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When stereotypes meet robots: The double-edge sword of robot gender and personality in human–robot interaction

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ABSTRACT

With the emerging application of social and psychological concepts to human–robot interaction, we investigated the effects of occupational roles (security vs. healthcare), gender (male vs. female), and personality (extrovert vs. introvert) on user acceptance of a social robot. In a laboratory experiment, a robot performed two different roles of a healthcare and security to address the potential usage of social robots at home. During the task, the robot manifested different genders and personalities via nonverbal cues. The results showed that participants ($n = 164$) preferred the robot with matching gender-occupational role and personality-occupational role stereotypes. This finding implies that the gender and personality of social robots do not monotonically influence user responses; instead, they interact with corresponding role stereotypes to affect user acceptance of social robots. In addition, personality-occupational role stereotypes showed a stronger effect on users' responses than gender-occupational role stereotypes. The overall results lay a foundation for designers to reduce the wide design spaces of social robots by grouping the various parameters under the big umbrella of social role stereotypes.

1. Introduction

The role of social robots has increasingly become diversified when compared to industrial robots that perform monotonous and repetitive tasks in factory settings. In accordance with the rapid development of relevant technologies and the increasing demand for human resources in social settings, robots are expected to play roles that are generally filled by humans in a variety of social contexts, including the home, museums, subways, airports, and hospitals (Lee, Kiesler, & Forlizzi, 2010). Public acceptance of social robots, however, is not simple since successful social robots require a good mixture of state-of-the-art technology and a capacity for friendly social interaction. Among various issues concerning human–technology interaction, user acceptance has been identified as a key element for successful implementation of social robots (Ezer, Fisk, & Rogers, 2009; Heerink, Kröse, Evers, & Wielinga, 2010). Along these lines, interest has recently been rising for the development of socially interactive robots that can accurately mimic human characteristics. This dimension of research aims to develop natural and intuitive human–robot interactions to facilitate user acceptance. One such attempt is to design humanoid robots with human features as well as androids that are aesthetically similar to real human beings. In addition, researchers have started to apply social characteristics in the design of social robots, including exhibiting a natural gaze, gestures, and distinctive personalities (Hwang, Park, & Hwang, 2013; Looije, Neerincx, & Cnossen, 2010).

In spite of the preliminary success in anthropomorphizing robots, simply applying human characteristics to social robots may cause aversive and repugnant psychological responses. For instance, Mori's Uncanny Valley (1970) suggests that human responses toward human-like robots can be revulsive when these robots look and act almost, but not perfectly, like human beings. In other words, when robots become or behave human-like, people start to pay more attention to the subtle differences between the robots and human beings rather than the great resemblance between the two, and this tends to trigger negative responses from people. As such, human social characteristics blindly applied to social robots could negatively influence people's perceptions toward social robots, under certain circumstances (Eyssel & Hegel, 2012).

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Nevertheless, there has not been much empirical research to show the social and psychological implications of such design-related decisions with respect to human–robot interaction. Therefore, the objective of the current study is to identify and investigate human characteristics (i.e., social stereotypes) that influence people's perception and acceptance of social robots. In particular, this study focuses on two roles of home service robots (security and healthcare) to address the current trend of having robots in residential and elderly care environments.

2. Background

The recent shift of attention from industrial to social robots has suggested there is a need for reviewing social traits and concepts that could be applicable to social robots. The following review includes previous efforts toward anthropomorphizing social robots, such as having robots manifest human gender and personality traits in the context of occupational role stereotypes, a well-known social phenomenon in human–human interaction. In addition, we review the literature on the Theory of Planned Behavior (TPB) in order to provide a better understanding of the antecedents for user acceptance of social robots.

2.1. Computers are social actors: anthropomorphizing social robots

As efforts continue to produce social robots that act in a more intuitive manner, there has been a substantial number of studies that examine whether findings from interpersonal relationships can be applied to human–robot interaction (e.g., Eyssel & Hegel, 2012; Tapus, Tapus, & Matarić, 2008). These studies largely rely on the Media Equation or the Computers Are Social Actors (CASA) paradigm, positing that human beings mindlessly respond to computers and other non-human machines (e.g., television or virtual agents) during interactions as if these devices were actual social actors (Nass, Steuer, & Tauber, 1994). Such user responses to artificial human characteristics could be understood in two levels. First, in order to build a social relationship, the user should be able to recognize social cues manifested by the robots. Lee, Peng, Yan, and Jin (2006) defined such recognitions as first-degree social responses since the mere recognition of robots' having social characteristics themselves are mindless social responses that run against the ontological nature of robots. Upon acknowledgement of first-degree social responses, users may experience changes in attitudes and behavior in ways that conform to the recognized social characteristics, which can then be further defined as second-degree social responses.

2.2. Robots that manifest human gender and personality

Social cues of a specific trait tend to portray the social and intellectual attributes of an individual (Powers et al., 2005). Among various social traits, gender and personality have been found to be important for interpersonal relationships, affecting relationship management (Muscanell & Guadagno, 2012) and evoking social stereotypes (Glick, 1991; Glick, Zion, & Nelson, 1988). Hence, arguably, gender and personality can provide important social cues that may trigger certain user responses in human–robot interactions (Lee et al., 2006; Powers et al., 2005).

