$t_{\text{AI-human}} = 5.36^{***}$
A_{self}	4.79	0.77	$t_{\text{self-AI}} = 16.85^{***}$
$A_{\text{w/AI}}$	3.84	0.60	$t_{\text{self-human}} = 6.29^{***}$
$A_{\text{w/human}}$	4.37	0.58	$t_{\text{AI-human}} = -9.09^{***}$
E_{self}	4.05	0.41	$t_{\text{self-AI}} = 5.04^{***}$
$E_{\text{w/AI}}$	3.79	0.76	$t_{\text{self-human}} = -3.47^{**}$
$E_{\text{w/human}}$	4.21	0.73	$t_{\text{AI-human}} = -5.74^{***}$
C_{self}	4.66	0.47	$t_{\text{self-AI}} = 18.93^{***}$
$C_{\text{w/AI}}$	3.80	0.53	$t_{\text{self-human}} = 7.25^{***}$
$C_{\text{w/human}}$	4.29	0.59	$t_{\text{AI-human}} = -8.98^{***}$
SD_{self}	5.01	0.66	$t_{\text{self-AI}} = 24.53^{***}$
$SD_{\text{w/AI}}$	3.30	0.84	$t_{\text{self-human}} = 12.70^{***}$
$SD_{\text{w/human}}$	4.03	0.98	$t_{\text{AI-human}} = -7.67^{***}$
$\text{Control}_{\text{self}}$	4.30	0.49	$t_{\text{self-AI}} = 3.61^{***}$
$\text{Control}_{\text{w/AI}}$	4.10	0.81	$t_{\text{self-human}} = 3.95^{***}$
$\text{Control}_{\text{w/human}}$	4.01	0.69	$t_{\text{AI-human}} = 1.31$

Note: O = Openness; C = Conscientiousness; A = Agreeableness; E = Extraversion; N = Neuroticism; SD = Self-disclosure.
$^{***}p < 0.001$, $^{**}p < 0.01$.

interactions four times than in human-computer interactions. Our research is congruent with the Shechtman and Horowitz (2003) study in that users appear to be restrained in conversing with AI.

Lack of goals may also account for the low level of personality demonstration in conversation with chatbots. In human-human interaction, conversation is goal-driven. Three main categories of goals have been identified in prior research: Task goals, communication goals, and relationship goals (Clark, 1996; Hobbs & Evans, 1980). Those goals help set the tone of our daily conversation. But as HMC is an emerging communication phenomenon, humans may not be able to find appropriate motivation to develop social relationships with machines. That could be the reason why conversing with a chatbot brought about lower ratings on personality.

Another finding is the striking difference between the targets' self-evaluation and viewers' evaluation based on their interactions with Little Ice. The targets tended to rate themselves as more socially desirable, i.e., being agreeable and conscientious, but their interactions with AI tells a different story. The difference may lead us to further reflect on which version of the targets is the true self. Is it the person talking with AI or the person talking with his/her friends? The discrepancies between targets' self-evaluation and viewers' evaluation reflects the prior debates on personality as a trait versus a state. Steyer, Schmitt, and Eid (1999) suggested that the concept of personality can be operationalized as both trait and state. Thus, this “You think you are nice, but you're actually mean to AI” or “revealing the true self to AI” narrative could direct researchers to further inquire into the contexts where users' demonstrated personalities as a trait versus as a state.

Several limitations need to be considered in interpreting the results of this study. First, although Microsoft claimed that over 90 million users have conversed with Little Ice, it is difficult to find suitable targets for this study due to the strict criteria of conversation transcript. That is why only six targets were recruited in the study. Hence, the generalizability of this study is limited. Moreover, this study was conducted in China. While Chinese culture emphasizes compliance with social rules, individuals in Chinese culture may feel more pressured to behave in a socially desirable way in interpersonal communication contexts than their counterparts in other cultures (Hofstede, 1984). Stuart (2016) also suggested that humans' reactions to social robots could be affected by their cultural backgrounds. Future research may consider a cross-cultural comparison of individuals' attitude toward chatbot. In addition, the current study did not investigate the impression formation process from the viewers' perspective. In other words, we did not probe into what cues caused the viewers' judgments on the targets' personality traits and communicative attributes. Future study may use the lens model approach (Hall, Pennington, & Lueders, 2014) to explore this question.

