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Status processes in human-computer interactions: Does gender matter?

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ABSTRACT

This paper examines the conditions that cause status processes to emerge in groups of humans and computers. It presents the results from an experiment where participants worked on a gender-neutral task with a computerized partner described as being a man or woman. These participants evaluated the performance of their partner on a collective task and estimated the cost to purchase this machine. The gender descriptors of these machines did not affect the performance ratings by participants. These participants did estimate that male computers would cost significantly more money than female machines. The findings show how status characteristics shape user perceptions of their computers, which lack the human features that define these characteristics.

1. Introduction

In the late 1990s, Bavarian Motor Works (BMW) issued a recall for the voice-navigation system of their 5 series automobile. The reason for this recall was partly a response to customers who complained to BMW about their uneasiness with a woman's voice giving them directions while they drove (Griggs, 2011). This example aligns with research showing that social categories shape the way that users perceive their computers (Nass, Moon, & Green, 1997). Drawing on status characteristics theory in sociology, this paper examines a specific mechanism that generates these perceptions in human-computer interactions.

Status characteristics refer to human attributes that people use to formulate beliefs about task performance in groups (Berger, Rosenholtz, & Zelditch, 1980). A status organizing process occurs when such beliefs vary by the status of group members (Berger, Cohen, & Zelditch, 1972). Most research on status processes in sociology has focused on groups of two or more humans (Lovaglia & Houser, 1996; Lucas, 2003; Simpson, Willer, & Ridgeway, 2012; Willer, 2009). The present study expands this treatment by focusing on groups where humans work with partners that are computers. Using this broader definition of group, this paper examines the conditions that cause status processes to emerge in groups of humans and computers.

Status characteristics theory predicts when the observable features of group members affect their beliefs about task performance in groups (Berger, Webster, Ridgeway, & Rosenholtz, 1998). The theory assumes that these features will become salient in groups unless individuals actively try to dissociate them from their beliefs about task performance (Berger et al., 1998). This paper tests when these status characteristics become salient in groups of humans and computers. It describes results from an experiment where participants worked with a computer named James or Julie that had the capacity to learn from interactions with human users. The experiment tests whether status characteristics – defined by features of human beings – shape the way users view computers they know lack these defining features.

2. Theoretical background

2.1. Status characteristics theory

The expectation states theoretical research program in sociology explains how people formulate beliefs about themselves and others in groups. Status characteristics theory (SCT) describes how these beliefs vary by the observable features of people (Berger & Webster Jr., 2006; Berger et al., 1972; Berger et al., 1998). The theory refers to these features as status characteristics. Diffuse status characteristics are features that carry broad expectations for people in a variety of different group tasks. In comparison, attributes that are relevant to a narrow range of tasks are specific status characteristics. Intelligence is one example of a diffuse status characteristic, while mathematical ability is a specific status characteristic (Berger et al., 1998).

According to SCT, there are beliefs about social groups that people widely share in a society. When these beliefs shape the expectations and evaluations for members of a group, they operate as status characteristics. A central component of SCT is the

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burden-of-proof assumption. This assumption states that group members will consider a status characteristic to be task-relevant, unless they actively disassociate it from a task (Berger & Webster, 2006). There has been decades of research showing that group members routinely fail to disassociate these characteristics from task performance in groups (Berger et al., 1972; Lucas, 2003; Ridgeway, 2009; Webster & Driskell, 1978; Webster & Hysom, 1998). For example, group members have mistakenly associated sexual orientation (Webster & Hysom, 1998), race (Brezina & Winder, 2003; Webster & Driskell, 1978), gender (Lucas, 2003; Ridgeway, 2009), and ethnicity (Riches & Foddy, 1989) with innate abilities on tasks unrelated to these social categories.

Studies have found that gender is a salient, diffuse status characteristic in mixed-gender groups where partners work on gender-neutral tasks (Correll, 2004; Foschi, 1996; Lucas, 2003; Meeker & Weitzel-O'Neill, 1977). Experimental studies on double standards show that participants will give higher ratings for the same performance of a man than a woman (Foschi, 1996). These gender differences affect how people assess their own competency and, in turn, formulate their own performance goals (Correll, 2004). Gender also affects how group members perceive women and men in leadership positions (Ridgeway, 2001). Studies show that people rate the performance of groups led by women as lower compared to those with leaders who are men (Lucas & Lovaglia, 1998). However, these groups have the capacity to overcome these gender differences when they institutionalize the role of women as leaders (Lucas, 2003).