2.2.1. Gender stereotypes and social robots

When used appropriately, social cues for gender can reduce the efforts to find additional information during interactions. In this regard, researchers have postulated that the gender of social robots helps build a common ground between the users and the robots, thereby facilitating intuitive human–robot interaction (Eyssel & Hegel, 2012; Powers et al., 2005). Earlier research has consistently demonstrated that users have positive attitudes toward social robots that manifest human gender. For example, the gender of social robots can influence their persuasive power (Siegel, Breazeal, & Norton, 2009) and their task suitability (Eyssel & Hegel, 2012; Powers et al., 2005; Tay, Park, Jung, Tan, & Wong, 2013).

In the real world, gender stereotypes are a long-standing concept that highlights social implications resulting from gender cues. The term "stereotype" is defined as a gestalt view of individual perception that emphasizes the notion that certain traits, characteristics, or prototypes are more central and important in organizing our perceptions of other people than other traits (Asch, 1946). As cognitive misers, human judgments are susceptible to heuristics and biases (Tversky & Kahneman, 1974). A similar process happens when we are evaluating or judging others, and stereotypes are triggered automatically as an energy-preserving device inside our cognitive toolbox (Macrae, Milne, & Bodenhausen, 1994). Since the stereotypes of a group provide information about the typical characteristics of the group, this enables an observer to accordingly build certain expectations of an individual who belongs to that group. Having said that, expectancy violation refers to cases where such expectations made through snap judgments are not met. Interestingly, when such expectations are violated, the subjects showing an expectancy violation tend to be negatively evaluated (Mendes, Blascovich, Hunter, Lickel, & Jost, 2007).

One area where the effects of gender stereotypes have been well investigated is in the field of occupations. A plethora of research has shown that people clearly identify certain jobs as masculine or feminine (Crowther & More, 1972; McCauley & Thangavelu, 1991) and would be biased against individuals who do not explicitly conform to the specific gender of these occupational images or stereotypes (Gerdes & Garber, 1983; Rosen & Jerdee, 1974). There is a conspicuous trend for gender stereotyping in the field of social robotics. However, this stereotyping is not well colligated with occupational role stereotypes (Eyssel & Hegel, 2012; Eyssel & Kuchenbrandt, 2012; Powers et al., 2005).

2.2.2. Personality stereotypes and social robots

Along with gender, researchers have also claimed that personality is a key that triggers intuitive responses from users during human–robot interaction (Lee et al., 2006). Personalities often shape the very nature of social relationships and influence the level of satisfaction derived from such interactions (Dryer, 1999), and earlier research has demonstrated that the personalities of social robots influenced user preferences (Tapus et al., 2008), and also affected the perceived enjoyment of the interaction with respect to the perceived intelligence and overall attractiveness of social robots (Lee et al., 2006).

Unlike gender, having robots manifest personalities is much more complicated as a result of the multiple, distinctive dimensions of human personalities. This complexity is exemplified by Goldberg's (1992) proposed Big Five personality types: extroversion, agreeableness, conscientiousness, neuroticism, and openness. Dryer (1999) argues that, among these various dimensions, extroversion (i.e., outgoing-withdrawn) and agreeableness (i.e., cooperative-competence) play important roles in our interaction with non-human agents. In addition, extroversion was found to be the most accurately observable in humans and had the highest agreement among the observers (Kenny, Horner, Kashy, & Chu, 1992). Therefore, a large proportion of research exploring computer and robot personalities has focused on the dimension of extroversion (Dryer, 1999; Isbister & Nass, 2000; Lee et al., 2006; Tapus et al., 2008).

Similar to gender though, research in sociology has also demonstrated personality to be an important element in occupational role stereotypes. Studies have shown that people clearly associate some traditional occupations with typical personalities (Crowther & More, 1972; Walker, 1958). In addition, personality traits that are deemed appropriate for certain occupations could reinforce the positive effects of gender stereotypes in job applications (Glick, 1991; Glick et al., 1988). In this sense, Glick and his colleagues argue that, in addition to the gender-related occupational stereotype of nurses being women, women are preferred as nurses because women are thought to possess the appropriate traits of ideal nurses (e.g., warm and nurturing). This plausibly explains why candidates' personality is a strong predictor for successful job application and career success (Alter & Seta, 2005; Gianakos & Subich, 1988).

2.3. Acceptance of social robots: Theory of Planned Behavior

Researchers have proposed a number of attitude-behavior models to better understand the antecedents that drive individual behavior, including the aforementioned biases in hiring decisions and evaluations. The Theory of Planned Behavior (TPB) is one of the most well-known models that explain behavioral intention. TPB has been successfully applied to individual acceptance of technology products and information systems (Baker & White, 2010; Huang & Chuang, 2007). In this regard, we believe that TPB can be applied in the context of human–robot interaction and can provide a holistic understanding for user acceptance of social robots.

TPB posits that our behavior is influenced by intentions that can be further explained through three antecedents: attitudes toward the behavior, subjective norms, and perceived behavioral control (Ajzen & Fishbein, 1980). Attitudes in TPB represent an individual's evaluation on performing the target behavior; subjective norms reflect one's belief that the important referents would approve or disapprove of one's attempt to perform a given behavior; perceived behavioral control represents the perception of ease or difficulty in her performing the behavior of interest.

