Effects of robotic social cues on interpersonal attributions and assessments of robot interaction behaviors

Travis Wiltshire

Proceedings of the Human Factors and Ergonomics Society 59th Annual Meeting

Effects of Robotic Social Cues on Interpersonal Attributions and Assessments of Robot Interaction Behaviors

Travis J. Wiltshire[1], Emilio J. C. Lobato[1], David R. Garcia[1], Stephen M. Fiore[1], Florian G. Jentsch[1,]
Wesley H. Huang[2], and Benjamin Axelrod[2]
[1]University of Central Florida, [2]iRobot Corp.

We discuss an experiment investigating the influence of social cues expressed by a robot on human attributions of interpersonal characteristics towards a robot and assessments of its interaction behaviors. During a hallway navigation scenario, participants were exposed to varying expressions of proxemic behavior and gaze cues over repeated interactions with a robot. Analysis of participant perceptions of the robot's personality revealed that cues indicative of socially mindful behavior expressed by the robot promote positive interpersonal attributions and perceptions of safe robot behavior. Results of the present study contribute to the scholarly discussion on robotic design for encouraging natural and effective interactions between humans and robots.

INTRODUCTION

As the frequency of robotic interactions increases in public spaces, so too does the need to understand the complex relationship between social cues and the signals they create during human-robot interaction (Fiore et al., 2013). Though advances in the capabilities of artificial social intelligences have progressed thanks to efforts drawing from, for example, biologically inspired approaches to artificial cognition (e.g., Franklin, Strain, McCall, & Baars, 2013), modern robots still lack the ability to engage in non-verbal communication in natural ways that effectively convey their intentionality. Advances in addressing this challenge have benefitted from research investigating the influence of a variety of social cues expressed by robot platforms on the perceived social signals by human interactors (Hegel, Gieselmann, Peters, Holtahus, & Wrede, 2011; Saulnier, Sharlin, & Greenberg, 2011). In this context, we studied how cues exhibited by a robotic platform are interpreted during a human-robot interaction (HRI).

This research has both theoretical and practical aims. From a theoretical perspective, we aim to shed further insight into the examination of the social cue and signal relationship in HRIs. Although much research has examined or worked to develop social aspects of robotics (e.g., Hegel et al., 2011), little research has studied actual interactions in an ecologically valid setting and how these relate to the attributions humans make regarding the robot based on the social cues it displays. In this way, we are able to study direct forms of interaction in an environment mimicking situated social interaction (cf. Delaherche et al., 2012).

From a practical perspective, our goal was to demonstrate how research in HRI can benefit from a combination of interdisciplinary methodologies. From Psychology, we utilize measures of mental state attribution examining interpersonal dimensions. From Computer Science, we draw from anthropomorphic design to study how behavioral characteristics (e.g., gaze, proxemics) can be implemented to help HRI researchers study the factors influencing perception of social interactions (Chang et al., 2014; Fiore et al., 2013). The combination of these factors can help provide an empirical foundation for developing automated social signal processing methods (e.g., Rozgic et al., 2011).

In this paper, we focus on examining the role of two social cues, proxemic behavior and gaze, in HRI. Whereas prior work investigated the influence of these cues on the perceptions of social presence and the attribution of emotional states to the robot (Fiore et al., 2013; Wiltshire, Lobato, Wedell, Huang, Axelrod, & Fiore, 2013), the present paper examines how these social cues influence the interpersonal attributions humans make based on a navigational interaction with a robot. Further, we also examine participants' perceptions of the interactions that are informative for how the robot is designed.

For this paper, we first describe our social cues and signals theoretical foundation in social signals theory, which we used to examine mental state attributions in the context of HRI. We then review research related to the specific social cues we examined. Finally, we detail our experimental approach and the analytical methods used to broaden our understanding of how robotic social cues alter interpersonal attributions towards the robot and perceptions of the robot's interaction behaviors.

Social Cues and Signals and Non-Verbal Communication

Social Signal Processing (SSP) is an emerging interdisciplinary field that aims to address the challenges inherent in designing socially intelligent systems (e.g., Vinciarelli, Pantic, & Bourland, 2009). For HRI, techniques from SSP can be leveraged to facilitate the development of socially intelligent systems that can interact naturally with humans. For the purposes of the present experiment, we utilize social cues and signals to ground our work on understanding the relationship between robot behavior and the human's perceptions of that robot as a function of the specific social cues exhibited (Fiore et al., 2013).

