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Gender role stereotypes at work in humanoid robots

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ABSTRACT
Research on gender role stereotypes activated in interactions with humanoid robots has yet to produce conclusive knowledge. To analyse how much, and in which way, gender role stereotypes used in interactions with humans are also called into play in interactions with humanoid robots, a study was conducted with 240 participants. The study was an online survey in which a scale was used for determining the appropriateness for performing four stereotypically masculine and four feminine by humans and robots. Overall, eight humanoid robots – four judged feminine and four masculine – were considered. Results showed that gender role stereotypes are activated for both genders, but men most strongly activate those pertaining to male roles. These stereotypes are also adopted in reference to humanoid robots, though robots are generally considered less suitable for performing female roles. Furthermore, an increased degree of similarity of robots to humans has a positive effect in assessing the appropriateness to perform female roles only for female robots. The same does not happen with male robots. These results suggest that male and female robots are not categorised in the same way. Robots are essentially perceived as male entities, a particularly relevant hypothesis for the gender-sensitive design of humanoid robots.

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Human–robot interaction; female robot; male robot; gender roles; stereotypes; robot human likeness

1. Introduction

Gender stereotypes affect behaviour, regulate relationships and shape perceptions. Repeatedly observing a group of individuals in a given context, and then seeing them perform certain activities (e.g. men leaving home to go to work), leads to the formulation of expectations, and therefore behavioural references that we try to confirm (Bakan 1966). Similarly, knowing that there are expectations related to our behaviour can foster us to attempt to match the gender stereotype of reference so as not to contradict those expectations. And thus, women in a negotiation tend to make less aggressive counteroffers so as not to appear too competitive (Amanatullah and Morris 2010).

It is clear that stereotypes are not just about humans. One widespread stereotype, for example, concerns the consideration that technologies are more trustworthy than people. And in fact, we are more likely, when making a transaction, to give our credit card to an artificial agent rather than a human being (Sundar and Kim 2019).

With the increasing implementation of humanoid robots, it makes sense to ask whether the activation of gender stereotypes also occurs for these technologies, as some studies seem to show (see, for example, Nomura and Takagi 2011; Eyssel and Hegel 2012; Seo 2022).

Above all, the relationship between gender stereotypes that concern human–human interactions and gender stereotypes concerning human–robot interactions still need to be further clarified. So far, in fact, studies on gender stereotypes related to technologies have assumed that interactions with artificial systems are based on the same cognitive and behavioural bias that guides in interactions with humans. Gender stereotypes, however, are extremely sensitive to different contexts (Tabassum and Nayak 2021; Barth, Masters, and Parker 2022), and cultures (Santos and Neumeyer 2022). It is relevant, therefore, to ask whether gender stereotypes are called into play, with the same strength and in the same direction, whether interacting with humans or humanoid robots.

1.1. Gender stereotypes

Psychological research on gender stereotypes has been conducted to test two contrasting hypotheses, the one related to similarity between genders (Hyde 2005), which has been less debated, and the one that instead, and much more frequently, sought to highlight differences between genders (Buss and Schmitt 1993; Wood and Eagly 2012). Generally, these two hypotheses have

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been evaluated through analyses that mainly focused on aspects such as personality traits (Costa, Terracciano, and McCrae 2001), attitudes (Maccoby and Jacklin 1974; Else-Quest, Hyde, and Linn 2010; Breda and Napp 2019) and cognitive abilities (Hedges and Nowell 1995; Rideout, Foehr, and Roberts 2010). But other aspects have also been considered, such as the willingness to enact different types of aggressive behaviours (Crick and Grotpeter 1995), or the attribution of past aggression perpetrated or received (Bracci et al. 2021).

Despite the diversity of approaches and factors considered, the results of these analyses are still far from conclusive. A fundamental study on psychological similarities and differences between genders was conducted through a meta-analysis of 46 studies, highlighting that for 78% of these, the differences were irrelevant or non-existent (Hyde 2005). Therefore, even if only from a numerical standpoint, the similarities between genders are greater than the differences (Hyde 2014).

Notwithstanding these results, which would justify the absence of stereotypes because of the apparent similarities between the genders, the fact remains that stereotypes nonetheless exist. The reason for the development of stereotypes would lie in a natural tendency to emphasise the differences between groups by taking as a reference point only the most representative examples of each group. Non-representative examples would be left out, decreasing the level of accuracy in which the features of the gender are represented, because the consideration in their entirety of the distributions of occurrences of the phenomena under observation would be too onerous (Kahneman and Tversky 1972; Bordalo et al. 2016). More recently, (Eyal and Epley 2017) put forward a hypothesis to explain the differences in the level of accuracy of gender stereotypes. According to their proposal, stereotypes would emphasise the characteristics that differentiate genders, thus loosing accuracy. However, when less accessible content is retrieved, or when individuals are taken into account, stereotypes could become more accurate.

As socioeconomic contexts and cultures change, gender stereotypes can therefore modulate to account for changing needs to represent, emphasise or differentiate reality. Eagly et al. (2019) considered a time frame of over 70 years and conducted a meta-analysis of 16 polls in the United States on gender stereotypes. The results showed, in the last seven decades, a substantial advancement of the trait of communion (e.g. affectionate, emotional) in the stereotype of women. The stereotype of males retained the relative advantage referable to agency (e.g. ambitious, courageous), while beliefs related to an equality of competence (e.g. intelligent, creative) between the two genders have increased over time (Eagly et al. 2019). This analysis also showed that gender stereotypes are not coincidental between male and female evaluators. Rather, there is evidence of an ingroup effect in which each gender evaluates its own gender more positively. However, as the years go by, men attribute more competence to women (Eagly et al. 2019).

Another study compared data collected in 1980 with data from a sample structured more than 30 years later in 2014 (Haines, Deaux, and Lofaro 2016). In this study, a general stability of gender stereotypes was highlighted. At least two findings, however, are not in this direction. As the years pass, it appears that gender role stereotyping for women has increased. In addition, differences referable to the gender of the participants emerge in that men are more likely than women to believe that women have typical female physical characteristics.

A study conducted using a very different method of inquiry (Bhatia and Bhatia 2021), produced results partly in line with those of (Eagly et al. 2019). In this study, a corpus of twentieth-century natural linguistic expressions was analysed using machine learning techniques combined with psychological measures. As a result, the authors were able to report that the biases structuring gender stereotypes have not changed over the years; if anything, they have lost some of their strength (Bhatia and Bhatia 2021).

Many studies have attempted to assess gender stereotypes about activities and occupations. Charlesworth and Banaji conducted a very extensive study, with nearly 1.4 million fully completed gender stereotype tests. The tests were both implicit and explicit and were administered between 2007 and 2018. Implicit tests for the labels ‘male’ and ‘female’ assessed male/science female/arts and male/career and female/family associations. Interestingly, over the twelve years considered, the strength of both male and female stereotypes decreased. For implicit tests, the decreases toward neutrality were 13% and 17%, and for explicit tests 19% and 14%. The decrease was found across all geographic areas from the United States to sub-Saharan Africa, and from Latin America to Asia (Charlesworth and Banaji 2021).

Despite these findings, gender stereotypes are still a source of bias and discrimination in employment (Truong and Duong 2022). Therefore, there is still a need to understand in which activities and occupations gender stereotypes are most called upon. To this aim, Mills et al. (2012) developed and validated a scale to assess gender role stereotypes with as few items as possible. The result of the validation process is a scale, the Gender Role Stereotypes Scale (GRSS) with only eight items, and a two-factor (male/female) construct in which the more female items relate to roles such as

'Staying home with a child who is sick' and 'Decorate the house', while the male items relate to roles such as 'Shovel snow to clear driveways and sidewalks' and 'Mow the lawn'.

