Why Should We Gender? The Effect of Robot Gendering and Occupational Stereotypes on Human Trust and Perceived Competency

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ABSTRACT

The attribution of human-like characteristics onto humanoid robots has become a common practice in Human-Robot Interaction by designers and users alike. Robot gendering, the attribution of gender onto a robotic platform via voice, name, physique, or other features is a prevalent technique used to increase aspects of user acceptance of robots. One important factor relating to acceptance is user trust. As robots continue to integrate themselves into common societal roles, it will be critical to evaluate user trust in the robot's ability to perform its job. This paper examines the relationship among occupational gender-roles, user trust and gendered design features of humanoid robots. Results from the study indicate that there was no significant difference in the perception of trust in the robot's competency when considering the gender of the robot. This expands the findings found in prior efforts that suggest performance-based factors have larger influences on user trust than the robot's gender characteristics. In fact, our study suggests that perceived occupational competency is a better predictor for human trust than robot gender or participant gender. As such, gendering in robot design should be considered critically in the context of the application by designers. Such precautions would reduce the potential for robotic technologies to perpetuate societal gender stereotypes.

CCS CONCEPTS

Human-centered computing → Empirical studies in HCI

KEYWORDS

Robot gender; Gender stereotypes; Human-Robot Interaction; Gendering; Human-Robot Trust; Occupational Competency; Pepper robot

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1 Introduction

Robots are increasingly being used in interactive scenarios to support, assist, and serve humans [1]. Many of these scenarios situate the robot into an established social role with preexisting human expectations for factors such as competency, reliability and behavior. These factors have been shown to impact the complex trust relationship between humans and robots [2]. However, recent works suggest that other factors related to the anthropomorphism of robots also have an influence on human trust development [2, 3]. One such factor is robot gender, an attribute often manipulated by robot designers to purposely elicit a desired interaction with human users.

For the purposes of this discussion, robot gendering is defined as the assigning or attribution of gender onto a robotic platform via voice, name, or physique [4]. The practice of gendering is often motivated by societal gender norms. For example, a study on the acceptance of an assistive humanoid robot by preschool and elementary school teachers utilized the NAO robot speaking in a female voice which the researchers note is commonly associated with kindergarten staff [5]. Such gender attribution is common in human-robot interaction studies and has situationally demonstrated positive results related to human attitudes and acceptance [5, 6, 8-12]. Conversely, other works have cautioned against the use of "gendered" robots to avoid the risk of reinforcing societal gender stereotypes [7]. Here, stereotype is defined as a widely held but fixed and oversimplified image or idea of a particular type of person or thing [8]. Frequently, the target of a stereotype can experience some form of harm as a result of the stereotype. Gender stereotypes are of key interest when considering the occupational roles that a robot may undertake.

Tay, Jung and Park investigated the role of occupational gender stereotypes in the perception and trust of a home-service humanoid robot in two occupations with longstanding gender associations: healthcare and security [13]. The results from the study revealed that participants evaluated robots that matched their respective gender stereotypes as being more capable of performing the behaviors of interest. Yet, the gender of the robot had no significant influence on the perceived trust of either the healthcare or security robot. This finding is consistent with prior work suggesting that performance-based factors (i.e. reliability, transparency, behavior, etc.) are the largest influencers on perceived trust in robots [2].

Though these collective works have suggested that attributed robot gender has a minimal effect on human trust in a robot's ability to operate in an occupational role, little to no work has supported the generalization of this finding to various occupations. The motivation for this current work is to further investigate the effect of robot gender on human trust in perceived robot occupational competency when considering various occupations. Throughout this discussion, we adapt the definition of trust from [38] as the belief that the system performs with personal integrity and reliability. We define occupational competence as the ability to complete the tasks associated with a given occupation [14] and propose the following research question.

R1: How are participants' trust in the robot's occupational competency affected when the **robot's gender** matches the **occupation's associated gender?**
The authors in [13] hypothesized that a social robot matching gender and occupational role stereotypes would obtain higher ratings of perceived trust. We adapt this belief and propose the following hypothesis to R1.

H1: There will be **an increase in perceived trust** of the robot's occupational competency when the robot's gender matches the stereotypical gender associated with the occupation.
[12] additionally presents evidence that perceived robot gender may interact with the user's gender to influence the user's overall perception and response to the robot. In the experiment, the authors examined the use of a female and male robot voice. We introduce R2 to examine if such an interaction would impact perceived trust in this study.

R2: How are participants' trust in the robot's occupational competency for a given occupation affected when the **robot's gender** matches the **participant's gender?**
The authors in [12] presented the Gender Alignment hypothesis which suggests that a social robot gendered to match the user's gender elicits social identification effects in subjects. To apply this hypothesis to the current study, we propose the following hypothesis to R2.

H2: There will be **an increase in perceived trust** of the robot's occupational competency when the robot's gender matches the participant's gender.

Included in this investigation are occupations historically influenced by human gender roles and occupations that are considered gender neutral. The results of a pilot study and a between-subjects experiment are presented. The pilot study seeks to verify the gender role stereotypes associated with various occupations for which robots are being considered. The experimental study measures the relation of the examined occupational gender-roles to human robot-trust when being asked about a male, female, or gender-neutral humanoid robot. Data about the tasks a robot could perform were collected as well but are not included here. Results are presented in relation to previous findings in human-robot trust and implications for future work in HRI are discussed.