2.3.1. Affective, cognitive evaluations, and perceived trust

Although TPB can successfully predict one's behavioral intention, researchers have attempted to extend the original model by adding antecedents to better predict specific user behavior. For instance, attitude theorists have long argued for a distinction between affect-based and cognition-based judgments as two different components of attitudes (Breckler, 1984; Verplanken, Hofstee, & Janssen, 1998). Affect-based judgments are evaluations based on affective responses to an attitude object, thereby referring to feelings or emotions toward that object. Cognition-based attitudes are evaluations based on cognitive responses, thereby referring to beliefs, thoughts, or rational arguments (Verplanken et al., 1998). The predictive power of affective- and cognitive-based evaluations toward certain behaviors may vary across different targets, and this can clarify how attitudes are formed toward different products and behaviors (Crites, Fabrigar, & Petty, 1994).

Along with this dual process for attitudes, precipitated risks rooted in uncertainty of technological products become significant to the users when these technologies are granted the power of automation. As the decision making role is transferred from the human-side to an agent with artificial intelligence, poor partnership between people and automated devices becomes increasingly costly, and sometimes it results in an unexpected accident (Parasuraman & Riley, 1997). Among the various issues in human–automation interaction, trust was nominated as one of the primary factors to be considered. Trust determines the acceptance level of suggestions made by the automated devices, and proper trust is pivotal in helping users overcome the perception of risk and uncertainty before the use of a new technology. Pitfalls of trust could inhibit user acceptance of information given by sophisticated robotic systems, thereby compromising the inherent advantages of such technology (Freedy, DeVisser, Weltman, & Coeyman, 2007).

Historically, expectancy violation in role stereotypes has been found to negatively influence one's attitudes and hiring decisions in occupational fields. Preliminary studies of social robots have found such tendencies with respect to gender (Eyssel & Hegel, 2012) and racial (Gong, 2008) stereotypes. However, it is still uncertain whether heuristic judgment based on the gender and personality of social robots would influence user acceptance when transferring conventional occupational roles to social robots. Thus, this study empirically investigated the impact of social characteristics on the acceptance of occupational robots.

3. Conceptual model and hypotheses

To summarize the literature reviewed, the CASA paradigm suggested that people behave and treat social robots as if they were social actors as long as the robots provide social cues. The present study operates under the same framework to examine the impact of socially prominent phenomena (i.e., role-stereotypes) on user acceptance. Specifically, we aim to examine the effects of gender and personality stereotypes on user acceptance for occupational roles.

The literature showed that gender, personality, and occupational roles together form certain expectations resulting from general stereotypes. When such stereotypes are violated, the target is often negatively evaluated (Rosen & Jerdee, 1974). In addition, violating role expectancies also reduces predictability by increasing the uncertainty during an interaction (Mendes et al., 2007). With a lower level of predictability and an increased uncertainty, people may experience a low level of perceived behavioral control over social robots (Wortman, 1975). In a similar vein, a number of studies on expectancy violation showed that targets that violated a specific expectancy were seen to be less trustworthy and credible than those that did not (Kalman & Rafaeli, 2011; Mendes et al., 2007). When occupational gender stereotypes are violated, people's acceptance of others is negatively affected, and these effects can influence job assignments (Reskin, 1993) and hiring biases (Gerdes & Garber, 1983). Such effects could be applicable to human–robot interaction.

Tay, Park, and Jung (Unpublished work) surveyed 198 young adults and found that respondents have vivid gender stereotypes with respect to healthcare robots (to be female) and security robots (to be male). Thus, we hypothesize that a social robot that matches gender and occupational role stereotypes will obtain better user responses, including affective and cognitive evaluations, perceived behavioral control, perceived trust, and acceptance. We propose the following hypothesis:

H1. People will show a more positive response when (a) the gender of a healthcare robot is female rather than male and when (b) the gender of a security robot is male rather than female.

In addition to gender, researchers showed that personality is another important element in occupational stereotypes and biases. Glick (1991) found that an individual who possessed the required personality traits for particular occupations received a higher chance of being hired. Likewise, studies also found personality as a strong predictor of successful career and job applications in addition to gender (Alter & Seta, 2005; Gianakos & Subich, 1988). Based on a similar research paradigm for CASA, a robot manifesting a personality trait that conforms to its occupational role stereotypes is likely to invite a positive response from people. Since Tay et al. (2013) found that people stereotyped healthcare robots to be more extroverted than security robots, we hypothesize that people will show positive responses to a social robots manifesting a personality that matches occupational role stereotypes. Therefore, the following hypothesis is proposed:

H2. People will have a more positive response when (a) the personality of a healthcare robot is extroverted rather than introverted and when (b) the personality of a security robot is introverted rather than extroverted.

Previous studies have demonstrated that the general acceptance model for technology remains predictive when it comes to studying user acceptance of social robots in the home (Ezer et al., 2009; Heerink et al., 2010). Since TPB is robust in the context of new technological implementations (Baker & White, 2010; Huang & Chuang, 2007), various antecedents of TPB sufficiently explain user acceptance of healthcare and security robots. Furthermore, earlier research found that pitfalls of trust negatively affected user acceptance (Freedy et al., 2007). Taken together, perceived trust could be another important factor affecting user acceptance, in addition to various antecedents of TPB. Therefore, we propose the following hypothesis with respect to the extended TPB model:

H3. Users' (a) attitudes, (b) subjective norms, (c) perceived behavioral control, and (d) perceived trust of a social robot positively affect their acceptance of the robot.

