

## **Problem and Motivation**

Despite the fact that both males and females have been found to exhibit traditionally masculine, feminine, and androgynous traits (1), gender has been found to be a factor that can significantly bias perception (e.g., 7, 10). Many questions arise with reference to how exactly our perceptions are biased. For example, what are the basic cues (voice, physical appearance, et cetera) that are necessary for gender perception and a consequent change in behavior? Do different perceptions arise based on which of these cues, or combination of cues, are presented? A complete analysis managing each potential variable that could be a factor in gender perception is required to fully understand how humans use gender information.

## **Background and Related Work**

Subject response to the gender of a voice alone has been explored considerably, with seemingly contradictory results with regards to a theory of “computers as social actors”, or CASA (10). The theory states that humans apply anthropomorphisms to non-human entities, and has been verified in multiple human-robot interaction (HRI) studies (2, 7, 9, 10). Furthermore, people have been found to treat computers with female voices differently than those with male voices. For instance, “female” computers were expected to be more knowledgeable about relationships, while “males” were assumed to know more about “masculine” topics, such as technology (9). An evaluation of voice gender in HRI research concluded that “choosing a computer voice’s gender is one of the most important design decisions that can be made” (7, p. 154).

Conversely, studies have also been performed which have the exact opposite conclusion. One technical paper reviewed the effects of a male and a female voice for the analysis of Audio Computer Assisted Self Interview (ACASI), and reasoned that “voice gender does not appear to have much of an effect on responses” when respondent race and gender were controlled (11, p. 1047). Numerous other publications have examined the effects of voice gender as well, and have thus far found no evidence to support CASA (3, 12). After conducting a sex survey by way of CASI technology, several investigators boldly stated, “the gender of the voice is unimportant” (13, p. 466).

Conflicting results over the existence of CASA indicate the experimental set-up is more complex than previously believed. It is probable that factors yet to be identified induce the CASA effect, and the presence or absences of these factors could discriminate these situations of drastically different results. For instance, several authors acknowledged that while their data do not support CASA, their experiment took place in a “survey setting” where the computers merely functioned as interviewers (3). Embodiment has also been proposed to play a role (4). More involved interaction might thus be a key component in inducing the CASA effect.

## **Approach and Uniqueness**

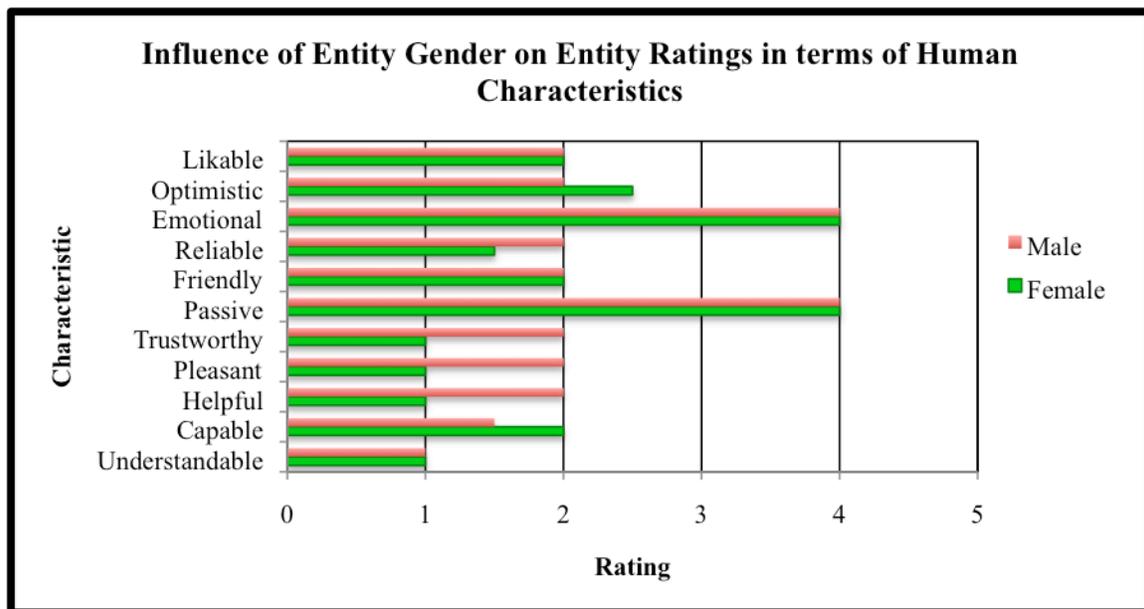
Because few investigations have focused on task-specific HRI, the objective of the present study was to determine if more specific judgments about entity personality and capability are made on the basis of a perceived gender through a voice cue during a

task-oriented scenario. A task-specific artificial intelligence engine was developed exclusively for the project. In addition, several Java and RoboBasic programs were created to connect the engine with a simple computer terminal and a Robonova robot.