2.2. Gender and user perceptions of computers

There have been decades of research investigating the effects of gender on individual perceptions of using computer technology (Compton, Burkette, & Burkett, 2002; Havelka, 2003; Huffman, Whetten, & Huffman, 2013; Imhof, Vollmeyer, & Beierlein, 2007; Nass, Moon, & Green, 1997; Ong & Lai, 2006; Rosen & Maguire, 1990). Some of these studies have found that men and boys feel more comfortable with using computers than women and girls, while other research has found little to no gender difference (Whitley, 1997). In one recent study, Huffman et al. (2013) administered a survey to college students that asked them about masculine gender roles and their beliefs surrounding technology self-efficacy. The results showed that men report higher levels of self-efficacy with using new technology than women. This study also found a similar effect from masculine gender roles that was independent of participants' gender (Huffman et al., 2013).

Gender roles not only influence the self-perceptions of those who use computer technology, it could also affect how users perceive these machines. This is what Nass, Moon, and Green (1997) found in one study where participants worked on a gender-stereotypical task (e.g. computer technology versus love and relationships) with computerized tutors than delivered instructions using a male or female voice. Participants rated their tutor as more informative about computer technology when it delivered information in a male rather than female voice. The opposite was true with participants rating their tutor as more informative about love and relationships when it used a female instead of a male voice (Nass et al., 2006). The present study advances this line of research by examining the specific process that leads human users to rely on status characteristics (e.g. gender) when forming beliefs about their computers.

Human attributes define diffuse status characteristics, which some people mistakenly associate with task performance in groups (Berger et al., 1972). If people make this mistake in groups of humans, they may also make a similar association with objects lacking the human features that define diffuse status characteristics (e.g. computers). This may cause some people to formulate different beliefs about the task performance of a computerized partner that they personify as being a man or woman. Under the assumption that people rely on these beliefs when determining the value of objects, it follows that gender would affect their estimates of economic value for these computers.

3. Predictions

This papers draws from status characteristics theory to test when status processes emerge in groups of humans and computers. Studies on groups of humans find that people have different performance expectations for men and women. Such research also has found that people rate the same performance of women lower than men on gender-neutral tasks (Correll, 2004; Eagly & Karau, 2002; Foschi, 1996; Lucas, 2003). Following this research, Hypothesis 1 predicts that naming a computerized partner James or Julie will affect the performance expectations that human users have for this machine:

Hypothesis 1. People will expect a computerized partner that is personified as a man to perform better on a gender-neutral task than when this machine is described as being a woman.

There is some evidence from research on human and computer interactions that people evaluate computers differently when they are personified as being a man or a woman (Nass & Moon, 2000; Nass et al., 1997). Nass and colleagues (1997) found that users rated a computer with a man's voice more positively than a machine using a woman's voice on gender-stereotypical tasks. Hypothesis 2 predicts a similar effect when people work in groups with a computerized partner named James or Julie on a gender-neutral task:

Hypothesis 2. People will rate the performance of a computerized partner that is personified as a man higher on a gender-neutral task than the same partner that is described as being a woman.

The first hypothesis predicts that people will expect a computer to perform better on a gender-neutral task when this machine is personified as being a man rather than a woman. The second hypothesis predicts that people will rate the overall performance of this machine higher when it has the name James compared to one named Julie. If people rely on these considerations when estimating the economic value of a partner than is a computer, then it follows that people would estimate a higher cost for a computerized partner that has the name James compared to one named Julie. This assumption leads to the following prediction:

Hypothesis 3. People will estimate a higher economic value of a computerized partner that is personified as a man compared to the same partner that is described as being a woman.

4. Methods

4.1. Participants

The study recruited undergraduate students from a large, research university located in the Mid-Atlantic. These participants completed the same computerized task, in private rooms, using the same model of a touch-screen computer (Hewlett Packard Touch-Smart 320 PC). The study instructions told participants they would receive up to $20 for their participation. Study instructions stated that participants were paid based on their performance on a meaning-insight task.