4. Methods

4.1. Independent variables and manipulations

4.1.1. Occupational roles

Tay et al. (2013) found that people have rather opposite gender and personality expectations for healthcare and security robots. As such, we developed two different task-scenarios for each occupational role (see Section 4.4 for the detailed role scenarios).

4.1.2. Gender of the robot

We manipulated the gender of the robot by changing the vocal characteristics and name. Text-to-speech software was used to generate male and female voices for the robot. In addition, the male-gendered robot was given a typically male name, John; the female-gendered robot was given a typically female name, Joan.

4.1.3. Personality of the robot

We used non-verbal cues to manipulate personality. According to prior research, non-verbal cues are effective in manifesting extroversion in synthesized speech (Nass & Lee, 2001) and in social robots (Lee et al., 2006). Extroverts generally speak faster and louder with a higher pitch (i.e., paralanguages as nonverbal communication; Nass & Lee, 2001) and show bigger movements and poses that spread their limbs at a greater distance from their bodies (Isbister & Nass, 2000). In addition to the aforementioned vocal and gesture cues, we also employed the psychology of colors (i.e., red for extroverted and grey for introverted) in order to manifest the extroversion of the social robots (see Fig. 1).

Details of each parameter manifesting extroversion of the social robots are documented in Table 1.

A manipulation check was performed to ensure that the robots could manifest human gender and personality successfully. The *perceived gender* of the robots was measured through two items: *perceived masculinity* and *perceived femininity*; *perceived extroversion* ($\alpha = .74$; modified from Wiggins, 1979) was measured through 10 items (e.g., cheerful, extroverted, and enthusiastic).

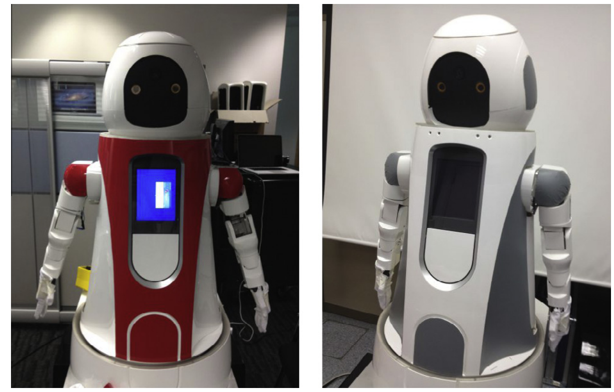

Fig. 1. Extroverted (left) and introverted (right) robots.

4.2. Dependent measures

After the experiment, the participants filled out a survey measuring their attitudes toward and perceptions of the robots. Each of the antecedents in the augmented TPB model, except affective and cognitive evaluations, was assessed on a 7-point Likert scale ('1' = strongly disagree, '7' = strongly agree; see Table 2).

4.3. Participants

A total of 164 young adults (84 males; 79 females; 1 undisclosed) between 20–35 years old ($M = 22.40$, $SD = 2.51$) participated in the between-subject experiment. Participants were mostly students from various faculties of a public university in Singapore. They were recruited through email advertisements on a first-come, first-served basis.

4.4. Procedures

Participants were randomly assigned to and underwent one of the eight experimental conditions. Each participant was given an individual appointment to visit a laboratory for the experiment. Upon arrival, the participant was escorted to the experiment room where he/she could be discreetly observed through a one-way mirror from the operating room. An experimenter controlled the robot as a "wizard" in a *Wizard-of-Oz* setting. In other words, we presented the robot as a completely autonomous system although the robot was controlled by the experimenter from behind the one-way mirror. The healthcare and security scenarios presented were kept identical across different types of gender and personality conditions, and the participant was allowed to interact with the social robot based on these scenarios.

In the healthcare scenario, after a brief self-introduction by the healthcare robot, the participant was asked whether or not the robot could measure the body temperature and blood pressure of the participant. If the participant agreed, then he/she put on a bio-clip on his/her finger for the healthcare robot to measure the body temperature and blood pressure. After the measurement, the healthcare robot presented the results to the participant and informed them their blood pressure was slightly higher than normal regardless of the actual reading. Then, the robot provided some healthcare advice to the participant and offered to book an appointment with a doctor in a nearby medical center for a further check-up. Finally, the healthcare robot reminded the participant to take daily supplements and to have an annual check-up in order to stay healthy. After finishing the experiment, participants were informed that the reading of their blood pressure and diagnosis is not real.

For the security scenario, the participants were requested to view a closed-circuit television of four surveillance cameras placed

Table 1
Manipulations of robot personality.

	Extroverted robot	Introverted robot
Visual		
Autonomous behaviors	Initiated the conversation before the participants	Responded only after participants initiated the conversation by waving or greetings
Appearance	Shiny red as complementary color	Matte grey as complementary color
Moving speed	1.64–2.28 Times faster compared to the introverted robot	44–61% Slower compared to the extroverted robot
Gesture types	Frequently use wide-angle and two-arm gestures	Frequently use small-angle and one-arm gestures
Paralinguistic		
Speech rate	216 Words per minute less pauses between sentences	184 Words per minutes more pauses between sentences
Pitch	Pitch set at 90% of the maximum pitch of the software pack	Pitch set at 10% of the maximum pitch of the software pack
Volume	Volume level set at 80% of the maximum	Volume level set at 20% of the maximum

Table 2
No. of items, scale of measures, and items measuring each factor in the augmented Theory of Planned Behavior.