In this context, we draw a theoretical and practical distinction between social cues and social signals, both of which serve as the foundation for the development of social intelligence necessary for successful interaction between robots and humans (Wiltshire, Snow, Lobato, & Fiore, 2014). *Social cues* refer to discrete biologically or physically determined features of a person or group. They serve as useful channels of information. Social cues can further be categorized as either physical cues or behavioral cues. *Physical cues* refer to aspects of physical appearance or the environment, such as the proximity between agents in an interaction, while *behavioral cues* refer to the non-verbal aspects of communication that accompany or replace verbalizations, such as maintaining or breaking eye contact. These social cues manifest during interactions and facilitate the transfer of underlying meaning imparted by one agent to another. This underlying meaning of the cues is the *social signal*, which is influenced not only by the social cues, but also the larger social, cultural, emotional, and cognitive systems of the agent (Fiore et al., 2013).

In recent work, this framework for understanding the relationship between social cues and social signals has contributed to advancing knowledge of human social cognition (Wiltshire, Lobato, McConnell, & Fiore, 2015) and specifically, a better understanding of the social dynamics of HRI (Fiore et al., 2013; Wiltshire et al., 2013; Wiltshire et al., 2014). In our earlier work we examined how the social cues of proxemic behavior and gaze influenced human perceptions of a robot as a socially present agent and the types of socio-emotional states attributed to its behavior during a navigation scenario, a routine hallway crossing (Fiore et al., 2013; Wiltshire et al., 2013). Results suggested that, in this context, people perceived the robot as more sociable and exhibiting more positive socio-emotional states when it behaved in a way congruent with expectations of *social mindfulness*. This is a construct from research on social interactions between humans that denotes cognizance of the ability of other agents to choose their own behavior during interdependent interactions (see Van Doesum, Van Lange, & Van Lange, 2013). By contrast, a robot behaving without apparent regard to the behavior of co-present humans is not perceived as particularly socially present, but is attributed socio-emotional states, albeit ones characterized by negative valence (Fiore et al., 2013).

Understanding how robot behavior influences peoples' perceptions of the robot's capacity for social intelligence, including its ability to convey its intentions and signal its mental states, is a vital component to advancing robotics. We aim to add to the literature on how robotic expression of social cues, specifically proxemic behavior and gaze, influences the interpersonal attributions made towards the robot and assessments of the robot's interaction behaviors.

Proxemics and Gaze

The term *proxemics* was coined to describe the interrelated observations and theories of humans' use of space (Hall, 1963). The concept of proxemic distance and behavior has been useful for the study of HRI, as robots become increasingly mobile and able to navigate their environments. Many factors influence proxemics in HRI, including age, personality, familiarity with robots, and gender (Takayama, 2009; Rios-Martinez, Spalanzani, & Laugier, 2014). How robots utilize space when navigating around co-present humans also affects how humans attribute socio-emotional states to the robot. Mental states characterized by a positive valence have been shown to be attributed to robots navigating with apparent concern to the trajectory of nearby people (Fiore et al., 2013). More generally, Takayama (2009) posited that people would engage in their typical proxemic behaviors when robots exhibit proxemic behavior that is similar to their own.

Gaze has been found to be an important social regulator and indicator of the underlying mental states and intentions of an agent (Castiello, 2003; Fiore et al., 2013; Gangopadhyay & Schilbach, 2012; Kleinke, 1986; Wiltshire et al., 2013). Gaze behaviors provide information a human can use to understand the intentions and behavior of the robot (Srinivasan, Bethel, Murphy, & Nass, 2012). Further, robot gaze behavior has been shown to modulate human behavior (Mumm & Mutlu, 2011; Pitsch, Vollmer, & Mühlig, 2013), even resulting in improved performance by humans on a task that requires understanding the mental states and intentions of their robotic partner (Mutlu, Yamaoka, Kanda, Ishiguro, & Hagita, 2009).

Taken together, the social cues of proxemic behavior and gaze are of particular importance in HRI, given that these cues can be instantiated in almost any mobile robotics platform. As noted above, we have investigated the effects these cues have on perceptions of a robot's social presence and attribution of emotional states (Fiore et al., 2013; Wiltshire et al., 2013). Here, we expected there would be effects of proxemic behavior and gaze on the perception of interpersonal attributions of the robot as well as perceptions of the interaction; however, our analyses were exploratory.