2 Related Work

Social robots are often desired to operate in real-world environments. These environments call for interactions with humans of various gender and cultural identities. It has been common practice in HRI studies involving humanoid robots to manipulate factors such as robot physique [3], voice [12, 16], personality [13, 18], emotional intelligence [15, 17], and name [26] to match the gender traditionally associated with a given role. However, this practice of generalizing aspects of human-human relationships to human-robot relationships may actually "oversimplify the complexities of gender" and result in "designs that may re-enforce potentially harmful stereotypes" [7]. The following subsections present an overview of relevant literature in the concepts of occupational gender roles, the gendering of humanoid robots, and human-robot trust.

2.1 Occupational Gender Roles & Stereotypes

There have been substantial contributions from fields such as psychology, sociology, and gender studies toward understanding gender roles and stereotypes in human occupations [19]. Prior work has shown that individuals tend to identify certain jobs with the male or female identity and exhibit an inherent bias against individuals perceived as the opposing gender in those roles [20, 21]. Such occupational gender roles are often rooted in historical, cultural, and political phenomena. However, occupational gender roles have sometimes been shown to shift over time. For example, in the 1980's the United States saw a great migration of women into occupations traditionally reserved for men [22]. Even early computer programmer and software development roles were once dominated by women in the mid-late 1900's before a gender role shift occurred [23]. As these and other historical examples indicate, gender roles in society are not permanent assignments. Therefore, it is important to continually assess and control the influence such roles in society may have on social human-robot interactions in relation to perceived competency and trust.

2.2 Gendering Humanoid Robots

The design choice to anthropomorphize humanoid robots is not a new approach. Several studies have shown that attributing human characteristics to robots elicits similar social reactions from humans that are usually seen in human-human interactions. These robot characteristics have been linked to increased user acceptance and reliability in the robotic system. Gendering is one technique, often used in addition to other anthropomorphism techniques, which has shown to impact certain aspects of the human-robot relationship [6]. For example, Crowley et al. found that perceived robot gender in conjunction with human gender and pre-experimental attitudes influence how people respond to robotic entities [12]. [24] demonstrated that men are more likely to express positive attitudes toward female robots than toward male robots. It has also been reported that people's expectations for a robot's knowledge base and usefulness is contingent on its perceived gender [7, 8]. These works collectively suggest that robot gender can provide important social cues that help to facilitate the improved human-robot relationship, often increasing task success and overall attitudes towards robots.

However, other works have questioned the use of gendering for facilitating social human-robot interactions. Rea, Wang and Young suggest that gender role stereotypes play a minimal to nonexistent role when considering a robot for household tasks such as preparing meals and taking care of children [7]. These findings imply that occupational role stereotypes are introduced when robot designers use gendering to purposely prime and elicit similar cognitive behaviors seen in normative human-human interactions. To consider this alternate stance, we include a gender-neutral robot condition in addition to the male and female robot conditions in the present study.

2.3 Human-Robot Trust

The relationship between robot gender and human trust has not been investigated thoroughly in the context of occupational roles with potential gender stereotypes. [13] reports that trust was minimally impacted by robot gender when evaluated separately from other attributes of robot acceptance (i.e., attitude towards robot, affective evaluations, cognitive evaluations, and perceived behavioral control). This initial finding is supported by work in [2, 9] indicating that performance factors are more highly correlated with robot trust than perceived robot characteristics. However, [13] investigates the effect of robot gender on perceived trust while considering only two occupations with very notable gender associations. This work seeks to further investigate the generalizability of such findings to a variety of occupations.

As the level of trust in a robot has been correlated to attributes related to robot reliability and competency [2], we first evaluate the human perception of the utilized robot's ability to complete the tasks associated with given occupations. We then seek to further investigate the occupational roles that the majority of participants felt the robot was competent enough to do.

3 Methodology

3.1 Validating Occupational Gender Role Association

The aim of the pilot study was to establish the perceived gender roles associated with a given occupation given that such an association exists in the current societal climate. A list of occupations was derived from current occupational activities that have been considered for social robots [1, 26]. The list was carefully selected to include occupations that would fall into various areas of the gender spectrum. This list included the following occupations: **banker, comedian, firefighter, home-health aid, musician, nanny, news anchor, nurse, package deliverer, receptionist, restaurant server, security guard, surgeon, teacher, therapist, and tour guide**.

3.1.1 Materials & Measures. A gender role association questionnaire was developed using the online Qualtrics software. For each occupation in the list mentioned above, the participants were asked to answer the following question, "*Which gender do you think is typically associated with the following occupation?"* They responded by selecting a radio button corresponding to either male, female or neither. These responses were calculated into ratio data representing overall perception of gender roles by the sample population.

3.1.2 Participants. We administered the Qualtrics questionnaire to 50 United States participants ranging in age from 22-72 (male = 68%, female = 32%, mean age = 35.65, SD = 9.34) recruited through the Amazon Mechanical Turk (AMT) platform. Data was collected in June 2019. All participants indicted that English was their native or preferred language. When asked about highest level of education, 40% of responded with as pre-college, 54% of participants selected undergraduate degree, and 6% of participants selected master's degree.