Factors	No. of items	Alpha	Scale	Items	Source
Attitude toward robots	3	0.95	Likert scale	I think it's a good idea to use the security/healthcare robot The healthcare/security robot would make my life more interesting	Heerink et al. (2010)
Affective evaluations	8	0.84	Semantic differential	Love/hateful, delighted/sad, happy/annoyed, calm/tense, excited/bored, relaxed/angry, acceptance/disgusted, joy/sorrow	Crites et al. (1994)
Cognitive evaluations	8	0.83	Semantic differential	Useful/useless, wise/foolish, safe/unsafe, beneficial/harmful, valuable/worthless, perfect/imperfect, capable/incapable	Crites et al. (1994)
Perceived behavioral control	6	0.81	Likert scale	I could complete the job using a robot if there was no one around to tell me what to do as I go I could complete the job using a robot if I had only the software manuals for reference I could complete the job using a robot if someone else had helped me get started I have control over the robot I have the knowledge necessary to use the robot Given the resources, opportunities, and knowledge it takes to use the robot, it would be easy for me to use the robot	Venkatesh (2000)
Subjective norms	2	0.69	Likert scale	I think those who are important to me would like me using this robot I think it would give a good impression if I use this robot	Heerink et al. (2010)
Perceived trust	3	0.81	Likert scale	I would trust the security/healthcare robot, if he/she gave me advice I trust that the security/healthcare robot [can keep me away from danger/can enhance the healthcare of my family] I would follow the advice that the security/healthcare robot gives me	Heerink et al. (2010)
Acceptance	3	0.71	Likert scale	If given a chance, I think I'll use this robot in the near future If given a chance, I'm certain to use this robot in the near future If given a chance, I plan to use the robot during in the near future	Heerink et al. (2010)

outside of the experiment room. An alert was triggered when the security robot detected a suspicious intrusion outside the room. The security robot asked the participants whether they wanted to zoom in on the specific camera view where the intrusion was detected. The robot determined the intrusion to be safely resolved after the stranger had left the surveillance zone. After that, the robot found that the participants had left their belongings unattended in the unlocked briefing room. Hence, the security robot asked if the participants would like the door to be locked via its tele-remote system. Next, the security robot alerted the participants that an electric kettle inside the experiment room had been unintentionally left switched on.

During the experiment, the participants could respond to the robots voluntarily. If they first declined a scenario, the robots re-prompted the participants with additional explanation on the need to carry out the requested actions. If the participants declined again, the robots omitted the scenario and continued with the next one. The robots ended the conversation at the end of all the task scenarios, which lasted around 20 min. After the experiment, the participants took a questionnaire where they reflected on their responses to the robot with which they had interacted.

4.5. Data analyses

A one-way ANOVA was conducted for the manipulation checks. The robot gender and personality were treated as the independent variables, and the participant's perceived masculinity/femininity and personality with respect to the robot were treated as the dependent variables. To test H1 and H2, multiple three-way ANOVA were conducted with the type of role, gender, and personality as the independent variables while the participant's affective attitudes, cognitive evaluations, perceived behavioral control, perceived trust, and acceptance were the dependent variables.

5. Results

5.1. Internal consistency

We calculated Cronbach's alpha values to assess the internal consistency of each psychometric measure. The reported alpha values were between 0.69–0.96 (Table 2), indicating acceptable internal consistencies of the psychometric measures (Kline, 1999).

5.2. Inferential statistics

5.2.1. Manipulation checks

The ANOVA showed that participants perceived the male-gendered robots ($M = 4.76$, $SD = 1.39$) to be more masculine than the female-gendered robots [$M = 3.66$, $SD = 1.41$; F (1, 162) = 22.12; $p < 0.01$; $\eta_p^2 = 0.13$]. On the other hand, the participants perceived the female-gendered robots ($M = 4.89$, $SD = 1.51$) to be more feminine than the male-gendered robots [$M = 3.05$, $SD = 1.35$; F (1, 162) = 60.01; $p < 0.01$; $\eta_p^2 = 0.30$]. The participants perceived the extroverted robot ($M = 4.75$, $SD = 0.71$) to be more extroverted than the introverted robot [$M = 3.93$, $SD = 0.74$; F (1, 162) = 52.16; $p < 0.01$; $\eta_p^2 = 0.24$]. According to these results, the gender and personality manipulations were successful.

5.2.2. The effect of conforming gender and personality stereotypes on user responses of social robots

The results of the ANOVA are presented in Tables 3 and 4 according to the two different roles of the robots in this study.

For the healthcare robot, participants showed greater affective evaluations, perceived behavioral control, and a marginally greater acceptance toward the female-gendered healthcare robot. On the other hand, participants showed greater affective, cognitive evaluations, attitudes, subjective norms, perceived trust, and acceptance for the extroverted than for the introverted healthcare robots.

For the security robot, participants showed more positive affective evaluations, attitudes (marginally), cognitive evaluations (marginally), greater perceived behavioral control (marginally), subjective norms, and acceptance (marginally) toward the male security than the female security robot. With respect to the personality of the security robot, participants showed more positive affective and cognitive evaluations and greater perceived behavioral control, subjective norms (marginally), perceived trust, and acceptance toward the introverted rather than the extroverted security robots.

The opposite outcomes of user acceptance with respect to robot gender and personality between in the healthcare and security roles are presented in Fig. 2. The results of the interaction effect of other dependent variables largely follow the same pattern.