METHOD

This paper used data from the experiment reported in Fiore et al. (2013). Thus, the method is the same. While Fiore et al. (2013) examined attributions of social presence and emotions; here we examine interpersonal attributions and assessments of robot interaction behaviors.

Participants. A total of 74 participants (37 females and 37 males) from a large southeastern university were recruited to participate in this study in exchange for course credit. Ages ranged from 18 to 27 years (M = 19.2 years). Due to technical difficulties, data from three participants were excluded from the analyses.

Materials. A prototype iRobot® Ava™ model robot was used throughout this experiment. To collect data on subjective measures, Qualtrics survey software was used. A 5 ft. by 30 ft. hallway, with a 5 ft. by 5ft. hallway alcove intersecting at the midpoint on participant's right side of the hallway was constructed for this experiment (see Fiore et al., 2013).

Design. The design of the experiment was a 3 x (2 x 4) mixed model design with gaze as the between-factor with three levels (congruent, person-oriented, variable) crossed with two within-factors: proxemic behavior (Passive vs. Assertive) and measurement trial (after trials 1, 6, 7, and 12). Each participant was randomly assigned to one of the gaze conditions and participated in 12 trials, six for the Passive condition and six for the Assertive. Whether participants encountered the Passive or Assertive condition was counterbalanced. Participants responded to the subjective measures after the first and sixth trial for each of the proxemic behavioral conditions equally a total of four measurement trials.

Independent variables (IV). The IVs of this experiment were robot gaze and proxemic behavior. *Gaze* was operationalized as the direction that the robot's primary sensors were oriented in terms of pan and tilt, and had three levels: congruent, person-oriented, and variable. *Congruent gaze* was defined as the robot's head consistently being oriented in the direction of the robot's movement throughout the interaction, and was considered the least natural gaze behavior. *Person-oriented gaze* was defined as the robot's head consistently being oriented approximately towards the head of the participant, and was considered more natural than the congruent gaze behavior. *Variable gaze* was defined as an initial orientation of the robot's head towards the participant's head and then towards the navigation goal, which was considered the most natural gaze behavior as it provided both the cue of sensing the human and the signal of intended direction of travel. The IV of *Proxemic Behavior* was operationalized by having the robot modify its path and change speed at two levels: Passive behavior and Assertive behavior. The *Passive Behavior* slowed the robot and modified the path to the side of the hall to provide more space for the participant to pass in front of the robot. The *Assertive Behavior* sped up the robot and modified the path to "cut the corner" leading the robot to pass in front of the participant.

Dependent variables (DV). The DVs in the study were the responses to each item of two sets of questionnaires used to assess interpersonal attributions and participants' assessments of robot interaction behaviors based on participant perceptions of the robot. Both sets of questions are listed in Table 1.

Table 1.
Interpersonal Attributions and Assessments of Robot Interaction Behaviors Questions

Interpersonal Attributions	1.	How antagonistic was Ava?
6-point Likert scale, from 1	2.	How controlling was Ava?
(not at all) to 6 (very)	3.	How cooperative was Ava?
	4.	How docile was Ava?
Assessments of Robot	1.	How safe was the robot's behavior?
Interaction Behaviors	2.	How natural was the robot's behavior?
7-point Likert scale, from 1	3.	How comfortable did you feel near the robot?
(not at all) to 7 (very)	4.	Did the robot come too close to you?
	5.	Were you able to anticipate the robot's movements?
	6.	Did the robot get in your way?

Procedure. After providing informed consent, participants interacted with the Ava robot across 12 trials. One trial corresponds to one interaction event with the robot in a hallway setting. For each trial, participants were required to walk from an initial starting point at one end of the hallway to the opposite end while the robot, initially navigating in the opposite direction from the other end of the hallway, crossed the participant's path perpendicular to the trajectory of the participant, at the midpoint of the hallway. Participants were block-randomly assigned to an experimental condition consisting of one gaze condition and a counterbalanced display of the two levels of proxemic behavior. That is, participants interacted with the robot programmed to behave in the Passive condition for six consecutive trials and Assertive condition for six consecutive trials or vice versa.