As an exploratory study, this project did not control for some potential confounding variables. For instance, we did not control for the gender and age of the human friend, since we did not want the interlocutors to initiate a conversation upon our request. Instead, we collected the conversation transcripts of natural conversations. This choice might suffer from lower internal validity, but the external validity was boosted. Although Microsoft artificially assigned gender, age and personality traits to Little Ice, Little Ice's conversational response is based on the big data from open public online sites. That is why we did not equate Little Ice with a regular 17-year old girl. The personality of the targeted interlocutor would be an underlying confounding factor as well. But the results indicated that each individual's responses remain consistent with the overall pattern (see Appendix).

On the last note, HMC heavily depends on the evolvement of technology. Past generations of chatbot such as ELIZA could only provide scripted conversational responses, while Little Ice responds autonomously based on the big data of the Internet (Bingblog, 2014). Along with the fast development of speech recognition technology and other similar technologies, human-machine interface is becoming more and more natural. Therefore, it would be premature to draw conclusions on how humans socially react to machines purely based on today's technology. Future studies should proceed to study human-machine relationships.

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Appendix. The comparisons of each target

For Target 1:

Trait	Mean	SD	Comparison (all df = 41)
O_{self}	5.60	–	$t_{self\text{-}AI} = 20.26^{***}$
$O_{w/AI}$	3.93	0.53	$t_{self\text{-}human} = 20.22^{***}$
$O_{w/human}$	4.12	0.47	$t_{AI\text{-}human} = -1.92^{\#}$
N_{self}	2.50	–	$t_{self\text{-}AI} = -21.95^{***}$
$N_{w/AI}$	4.09	0.47	$t_{self\text{-}human} = -16.59^{***}$
$N_{w/human}$	3.70	0.47	$t_{AI\text{-}human} = 3.58^{**}$
A_{self}	5.60	–	$t_{self\text{-}AI} = 17.39^{***}$
$A_{w/AI}$	3.93	0.62	$t_{self\text{-}human} = 14.52^{***}$
$A_{w/human}$	4.31	0.57	$t_{AI\text{-}human} = -3.02^{**}$
E_{self}	4.60	–	$t_{self\text{-}AI} = 5.35^{***}$
$E_{w/AI}$	3.95	0.79	$t_{self\text{-}human} = 4.29^{***}$
$E_{w/human}$	4.21	0.59	$t_{AI\text{-}human} = -1.68^{\#}$
C_{self}	5.20	–	$t_{self\text{-}AI} = 21.03^{***}$
$C_{w/AI}$	3.79	0.43	$t_{self\text{-}human} = 10.25^{***}$
$C_{w/human}$	4.43	0.48	$t_{AI\text{-}human} = -6.64^{***}$
SD_{self}	6.00	–	$t_{self\text{-}AI} = 20.31^{***}$
$SD_{w/AI}$	3.52	0.83	$t_{self\text{-}human} = 26.75^{***}$
$SD_{w/human}$	3.95	0.52	$t_{AI\text{-}human} = -3.40^{**}$
$Control_{self}$	4.00	–	$t_{self\text{-}AI} = -0.03$
$Control_{w/AI}$	4.00	0.82	$t_{self\text{-}human} = -1.69^{\#}$
$Control_{w/human}$	4.18	0.68	$t_{AI\text{-}human} = -1.23$

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

For Target 2:

Trait	Mean	SD	Comparison (all df = 38)
O_{self}	6.00	–	$t_{self\text{-}AI} = 29.71^{***}$
$O_{w/AI}$	3.83	0.46	$t_{self\text{-}human} = 14.95^{***}$
$O_{w/human}$	4.24	0.73	$t_{AI\text{-}human} = -2.85^{**}$
N_{self}	4.20	–	$t_{self\text{-}AI} = 4.12^{***}$
$N_{w/AI}$	3.81	0.59	$t_{self\text{-}human} = 4.66^{***}$
$N_{w/human}$	3.76	0.58	$t_{AI\text{-}human} = 0.31$
A_{self}	3.20	–	$t_{self\text{-}AI} = -5.14^{***}$
$A_{w/AI}$	3.53	0.40	$t_{self\text{-}human} = -16.40^{***}$
$A_{w/human}$	4.66	0.58	$t_{AI\text{-}human} = -8.55^{***}$
E_{self}	4.10	–	$t_{self\text{-}AI} = 3.40^{**}$
$E_{w/AI}$	3.77	0.61	$t_{self\text{-}human} = -2.49^{*}$
$E_{w/human}$	4.42	0.80	$t_{AI\text{-}human} = -3.76^{**}$
C_{self}	4.30	–	$t_{self\text{-}AI} = 3.79^{**}$
$C_{w/AI}$	3.91	0.64	$t_{self\text{-}human} = -0.56$
$C_{w/human}$	4.35	0.54	$t_{AI\text{-}human} = -2.77^{**}$
SD_{self}	4.20	–	$t_{self\text{-}AI} = 7.23^{***}$
$SD_{w/AI}$	3.23	0.84	$t_{self\text{-}human} = -0.50$
$SD_{w/human}$	4.30	1.26	$t_{AI\text{-}human} = -3.40^{**}$
$Control_{self}$	4.50	–	$t_{self\text{-}AI} = 1.17$
$Control_{w/AI}$	4.34	0.84	$t_{self\text{-}human} = 5.41^{***}$
$Control_{w/human}$	3.99	0.59	$t_{AI\text{-}human} = 2.02^{\#}$