Occupation	M_P	F_P	N_P	$Majority_P$	$Majority_a$	M_a	F_a
Comedian*	**68%**	2%	30%	M	M	**85%**	15%
Firefighter	**94%**	2%	4%	M	M	**95%**	5%
Home health aid	0%	**94%**	6%	F	F	11%	**89%**
Nanny	0%	**98%**	2%	F	F	6%	**94%**
News Anchor	32%	26%	**42%**	N	N	48%	52%
Nurse	2%	**94%**	4%	F	F	11%	**89%**
Package deliverer	**84%**	2%	14%	M	M	**60%**	40%
Receptionist	0%	**92%**	8%	F	F	10%	**91%**
Restaurant Server	2%	**60%**	38%	F	F	18%	**82%**
Security Guard	**94%**	2%	4%	M	M	**78%**	22%
Surgeon	**70%**	2%	28%	M	M	**60%**	40%
Teacher	0%	**78%**	22%	F	F	29%	**71%**
Therapist	8%	**64%**	28%	F	F	21%	**79%**
Tour guide	24%	28%	**48%**	N	N	56%	44%

Table 1: The distribution of perceived gender association with various occupations as resulting from the gender association questionnaire (left side) and compared to the actual gender distribution of men and women in those occupations according to the BLS (right side). p = perceived by participants, a = actual distribution according to BLS, M = male, F = female, N = neither.

3.1.3 Procedure. All participants were first navigated from the AMT platform to the Qualtrics questionnaire. They agreed to participate after reviewing a consent form approved by the institutional review board (IRB). They then answered the gender role association questionnaire. Demographic related questions (age, gender, ethnicity, location, highest level of education, and occupation) were asked after the gender role association questionnaire was administered. Participants received $2.00 in compensation for their participation.

3.1.4 Results. To examine the results of the questionnaire, we first took a subset of the original occupation list for occupations which had a gender attribution agreement >60%. The resulting subset of occupations and their responses are shown in Table 1. The occupations of home health aid, nanny, nurse, receptionist, restaurant server, teacher, and therapist were rated as typically being associated with the female gender. The occupations of comedian, firefighter, package deliverer, security guard, and surgeon were rated as typically being associated with the male gender. The occupations of news anchor and tour guide did not meet the >60% agreement threshold but are also included in the analysis as the majority of participants ranked them as neither having an association with the male or female gender.

With the exception of comedian, the right-hand side of Table 1 illustrates the 2018 gender population distribution according to the US Department of Labor's Bureau of Labor and Statistics (BLS) [27]. As comedians are grouped into the occupational category of actors according to the BLS, the statistics shown for the current gender makeup of comedians are taken from [28]. As the table indicates, the perceived gender association for each of the selected occupations are consistent with the current population breakdown of gender for those roles in the US. These 14 occupations with validated gender role associations were utilized in the questionnaires developed for the perceived occupational competency and trust questionnaires detailed in section 3.2.3.

3.2 Perceived Occupational Competency & Trust

The aim of this experiment was to examine the impact that robot gender has on the perceived occupational competency of and trust in a humanoid robot to test RQ1 and RQ2. We utilized three experimental conditions where we manipulated a robot's voice and name to attribute gender to itself. The following subsections document the experimental measures chosen and data collected during the experiment.

3.2.1 Materials: The Pepper Robot. The Pepper humanoid robot, Figure 1, was utilized in this study. Pepper is a 1.2m tall humanoid robot with a large range of motion and vocal capability. Pepper's creators purposefully designed it to be "gender neutral (with no explicitly defined gender characteristics) to avoid stereotyping effect [29]," making it a suitable platform for the present study. Using Pepper, we introduced three experimental conditions where it is gendered as a male, female or gender-neutral robot in terms of its name and voice.

3.2.2 Materials: Gendered Robot Introduction Video. One expressive video of Pepper was recorded to be used for the three experimental conditions. In the video, the robot performs the script, *"Hi, my name is {James/Mary} and I am a humanoid robot. I am programmed to perform a variety of different occupations. I can also assist people with lots of daily tasks,"* where James and Mary are used for the male and female robot conditions respectively. The gender-neutral robot began its introduction with, "Hi, I am a humanoid robot," omitting the presentation of a formal name. While some names may be considered gender-neutral, we elected to omit a formal name to avoid any subjective gender-associations from participants. Three audio clips of equal length were generated from the script and manually placed over the expressive video of Pepper to assure consistency between conditions. The timing of each script was carefully monitored to match the respective robot movements. The audio clips were computer-generated male, female and gender-neutral voices. Several potential voice clips were generated ranging in pitch. We then conducted a small pilot study to evaluate the most appropriate sample for each condition. Time sampled shots from the final videos are shown in Figure 1.

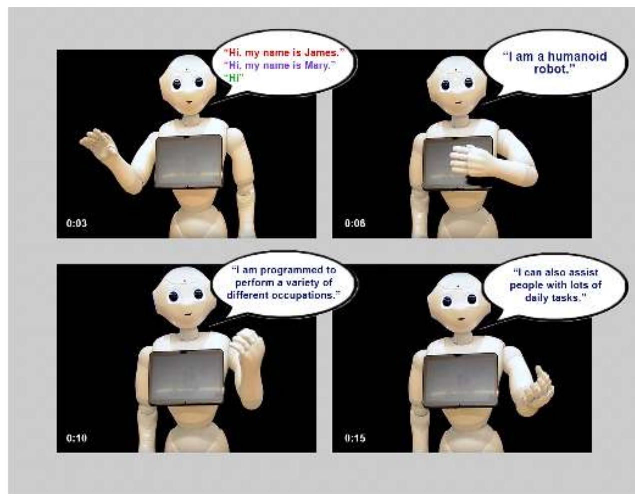

Figure 1: This illustrates the script performed by the expressive Pepper humanoid robot. In the top left corner, the three lines represent the gendered name manipulation where the first line is performed by the male robot, the second by the female robot, and the third by the gender-neutral robot (formal name omission).