5.2.3. Determinants of behavioral intention

The results of the multiple linear regression show that attitudes, subjective norms, and trust are the antecedents for acceptance of social robots ($R^2 = 0.68$, see Table 5). With the exception of the perceived behavioral control, all other proposed antecedents are significant.

6. Discussions

In general, the results confirmed that matching gender-occupational role and personality-occupational role stereotypes result in positive user responses, measured through cognitive and affective evaluations, subjective norms, perceived behavioral control, trust, and acceptance. The detailed outcomes are hereby discussed in accordance to the proposed hypotheses.

H1. Violating role-gender stereotypes in human–robot interaction.

The participants showed more positive affective evaluations, greater perceived behavioral control, and marginally greater acceptance toward the female-gendered healthcare robot. However, there was no significant difference in cognitive evaluations and perceived trust. Therefore, H1(a) is partially supported. On the other hand, participants showed more positive affective and cognitive evaluations, greater perceived control, and greater acceptance for the male rather than the female security robot. As such, H1(b) is also partially supported with no significant impact on perceived trust.

The rather opposite user responses to the gender of the healthcare and security robots reinforce the influence that gender stereotypes play on a user's evaluation and initial acceptance of a robot. It is interesting to note that gender-occupational role conforming, vs. violation, influences participants' affective evaluations significantly, but not their cognitive evaluations, for both the healthcare and security robots. This could be explained by the nature of expectancy violations. Although early research found effects of expectancy violations on one's cognitive processing (Bettencourt, Dill, Greathouse, Charlton, & Mulholland, 1997), other studies prioritized the negative affective responses (Mandler, 1990; Olson, Rose, & Zanna, 1996). On the other hand, gender-occupational role stereotype violations did not significantly influence participants'

Table 3
ANOVA results from the combined analysis of the healthcare robots.

Dependent variables	Means and standard deviations Healthcare robots				F values and effect sizes (η_p^2)					
	Male robot		Female robot		Main effects				Interaction effects	
	Extrovert robot	Introvert robot	Extrovert robot	Introvert robot	Gender (G)		Personality (P)		G × P	
					F	η_p^2	F	η_p^2	F	η_p^2
Attitudes	5.51 (0.77)	4.98 (1.37)	5.83 (0.71)	5.16 (1.03)	1.23	0.02	7.12**	0.09	0.11	0.00
Affective evaluation	5.29 (0.74)	5.08 (0.81)	5.78 (0.57)	5.25 (0.70)	4.22*	0.05	5.31*	0.06	1.01	0.01
Cognitive evaluation	5.63 (0.64)	5.33 (0.80)	5.99 (0.33)	5.26 (0.81)	0.94	0.01	11.75**	0.13	2.08	0.03
Perceived behavioral control	5.09 (0.96)	5.03 (0.76)	5.59 (0.53)	5.4 (0.83)	6.27*	0.08	0.50	0.01	0.14	0.00
Subjective norms	5.13 (0.96)	4.57 (1.30)	5.53 (0.75)	4.76 (1.08)	1.58	0.02	8.10**	0.10	0.19	0.00
Perceived trust	5.53 (0.71)	4.87 (1.19)	5.6 (0.58)	5.25 (0.91)	1.34	0.02	6.47*	0.08	0.61	0.01
Acceptance	4.98 (1.44)	4.22 (1.58)	5.68 (0.74)	4.68 (1.48)	3.72+	0.05	8.56**	0.10	0.16	0.00

Note.
+ $p < .10$, Two-tailed.
* $p < .05$, Two-tailed.
** $p < .01$, Two-tailed.

Table 4
ANOVA results from the combined analysis of the security robots.

Dependent variables	Means and standard deviations Security robots				F values and effect sizes (η_p^2)					
	Male robot		Female robot		Main effects				Interaction effects	
	Extrovert robot	Introvert robot	Extrovert robot	Introvert robot	Gender (G)		Personality (P)		G × P	
					F	η_p^2	F	η_p^2	F	η_p^2
Attitudes	5.25 (1.58)	5.67 (1.02)	4.8 (1.13)	5.21 (1.05)	2.93^{+}	0.04	2.35	0.03	0.00	0.00
Affective evaluation	4.89 (0.80)	5.50 (0.60)	4.39 (1.00)	5.24 (0.74)	4.65*	0.06	17.70**	0.18	0.51	0.01
Cognitive evaluation	5.42 (0.65)	5.77 (0.52)	5.14 (0.70)	5.56 (0.72)	2.93^{+}	0.04	7.16**	0.08	0.05	0.00
Perceived behavioral control	5.09 (0.62)	5.63 (0.54)	4.9 (0.90)	5.23 (0.58)	4.14^{+}	0.05	8.79**	0.10	0.48	0.01
Subjective norms	5.00 (1.02)	5.45 (1.09)	4.5 (1.10)	4.88 (0.74)	5.96^{+}	0.07	3.61^{+}	0.04	0.03	0.00
Perceived trust	5.29 (0.78)	5.62 (0.74)	5.03 (1.03)	5.38 (0.53)	2.02	0.03	3.89*	0.05	0.00	0.00
Acceptance	4.78 (1.74)	5.54 (1.25)	4.07 (1.36)	5.14 (1.30)	3.14^{+}	0.04	8.64**	0.10	0.25	0.00

Note.
$^{+}$ $p < .10$, Two-tailed.
* $p < .05$, Two-tailed.
** $p < .01$, Two-tailed.