In the study, male and female subjects interact with an entity that was either a robot or a disembodied voice. Each entity's voice is gendered male or female. The interaction included a Marlowe-Crowne survey and a cooperative task between the subject and the machine. Subject reactions to the entity in each situation were recorded to determine if context, physical embodiment or voice gender induce the CASA effect.

### **Results and Contributions**

Examination of the median characteristics applied to the entities in each case demonstrates that while subjects do not object to the personification of entities, subject gender, entity gender, physical embodiment, and context did not affect whether a subject perceived an entity to be described by a single characteristic (e.g., refer to Fig. 1). However, analysis using Spearman coefficient matrices revealed that subjects tended to correlate different characteristics of the entity depending on the entity's embodiment and gender (refer to Tables 1 and 2).



*Fig. 1:* An example displaying median ratings for all subjects, wherein subjects rated how well the entity corresponded to human characteristics. The blue bars indicate ratings of a male entity; the green, a female entity.

Correlated Ratings	Male Entity	Female Entity	Significant Conditions
Reliable/Emotional	0.1870	-0.4065	Female
Understandability/Passive	0.2390	-0.5580	Female
Reliable/Likable	0.5127	-0.1089	Male
Passive/Likable	-0.6337	-0.1615	Male
Capable/Passive	-0.0837	-0.5378	Female
Understandable/Pleasant	0.7355	0.7262	Female, Male

*Table 1:* Correlations between ratings the entity received when it was gendered male or female. The data suggest that the gender of the entity affects how the subject deems the characteristics of the entity with respect to each other ( $|r| > 0.4$  significance;  $|r| > 0.6$  high significance).

Correlated Ratings	Terminal	Robot	Significant Condition
Understandable/Capable	0.7222	0.0000	Terminal
Pleasant/Reliable	0.6902	0.1900	Terminal
Understandable/Pleasant	0.6441	0.8413	Terminal, Robot
Understandability/Trustworthy	0.6172	0.3183	Terminal
Helpful/Reliable	0.7127	0.3651	Terminal
Friendly/Optimistic	0.5342	0.7305	Terminal, Robot

*Table 2:* Correlations between ratings the entity received when it was physically embodied as either a terminal or a robot. The data suggest that the degree of the entity's embodiment influences how the subject deems the characteristics of the entity with respect to each other ( $|r| > 0.4$  significance;  $|r| > 0.6$  high significance).

Perceived gender significantly affected subject perception of the entity's characteristics. For instance, if the entity was perceived to be female, subjects rated the entity as more reliable if they believed it was less emotional, and vice versa ( $|r| > 0.4$ ). Yet, if the entity was perceived to be male, there was no observed correlation between the "emotional" and "reliability" characteristic. Similarly, if a male voice-gendered entity was rated as more passive, subjects tended to rate it as less likable ( $|r| > 0.4$ ); female voice-gendered entities did not induce a statistically significant effect. All of these results indicate that perceived gender affects subject perception of the artificial entity.

Embodiment similarly played a role in subject perception of entity characteristics. The disembodied condition produced highly statistically correlated positive characteristics ( $|r| > 0.6$ ) such as understandability and capability. In contrast, the embodied voice condition (robot) produced fewer significant results. One possible explanation for these results may be that in the disembodied condition, social cues had to be derived purely from voice. Thus, it is reasonable to expect that positive characteristics would be strongly correlated. In the robot condition, subjects consider appearance, body language, and context as well as voice. Because more factors influenced subject perception of the entity, it is probable that classifying the robot was more complex and

hence resulted in fewer statistically significant instances than the disembodied voice condition.

In all cases (male, female, disembodied voice, and robot), subjects who rated the entity as more understandable also rated the entity as more pleasant ( $|r| > 0.6$ ). This effect was highly significant, which suggests that artificial entities should be designed to be as understandable as possible to ensure that the user considers the interaction to be pleasant. Additionally, the data suggests that for artificial entities that do not have a physical embodiment, voice understandability is a key factor that determines whether subjects perceive the entity as having more positive characteristics.