3.2.3 Materials: Occupational Competency & Trust Questionnaire. We developed an occupational competency and trust questionnaire for the 14 occupations identified in Section 3.1.4. These occupations are validated to have a male, female or neutral gender association as seen in Table 1. To measure occupational competency for each occupation, participants were asked to answer the following question, *"How likely is it that you think the robot could perform the tasks required for the following occupation?"* on a 5-point Likert scale ranging from 1=Very unlikely to 5=Very likely. To measure trust in the robot's occupational competency for each occupation, participants were asked to answer the following question, "*How much would you* *trust the robot to perform the tasks required for the following occupation?"* on a 5-point Likert scale ranging from 1=Strongly distrust to 5=Strongly trust. The participants were also asked to complete a Task Competency and Trust questionnaire following the Occupation Competency and Trust questionnaire. Data from the task-related questions are not discussed further in this paper. Finally, participants were asked to identify the perceived gender of the robot and provide demographic information (age, gender, level of education, ethnicity, comfortability with computing technology and comfortability with robotic technology).

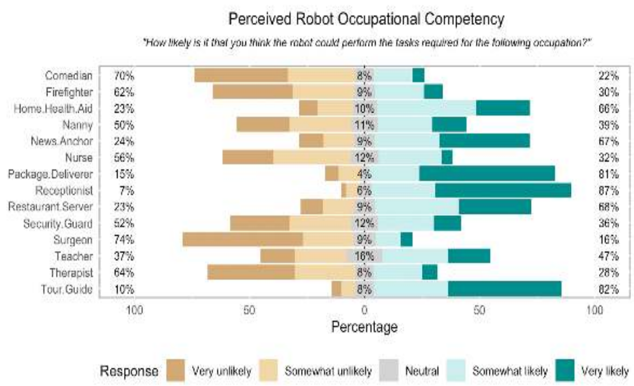

Figure 2: The collective responses from all participants regarding perceived robot occupational competency. Participants from all experimental conditions are considered to assess which occupations are of most relevance with the utilized robotic platform.

3.2.4. Participants. We administered the Qualtrics questionnaire to 150 United States participants aged 22-73 (male = 51%, female = 49%, mean age = 40.02, SD = 11.22) recruited through the Amazon Mechanical Turk platform. Data were collected in July 2019. 97% of participants were at least somewhat comfortable with computing technology. When asked about robotic technology specifically, 67% of participants were at least somewhat comfortable with the technology with 18% of participants being somewhat or very uncomfortable with it. 80% of participants self-identified as White, 4.67% as Hispanic or Latino, 8% as Black or African-American, and 6.67% as Asian. When asked about highest level of education, 35% of participants indicated pre-college, 51% selected undergraduate degree, 9% selected master's, doctoral or other professional degree, and 5% identified other (the 7 write in answers included trade school and associate's degrees).

3.2.5. Procedure. Participants were randomly assigned to one of the three experimental conditions to either be exposed to a male, female, or gender-neutral robot. Participants were given a consent form approved by the IRB before starting the survey. Next, they watched the short 15 second robot introduction video described in 3.2.2. After watching the short video, they were instructed to complete the survey. While responding to the survey, participants were asked to answer the following question as a manipulation check, *"What would you describe the robot in the video as being?"* by selecting either "a male robot", "a female robot", or "neither a male nor a female robot". An attention check question was asked next where the participants were instructed to select the answer D. Demographic related questions (age, gender, ethnicity, location, highest level of education, and occupation) were asked after the questionnaires and checks were answered. Participants were compensated $2.00 for their participation.

3.2.6. Variables. Trust in the robot's perceived occupational competency is the primary dependent variable of interest. We measure occupational competency to identify the occupations which participants believed the robot could undertake.

By analyzing occupational competency separately, the analysis in Section 4 differentiates the effects that competence may have on trust to isolate the independent variables: robot gender, associated occupation gender, and participant gender to investigate the dependent variable: human trust in the robot's occupational competency.

	Median				Mean				KW Results	
	M	F	N	O	M	F	N	O	χ^2 (2)	P
Comedian	2	2	2	**2**	1.96	2.18	2.36	**2.17**	2.51	0.29
Firefighter	2	2	2	**2**	2.34	2.52	2.37	**2.41**	0.17	0.92
Home Health Aid	4	4	4	**4**	3.60	3.71	3.46	**3.59**	0.56	0.76
Nanny	2	3	2	**2.5**	2.71	2.96	2.73	**2.80**	1.23	0.54
News Anchor	4	5	4	**4**	3.63	3.91	3.63	**3.72**	2.36	0.31
Nurse	2	3	2	**2**	2.44	2.76	2.57	**2.59**	1.80	0.41
Package Deliverer	5	5	4	**5**	4.57	4.15	3.87	**4.18**	5.12	0.08
Receptionist	5	5	4.5	**5**	4.48	4.40	4.23	**4.36**	2.43	0.30
Restaurant Server	4	4	4	**4**	3.81	3.69	3.49	**3.66**	1.31	0.52
Security Guard	2	3	2	**2**	2.69	2.78	2.63	**2.70**	0.28	0.87
Surgeon	1	2	1	**1**	2.00	2.06	1.78	**1.95**	1.24	0.54
Teacher	3.5	3	3	**3**	3.10	3.28	3.00	**3.13**	0.88	0.64
Therapist	2	2	2	**2**	2.40	2.35	2.22	**2.32**	0.47	0.79
Tour Guide	5	4	4	**4**	4.26	4.04	4.19	**4.16**	0.39	0.82

Table 2: The means, medians and Kruskal-Wallis results from the three experimental robot conditions regarding occupational competency. M = male robot condition, F = female robot condition, N = neutral robot condition, O = overall result.

4 Results

The results presented here are organized into two sets of key findings: occupational competency and trust. The analysis uses both descriptive statistics and nonparametric analysis techniques to digest the wealth of data. The results for all occupations are presented first and then the seven occupations that a majority of participants agreed the robot was competent enough to perform are highlighted.