1.2. Gender stereotypes about humanoid robots

The development of social robotics in recent years has favoured the development of increasingly humanoid robots that embody gender cues with different degrees of anthropomorphic physical characteristics (Duffy 2003; Złotowski et al. 2015; Damiano and Dumouchel 2018). There is abundant evidence that people interact with computers and robots applying the same social rules and likely the same gender stereotypes they apply to human–human interaction (Nass, Steuer, and Tauber 1994; Nass and Moon 2000; Powers et al. 2005; Schermerhorn, Scheutz, and Crowell 2008; Kuchenbrandt et al. 2014; Parlangeli, Caratozzolo, and Guidi 2014; Tay, Jung, and Park 2014; Ye et al. 2019). Robot design features, such as hair length, voice, appearance, behaviour and personality (Siegel, Breazeal, and Norton 2009; Eyssel and Hegel 2012) are able to trigger a male or female robot perception and activate gender stereotype expectations (Fiske, Cuddy, and Glick 2007; Eyssel and Hegel 2012; Kulms and Kopp 2018; Christoforakos et al. 2021).

Usually, these studies have been conducted taking a robot and modifying its physical characteristics, feminising or masculinising it, to see what features were necessary for either gender to be perceived. In this regard, Eyssel and Hegel (2012) focused on a specific detail, long or short haircuts. The results indicated a stereotypical response, the male robot was perceived as more agentic and more suited to tasks such as making technical repairs or taking care of home security, just as the female robot was perceived as more communal and capable to perform tasks such as domestic or healthcare services.

Tay, Jung, and Park (2014) conducted an analysis on gender and occupational roles of robots in relation to two occupations scenarios in healthcare and security. The results showed that the male robot was preferred in the security scenario while the female robot was preferred in the healthcare scenario, revealing a gender stereotype at play.

Another study, on a single robot in two versions, male and female, involved participants in learning two tasks that, according to stereotypes, are one a male task (putting tools in a toolbox) and the other a female task (machine sewing). The results showed that following the completion of the male task, participants made fewer mistakes, attributed more human characteristics to the robot, and were more willing to interact with the robot in the future, regardless of its gender (Kuchenbrandt et al. 2014).

These results, however, are not always in the same direction. A study, conducted again on a single robot gendered in two versions, one male and one female, aimed to assess whether gender stereotypes were also elicited as a result of real interactions. In this case, the results indicated little or no significant transfer of gender stereotypes to robots (Rea, Wang, and Young 2015).

However, what seems evident is that the studies conducted so far, having focused on a single robot in two gendered versions of the same robot, have not adequately considered the different characteristics of the many robots present in the current scenario. Therefore, the results of these studies are difficult to extend to the larger populations of male and female robots.

A recent study by Perugia et al. (2022) considered all the robots in the ABOT database (Phillips et al. 2018), a collection of 251 images of robots evaluated for their degree of human likeness, and in which this variable is correlated with characteristics such as the skin surface of the robot, its facial features and the presence of body manipulators (legs, arms, etc.). Perugia et al. (2022) produced another database, named ROBO-GAP,[1] in which the same 251 robots have been evaluated on 7-point scales for characteristics such as femininity, masculinity, gender neutrality and, on 100 point scale, for age. In this study, each participant had to fill in an online questionnaire aimed at obtaining ratings for the variables considered in relation to the 50–51 robots in its allotted group. The results clearly indicate that the majority of humanoid robots in the dataset are perceived as male, or gender neutral, and young.

Another recent study also considered multiple robots ($n = 9$) extracted from the ABOT database (Roesler et al. 2022). For those robots, it was highlighted that a higher degree of anthropomorphism is not perceived as an advantage in cases where robots are involved in industrial-type contexts and that people generally prefer to call robots by a male name. Therefore, the degree in which a robot must be human-like for gender stereotypes to be activated seems to be an open question, and one that to be answered will require a consideration of the contexts where the human–robot interaction occurs.

Considering all these open issues and given the increasing prevalence of robots in daily life, it is increasingly relevant to understand the extent to which robots can activate stereotypes, or even reinforce gender stereotypes that are likely to have negative consequences. Therefore, it seems necessary to shed further light on how men and women attribute gender role stereotypes to humanoid robots that present, with greater or lesser evidence, cues suggesting their gender.

2. The study

Research on robot gender role stereotypes have either been conducted considering a single robot in its male and female versions, or a single task category. In addition, and perhaps more importantly, the studies cited thus far have not considered the tendencies of participants to use gender stereotypes, while it seems that a number of individual features from gender to personality to education level (Costa, Terracciano, and McCrae 2001; Else-Quest, Hyde, and Linn 2010; Nomura and Takagi 2011) may influence the propensity to use gender stereotypes toward human beings, and it is still not clear whether this same tendency manifests itself equally in reference to humanoid robots. In fact, role gender stereotypes concerning robots have been analysed per se, without relating these tendencies to those that participants can exhibit in relation to human beings.

To fill the lack of knowledge about the relations between gender role stereotypes for humans and those eventually used for humanoid robots we conducted an online study involving 240 participants. The study aimed at exploring the following research questions:

RQ1: Is there any difference in the use of gender stereotypes by male and female evaluators?

RQ2: The more individuals are biased in structuring gender role stereotypes for humans -if they do at all- the more they do for robots as well?

RQ3: Are eventual gender role stereotypes for male and female robots of the same strength?

RQ4: What is the effect of human likeness in the activation of gender role stereotypes about robots?

The aims of the study and the procedure were approved by the Ethical Committee for Human and Social Science of the University of Siena (Careus act: 46/2022).

3. Method

3.1. Participants

Two-hundred and forty Italian participants were recruited for the study. The mean age of participants was 33.2 (SD = 13.7, range = 18–78), and most of them were female ($N = 146$, 60.8%). Almost half of the participants were students ($N = 107$, 44.6%), and about a quarter of them were office workers ($N = 58$, 24.2%). About 11% were freelance professionals ($N = 26$, 10.8%), 5.8% ($N = 14$) were unemployed and 5% ($N = 12$) were factory workers. Participants were recruited through the online platform Prolific[2] and received a small fee for completing an online survey (1 euro), implemented on Lime Survey™. Each participant was randomly assigned to one of four different groups to evaluate two different robots, one male and one female.

3.2. Robots

Eight robots from the ABOT database (Phillips et al. 2018), a comprehensive database including 251 commercial robots each provided with a human likeness score (on a scale from 1 to 100), were selected for the experiment. The robots were chosen mainly based on their perceived gender ratings (on a scale from 1 to 7), as reported in the ROBO-GAP database (Perugia et al. 2022), including four robots considered feminine and four considered masculine. The selection of the eight robots was conducted by a group of 13 students from the Cognitive Psychology course (University of Siena), who in a focus group examined the entire ROBO-GAP database. Their goal was to select four female and four male robots, so that the two sets (female, male) were balanced with respect to age (a variable in the ROBOG-GAP database, on a scale from 0 to 100) and human likeness. The resulting sample of robots included both android robots with very high human likeness (both male and female), as well as robots with intermediate levels of HL. The images of the robots used in the experiment are presented in Figure 1, and their gender, age and HL scores are reported in Table 1. A series of independent samples Welch's t-tests showed male robots had significantly higher ($t(4.21) = 5.73$, $p < .01$) masculinity ratings ($M = 5.19$) and significantly lower ($t(5.06) = -5.62$, $p < .01$) femininity ratings ($M = 1.82$) than female ones ($M_{masc} = 1.5$, $M_{fem} = 5.6$). Male and female robots were instead not significantly different in the mean human likeness ($M_{male\ robot} = 63.7$, $M_{female\ robot} = 53.4$, $t(5.45) = 0.57$, $p = .59$) and age ($M_{male\ robot} = 41.5$, $M_{female\ robot} = 43.4$, $t(5.91) = -0.26$, $p = .80$) scores. Four pairs of robots were then formed, each comprising a male robot and a female one, to be presented to different groups of participants in the study.