This study has made several leaps in our understanding of the interaction that takes place between human and machine. First and foremost, we have established that the CASA effect occurs in a non-interview situation and that people are comfortable with applying human traits to artificial entities. This implies that regardless of whether human perception is considered in the design of artificial entities, the entities will be personified, especially in situations where the human-robot interaction is more complex. Further, it is likely that this personification will impact the interaction between entity and user.

We have also shown here that different perceptions occur in response to entity gender and level of embodiment, which implies that the decisions which impact these during the artificial entity design process are crucial to how the resulting entity will ultimately be perceived by its user. The data described here call for more experimentation to construct a detailed map of how features of an artificial entity influence perception. Only when these variables are identified will we have a solid grasp of how we view artificial entities, social constructs, and ourselves.

Finally, this study provides the first evidence that the CASA effect occurs in a HRI situation where a robot and a human must collaborate. This is an important step in the field of robotics, especially because future HRI will likely involve collaboration. Computational neuroscience is a rapidly expanding field, and it is expected that true humanoid robots will soon become available for manufacture. Henry Markram, who manages the Blue Brain Project, claims that a complete mechanical model of the human brain will be constructed within a decade (5). Analyses of past trends in technological pace and inspection of budding modern technologies suggest that huge leaps will be made in robotic intelligence by 2050 (6). If we are truly entering an age where robotic intelligence is no longer merely a product of fiction, we must carefully consider how humans will perceive robots and how we wish to represent them to provide society with the greatest benefit.

## **References**

- [1] Bem, S. (1974). The measurement of psychological androgyny. In *The Journal of Consulting and Clinical Psychology*. 42, 155-62.
- [2] Carpenter, J., Davis, J., Lee, T., Erwin-Steward, L., Bransford J., and Vye, N. (2009). Gender Representation and Humanoid Robots Designed for Domestic Use. In *The International Journal of Social Robotics*, 1, 261–265.
- [3] Couper, M., Singer, E., and Tourangeau, R. (2004). Does Voice Matter? An Interactive Voice Response (IVR) Experiment. In *Journal of Official Statistics*, 20(3), 551-570.
- [4] Crowell, C. R.; Scheutz, M., Schermerhorn, P., and Villano, M. (2009). Gendered Voice and Robot Entities: Perceptions and Reactions of Male and Female Subjects. In *The Proceedings of the 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '09)*, St. Louis, MO, October 2009.
- [5] McNealy, K. (2009). Scientists Predict Artificial Brain in 10 Years. In *Family Health Guide*. Retrieved Dec. 3 2009 from <<http://www.familyhealthguide.co.uk/scientists-predict-artificial-brain-in-10-years.html>>.
- [6] Moravec, H. (2000). *Robot: Mere Machine to Transcendent Mind*. US: Oxford University Press.
- [7] Nass, C., Moon, Y., and Green, N. (1997). Are Machines Gender Neutral? Gender-Stereotypic Responses to Computers with Voices. In *Journal of Applied Social Psychology*, 27, 864–876.

- [8] Nass, C., Moon, Y., Morkes, J., Kim, E.-Y., and Fogg, B. (1997). Computers Are Social Actors: A Review of Current Research. In *Human Values and the Design of Computer Technology*, B. Friedman (ed.). Stanford, CA: CSLI Press.
- [9] Powers, A., Kramer, A., Lim, S., Kuo, J., Lee, S., and Kiesler, S. (2005). Eliciting Information from People with a Gendered Humanoid Robot. In *Proceedings of the 14th IEEE International Workshop on Robot and Human Interactive Communication (RO-MAN 2005)*, 158- 163.
- [10] Reeves, B., and Nass, C. (1996). The media equation: How people treat computers, television, and new media like real people and places. Cambridge: Cambridge University Press.
- [11] Rogers, S., Miller, H., Forsyth, B., Smith, T., and Turner, C. (1996). Audio-CASI: The Impact of Operational Characteristics on Data Quality. In *Proceedings of the Section on Survey Research Methods*, American Statistical Association, Alexandria, VA: 1042–1047.
- [12] Tourangeau, R., Couper, M., and Steiger, D. (2003). Humanizing Self-Administered Surveys: Experiments on Social Presence in Web and IVR Surveys. In *Computers in Human Behavior*, 19, 1–24.
- [13] Turner, C., Forsyth, B., O'Reilly, J., Cooley, P., Smith, T., Rogers, S., and Miller, H. (1998). Automated Self-Interviewing and the Survey Measurement of Sensitive Behaviors. In *Computer Assisted Survey Information Collection*, M. Couper, R. Baker, J. Bethlehem, C. Clark, J. Martin, W. Nicholls II, and J. O'Reilly (eds). New York: Wiley. 455-473.