	RQ1		RQ2	
	χ^2 (2)	P	χ^2 (3)	P
Comedian	4.24	0.12	7.04	0.07
Firefighter	1.66	0.44	2.35	0.50
Home Health Aid	5.34	0.07	0.88	0.83
Nanny	1.13	0.57	0.05	0.99
News Anchor	0.908	0.64	0.97	0.81
Nurse	2.52	0.28	4.04	0.26
Package Deliverer	4.18	0.12	3.18	0.37
Receptionist	0.09	0.96	0.65	0.88
Restaurant Server	0.9	0.64	2.23	0.53
Security Guard	1.94	0.38	4.65	0.20
Surgeon	2.68	0.26	1.8	0.62
Teacher	1.38	0.5	0.41	0.94
Therapist	1.37	0.5	4.87	0.18
Tour Guide	0.6	0.74	0.92	0.82

Table 3: The Kruskal-Wallis statistical results from the analysis of RQ1 and RQ2. RQ1 explored the impact on trust between the three robot gender conditions and RQ2 explored the robot gender (male/female) x participant gender (male/female) impact on trust.

4.1 Manipulation & Attention Checks

When asked to select the answer D as an attention check, 100% of participants answered correctly. When asked to identify the gender of the robot seen after completing the questionnaires detailed in Section 3.2.5, 90% of participants in the Male robot condition classified the robot seen as a male robot, with 10% classifying it as neither a male nor female robot. 84% of participants in the female condition classified the robot seen as a female robot, with 4% classifying it as a male robot and 12% classifying it as neither a male nor a female robot. 30% of participants in the neutral robot condition classified the gender-neutral robot as neither a male nor female robot, with 64% of participants classifying it as a male robot and 6% of participants classifying it as a female robot. To account for the effect of participants' perceived robot gender on the results, we first conducted the analysis on data from all participants and then on data only from the participants who passed the robot gender manipulation check. However, the conclusions drawn and detailed in the discussion remain the same. We discuss the difficulties with designing an actualized gender-neutral robot further in the limitations section.

4.2 Occupational Competency

Figure 2 illustrates the collective responses to the robot's perceived occupational competency. The left portion of Table 2 shows the means and medians for the three experimental groups. Considering the ordinal nature of the Likert data and the observed non-normal distribution, the nonparametric Kruskal-Wallis statistical test was used to determine if there were any statistical differences in the perception of occupational competency between the groups. Overall results illustrate that a majority of participants agreed the robot was competent enough to perform the following occupations: **home health aid, news anchor, package deliverer, receptionist, restaurant server, teacher, and tour guide** (mean and median ≥ 3). Occupations the majority of participants could not see the robot competently performing are comedian, firefighter, nanny, nurse, security guard, surgeon and therapist (mean and median < 3). As Table 2 illustrates, multiple Kruskal Wallis comparisons revealed there were no significant effects of robot gender on perceived occupational competency (all $p > 0.05$). The same conclusion was reached when considering only participants who passed the robot gender manipulation check. When considering the effect that participant gender had on perceived competency, there was a small effect ($\varepsilon^2 = 0.0525$) on the package deliverer occupation where female participants' belief in the robot's competence was greater than that of the male participants, regardless of which robot was seen ($X^2(1) = 7.8296$, $p = 0.00514$). Participant gender had no effect on any of the other experimental occupations (all $p > 0.05$).

4.3 Trust in Occupational Competency

Figure 3 highlights the overall perception of trust in occupational competency for the selected list of occupations that a majority of participants perceived the Pepper robot as being able to handle competently. Considering the ordinal nature of the Likert data and the shape of the distribution, the nonparametric Kruskal-Wallis statistical test was used to determine if there were any statistical differences in the perception of trust in occupational competency between the groups.

To answer RQ1, we compared the level of trust in the robot for each of the three experimental conditions. As Table 3 shows, the results of multiple Kruskal Wallis comparisons bore no significant effects of robot gender on trust in perceived

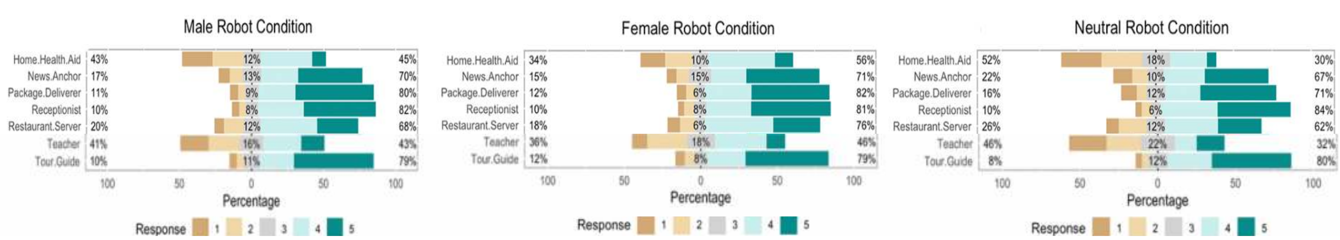

Figure 3: The responses from all participants regarding perceived trust in robot occupational competency for selected occupations by the gendered robot seen. 1 = strongly distrust, 2 = somewhat distrust, 3 = neutral, 4 = somewhat trust, and 5 = strongly trust.

occupational competency (all $p > 0.05$). The same conclusion was reached when considering only participants who passed the robot gender manipulation check. Therefore, our results do not provide evidence to support H1.