3.3. Procedure and measures

From the prolific platform participants were directed to the online survey, where they were initially informed about the objectives of the study, the nature of the procedure and their right to withdraw. Once they expressed informed consent, they started completing the questionnaire.

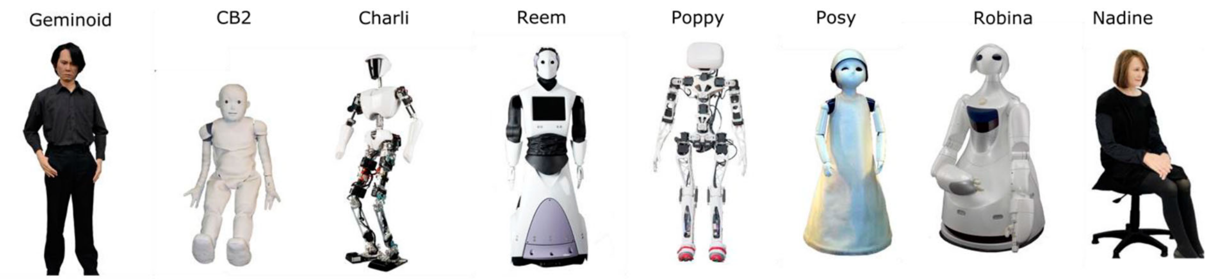

Figure 1. Robots used in the experiments. The robots on the left are generally perceived as masculine, while the ones on the right are generally perceived as feminine. Robots at the extremities of the row have higher human likeness and are more clearly perceived as either masculine or feminine. Moving to the centre, robots in the figure tend to be less human-like and more gender neutral. Sources Phillips et al. (2018) and Perugia et al. (2022).

The questionnaire had three sections. The first section collected socio-demographic information on the participants on variables such as age, gender, work or study. In the second section, we measured participants' attitudes to gender role stereotyping using a set of eight items, four for male role stereotypes and four for female role stereotypes. The items were selected choosing tasks that were plausible for both humans and robots. Four items were taken from the GRSS(Mills et al. 2012), two about male roles ('Mow the lawn' and 'Shovel snow') and two about female ones ('Decorate the house' and 'Prepare meals"). Two other items were added about typically male ("Driver') and female ('Teacher') professions (Anliak and Beyazkurk 2008; Moè, Cadinu, and Maass 2015). Finally, we included two additional items to reflect the view (Tay, Jung, and Park 2014) that in society women are attributed a 'caring' role while men a 'protecting' role (female: 'Stay home with a child who is sick', male: 'Bodyguard'). All the items were answered on a 5-point Likert scale (1 = 'role should be always played by a man', 5 = 'role should be always played by a woman'). Cronbach's alpha for the factors of male and female roles, however, showed questionable internal consistency for both factors (alpha = 0.65–0.67).

In the third section of the questionnaire, the image of a robot was shown, either male or female, and participants were asked to rate how much they believed the robot was fit for each of the eight tasks previously described, on a scale from 1 ('very little') to 5 ('very much'). After providing their answer, the image of a second robot was presented, having opposite gender than the one they had been previously shown, and participants were again asked to rate the robot fitness to fill the same eight roles. The presentation order of the male and female robots was balanced across participants. The images of the robots were displayed at the top of the page, centred on the screen. Each pair of robots was rated by 60 participants.

4. Results

4.1. Gender role stereotypes

Given that internal consistency for the factors was not high, we conducted further analyses based on the ratings for the individual items.

We first conducted a linear mixed-effects models (LMM) analysis on the role genderedness ratings, including role gender, participant gender and their interaction as fixed effects, role type and participant as random effects. *P*-values for main effects and interactions were computed using Satterthwaite's approximation for degrees-of-freedom which should provide the best control for Type I errors (Luke 2017). The complete results are available in the Appendix on OSF.[3] The results showed a significant main effect of *role gender* ($F(1, 6.02) = 15.92$, $p < .01$), a significant

Table 1. Average age, gender and HL ratings for the robots used in the experiment, from the ROBO-GAP and ABOT databases.

Robot name	Robot gender	Femininity ratings (1–7)	Masculinity ratings (1–7)	Human likeness (0–100)	Age ratings (0–100)
Geminoid	Male robot	1.03	6.84	92.60	46.4
Cb2-humanoid	Male robot	1.53	4.80	64.52	28.1
Charli	Male robot	2.03	5.00	55.28	41.3
Reem	Male robot	2.70	4.13	42.60	50.3
Poppy	Female robot	4.30	1.97	37.56	37.1
Posy	Female robot	5.03	2.03	48.67	31.2
Robina	Female robot	6.13	1.13	31.21	51.3
Nadine	Female robot	6.84	1.03	96.38	54

Sources: Phillips et al. (2018) and Perugia et al. (2022).

effect of *participant gender* (F(1, 238.01) = 7.22, $p < .01$), and a significant *role gender by participant gender* interaction effect (F(1, 1672.01) = 26.7, $p < .001$). Mean ratings for female roles ($M = 3.15$) were significantly higher than for male roles ($M = 2.6$), consistently with the rating scale in which higher ratings meant a role was judged more feminine. Female participants' ratings ($M = 2.9$) were slightly, but significantly, higher than males' ratings ($M = 2.8$). However, the post-hoc analysis following the significant interaction showed that this was only true for male roles ($M_{\text{women}} = 2.67$, $M_{\text{men}} = 2.51$, $t(803) = 4.78$, $p < .001$), but not for female roles ($M_{\text{women}} = 3.13$, $M_{\text{men}} = 3.16$, $t(803) = -0.93$, $p = .35$).

We then analysed gender role-fit ratings using a two-way mixed ANOVA, including *role type* as a within-subject factor (with eight levels, corresponding to the roles described in 2.2), and *participant gender* as a between-subjects factor. The results showed that both the main effects and the interaction were significant (*role type*: F (1, 1666) = 114.36, $p < .0001$; *participant gender*: F(1, 238) = 7.22, $p = .008$; *role type* x *participant gender*: F (1, 1666) = 3.41, $p = .001$). Mauchly's test showed that the assumption of sphericity was violated ($p < .001$) for both the effects involving role (role type and the interaction between role type and participant gender), but all the effects remained significant when Greenhouse-Geisser and Huynh-Feldt corrections for departure from sphericity were applied.

Post-hoc comparisons revealed that female participants tended, on average, to rate roles slightly, but significantly, more feminine than male participants (Diff = 0.065, $t(238) = 2.69$, $p = .008$). Concerning the significant effect of role type, the post-hoc comparisons showed clear differences among the roles in the gender role fit (Figure 2). The average gender fit of roles was significantly above the midpoint of the scale (3) for the roles that we had included as female roles, and significantly below the midpoint for the roles that we had included as a male role. Further differences can be found between different male roles as well as between female ones. Concerning the interaction effect that was significant in the ANOVA, post-hoc pairwise comparisons confirmed that significant differences in the ratings from male and female participants were only found for two male roles, 'Mow the lawn' ($p = .0091$) and 'Shovel snow' ($p = .0016$). In both cases, male participants judged the role significantly more masculine than female ones.