Participants gave their consent, answered a standard demographic questionnaire, completed 10 questions from a meaning insight test, and responded to a series of questions about their impressions of this computer. This experiment involved 63 participants (46 women and 17 men). This paper excluded one participant who incorrectly identified the gender of their computerized partner. Of the remaining 62 participants, 31 worked with a computer named James and the other 31 worked with a machine that had the name Julie.

4.2. Procedure

Researchers in this experiment placed participants into private rooms that were equipped with touch-screen desktop computers. These computers displayed the study instructions using Qualtrics data collection software. Participants used the touch-screen interface when completing each part of this experiment. The study instructions said this experiment was testing a new computer program that grades student answers to exam questions.

These instructions stated that a mid-Atlantic university planned to use this software to grade student exams in the near future. The study told participants this software represents a new advancement in natural language processing by computers. It said this software is capable of applying technical analytical weights to evaluate human answers based on relevant information. The instructions told participants this software could learn from prior interactions with humans to improve its accuracy in evaluating answers in the future.

Participants completed 10 questions from a meaning insight test and study instructions stated they would receive $2 for every question they answered correctly. This test had participants' chose from a list of four words from a foreign language dictionary that shared the same meaning as an English word displayed on their screen. All the answer choices were from an aboriginal language that is native to Australia. The answer choices did not share a common meaning with the English words displayed.

After choosing an answer, the computerized partner told participants if it believed their answer was correct or incorrect. The computer also displayed a percentage representing the machine's confidence in this evaluation. Upon seeing this evaluation, participants rated how confident they were in their original answer and could change this answer before moving onto the next question. The experiment never told participants if their final answers were correct or incorrect.

To illustrate, one question asked participants, "Which one of these words means APPLE?" Participants choose a word from this list: jabalng, wagalmiyan, gadamalga, or birndi. After participants choose one of these words, a new screen appeared that stated: "[Julie/James] does not agree with you. [She/He] is 50% confident that your answer is correct." Below this statement, participants saw two questions that asked them to rate their confidence in the answer they just chose using a sliding scale ranging from 0% to 100%. Another question appeared below the scale that asked participants if they would like to change their answer, displayed the previous question, and their answer choice of the English translation of "apple".

Participants completed 10 of these questions from the meaning-insight test. For each question in both conditions, the computer gave a 25% confidence level for the same three question answers; 50% confidence for the same five question answers; and a 75% confidence level for two question answers. The ordering of these questions did not vary between experimental conditions.

After completing the meaning insight test, the study asked participants to rate their impressions of James or Julie. The experiment displayed a series of adjectives used to characterize people in general. Next to each of these adjectives, participants rated each using a 5-point scale where the highest category (5) represents "Characteristic," the middle category (3) was "N/A," and the lowest category (1) represents "Not Characteristic".

Next, participants answered a series of questions that asked them to estimate how much they believe it would cost to purchase one unit of this computer system. Answer choices ranged along a 11-point scale where 1 represents "Below $1000," and 11 represents "Over $10,000." Each answer choice differed by a factor of $1000. After completing the study, experimenters debriefed and paid each participant $20.

4.3. Manipulation

The Qualtrics software randomly assigned participants to one of two experimental conditions. Both conditions were the same, except the gender used to describe this computerized partner. In one condition, participants read instructions that referred to the computerized partner as "James" and displayed an image of a blue computer hard-drive. Participants in a second condition read the same instructions that referred to their computerized partner as "Julie" with an image of a pink computer hard-drive. Fig. 1 displays the image of these hard drives.

4.4. Dependent measures

Performance expectations. Participants completed 10 questions from a meaning insight test. In both experimental conditions, a computerized partner gave the same result by telling participants if their answer was correct or incorrect and the computer's confidence level in this determination. When participants saw this response, the study asked them to rate their confidence in the original answer using a sliding scale that ranged from 0% to 100%. I combined these 10 ratings into a single index (Cronbach's $\alpha = 0.90$), $M = 26.40$; SD = 14.32. Next, I summed the confidence levels given by the computer that was the same across conditions, $M = 47.5$. The first measure of performance expectations is the absolute difference between the average confidence level of a computer's response and the average confidence level given by the participant, $M = 21.56$; SD = 13.60.