To answer RQ2, we compared the level of trust in the robot for the following subgroups: male robot/male participants, female robot/male participants, male robot/female participants, and female robot/female participants. In analyzing the impact of participant gender, there were no participants to self-identify as gender neutral or other. As such, we exclude the gender-neutral robot from this comparison, leaving the four groups mentioned above. The right half of Table 3 holds the results from the statistical analyses conducted for RQ2. These collective results show that participant gender had no significant effect on the level of trust in the robot, providing no evidence to support H2. We also examined the effects on participant trust when the robot's gender matched the participant's gender and the occupation gender. However, still no significant results were uncovered. We exclude official analyses from these tests as the sub-sample sizes were not large enough to draw any official conclusions.

Upon further inspection of the data, an interesting observation can be made. To illustrate, Figure 4 compares the median rating for occupational competency to the median rating for trust. This correlation suggests that perceived occupational competency may be a better predictor for human trust than robot gender or participant gender. An ordinal logistic regression analysis was conducted to determine how effective a predictor perceived competency was for perceived trust when also considering robot gender and participant gender. Results indicate that for 11 of the 14 occupations, perceived competency was a highly significant predicter of perceived trust ($p < 0.01$). For package deliverer, news anchor and security guard, neither perceived competency, robot gender, or participant gender were significant predictors for perceived trust.

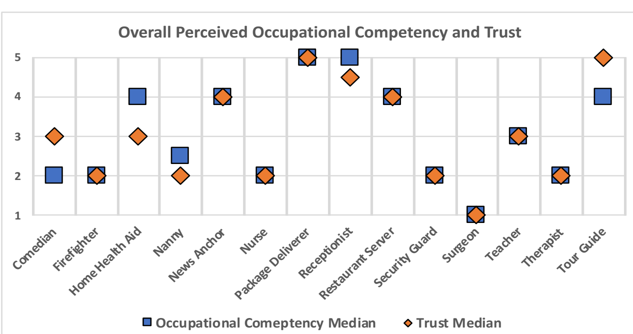

Figure 4: The medians of overall perceived occupational competency and trust in each of the 14 occupations.

5 Discussion

Prior work in trust relating to occupational competency for robots found that robot gender did not have an impact on user trust when considering a personal healthcare and a security robot [13]. The present study expands the prior analysis by including a larger range of occupations and a neutral robot condition so as to not force a priming condition. The results of the current study present evidence that lend further credence to the hypothesis that gendering robots does not have an impact on the level of trust in the robot to do the tasks associated with its job.

In regard to occupational competency, 7 of 14 occupations were isolated for further analysis. These 7 occupations had the highest overall ratings for perceived occupational competency with each median and mean score above a 3.0 cutoff. These occupations were home health aid, news anchor, package deliverer, receptionist, restaurant server, teacher, and tour guide. It can be noted that 5 of these 7 occupations were classified as having a female occupational gender association. One potential explanation for this higher competence in female occupational roles is that the nature of the tasks necessary for the selected female occupations could have been perceived as easier for the robot to perform after watching the short introductory video. Another potential explanation could be the underlying gender cues from the robot's physique. The Pepper robot was intentionally designed to be a gender-neutral robot [29]; however, McGinn and Torre found that Pepper was more often associated with a female robot voice than with a male robot voice [16]. The authors note in their discussion that more machine-like, square headed robots tend to be perceived as male. Goetz et al. further suggest that a robot's physical appearance, humanlikeness and demeanor provide cues to the robot's abilities [37]. This could suggest a subconscious gender attribution bias from Pepper's physique that did not present itself in our robot gender manipulation check. However, another explanation that may explain the data is the perceived level of risk associated with the occupation. For example, surgeon was rated as the lowest in perceived competency and overall trust, an occupation known for its associated risks [1, 25]. This explanation could further explain the low competence scores for nanny, firefighter, nurse and therapist.

Oftentimes, gendering is used in HRI to better facilitate social interactions and cooperation between humans and robots. [37] presented a study that demonstrated participants' increased compliance and acceptance of robots that appeared and behaved in a manner that matched their expectations for a given task scenario. However, when analyzing the relationship between robot gender and perceived trust in occupational competence for this study, it was discovered that no significant differences existed between the participants who saw the male, female, or gender-neutral robots. Otherwise stated, the gender-neutral robot did not affect the level of trust in the robot's occupational competency when compared to the male and female robot for any of the 14 occupations. Rae, Wang and Young caution that gender role associations may not be as pronounced in human-robot interactions as intuition would lead one to believe [7]. [4] further brings awareness to the risk of designing gendered robots.

As an example, the present analysis confirms that comedian is associated with a traditionally male gender role. However, the gender imbalances in pay and in appearances for women in comedy have been a popular topic of discussion in recent years. "It is not only the pay-gap between male and female performers that is notable, but the vast disparity in representation on the stage," journalist Will Humphries notes in an article titled, *It's Really No Joke* [28]. Comedian Meredith Kachel even suggests that the actual gender makeup of people in comedy may be very different from the statistics presented earlier about current comedians in the U.S. [30]. Organizations such as Women in Comedy have worked tirelessly to bring light to and disrupt the longstanding disparities for women in in comedy [31]. It would be ill-advised and ethically concerning for robotic technology, even for entertainment applications, to potentially stagnate the progress made by such organizations with their technology. To further illustrate this point, a Google image search conducted in September 2019 on the word, "comedian" displayed only one woman in the first 30 results. Unequal representation and gender stereotypes perpetuated through image search have also been reported for several other occupations [34]. As the curators and designers of technologies that have the potential to impact the lives of millions of people, we argue that the HRI and larger technological community should be more discerning and evaluative of which aspects of human social phenomena are incorporated into our technological applications.