4.2. Robot fitness to different roles

We computed, for each role, the average of the role-fit ratings of each robot across participants. The average ratings are plotted in Figure 3. In the top row are plotted the ratings for female roles, ordered from the most (left) to the least feminine (right). In the bottom rows are plotted the ratings for male roles, ordered again from the least to the most masculine role. In each box, the robots on the y axis are ordered according to the difference between their femininity and masculinity ratings in the ROBO-GAP database (Perugia et al. 2022), from the most (top) to the least feminine (bottom). The pattern of means shows clear differences in how the various robots were considered fit for the different roles, and in some cases seems to indicate an effect of gender role stereotyping. This is more evident for male roles which, apart from 'being a driver', show higher role-fit ratings for male robots than for female ones. For female

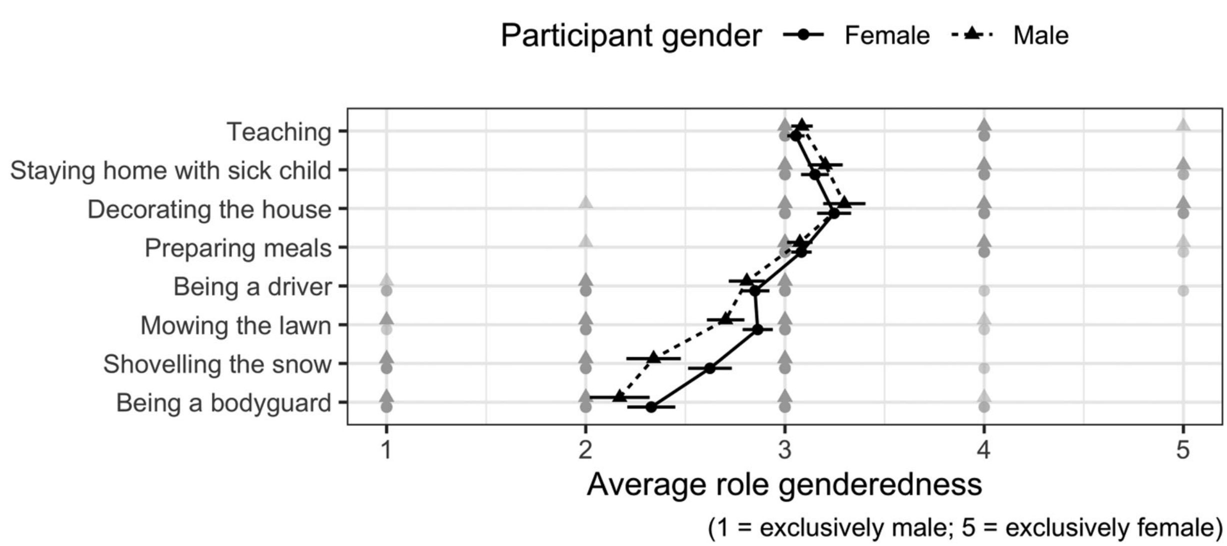

Figure 2. Average role genderedness ratings across role types and participants' gender. Error bars are 95% confidence intervals for the means.

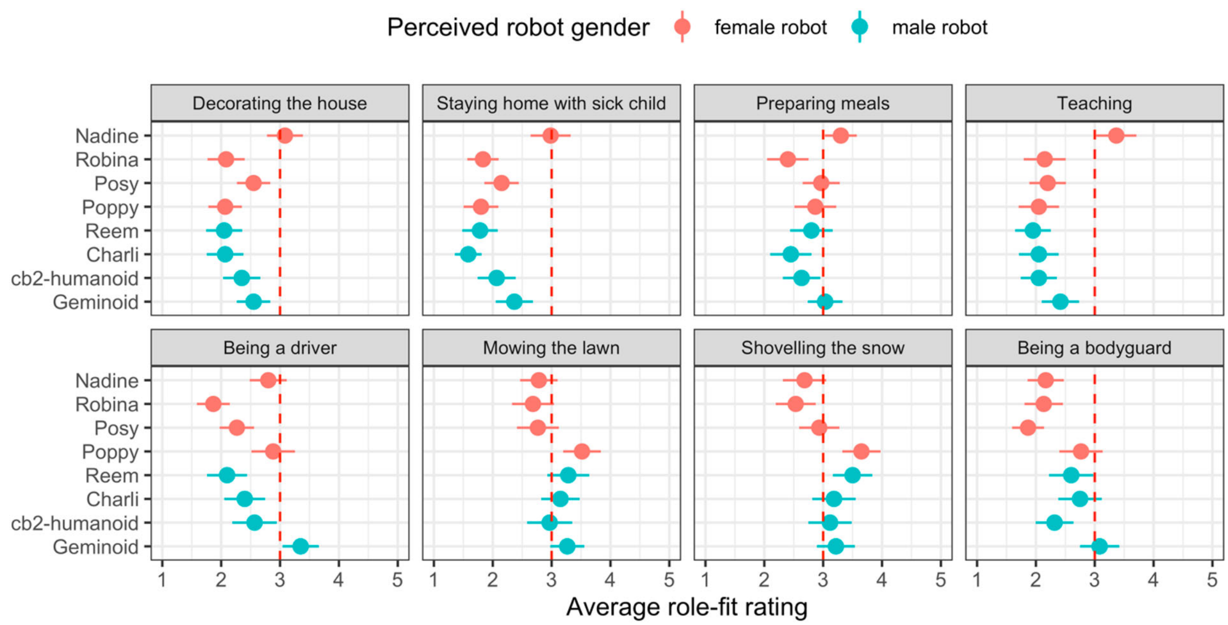

Figure 3. Average role-fitness ratings for different robots across roles. The colour of the points represents the robot gender label in the ROBO-GAP database. Error bars are 95% confidence intervals for the means. The plots in the top row are relative to more stereotypically feminine roles, and the ones in the bottom row to masculine roles.

roles, however, gender role stereotyping is less evident, and it seems to be clear only for one robot, Nadine, which is a feminine android very high on human likeness, and which stands out as better fit than all the other robots (males or females) for 'decorating the house', 'staying home with a sick child' and 'teaching'. Interestingly, at least for roles such as 'decorating the house' and 'staying home with a sick child' the pattern of means across robots seems to follow a U-shaped curve, possibly reflecting the degree of human likeness of the robots, which was highest for the most gendered robots (i.e. more feminine or more masculine), and lowest for the more neutral ones (less gendered).

4.3. Transfer of gender role stereotypes to robots and role of robot human likeness

To investigate whether participants' gender role stereotypes are transferred to robots, we conducted a moderation analysis using LMM. The dependent variables in the analysis were the ratings given by participants on how to fit each robot was for a given role. The predictors were the genderedness ratings for the role (masculine to feminine role, 1–5), the robot gender category in ROBO-GAP database (based on its masculinity and femininity ratings, and sum-coded as predictor), the robot HL score in the ABOT database (centred on the mean for the sample) and all the 2-way and the 3-way interactions between these predictors, constructed as product terms. Participant gender (sum-coded) was also included as a predictor, not in interaction with any other predictor. The role genderedness scores were centred on 0 (by subtracting 3) to ease the interpretation of the interactions. In this way, the predictor varies between −2 (exclusively male role) to +2 (exclusively female role). For the random effects part of the model, we included crossed random effects for robot type (random intercept) and participant (random intercept and slopes). We reasoned that if gender stereotyping was influencing role-fit ratings, a significant interaction between robot gender and role genderedness should have been found. Moreover, a significant 3-way interaction between robot gender, role genderedness and robot HL should have been found if robot HL moderated the effect of gender stereotyping.