The second measure of performance expectations is influence, defined here as socially induced changes in beliefs or behaviors (Willer, Lovaglia, & Markovsky, 1997). Influence is a proposed theoretical consequence of performance expectations that, according to status characteristics theory, may vary in groups when members possess different status characteristics (Berger et al., 1972). To measure influence, the study observed the percentage of times that participants changed their answers after the computerized partner gave them an evaluation of their original answer's accuracy.

Participants chose an answer, viewed their computer's evaluation about whether this answer was correct or incorrect, and could change their original answer choice before moving onto the next question. For each question, I constructed dichotomous variables where participants received a 1 if they changed their answer or a

Fig. 1. Gendered Images for Computerized Partners.

0 if they did not switch answer choices. I coded participants who choose an answer and then selected the same answer again as 0. I summed the total number of times that a participants changed their answers for the 10 questions from the meaning-insight test, $M = 6.90$; SD = 2.28.

Performance evaluation. The experiment asked participants to evaluate the overall performance of their computerized partner and the personality of this computer. To measure overall performance, the study asked participants after they completed the entire meaning insight test, "How reliable was your computerized grader?" Participants answered this question using a sliding scale that ranged from 0% to 100%; $M = 53.15$; SD = 21.05.

To measure a participant's impressions of their computerized partner, the study displayed a series of descriptive terms used to characterize people in general. Participants chose one of these five answers next to each term: (1) characteristic, (2) somewhat characteristic, (3) N/A, (4) somewhat uncharacteristic, and (5) not characteristic. I constructed an index of participant answers for the following five adjectives: kind, sociable, understanding, cheerful, and sympathetic (Cronbach's $\alpha = .82$); $M = 3.11$; SD = .83.

Estimate of economic value. The final measure is a participant's estimate of their computer's economic value. This experiment asked participants, "How much do you think it costs the mid-Atlantic University to purchase [James/Julie]? (Cost for 1 computer system)." Participants chose one of the following answers: (1) Below \$1000, (2) \$1000 – \$1999, (3) \$2000 – \$2999, (4) \$3000 – \$3999, (5) \$4000 – \$4999, (6) \$5000 – \$5999, (7) \$6000 – \$6999, (8) \$7000 – \$7999, (9) \$8000 – \$8999, (10) \$9000 – \$9999, (11) Over \$10,000. This variable ranges from a low of 1 to 11; $M = 6.12$; SD = 2.71.

4.5. Control measures

This study included three control measures in each model displayed below. The first control measure was gender where 1 represents women (74%) and 0 represents participants who were men (26%). The second control variable was the race of participants where 1 represented White participants (58%) and 0 were non-White participants (42%). The last control measure is the number of years that participants were enrolled as an undergraduate student. This measure ranged along a five-point categorical scale where 1 represents, "freshman," 2 is "sophomore," 3 is "junior" and 4 is "senior" ($M = 2.24$; SD = 1.25).

5. Results

5.1. Performance expectations

Hypothesis 1 predicted that people would expect a computerized partner personified as a man to perform better on a gender-neutral task than one described as a woman. The first measure of performance expectations is the absolute differences between the confidence levels displayed by the computerized partner and the confidence of participants. The results in Table 1 do not support Hypothesis 1. There was no significant difference in confidence levels for participants working with a computer named James ($M = 19.02$; SD = 12.00) or Julie ($M = 24.1$; SD = 14.80). The overall model was also non-significant, $F(4,57) = 0.63$; $p < .65$.

The second measure of performance expectations is the number of times that participants changed their original answers for each of the 10 questions on the meaning insight test. Again, the results in Table 1 do not support Hypothesis 1, $F(4,57) = 0.59$; $p < .44$. The average number of changes in answers by participants did not significantly differ for a computer with the name James ($M = 7.16$; SD = 2.27) compared to one named Julie ($M = 6.65$; SD = 2.30). This overall model was non-significant, $F(4,57) = 0.38$; $p < .82$.