Nevertheless, we must recognize that a challenge in this work—and a challenge for HRI in the present—is the actualization of a gender-neutral/gender-less robot. With a majority of participants in the gender-neutral condition identifying the robot as male, our analysis of the neutral robot may not have captured a relationship between the absence of gender and human trust that may still exist. Other works have also manipulated gender with similar realizations. For example, [15] observed how people would make preferential gender projections onto robots even without apparent gender markers (i.e., no formal name or gendered voice). In their study, the authors concluded that gender markers were important considerations to be aware of as they may elicit stereotypical expectations from users. All things considered, designing more effective gender-neutral social robots is a promising direction but may prove to be no easy feat. Still, this research advocates for the critical analysis of project goals and user outcomes before the decision to manipulate gender is made in social robot design.

6 Limitations

The present study had several limitations. As the questionnaires were administered online via Amazon Mechanical Turk, we could not control the gender distribution of participants. We note that the occupational gender association validation questionnaire was taken by more men than women. However, we included the statistics from current population trends to further validify the associated gender roles. Also, there may be forms of sampling bias associated with relying on the AMT platform, including that MT workers might not fully represent the broader US population.

Secondly, to examine perceptions around a larger number of occupations, we note that the measures of trust and competency used in this study are different than other metrics used in previous HRI studies [35]. To gather meaningful responses for each of the 14 occupations while also keeping the survey instrument at a reasonable length, the definition of trust used in this study generalizes aspects of cognitive and affective trust which are sometimes evaluated separately in other work. Future work will consider cognitive and affective trust separately.

Only 15 of the 50 participants in the gender-neutral robot condition passed the robot gender manipulation check. To account for this, affected results are discussed in regard to all participants and then with only the subset of participants passing the manipulation check. This also calls into question the actualization of a gender neutral robot which is also discussed.

7 Conclusion

Prior works have begun to investigate the role of gender roles in robot occupations. In this paper, we examined the relationship between robot gender and human trust in a robot's ability to complete the necessary tasks associated with 17 separate occupations. We expand on prior research by including a variety of occupations and introducing a neutral robot condition. We first present a validation study where we determine the gender association for each of the occupations. 14 occupations of interest with either a female, male or neutral gender association were included in an occupational competency and trust questionnaire. We then administered the questionnaire in a between-subjects online study to determine if the occupation's associated gender role, the robot gender, and the participant gender would impact the level of trust in the robot.

Results from the questionnaire indicate that there was no significant difference in the perception of trust in the robot's competency when considering the gender of the robot seen. When considering the cases where the robot's gender matched the participant's gender compared to when there was a gender mismatch, there were also no significant differences in the level of trust between conditions. A regression analysis further illustrated that perceived competency was a significantly better predictor of perceived trust than robot gender or participant gender for 11 of the 14 highlighted occupations. This suggests and supports prior literature on robot competency (and other performance-based metrics) having a larger influence on human trust than perceived robot characteristics [2].

This study also sought to investigate how a gender-neutral robot would be perceived in occupational roles compared to a male and female robot. Results indicated that there were no significant differences in the perceived competency or trust in the gender-neutral robot, even when considering only participants who identified the robot as gender-neutral. This calls into question the use of robot gendering as a manipulation technique to facilitate human-robot trust. As such, the robotics community should carefully consider the application goals, desired user outcomes, cultural implications and societal relevance of using gendering in the design of social robots.

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REFERENCES

[1] Savela, N., Turja, T. and Oksanen, A., 2018. Social acceptance of robots in different occupational fields: A systematic literature review. International Journal of Social Robotics, 10(4), pp.493-502.

[2] Hancock, P.A., Billings, D.R., Schaefer, K.E., Chen, J.Y., De Visser, E.J. and Parasuraman, R., 2011. A meta-analysis of factors affecting trust in human-robot interaction. Human factors, 53(5), pp.517-527.

[3] Bernotat, J., Eyssel, F. and Sachse, J., 2017, November. Shape it–the influence of robot body shape on gender perception in robots. In International Conference on Social Robotics (pp. 75-84). Springer, Cham.

[4] Robertson, J., 2010. Gendering humanoid robots: Robo-sexism in Japan. Body & Society, 16(2), pp.1-36.

[5] Fridin, M. and Belokopytov, M., 2014. Acceptance of socially assistive humanoid robot by preschool and elementary school teachers. Computers in Human Behavior, 33, pp.23-31.

[6] Ye, H., Jeong, H., Zhong, W., Bhatt, S., Izzetoglu, K., Ayaz, H. and Suri, R., 2019, July. The Effect of Anthropomorphization and Gender of a Robot on Human-Robot Interactions. In International Conference on Applied Human Factors and Ergonomics (pp. 357-362). Springer, Cham.

[7] Rea, D.J., Wang, Y. and Young, J.E., 2015, October. Check your stereotypes at the door: an analysis of gender typecasts in social human-robot interaction. In International Conference on Social Robotics (pp. 554-563). Springer, Cham.

[8] Eyssel, F. and Hegel, F., 2012. (s)he's got the look: Gender stereotyping of robots 1. Journal of Applied Social Psychology, 42(9), pp.2213-2230.

[9] Ghazali, A.S., Ham, J., Barakova, E.I. and Markopoulos, P., 2018. Effects of robot facial characteristics and gender in persuasive human-robot interaction. Frontiers in Robotics and AI, 5, p.73.