The results showed significant main effects of participant gender ($F(1, 235.14) = 5.68$, $p = .018$) and robot HL ($F(1, 2.81) = 11.48$, $p = .047$), significant 2-way interactions between robot gender and role genderedness ($F(1, 157.04) = 47.93$, $p < .001$), and between robot HL and role genderedness ($F(1, 262.7) = 4.87$, $p = .028$) and a significant 3-way interaction between robot gender, robot HL and role genderedness ($F(1, 227.62) = 9.56$, $p = .002$).

Overall, male participants rated robots slightly but significantly better fit to any role than female ones (averaging across roles and robots) (Figure 4(A)). As it can be seen from the slope of the regression line in Figure 4(B), robots that were higher in HL on average tended to be rated as a better fit for the role ($B = 0.01$, $SE = 0.0029$,

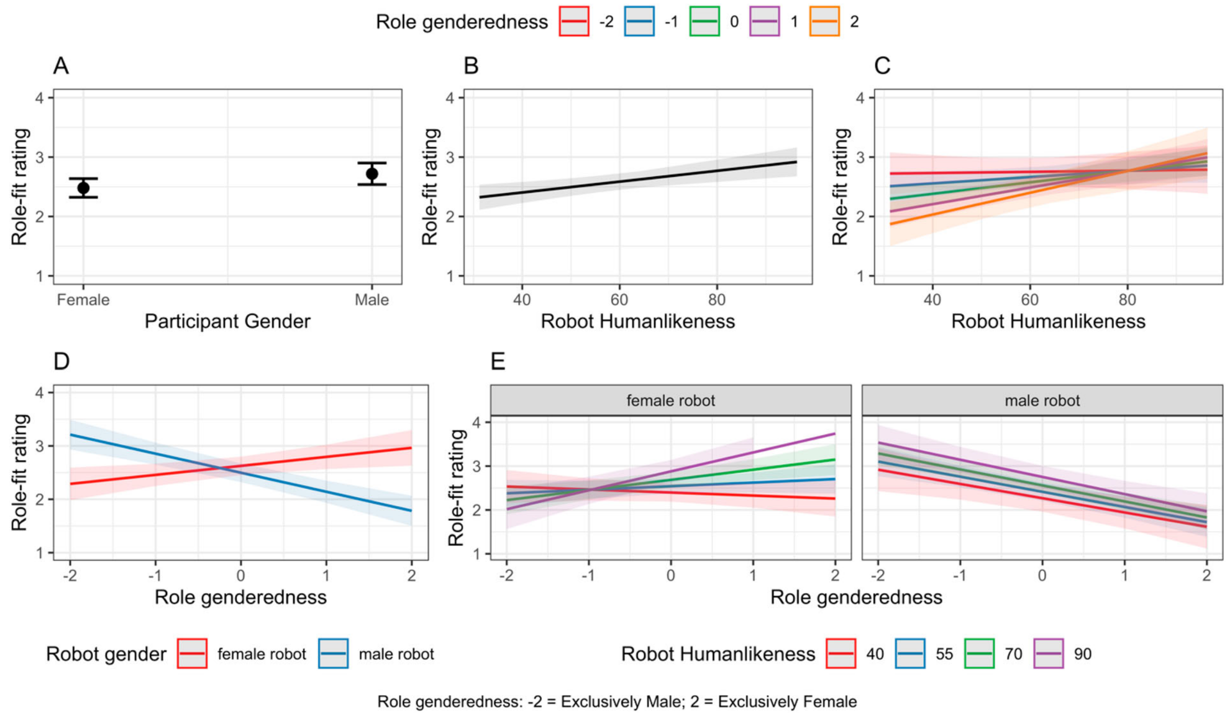

Figure 4. Plots of the estimated (marginal) effects in the linear mixed-effects model of the ratings about robot fitness to different roles.

$p = .047$). The interaction plot in Figure 4(C), however, reveals that the effect of human likeness was stronger (and the more positive) the more a role was judged as feminine, and it was basically null for roles judged as exclusively masculine. The post-hoc analysis of the interaction between robot gender and role genderedness (Figure 4(D)) showed clearly that for male robots the slope for the effect of role genderedness on fit ratings was negative ($B = -0.357$, $SE = 0.0559$), while it was positive for female robots ($B = 0.169$, $SE = 0.0689$). This confirms that gender role stereotypes were applied to robots as well as to human beings. As it can be seen in the 3-way interaction plot in Figure 4(E), however, a stereotype effect in fit ratings was found for male robots at all levels of HL, while for female robots was only found with high HL.

5. Discussion and conclusion

The results obtained have made it possible to highlight that gender role stereotypes are active in reference to both humans and robots: women and feminine robots are considered better at stereotypically female roles and men and masculine robots at stereotypically male roles. However, there are some specifications that are worth pointing out. It appears, in fact, that in addition to the distinction between male and female roles, which are in line with what is expected, there is a tendency for men to consider some male roles as more specifically masculine. Women, on the other hand, show more attenuated stereotypes for those roles that males consider very masculine (mowing the lawn and shovelling the snow) (RQ1) (McHale, Crouter, and Tucker 1999; Crouter et al. 2007; Bracci et al. 2021).

Parallel to this result, it was found that also in reference to robots, women, in general, tend to consider them less fit than men for any role. Men, on the other hand, tend to consider robots more suitable for male roles (RQ2).

Gender role stereotypes for masculine and feminine robots evidently do not have the same strength (RQ3). Masculine robots are considered stereotypically fit for male roles regardless of their HL level. Feminine robots, on the contrary, must be as human-like as possible to be suitable for feminine roles (RQ4). Thus, arguably, the stereotype of humanoid robots implies that they are inherently masculine entities, implemented as such, perceived as such. This is something that reminds the concept of markedness in linguistics (Sergeevič Trubetzkoy 1969), that is to say that robots, in order to be seen as female entities, need to be defined as such in opposition to the usual masculine representation. The result of this study, together with those coming from other research (Kuchenbrandt et al. 2014; Perugia et al. 2022; Roesler et al. 2022) point to this conclusion, though this hypothesis has not been explicitly tested yet.

This hypothesis, along with the evidence that gender role stereotypes are more pronounced for men and masculine robots, in that they are seen more fit for any role, leads to the suggestion that special caution should be used when implementing humanoid social robots that exhibit gender characteristics. Nudging users to interact with an artificial system that has gender characteristics could lead to reinforcing discriminatory stereotypes. This, at least, towards the system itself, but possibly also towards people of the represented gender.

Discrimination in relation to artificial systems has been analysed from different point of view, also from a feminist perspective, as a phenomenon that may depend on several causal factors and having various consequences (Bardzell 2010; Esposito et al. 2020). It has been pointed out, for example, that it is important to ensure that artificial agents implemented with learning algorithms do not have biases within these same algorithms regarding some characteristics of the target populations (Hurtado and Mejia 2022). Otherwise, they could lead to the exclusion of some contexts, or parts of the population, from their learning algorithms, and thus perpetuate or emphasise some features and domains at the expense of others. Even in a perspective more referring to legal aspects, it emerges how the context of reference can be the key aspect in order not to replicate, in reference to robots as well, inequalities that affect humans (Karnouskos 2022). Inequalities that, for example, are evident in the production of exoskeletons, for which it is blatant that the production process is based on masculine perspectives and does not consider the intersection of the different identity dimensions of patients (not only gender dimensions) that will have to enter into symbiosis with those technologies (Søraa and Fosch-Villaronga 2020).