5.2. Performance evaluation

Hypothesis 2 predicted that people would rate the performance of a computerized partner personified as a man higher than a woman. This study measured these performance evaluations in two ways. The first way measured people's impression of their computerized partner's behavior. To measure these impressions, the study used an index of five questions that ask participants to rate their computer's personality traits. The results in Table 1 do not support Hypothesis 2 when comparing James ($M = 3.17$; SD = .96) and Julie ($M = 3.05$; SD = .69). Positive personality impressions did not significantly differ by the gender used to describe a computerized partner ($p < 0.77$). The overall model is also non-significant, $F(4,57) = 0.67$; $p < .60$.

The second measure is participant's rating of their computerized partner's performance on the meaning-insight task. To measure this evaluation, the study asked participants to rate their computerized partner's overall accuracy rate during the experiment. Again, Table 1 does not support Hypothesis 2. Participants did not significantly differ in the estimated accuracy rates for James ($M = 57\%$ accuracy) compared to Julie ($M = 49\%$ accuracy). The overall model was non-significant, $F(4,57) = 1.49$; $p < .22$. Results from a one-way ANOVA predicting significant differences in accuracy rates between experimental conditions was also non-significant, $F(1,61) = 2.58$; $p < .11$ (see Table 2).

5.3. Estimate of economic value

Hypothesis 3 predicted that people would estimate a higher cost for a computer named James compared to one named Julie. After completing the meaning-insight task with a computerized partner, the experiment asked participants to estimate the cost of purchasing one unit of this computer system. The results in Table 3 support Hypothesis 3. There was a significant difference in cost estimates, with participants predicting a higher average cost for James ($M = 6.61$; SD = 2.80) compared to Julie ($M = 5.65$; SD = 2.58) ($p < .05$, two-tailed).

Each category represents a \$1000 increase in price where the lowest category (1) represents "below \$1000" and the highest answer choice (11) represents "over \$10,000." The significant difference by gender in the ANCOVA model from Table 3 shows that participants, on average, estimated that James cost approximately \$5870 (where category 6 represents a range from \$5000 - \$5999) and Julie's worth was \$4380 (where category 5 represents a range from \$4000 to 4999). This difference equals \$1490 (\$5874 - \$4384 = \$1490).[1] The overall model displayed in Table 3 is statistically significant, $F(1,57) = 4.23$; $p < .01$. The interaction between participant's race and their computerized partner's gender was non-significant. This non-significant interaction effect is not shown in Table 3.

6. Discussion

Decades of research show that people rely on diffuse status characteristics when they formulate beliefs about others' task performance in groups (Berger et al., 1972; Berger et al., 1980, 2006; Correll, 2004; Foschi, 1996; Lovaglia & Houser, 1996; Lucas, 2003; Lucas & Lovaglia, 1998). This study examined the conditions under which these status processes emerge in groups where humans have partners that are computers. The results from this

[1] I calculated this difference based on the predicted marginal values from the ANCOVA model displayed in Table 3.

Table 1
ANCOVA models testing Hypothesis 1.

Confidence level					Percent of answers changed				
Source	SS	*df*	MS	*F*	Source	SS	*df*	MS	*F*
Model	468.78	4	117.19	.62	Model	8.26	4	.02	.38
James	342.62	1	342.62	1.81	James	3.22	1	.03	.59
Woman	25.08	1	25.08	.13	Woman	3.69	1	.04	.68
White	2.05	1	2.05	.01	White	.05	1	.00	.01
Year	60.17	1	60.17	.32	Year	.004	1	.00	.00
Error	10816.51				Error	309.16			
R-square	.04				*R*-square	.03			

* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed).

Table 2
ANCOVA models testing Hypothesis 2.

Impression of computer's personality					Overall accuracy				
Source	SS	*df*	MS	*F*	Source	SS	*df*	MS	*F*
Model	1.69	4	.42	.60	Model	.26	4	.06	1.49
James	.06	1	.06	.08	James	.16	1	.16	3.80
Woman	1.18	1	1.18	1.67	Woman	.02	1	.02	.41
White	.23	1	.23	.32	White	.08	1	.08	1.98
Year	.45	1	.45	.63	Year	.08	1	.08	1.76
Error	40.52				Error	2.45			
R-square	.04				*R*-square	.09			

* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed).