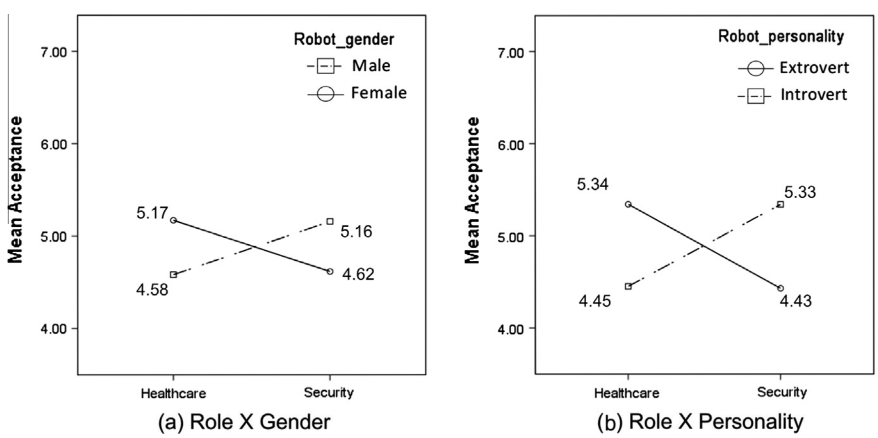

Fig. 2. Interaction between (a) role × gender and (b) role × personality on user acceptance of social robots.

Table 5
Multivariate regression analysis of acceptance of social robots.

Predictors	B	$s.e.$ B	β	t
Constant	−2.36	0.51		−4.62**
Attitudes	0.76	0.07	0.59	10.31**
Perceived behavioral control	0.16	0.1	0.08	1.57
Subjective norms	0.23	0.09	0.17	2.58*
Perceived trust	0.24	0.1	0.14	2.43*
		R	R^2	Adj R^2
Model		0.83	0.69	0.68

Note.
Attitudes, subjective norms, perceived trust, and constant explained a significant proportion of variance in acceptance, $F(4, 163) = 88.04$, $p < 0.01$.
* $p < .05$, Two-tailed.
** $p < .01$, Two-tailed.

perceived trust for both the healthcare and security robots. A plausible explanation for this non-significant result is that trust between a human and a robot could be deeply rooted in cognitive functions, such as the performances of the robot (Hancock et al., 2011). If this assumption is true, it is not so surprising that gender-occupational role stereotype violation did not significantly influence the perceived trust of the social robot since its impact was more significant for participants' affective evaluations.

H2. Violating role-personality stereotypes in human–robot interaction.

Except for the perceived behavioral control, participants had a more positive response to the extroverted than the introverted healthcare robot. Thus, H2(a) is partially supported. On the other hand, participants showed a more positive response to the introverted than the extroverted security robot. Therefore, H2(b) is fully supported. With few exceptions, the effect sizes of the personality-occupational role-stereotype conformation ($0.05 < \eta_p^2 < 0.17$) were consistently larger than those of the gender-occupational role-stereotype conformation ($0.01 < \eta_p^2 < 0.08$) in both the healthcare and security scenarios (see Table 4). These results imply that there is a more salient influence of the personality stereotypes than the gender stereotypes, and this is surprising because personality-stereotype violation has always been documented as a secondary predictor, in addition to gender, in the occupational fields (Glick et al., 1988).

In human society, gender stereotypes with respect to occupations can be viewed as an important heuristic link between an individual's capability and the respective job requirements (Schneider, 2004). Hence, people may utilize gender stereotypes to predict an individual's capability under certain circumstances. A plausible reason for our controversial results could be related to the amount of information exposed during the interaction. According to Kalin and Hodgins (1984), social category information (e.g. sex) is important when little relevant information for judgment is available. For example, when one makes hiring decisions based on an applicant's resume (Cohen & Bunker, 1975; Gerdes & Garber, 1983) or makes preliminary evaluations based on the perceptions of a robot's image (Eyssel & Hegel, 2012). However, the importance of gender-based information is reduced when other concrete trait evidence emerges. In the current study, the interaction cues of the social robot, combined with the task scenarios, offered participants more concrete information on the capability of the robots. The emergence of this new information might reduce the impact of the gender-stereotype violation on user's responses. In a similar vein, early research has shown a similar phenomenon that stereotyped personality could moderate the effect of sex discrimination (Glick, 1991). Taken together, the findings imply that robot personality could be more prominent than gender during interactions with social robots. This also corroborates the emerging interest in building robots that exhibit distinctive personalities through additional social cues to enhance the quality of the interactions (Lee et al., 2006; Tapus et al., 2008).

Overall, participants had a more positive response to social robots with in-role gender (i.e., male security and female healthcare) and personality (i.e., extroverted healthcare and introverted security robot) traits than those with role-violating gender and personality traits. Breazeal (2003) suggested that people would observe and react to robots according to social models. With a higher level of anthropomorphism and social intelligence, social stereotypes could be more significant in the development of social robots.

In the current study, stereotypes eventually influenced second-degree social responses, changes in users' evaluations, and acceptance. Often, occupational stereotypes arise when there is a common belief that these occupations call for certain traits. Hence, the violation of role-stereotypes may render a perceived insufficiency in trait fulfillment, thereby evaluating the violator as inferior. To a certain extent, the current study empirically examined such a scenario, which had not been well studied before.