In addition, even when strictly ethical issues are considered (e.g. when artificial systems may be involved in moral judgements), it emerges that robots can have an impact on the application of moral norms (Jackson and Williams 2019; Guidi et al. 2021). A recent study, for example, found that the way in which robots interact, whether in a more or less neutral, argumentative or aggressive style, can change girls' levels of acceptance of robots. Most importantly, however, it was highlighted that in the condition in which the robot responded in an argumentative way, boys showed less gender-bias in assessing girls' ability to understand computer science (Winkle et al. 2021).

Perhaps the phenomenon that emerges with increasing evidence concerns the fact that the attribution of gender to robots can impact on the levels of acceptance of these systems (Ghazali et al. 2019). In a task in which robots must be chosen to perform a collaborative task, participants seem to prefer as teammates those who are more competent. At the end of the task, however, those who are given more trust were those for whom an affinity bias based on consideration of outward aspects could be evidenced (Trainer, Taylor, and Stanton 2020).

Thus, given the results reported here, and in the light of the other studies cited above, it can be said that there is probably a need for a proactive approach, i.e. one that involves ethically acceptable design of artificial systems (Fossa and Sucameli 2022). It would then be possible to implement technologies that counteract discrimination towards people suffering from negative stereotypes.

6. Limitations

The study presented in this paper has some limitation that should be acknowledged. First, we only used images of robots present in two datasets (ABOT and ROBO-GAP). Participants' interactions with these robots were thus obviously constrained to visual explorations of static stimuli. Real interactions – in specific contexts and with the goal of completing specific tasks – could reveal the emergence of stereotypes, more or less pronounced, in the same direction or not, than those highlighted here.

In addition, the sample of robots used in the experiment was not so large, including only 8 robots out of the 251 included in the last update of the ABOT database. Moreover, given that for each robot participants assessed the fitness to eight different roles, to contain the duration of the experiment each participant was presented with only two robots, one feminine and one masculine. Although the robot stimuli in the analysis were used as random factors, in order to make results generalisable across other robots, a larger sample would have allowed greater power to estimate the variability due to robots in the effects, and increase confidence in the replicability of the findings. Another limitation related to the robot sample is that robot human likeness was not equally distributed across robot genders (masculine vs feminine), and it was more uniformly distributed among masculine robots, while for feminine robots we had only one very HL robot and three low-intermediate HL robots, all quite similar in HL. A further limitation of the study concerns the relatively low internal consistency of the scale used to measure participants' gender role stereotypes. However, the main analysis that we have conducted to test our hypothesis about the transfer of stereotypes to gendered robots did not use the GRSS scales scores, but the scores on the single items. Therefore, even if the composite scores were not extremely internally consistent, this should not undermine our main findings. Lastly, we need to notice that the perceived gender ratings from the ROBO-GAP database, on which gender categories for the robots are derived, are estimates computed aggregating the ratings of a panel of observers, and it is not sure that individuals in our sample were actually perceiving the robots as gendered (in terms of femininity or masculinity or neutrality). Further studies should be therefore conducted to address these limitations.

Notes

1. https://robo-gap.unisi.it/.
2. https://www.prolific.co/.
3. https://osf.io/jd7as?view_only=150a1ad7f1fc4f778322cbbba5299725.

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No potential conflict of interest was reported by the author(s).

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References

Amanatullah, Emily T., and Michael W. Morris. 2010. “Negotiating Gender Roles: Gender Differences in Assertive Negotiating are Mediated by Women’s Fear of Backlash and Attenuated When Negotiating on Behalf of Others.” *Journal of Personality and Social Psychology* 98 (2): 256–267. doi:10.1037/a0017094.

Anliak, Sakire, and Derya Sahin Beyazkurk. 2008. “Career Perspectives of Male Students in Early Childhood Education.” *Educational Studies* 34 (4): 309–317. doi:10.1080/03055690802034518.

Bakan, David. 1966. *The Duality of Human Existence*. Chicago, IL: Rand McNally.

Bardzell, Shaowen. 2010. “Feminist HCI: Taking Stock and Outlining an Agenda for Design.” In *CHI ‘10: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1301–1310. Atlanta, GA, USA. doi:10.1145/1753326.1753521.

Barth, John M., Stephanie L. Masters, and Jeffrey G. Parker. 2022. “Gender Stereotypes and Belonging Across High School Girls’ Social Groups: Beyond the STEM Classroom.” *Social Psychology of Education* 25: 275–292. doi:10.1007/s11218-021-09683-2.

Bhatia, Nazli, and Sudeep Bhatia. 2021. “Changes in Gender Stereotypes Over Time: A Computational Analysis.” *Psychology of Women Quarterly* 45 (1): 106–125. doi:10.1177/0361684320977178.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2016. “Stereotypes*.” *The Quarterly Journal of Economics* 131 (4): 1753–1794. doi:10.1093/qje/qjw029.

Bracci, Margherita, Stefano Guidi, Enrica Marchigiani, Maurizio Masini, Paola Palmitesta, and Oronzo Parlangeli. 2021. “Perception of Faces and Elaboration of Gender and Victim/Aggressor Stereotypes: The Influence of Internet use and of the Perceiver’s Personality.” *Frontiers in Psychology* 12. doi:10.3389/fpsyg.2021.561480.

Breda, Thomas, and Clotilde Napp. 2019. “Girls’ Comparative Advantage in Reading Can Largely Explain the Gender Gap in Math-Related Fields.” *Proceedings of the National Academy of Sciences of the United States of America* 116 (31): 15435–15440. doi:10.1073/pnas.1905779116.

Buss, David M., and David P. Schmitt. 1993. “Sexual Strategies Theory: An Evolutionary Perspective on Human Mating.” *Psychological Review* 100 (2): 204–232. doi:10.1037/0033-295X.100.2.204.

Charlesworth, Tessa E.S., and Mahzarin R. Banaji. 2021. “Patterns of Implicit and Explicit Stereotypes III: Long-Term Change in Gender Stereotypes.” *Social Psychological and Personality Science* 13 (1): 14–26. doi:10.1177/1948550620988425.

Christoforakos, Lara, Alessio Gallucci, Tinatini Surmava-Große, Daniel Ullrich, and Sarah Diefenbach. 2021. “Can Robots Earn Our Trust the Same Way Humans Do? A Systematic Exploration of Competence, Warmth and Anthropomorphism as Determinants of Trust Development in HRI.” *Frontiers in Robotics and AI* 8: 640444. doi:10.3389/frobt.2021.640444.

Costa, Paul T., Antonio Terracciano, and Robert R. McCrae. 2001. “Gender Differences in Personality Traits Across Cultures: Robust and Surprising Findings.” *Journal of Personality and Social Psychology* 81 (2): 322–331. doi:10.1037/0022-3514.81.2.322.

Crick, Nicki R., and Jennifer K. Grotpeter. 1995. “Relational Aggression, Gender, and Social-Psychological Adjustment.” *Child Development* 66 (3): 710–722. doi:10.2307/1131945.

Crouter, Ann C., Shawn D. Whiteman, Susan M. McHale, and D. Wayne Osgood. 2007. “Development of Gender Attitude Traditionality Across Middle Childhood and Adolescence.” *Child Development* 78 (3): 911–926. doi:10.1111/j.1467-8624.2007.01040.x.