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

For Target 3:

Trait	Mean	SD	Comparison (all df = 37)
O_{self}	4.30	–	$t_{\text{self-AI}} = 4.28^{***}$
$O_{w/AI}$	3.98	0.46	$t_{\text{self-human}} = -2.71^{*}$
$O_{w/human}$	4.63	0.75	$t_{\text{AI-human}} = -3.98^{***}$
N_{self}	3.20	–	$t_{\text{self-AI}} = -6.98^{***}$
$N_{w/AI}$	3.93	0.64	$t_{\text{self-human}} = -0.98$
$N_{w/human}$	3.32	0.75	$t_{\text{AI-human}} = 4.51^{***}$
A_{self}	4.60	–	$t_{\text{self-AI}} = 5.74^{***}$
$A_{w/AI}$	4.00	0.64	$t_{\text{self-human}} = 3.62^{**}$
$A_{w/human}$	4.24	0.61	$t_{\text{AI-human}} = -1.83^{\#}$
E_{self}	4.40	–	$t_{\text{self-AI}} = 6.11^{***}$
$E_{w/AI}$	3.66	0.75	$t_{\text{self-human}} = -0.83$
$E_{w/human}$	4.52	0.90	$t_{\text{AI-human}} = -3.59^{**}$
C_{self}	4.30	–	$t_{\text{self-AI}} = 5.60^{***}$
$C_{w/AI}$	3.92	0.42	$t_{\text{self-human}} = -0.98$
$C_{w/human}$	4.41	0.70	$t_{\text{AI-human}} = -3.95^{***}$
SD_{self}	4.90	–	$t_{\text{self-AI}} = 9.54^{***}$
$SD_{w/AI}$	3.26	1.06	$t_{\text{self-human}} = 4.05^{***}$
$SD_{w/human}$	4.15	1.14	$t_{\text{AI-human}} = -2.89^{**}$
$Control_{self}$	3.83	–	$t_{\text{self-AI}} = -7.21^{***}$
$Control_{w/AI}$	4.43	0.51	$t_{\text{self-human}} = -3.21^{**}$
$Control_{w/human}$	4.19	0.70	$t_{\text{AI-human}} = 1.59$

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

For Target 4:

Trait	Mean	SD	Comparison (all df = 42)
O_{self}	5.60	–	$t_{\text{self-AI}} = 17.18^{***}$
$O_{w/AI}$	4.06	0.59	$t_{\text{self-human}} = 24.84^{***}$
$O_{w/human}$	3.92	0.44	$t_{\text{AI-human}} = 0.95$
N_{self}	2.60	–	$t_{\text{self-AI}} = -17.23^{***}$
$N_{w/AI}$	3.76	0.44	$t_{\text{self-human}} = -13.42^{***}$
$N_{w/human}$	3.67	0.52	$t_{\text{AI-human}} = 0.82$
A_{self}	5.40	–	$t_{\text{self-AI}} = 23.02^{***}$
$A_{w/AI}$	3.93	0.42	$t_{\text{self-human}} = 10.91^{***}$
$A_{w/human}$	4.39	0.61	$t_{\text{AI-human}} = -3.90^{***}$
E_{self}	3.90	–	$t_{\text{self-AI}} = -0.94$
$E_{w/AI}$	4.01	0.79	$t_{\text{self-human}} = -5.08^{***}$
$E_{w/human}$	4.30	0.52	$t_{\text{AI-human}} = -1.69^{\#}$
C_{self}	5.00	–	$t_{\text{self-AI}} = 14.36^{***}$
$C_{w/AI}$	3.93	0.49	$t_{\text{self-human}} = 7.97^{***}$
$C_{w/human}$	4.41	0.49	$t_{\text{AI-human}} = -3.83^{***}$
SD_{self}	5.40	–	$t_{\text{self-AI}} = 15.69^{***}$
$SD_{w/AI}$	3.62	0.74	$t_{\text{self-human}} = 9.79^{***}$
$SD_{w/human}$	4.30	0.74	$t_{\text{AI-human}} = -3.20^{**}$
$Control_{self}$	4.00	–	$t_{\text{self-AI}} = 3.45^{**}$
$Control_{w/AI}$	3.81	0.36	$t_{\text{self-human}} = 0.78$
$Control_{w/human}$	3.93	0.59	$t_{\text{AI-human}} = -1.09$