Table 3
ANCOVA models testing Hypothesis 3.

Cost estimate (in thousands of $)				
Source	SS	*df*	MS	*F*
Model	102.81	4	25.70	4.23**
James	32.65	1	32.65	5.38*
Woman	.99	1	.99	0.16
White	81.02	1	81.02	13.34***
Year	15.31	1	15.31	2.52
Error	346.16			
R-square	.23			

* $p < .05$.
** $p < .01$.
*** $p < .001$ (two-tailed).

experiment test whether status characteristics – defined by features of human beings – shape the way people view a computerized partner. In this experiment, participants completed a collective task with a computer that was named James or Julie. The study told participants this computer could learn from interactions with human users. The only difference between conditions was the name of this computerized partner and an image on the computer monitor that displayed a picture of a blue or pink hard drive.

There were three important findings from this experiment. First, gender did not operate as a salient status characteristic during the meaning-insight task. Participants were no more or less confident in their answers when their computer was named James or Julie. Similarly, these participants did not vary in changing their original answers when this computer was personified as being a man or woman.

Second, the performance evaluations of a computerized partner did not significantly vary when this machine was named James or Julie. After completing the meaning-insight task, participants reported similar estimates in the accuracy rate of this machine when it was described as being a man or woman. These participants did not give significantly different ratings for the personality of this machine when it was named James or Julie. The lack of findings in support of Hypotheses one and two show that participants knew their computers did not have a gender. These participants ignored gender when reporting their beliefs about the performance of this computerized partner.

Third, this study found that participants used gender when estimating the economic value of a computerized partner named James or Julie. Despite having the same performance evaluations for a computer named James or Julie, participants believed the former would cost significantly more than the later. The findings in Table 3 show that participants believe a computer named James is worth an average of $1490 *more* than one named Julie. This supports predictions from status characteristics theory by showing that asking about economic value activates the salience of gender in groups of humans and computers. Such a difference in cost estimates do not appear to be a function of participant beliefs about the performance of their computers, which did not significantly differ by gender descriptors.

According to status characteristics theory, human attributes become status characteristics when a categorical reference structure activates beliefs associated with observable features of people (Berger et al., 1972). In American society, evidence indicates that gender inequality exists within the labor market (Cech, 2013; Huffman, Cohen, & Pearlman, 2010; Petersen & Morgan, 1995). This inequality operates in the distribution of employee salaries (Petersen & Morgan, 1995) and with gender segregation between different occupations (Cech, 2013; Huffman et al., 2010). The economic marketplace could represent a categorical reference structure that reinforces an unequal distribution of valued resources (e.g. salary and career advancement) based on gender. Merely referencing economic value may activate the salience of these gender differences in small group settings where humans work with partners that are computers.

In this study, participants ignored gender when they reported beliefs about the performance of a computerized partner named James or Julie. However, these participants associated gender when estimating the economic value of this same computer. It could be that participants referenced broader patterns of inequality within society, including those found in the labor market (Cech, 2013; Huffman et al., 2010; Petersen & Morgan, 1995).

In the language of status characteristics theory, the economic marketplace is a categorical reference structure that participants used to link gender with value when they estimated the worth of a computerized partner named James or Julie. This reference structure may lead to significant gender differences in value estimates of a gendered computer by participants.

6.1. Limitations

This study has two limitations. First, the study draws from sociological theories that explain status processes in groups of two or more people, not humans and computers. Thus, the result are not a direct test of status characteristics theory. It does, however, draw on status characteristics theory to understand how gender affects a unique type of relationship: those between computers and human beings. Second, this study did not provide additional information about the details of partners that were computers. For example, participants did not know the technical specifications of the computer software (e.g. operating system) or hardware (e.g. type of micro-core processor). It should be noted, however, that participants in this study used the exact same model of computer (Hewlett Packard TouchSmart 320 PC), touch-screen user interface (Qualtrics Software), and did not use other peripheral devices (e.g. no mouse and keyboard).