Damiano, Luisa, and Paul Dumouchel. 2018. “Anthropomorphism in Human-Robot Co-Evolution.” *Frontiers in Psychology* 9, 468. doi:10.3389/fpsyg.2018.00468.

Duffy, Brian R. 2003. “Anthropomorphism and the Social Robot.” *Robotics and Autonomous Systems* 42: 177–190. doi:10.1016/S0921-8890(02)00374-3.

Eagly, Alice H., Christa Nater, David I. Miller, Michèle Kaufmann, and Sabine Sczesny. 2019. “Gender Stereotypes Have Changed: A Cross-Temporal Meta-Analysis of U.S. Public Opinion Polls from 1946 to 2018.” *American Psychologist* 75 (3): 301–315. doi:10.1037/amp0000494.

Else-Quest, Nicole M., Janet Shibley Hyde, and Marcia C. Linn. 2010. “Cross-national Patterns of Gender Differences in Mathematics: A Meta-Analysis.” *Psychological Bulletin* 136 (1): 103–127. doi:10.1037/a0018053.

Esposito, Anna, Terry Amorese, Marialucia Cuciniello, Maria Teresa Riviello, and Gennaro Cordasco. 2020. “How Human Likeness, Gender and Ethnicity Affect Elders’ Acceptance of Assistive Robots.” In *2020 IEEE*

International Conference on Human-Machine Systems (ICHMS), 1–6. Rome, Italy. doi:10.1109/ICHMS49158.2020.9209546.

Eyal, Tal, and Nicholas Epley. 2017. “Exaggerating Accessible Differences: When Gender Stereotypes Overestimate Actual Group Differences.” *Personality and Social Psychology Bulletin* 43 (9): 1323–1336. doi:10.1177/0146167217713190.

Eyssel, Friederike, and Franck Hegel. 2012. “(S)He's got the Look: Gender Stereotyping of Robots.” *Journal of Applied Social Psychology* 42 (9): 2213–2230. doi:10.1111/j.1559-1816.2012.00937.x.

Fiske, Susan T., Amy J.C. Cuddy, and Peter Glick. 2007. “Universal Dimensions of Social Cognition: Warmth and Competence.” *Trends in Cognitive Sciences* 11 (2): 77–83. doi:10.1016/j.tics.2006.11.005.

Fossa, Fabio, and Irene Sucameli. 2022. “Gender Bias and Conversational Agents: An Ethical Perspective on Social Robotics.” *Science and Engineering Ethics* 28, 23. doi:10.1007/s11948-022-00376-3.

Ghazali, Aimi Shazwani, Jaap Ham, Emilia Barakova, and Panos Markopoulos. 2019. “Assessing the Effect of Persuasive Robots Interactive Social Cues on Users' Psychological Reactance, Liking, Trusting Beliefs and Compliance.” *Advanced Robotics* 33: 325–337. https://www.tandfonline.com/doi/full/10.108001691864.2019.1589570.

Guidi, Stefano, Enrica Marchigiani, Sergio Roncato, and Oronzo Parlangeli. 2021. “Human Beings and Robots: Are There any Differences in the Attribution of Punishments for the Same Crimes?” *Behaviour & Information Technology* 40 (5): 445–453. doi:10.1080/0144929X.2021.1905879.

Haines, Elizabeth L., Kay Deaux, and Nicole Lofaro. 2016. “The Times They are a-Changing … or are They Not? A Comparison of Gender Stereotypes, 1983–2014.” *Psychology of Women Quarterly* 40 (3): 353–363. doi:10.1177/0361684316634081.

Hedges, Larry V., and Amy Nowell. 1995. “Sex Differences in Mental Test Scores, Variability, and Numbers of High-Scoring Individuals.” *Science* 269 (5220): 41–45. doi:10.1126/science.7604277.

Hurtado, Juana Valeria, and Valentina Mejia. 2022. “Feminist Perspective on Robot Learning Processes,” arXiv preprint arXiv:2201.10853. doi:10.48550/arXiv.2201.10853.

Hyde, Janet S. 2005. “The Gender Similarities Hypothesis.” *American Psychologist* 60 (6): 581–592. doi:10.1037/0003-066X.60.6.581.

Hyde, Janet S. 2014. “Gender Similarities and Differences.” *Annual Review of Psychology* 65: 373–398. doi:10.1146/annurev-psych-010213-115057.

Jackson, Ryan B., and T. Williams. 2019. “Language-Capable Robots may Inadvertently Weaken Human Moral Norms.” In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 401–410. Daegu, Korea. doi:10.1109/HRI.2019.

Kahneman, Daniel, and Amos Tversky. 1972. “Subjective Probability: A Judgment of Representativeness.” *Cognitive Psychology* 3 (3): 430–454. doi:10.1016/0010-0285(72)90016-3.

Karnouskos, Stamatis. 2022. “Symbiosis with Artificial Intelligence via the Prism of Law, Robots, and Society.” *Artificial Intelligence and Law* 30: 93–115. doi:10.1007/s10506-021-09289-1.

Kuchenbrandt, Dieta, Markus Häring, Jessica Eichberg, Friederike Eyssel, and Elisabeth Andrè. 2014. “Keep an Eye on the Task! How Gender Typicality of Tasks Influence Human–Robot Interactions.” *International Journal of Social Robotics* 6: 417–427. doi:10.1007/s12369-014-0244-0.

Kulms, Philipp, and Stefan Kopp. 2018. “A Social Cognition Perspective on Human–Computer Trust: The Effect of Perceived Warmth and Competence on Trust in Decision-Making with Computers.” *Frontiers in Digital Humanities* 5: 14. doi:10.3389/fdigh.2018.00014.

Luke, Steven G. 2017. “Evaluating Significance in Linear Mixed-Effects Models in R.” *Behavior Research Methods* 49 (4): 1494–1502. doi:10.3758/s13428-016-0809-y.

Maccoby, Eleanor E., and Carol N. Jacklin. 1974. *The Psychology of Sex Differences*. Stanford, CA: Stanford University Press.

McHale, Susan M., Ann C. Crouter, and Corinna J. Tucker. 1999. “Family Context and Gender Role Socialization in Middle Childhood: Comparing Girls to Boys and Sisters to Brothers.” *Child Development* 70 (4): 990–1004. http://www.jstor.org/stable/113257.

Mills, Maura J., Satoris S. Culbertson, Ann H. Huffman, and Angela R. Connell. 2012. “Assessing Gender Biases: Development and Initial Validation of the Gender Role Stereotypes Scale.” *Gender in Management: An International Journal* 27 (8): 520–540. doi:10.1108/17542411211279715.

Moè, Angelica, Mara Cadinu, and Anne Maass. 2015. “Women Drive Better if Not Stereotyped.” *Accident Analysis & Prevention* 85: 199–206. doi:10.1016/j.aap.2015.09.021.

Nass, Clifford, and Youngme Moon. 2000. “Machines and Mindlessness: Social Responses to Computers.” *Journal of Social Issues* 56: 81–103. doi:10.1111/0022-4537.00153.

Nass, Clifford, Jonathan Steuer, and Ellen R. Tauber. 1994. “Computers are Social Actors.” In *Conference Companion on Human Factors in Computing Systems (CHI '94)*, 204. New York, NY: Association for Computing Machinery. doi:10.1145/259963.260288.