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

For Target 5:

Trait	Mean	SD	Comparison (all df = 42)
O_{self}	5.17	–	$t_{\text{self-AI}} = 17.81^{***}$
$O_{w/AI}$	3.74	0.53	$t_{\text{self-human}} = 22.34^{***}$
$O_{w/human}$	4.16	0.30	$t_{\text{AI-human}} = -3.77^{**}$
N_{self}	3.17	–	$t_{\text{self-AI}} = -10.32^{***}$
$N_{w/AI}$	4.17	0.63	$t_{\text{self-human}} = -3.89^{**}$
$N_{w/human}$	3.49	0.54	$t_{\text{AI-human}} = 4.39^{***}$
A_{self}	5.00	–	$t_{\text{self-AI}} = 14.27^{***}$
$A_{w/AI}$	3.54	0.67	$t_{\text{self-human}} = 7.48^{***}$
$A_{w/human}$	4.48	0.45	$t_{\text{AI-human}} = -6.36^{***}$
E_{self}	4.00	–	$t_{\text{self-AI}} = 0.26$
$E_{w/AI}$	3.98	0.56	$t_{\text{self-human}} = -3.07^{**}$
$E_{w/human}$	4.20	0.43	$t_{\text{AI-human}} = -1.81^{\#}$
C_{self}	4.00	–	$t_{\text{self-AI}} = 4.12^{***}$
$C_{w/AI}$	3.63	0.59	$t_{\text{self-human}} = -3.47^{**}$
$C_{w/human}$	4.33	0.62	$t_{\text{AI-human}} = -4.32^{***}$
SD_{self}	5.12	–	$t_{\text{self-AI}} = 15.84^{***}$
$SD_{w/AI}$	3.09	0.84	$t_{\text{self-human}} = 7.99^{***}$
$SD_{w/human}$	4.28	0.69	$t_{\text{AI-human}} = -5.60^{***}$
$Control_{self}$	4.30	–	$t_{\text{self-AI}} = -0.99$
$Control_{w/AI}$	4.40	0.68	$t_{\text{self-human}} = 5.08^{***}$
$Control_{w/human}$	3.86	0.57	$t_{\text{AI-human}} = 5.28^{***}$

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

For Target 6:

Trait	Mean	SD	Comparison (all df = 39)
O_{self}	4.90	–	$t_{\text{self-AI}} = 17.07^{***}$
$O_{w/AI}$	3.66	0.46	$t_{\text{self-human}} = 11.60^{***}$
$O_{w/human}$	3.59	0.71	$t_{\text{AI-human}} = 0.47$
N_{self}	3.70	–	$t_{\text{self-AI}} = -5.94^{***}$
$N_{w/AI}$	4.10	0.43	$t_{\text{self-human}} = -7.13^{***}$
$N_{w/human}$	4.19	0.43	$t_{\text{AI-human}} = -0.91$
A_{self}	4.80	–	$t_{\text{self-AI}} = 8.21^{***}$
$A_{w/AI}$	4.14	0.51	$t_{\text{self-human}} = 7.42^{***}$
$A_{w/human}$	4.15	0.55	$t_{\text{AI-human}} = -0.06$
E_{self}	3.30	–	$t_{\text{self-AI}} = -0.30$
$E_{w/AI}$	3.34	0.85	$t_{\text{self-human}} = -2.58^{*}$
$E_{w/human}$	3.62	0.77	$t_{\text{AI-human}} = -1.47$
C_{self}	5.10	–	$t_{\text{self-AI}} = 17.66^{***}$
$C_{w/AI}$	3.63	0.52	$t_{\text{self-human}} = 18.80^{***}$
$C_{w/human}$	3.79	0.44	$t_{\text{AI-human}} = -1.41$
SD_{self}	4.44	–	$t_{\text{self-AI}} = 14.66^{***}$
$SD_{w/AI}$	3.08	0.59	$t_{\text{self-human}} = 9.62^{***}$
$SD_{w/human}$	3.14	0.85	$t_{\text{AI-human}} = -0.47$
$Control_{self}$	5.17	–	$t_{\text{self-AI}} = 8.76^{***}$
$Control_{w/AI}$	3.64	1.11	$t_{\text{self-human}} = 8.26^{***}$
$Control_{w/human}$	3.94	0.94	$t_{\text{AI-human}} = -1.31$

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

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