H3. Determinants of user acceptance of social robots.

Among the various antecedents of TPB, only perceived behavioral control is not predictive of participant's acceptance of social robots in this study. Hence, H3 is partially supported. A plausible explanation is that the *Wizard-of-Oz* setting possibly lowered the barrier of interaction by providing near-to-perfect speech recognition in the experiment. The robot understood not only the literal of the user's messages, but also the pragmatic meaning. Additionally, the experimental settings required the participants to ignore the potential monetary costs and constraints when evaluating their acceptance of the social robots. In this sense, the nature of the robot usage became a non-goal-oriented task with high volitional control. According to Ajzen and Madden (1986), perceived behavioral control is only predictive when the behavior in question is non-volitional, i.e., at least in part determined by factors beyond a person's control. Hence, the perception of full volitional control during the interaction in this experiment potentially attenuated the impact of the perceived behavioral control on intention.

Participants' acceptance of social robots was largely predicted by their general attitudes toward these social robots, relative to the other possible predictors. The results are similar to those of previous studies that found attitudes to be a powerful predictor of people's acceptance of social robots (Ezer et al., 2009; Heerink et al., 2010). On the other hand, both predictors of affective and cognitive evaluations were not disparate with respect to people's general attitudes toward social robots.

The perceived needs of the stakeholder at home seem to be heavily valued by participants as a function of subjective norms. During the exit interviews, six participants explained their acceptance of social robots for their family members, especially for the elderly at home. Similarly, eldercare stakeholders are likely to purchase healthcare robots, including those for family members or for elderly-care providers. To achieve wider commercial and public acceptance of social robots, the acceptance by a wider range of key eldercare stakeholders should be taken into consideration when designing the robots. In addition, the results also showed that participants reported greater perceived trust when a robot's personality conformed to the occupational role stereotypes. This finding implies that user trust can be built according to social cues that are not directly related to technological features. As in cases concerning the implementation of automated technology (Freedy et al., 2007; Lee & Moray, 1994; Parasuraman & Riley, 1997), trust is an important factor in user acceptance of social robots. Therefore, designers of social robots need to think about how to develop social robots to appear to be more trustworthy by incorporating the appropriate social cues in addition to reliable automated technological features.

Altogether, the results from the ANOVA and regression analysis support our original postulation. Upon recognizing the gender and personality of the social robots, violations of gender-occupational and personality-occupational role stereotypes negatively influenced user acceptance of social robots in the home, as tested according to the extended TPB. Theoretically, the current study reconfirmed the framework proposed in computers are social actors paradigm. In addition to treating artificial agents as actual human beings, people transfer their traditional gender and personality stereotypes to social robots that undertake human occupational roles. Conforming to expectations is preferable, at least in the case of a newly developed and uncertain social relationship (e.g., Mendes et al., 2007). User's attitudes and perceptions of social robots could be positively enhanced when these social robots manifest gender and personality traits that match role-stereotypes.

Our findings could provide a basis for the future design and development of social robots. With the emerging interest of having robots manifest human personalities, these findings can underpin designers' decisions to incorporate appropriate personalities that enhance user attitudes and acceptance of social robots. Subsequently, designers could develop other design parameters, such as interaction models, speech movements, and gestures, under the umbrella of stereotype matching or stereotype violation.

7. Conclusions and limitations

The results of the current study support our objectives to ascertain the underlying social schema that can influence users' acceptance of social robots. Participants more easily accepted social robots with gender and personality that conformed to their respective occupational role stereotypes. Except for the perceived behavioral control, various factors of TPB and perceived trust are predictive of user acceptance of social robots. It is possible that perceived behavioral control could be significant beyond experimental settings where people have incomplete volitional control over their interaction with social robots. Having said that, future research needs to be conducted in field settings.

With respect to user responses, we have successfully separated the effects of personality-stereotype violations from those of gender-stereotype violations. The results showed that in-role personality had a greater impact than in-role gender in terms of user response to a social robot.

In spite of the interesting findings, the current study is subject to some limitations. First, this study focuses on initial acceptance rather than on long-term usage or satisfaction. Although acceptance is important in new technological implementations, user behavior could still vary in the long term. Therefore, longitudinal research needs to be designed taking into consideration other factors that may influence user behavior in the long term, including the novelty of social robots and service quality of the manufacturer. Second, we should be cautious not to over-generalize the findings. Although we included two different roles for the social robots, the experiment was conducted solely with a humanoid robot. As such, the findings may not be fully applicable to non-humanoid robots. Future research needs to explore the effect of role stereotypes in other types of social robots, e.g., pet robots.

In a similar vein, the results may vary depending on the occupational roles, such as that of an administrative assistant. Hence, future studies need to examine the effects of in-role trait violations in occupations that may be more generic with fewer associative stereotypes. Such studies would provide a more holistic understanding of social stereotypes across different occupational roles.

Last but not least, one important limitation of this research is the convenience in sampling young college students. Future research is suggested to look at the stereotype effect in human–robot interactions on other potential user groups, such as the elderly. On the surface, we expect the effect of role stereotypes on elderly users to hold since they are supposed to have a greater personal need for structure and may have stronger stereotypes.

As a final remark, our findings confirm that social stereotypes can be applied to human–robot interactions, and these stereotypes can provide good insight for the design of social robots by demonstrating how the three different social stereotypes of gender, personality, and occupational role interact together to influence user responses.

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