Nomura, Tatsuya, and Satoru Takagi. 2011. “Exploring Effects of Educational Backgrounds and Gender in Human–Robot Interaction”. In *Proceedings of the 2nd International Conference on User Science and Engineering (i-USEr 2011)*, November 29–December 1, 24–29. Shah Alam, Selangor, Malaysia. IEEE, Piscataway, NJ. doi:10.1109/iUSEr.2011.6150530.

Parlangeli, Oronzo, Maria C. Caratozzolo, and Stefano Guidi. 2014. “Multitasking and Mentalizing Machines: How the Workload can have Influence on the System Comprehension.” In *Engineering Psychology and Cognitive Ergonomics, 11th International Conference, EPCE, Held as Part of HCI International*, edited by D. Harris, 50–58. Crete: Heraklion. doi:10.1007/978-3-319-07515-0_6.

Perugia, Giulia, Stefano Guidi, Margherita Bicchi, and Oronzo Parlangeli. 2022. “The Shape of Our Bias: Perceived Age and Gender in the Humanoid Robots of the ABOT Database.” In *Proceedings of the 2022 17th ACM/IEEE International Conference on Human-Robot*

Interaction (HRI22), 110–119, Sapporo, Hokkaido, JP. IEEE Press.

Phillips, Elizabeth, Xuan Zhao, Daniel Ullman, and Bertram F. Malle. 2018. "What is Human-Like? Decomposing Robots' Human-Like Appearance using the Anthropomorphic Robot (ABOT) Database." In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction (HRI '18)*, 105–113. New York, NY: ACM. doi:10.1145/3171221.3171268.

Powers, Aaron, Adam D.I. Kramer, Shirlene Lim, Jean Kuo, Sau-Iai Lee, and Sara Kiesler. 2005. "Eliciting Information from People with a Gendered Humanoid Robot." ROMAN 2005. IEEE International Workshop on Robot and Human Interactive Communication, 158–163. doi:10.1109/ROMAN.2005.1513773.

Rea, Daniel J., Yan Wang, and James E. Young. 2015. "Check your Stereotypes at the Door: An Analysis of Gender Typecasts in Social Human-Robot Interaction." In *Social Robotics. ICSR 2015. Lecture Notes in Computer Science, vol. 9388*, edited by A. Tapus, E. André, J. C. Martin, F. Ferland, and M. Ammi. Cham: Springer. doi:10.1007/978-3-319-25554-5_55.

Rideout, Victoria J., Ulla G. Foehr, and Donald F. Roberts. 2010. *Generation M2: Media in the Lives of 8- to 18-Year-Olds*. Menlo Park, CA: Kaiser Fam. Found.

Roesler, Eileen, Lara Naendrup-Poell, Dietrich Manzey, and Linda Onnasch. 2022. "Why Context Matters: The Influence of Application Domain on Preferred Degree of Anthropomorphism and Gender Attribution in Human–Robot Interaction." *International Journal of Social Robotics*. doi:10.1007/s12369-021-00860-z.

Santos, Susana C., and Xaver Neumeyer. 2022. "Culture and Gender in Entrepreneurial Teams: The Effect on Team Processes and Outcomes." *Small Business Economics* 58: 1035–1050. doi:10.1007/s11187-020-00432-x.

Schermerhorn, Paul, Matthias Scheutz, and Charles R. Crowell. 2008. "Robot Social Presence and Gender." In *Proceedings of the 3rd ACM/IEEE International Conference on Human Robot Interaction (HRI '08)*, 263–270. New York, NY: Association for Computing Machinery. doi:10.1145/1349822.1349857.

Seo, Soobin. 2022. "When Female (Male) Robot is Talking to Me: Effect of Service Robots' Gender and Anthropomorphism on Customer Satisfaction." *International Journal of Hospitality Management* 102, 103166. doi:10.1016/j.ijhm.2022.103166.

Sergeevič Trubetzkoy, Nikolaj. 1969. *Principles of Phonology*. Berkeley: University of California Press.

Siegel, Mikey, Cynthia Breazeal, and Michael I. Norton. 2009. "Persuasive Robotics: The Influence of Robot Gender on Human Behavior." In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2563–2568. Kyoto, Japan. doi:10.1109/IROS.2009.5354116.

Søraa, Roger A., and Eduard Fosch-Villaronga. 2020. "Exoskeletons for All: The Interplay Between Exoskeletons, Inclusion, Gender, and Intersectionality." *Paladyn, Journal of Behavioral Robotics* 11 (1): 217–227. doi:10.1515/pjbr-2020-0036.

Sundar, Shyam S., and Jinyoung Kim. 2019. "Machine Heuristic: When We Trust Computers More than Humans with Our Personal Information". In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (*CHI '19*), Paper 538, 1–9. New York, NY: Association for Computing Machinery. doi:10.1145/3290605.3300768.

Tabassum, Naznin, and Bhabani S. Nayak. 2021. "Gender Stereotypes and Their Impact on Women's Career Progressions from a Managerial Perspective." *IIM Kozhikode Society & Management Review* 10 (2): 192–208. doi:10.1177/2277975220975513.

Tay, Benedict, Younbo Jung, and Taezoon Park. 2014. "When Stereotypes Meet Robots: The Double-Edge Sword of Robot Gender and Personality in Human–Robot Interaction." *Computers in Human Behavior* 38: 75–84. doi:10.1016/j.chb.2014.05.014.

Trainer, Thomas, John R. Taylor, and Christopher J. Stanton. 2020. "Choosing the Best Robot for the Job: Affinity Bias in Human-Robot Interaction." In *Social Robotics: 12th International Conference, ICSR 2020*, 490–501, Golden, CO, USA, November 14–18. doi:10.1007/978-3-030-62056-1_41.

Truong, Thuy H., and Kim A. Duong. 2022. "Fostering Sustainable Development by Eliminating Gender Stereotypes in Career Choice." In *Global Changes and Sustainable Development in Asian Emerging Market Economies Vol. 1*, edited by A. T. Nguyen, and L. Hens. Cham: Springer. doi:10.1007/978-3-030-81435-9_42.

Winkle, Katie, Gaspar I. Melsión, Donald McMillan, and Iolanda Leite. 2021. "Boosting Robot Credibility and Challenging Gender Norms in Responding to Abusive Behaviour: A Case for Feminist Robots." In *Companion of the 2021 ACM/IEEE International Conference on Human-Robot Interaction* (*HRI '21*), 29–37. New York, NY: ACM. doi:10.1145/3434074.3446910.

Wood, Wendy, and Alice H. Eagly. 2012. "Biosocial Construction of Sex Differences and Similarities in Behavior." *Advances in Experimental Social Psychology* 46: 55–123. doi:10.1016/B978-0-12-394281-4.00002-7.

Ye, Hongjun, Haeyoung Jeong, Wenting Zhong, Siddharth Bhatt, Kurtulus Izzetoglu, Hasan Ayaz, and Rajneesh Suri. 2019. "The Effect of Anthropomorphization and Gender of a Robot on Human-Robot Interactions." In *Advances in Neuroergonomics and Cognitive Engineering (AHFE2019), Advances in Intelligent Systems and Computing, 953*, edited by H. Ayaz, 357–362. Cham: Springer. doi:10.1007/978-3-030-20473-0_34.

Złotowski, Jakub, Diane Proudfoot, Kumar Yogeeswaran, and Christoph Bartneck. 2015. "Anthropomorphism: Opportunities and Challenges in Human-Robot Interaction." *International Journal of Social Robotics* 7: 347–360. doi:10.1007/s12369-014-0267-6.