7. Conclusion

In 2011, 15-million people watched an International Business Machines's (IBM) computer, named Watson, beat human contestants on the television quiz show *Jeopardy*! (Markoff, 2011). Outside of television broadcasting, computers have been interacting with humans as restaurant servers (Ward, 2013), customer service representatives (Terdiman, 2010), health care providers (Sofge, 2013), and sexual partners (Hough, 2010). These examples highlight the rapid advancement in artificial intelligence of computers. Such advances now give computers a capacity to not only passively respond to human inputs, but also proactively interact with human users (Agre, 1997). If humans and computers are now socially interacting with each other, then it raises questions about the role of status inequities in these relationships that exist during interactions between human beings.

The findings in this paper have both applied and theoretical implications for understanding the way that human and computer interactions. From an applied perspective, technological advances have changed the way that humans interact with their computers. These machines not only serve as tools for humans; they may also become a partner that interacts with humans independent of user inputs. It may prove useful for designers of these machines to account for status processes that emerge in end-user experiences with computers. BMW's recall of a female voice-navigation system during the late 1990s illustrates how these status processes affect end-user interactions (Griggs, 2011).

As for theoretical implications, this paper applies status characteristics theory to the study of human and computer interactions. Studies have found evidence that gender of individuals affects their beliefs about using computers (Huffman et al., 2013; Imhof et al., 2007; Ong & Lai, 2006; Whitley, 1997). Further, research shows the gender descriptors of computers influences human perceptions of these interactions (Nass & Moon, 2000; Nass, Moon, & Green, 1997). Drawing from status characteristics theory, this study tests a specific mechanism that predicts the conditions under which humans formulate these perceptions of their computers. It demonstrates the applicability of status characteristics theory for research on human and computer interactions. When applied to computerized partners, this theoretical approach has the capacity to explain how various types of status characteristics (e.g. age, race, or ethnicity) affect user perceptions of their machines.

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References

Agre, P. (1997). *Computation and human experience*. Cambridge University Press.
Berger, J. & Webster Jr., M. (2006). Expectations, status, and behavior in P. Burke's Contemporary social psychological theories (pp. 268–300). Stanford, CA: Stanford University Press.
Berger, J., Cohen, B. P., & Zelditch, M. (1972). Status characteristics and social interaction. *American Sociological Review, 37*, 241–255.
Berger, J., Rosenholtz, S. J., & Zelditch, M. (1980). Status organizing processes. *Annual Review of Sociology, 6*, 479–508.
Berger, J., Webster, M., Jr., Ridgeway, C. L, & Rosenholtz, S. J (1998). Status cues, expectations and behavior. In J. Berger & M. Zelditch, Jr. (Eds.), *Status, power and legitimacy* (pp. 155–174). New Brunswick, NJ: Transaction Publishers.
Brezina, T., & Winder, K. (2003). Economic disadvantage, status generalization, and negative racial stereotyping by white Americans. *Social Psychology Quarterly, 66*, 402–418.
Cech, E. A. (2013). Ideological wage inequalities? The technical/social dualism and the gender wage gap in engineering. *Social Forces, 91*, 1147–1182.
Compton, D. M., Burkette, W. H., & Burkett, G. G. (2002). No sex difference in perceived competence of computer use among male and female college students in 2002. *Psychological Reports, 92*, 503–511.
Correll, S. J. (2004). Constraints into preferences: Gender, status, and emerging career aspirations. *American Sociological Review, 69*, 93–113.
Eagly, A. H., & Karau, S. J. (2002). Role congruity theory of prejudice toward female leaders. *Psychological review, 109*, 573–598.
Foschi, M. (1996). Double standards in the evaluation of men and women. *Social Psychology Quarterly, 59*, 237–254.
Griggs, B. (2011). Why computer voices are mostly female. CNN. (Accessed 31.03.13). <http://www.cnn.com/2011/10/21/tech/innovation/female-computer-voices/>.
Havelka, D. (2003). Predicting software self-efficacy among business students: A preliminary assessment. *Journal of Information Systems Education, 14*, 145–152.
Hough, Andrew (2010). "Foxy 'Roxxxy': World's first 'sex robot' can talk about football". The Telegraph. (Accessed 5.3.14). http://www.telegraph.co.uk/news/newstopics/howaboutthat/6963383/Foxy-Roxxxy-worlds-first-sex-robot-can-talk-about-football.html.
Huffman, M. L., Cohen, P. N., & Pearlman, J. (2010). Engendering change: Organizational dynamics and workplace gender desegregation. 1975–2005. *Administrative Science Quarterly, 55*, 255–277.
Huffman, A. H., Whetten, J., & Huffman, W. H. (2013). Using technology in higher education: The influence of gender roles on technology self-efficacy. *Computers in Human Behavior, 29*, 1779–1786.
Imhof, M., Vollmeyer, R., & Beierlein, C. (2007). Computer use and the gender gap: The issue of access, use, motivation, and performance. *Computers in Human Behavior, 23*, 2823–2837.
Lovaglia, M. J., & Houser, J. A. (1996). Emotional reactions and status in groups. *American Sociological Review, 61*, 867–883.
Lucas, J. W. (2003). Status processes and the institutionalization of women as leaders. *American Sociological Review, 68*, 464–480.
Lucas, J. W., & Lovaglia, M. J. (1998). Leadership status, gender, group size, and emotion in face-to-face groups. *Sociological Perspectives, 41*, 617–637.
Markoff, J. (2011). Computer wins on 'Jeopardy!': Trivial, it's not." *New York Times*. (Accessed 8.12.13). <http://www.nytimes.com/2011/02/17/science/17jeopardy-watson.html?pagewanted=all&_r=0>.
Meeker, B. F., & Weitzel-O'Neill, P. A. (1977). Sex roles and interpersonal behavior in task-oriented groups. *American Sociological Review, 42*, 91–105.
Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues, 56*, 81–103.
Nass, C., Moon, Y., & Green, N. (1997). Are machines gender neutral? Gender-stereotypic responses to computers with voices. *Journal of Applied Social Psychology, 27*, 864–876.
Ong, C. S., & Lai, J. Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in Human Behavior, 22*(5), 816–829.
Petersen, T., & Morgan, L. A. (1995). Separate and unequal: Occupation-establishment sex segregation and the gender wage gap. *American Journal of Sociology, 101*, 329–365.
Riches, P., & Foddy, M. (1989). Ethnic accent as a status cue. *Social Psychology Quarterly, 52*, 197–206.
Ridgeway, C. L. (2001). Gender, status, and leadership. *Journal of Social Issues, 57*, 637–655.