[10] Kuchenbrandt, D., Häring, M., Eichberg, J., Eyssel, F. and André, E., 2014. Keep an eye on the task! How gender typicality of tasks influence human–robot interactions. International Journal of Social Robotics, 6(3), pp.417-427.

[11] Nomura, T., 2017. Robots and gender. Gender and the Genome, 1(1), pp.18-26.

[12] Crowelly, C.R., Villanoy, M., Scheutzz, M. and Schermerhornz, P., 2009, October. Gendered voice and robot entities: perceptions and reactions of male and female subjects. In 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 3735-3741). IEEE.

[13] Tay, B., Jung, Y., & Park, T. (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.

[14] Le Deist, F.D. and Winterton, J., 2005. What is competence?. Human resource development international, 8(1), pp.27-46.

[15] Chita-Tegmark, M., Lohani, M. and Scheutz, M., 2019, March. Gender effects in perceptions of robots and humans with varying emotional intelligence. In 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 230-238). IEEE.

[16] McGinn, C. and Torre, I., 2019, March. Can you tell the robot by the voice? An exploratory study on the role of voice in the perception of robots. In 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 211-221). IEEE.

[17] Cameron, D., Millings, A., Fernando, S., Collins, E.C., Moore, R., Sharkey, A., Evers, V. and Prescott, T., 2018. The effects of robot facial emotional expressions and gender on child–robot interaction in a field study. Connection Science, 30(4), pp.343-361.

[18] Jewell, C.I., Elprama, S.A., Jacobs, A., Esteban, P.G., Bagheri, E. and Vanderborght, B., 2019, March. Why Children Prefer Extrovert or Introvert Robots: A Pilot Study Using Pairwise Robot Comparison. In 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 590-591). IEEE.

[19] He, J.C., Kang, S.K., Tse, K. and Toh, S.M., 2019. Stereotypes at work: Occupational stereotypes predict race and gender segregation in the workforce. Journal of Vocational Behavior, p.103318.

[20] Gerdes, E.P. and Garber, D.M., 1983. Sex bias in hiring: Effects of job demands and applicant competence. Sex Roles, 9(3), pp.307-319.

[21] Rosen, B. and Jerdee, T.H., 1974. Influence of sex role stereotypes on personnel decisions. Journal of Applied Psychology, 59(1), p.9.

[22] Reskin, B.F. and Roos, P.A., 2009. Job queues, gender queues: Explaining women's inroads into male occupations.

[23] Mundy, L., 2018. Code Girls: The True Story of the American Women Who Secretly Broke Codes in World War II (Young Readers Edition). Little, Brown Books for Young Readers.

[24] Siegel, M., Breazeal, C. and Norton, M.I., 2009, October. Persuasive robotics: The influence of robot gender on human behavior. In 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 2563-2568). IEEE.

[25] He, J.C., Kang, S.K., Tse, K. and Toh, S.M., 2019. Stereotypes at work: Occupational stereotypes predict race and gender segregation in the workforce. Journal of Vocational Behavior, p.103318.

[26] Wang, Y. and Young, J.E., 2014, May. Beyond pink and blue: Gendered attitudes towards robots in society. In Proceedings of Gender and IT Appropriation. Science and Practice on Dialogue-Forum for Interdisciplinary Exchange (p. 49). European Society for Socially Embedded Technologies.

[27] Labor Force Statistics from the Current U.S. Population Survey. US Department of Labor's Bureau of Labor and Statistics. https://www.bls.gov/cps/cpsaat11.htm

[28] Humphries, W. 2014. It's really no joke. Ozy: The Daily Dose. https://www.ozy.com/acumen/stand-ups-gender-gap/4661

[29] Pandey, A.K., Gelin, R. and Robot, A.M.P.S.H., 2018. Pepper: The First Machine of Its Kind. IEEE Robotics & Automation Magazine, 25(3), pp.40-48.

[30] https://www.meredithkachel.com/gender-and-comedy

[31] https://www.womenincomedy.org/

[32] Bartneck, C., Yogeeswaran, K., Ser, Q.M., Woodward, G., Sparrow, R., Wang, S. and Eyssel, F., 2018, February. Robots and racism. In Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction (pp. 196-204). ACM.

[33] Ogunyale, T., Bryant, D.A. and Howard, A., 2018. Does Removing Stereotype Priming Remove Bias? A Pilot Human-Robot Interaction Study. arXiv preprint arXiv:1807.00948.

[34] Kay, M., Matuszek, C. and Munson, S.A., 2015, April. Unequal representation and gender stereotypes in image search results for occupations. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (pp. 3819-3828). ACM.

[35] Kessler, T.T., Larios, C., Walker, T., Yerdon, V. and Hancock, P.A., 2017. A comparison of trust measures in human–robot interaction scenarios. In Advances in Human Factors in Robots and Unmanned Systems (pp. 353-364). Springer, Cham.

[36] Tamagawa, R., Watson, C.I., Kuo, I.H., MacDonald, B.A. and Broadbent, E., 2011. The effects of synthesized voice accents on user perceptions of robots. International Journal of Social Robotics, 3(3), pp.253-262.

[37] Goetz, J., Kiesler, S. and Powers, A., 2003, November. Matching robot appearance and behavior to tasks to improve human-robot cooperation. In The 12th IEEE International Workshop on Robot and Human Interactive Communication, 2003. Proceedings. ROMAN 2003. (pp. 55-60). Ieee.

[38] Heerink, M., Krose, B., Evers, V. and Wielinga, B., 2009, September. Measuring acceptance of an assistive social robot: a suggested toolkit. In RO-MAN 2009-The 18th IEEE International Symposium on Robot and Human Interactive Communication (pp. 528-533). IEEE.