Ridgeway, C. L. (2009). Framed before we know it: How gender shapes social relations. *Gender and Society, 23*, 145–160.
Rosen, L. D., & Maguire, P. (1990). Myths and realities of computerphobia: A meta-analysis. *Anxiety Research, 3*(3), 175–191.
Simpson, B., Willer, R., & Ridgeway, C. (2012). Status hierarchies and the organization of collective action. *Sociological Theory, 30*, 149–166.
Sofge, E. (2013). The robotic doctor is in. *Popular Mechanics*. (Accessed 8.12.13). <http://www.popularmechanics.com/science/health/med-tech/the-robotic-doctor-is-in-15204883>.
Terdiman, D. (2010). New virtual-agent software uses AI to help users. *C-Net*. (Accessed 8.12.13). <http://news.cnet.com/8301-13772_3-20007524-52.html>.
Ward, Alex. (2013). ''Mechanic master chef: Robots cook dumplings, noodles, and wait tables at restaurant in China.'' The Mail Online. (Accessed 5.3.14). <http://www.dailymail.co.uk/news/article-2261767/Robot-Restaurant-Robots-cook-food-wait-tables-Harbin.html>.
Webster, M., Jr, & Driskell, J. E. Jr, (1978). Status generalization: A review and some new data. *American Sociological Review, 43*, 220–236.
Webster, M., Jr., & Hysom, S. J. (1998). Creating status characteristics. *American Sociological Review, 63*, 351–378.
Whitley, B. E. Jr, (1997). Gender differences in computer-related attitudes and behavior: A meta-analysis. *Computers in Human Behavior, 13*(1), 1–22.
Willer, R. (2009). Groups reward individual sacrifice: The status solution to the collective action problem. *American Sociological Review, 74*(1), 23–43.
Willer, D., Lovaglia, M. J., & Markovsky, B. (1997). Power and influence: A theoretical bridge. *Social Forces, 76*, 571–603.