After the first, sixth, seventh, and twelfth trials, participants were asked to fill out measurements on a computer to assess their perceptions of the interactions. Thus, participants provided responses to questions about their perceptions of the robot after their initial interaction with the robot, after a series of interactions where the robot exhibited the same gaze and behavior settings, after interacting with the robot behaving in a different proxemic manner, and after interacting with the robot behaving in this way for several additional trials. In the results section, responses after the first and seventh trials represent the first measure time for the given proxemic condition, and responses after the sixth and twelfth trials represent the second measure time for the given proxemic condition.

RESULTS

We conducted a series of multiple mixed-model linear regression analyses with proxemic behavior and gaze entered as the IVs (fixed factors), and the responses to the four Interpersonal Attributions and six Design Consideration questions as DVs (see Table 1). Further, we used mixed-effects regression models to control for the lack of independence of our observations (Baayen, Davidson, & Bates, 2008), with participant and trial as random factors in each model. Given that this results in 10 regression analyses being conducted, we set the alpha level at .005 to control for family-wise error inflation. We used the *lme4* (Bates, Maechler, & Bolker, 2012) package in R to conduct these mixed-model analyses using the `lmer` function. All *p*-values were obtained using likelihood ratio tests comparing the full model with the particular fixed effect included with a null model without any fixed effects and without each particular fixed effect (see Baayen et al., 2008; Winter, 2013). All assumptions of the models were checked by visual examination of residual plots. No signs of deviation from homoscedasticity or normality were apparent. Further, the presence of collinearity was not detected. Tables 2 and 3 summarize the beta estimates, t-values, and effect sizes of the full model which include the fixed and random effects and then the delta of the full model compared to the null model.

In terms of interpersonal attributions, for "Antagonistic", the model was significant [(R^2 = .47), χ^2 = 94.01, $p < .001$], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of greater perceptions of the robot exhibiting antagonistic behavior (sr^2 = .26). For "Cooperative", the model was significant [(R^2 = .54), χ^2 = 60.24, $p < .001$], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of lower perceptions of cooperative behavior (sr^2 = .15). For "Docile", the model was significant [(R^2 = .43), χ^2 = 19.49, $p < .001$], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of lower perceptions of docile behavior (sr^2 = .06). For "Controlling", the model was significant [(R^2 = .48), χ^2 = 40.33, $p < .001$], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of greater controlling behavior (sr^2 = .10).

In terms of robot interaction behaviors, for "Safe", the model was significant [(R^2 = .08), χ^2 = 48.03, $p < .001$], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of lower feelings of safety around the robot (sr^2 = .08). For "Natural", the model was significant [(R^2 = .65), χ^2 = 25.004, $p < .001$], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of lower perceptions of natural movement (sr^2 = .04). For "Comfortable", the model was significant [(R^2 = .68), χ^2 = 21.26, p < .001], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of lower feelings of comfort around the robot (sr^2 = .04). For "Close", the model was significant [(R^2 = .53), χ^2 = 83.11, p < .001], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of greater perceptions of being too physically close to the robot (sr^2 = .46). For "Anticipate", the model was not significant [χ^2 = 3.66, p > .01]. For "In The Way", the model was significant [(R^2 = .45, χ^2 = 125.45, p < .001], with proxemic behavior as a significant predictor. The robot behaving according to the Assertive proxemic behavior setting was predictive of higher perceptions of the robot being in the way (sr^2 = .36).

Table 2.
Multiple Mixed Model Linear Regressions of Interpersonal Attributions

Dependent variable	**Independent variable**	**β**	***t***	**R^2 of full model**	**ΔR^2 from null model**
Antagonistic	Proxemic behavior	1.5	10.84*	.47	.19
	Gaze	-.08	-.71		
Cooperative	Proxemic behavior	-1.13	-8.36*	.54	.13
	Gaze	.002	.02		
Docile	Proxemic behavior	-.64	-4.50*	.43	.02
	Gaze	.03	.25		
Controlling	Proxemic behavior	.98	6.58*	.48	.07
	Gaze	.14	1.03		

Note: * p < .001

Table 3.
Multiple Mixed Model Linear Regressions of Robot Interaction Behaviors

Dependent variable	**Independent variable**	**β**	***t***	**R^2 of full model**	**ΔR^2 from null model**
Safe	Proxemic behavior	-.88	-7.34*	.69	.08
	Gaze	.06	.51		
Natural	Proxemic behavior	-.68	-5.06*	.65	.04
	Gaze	.17	.94		
Comfortable	Proxemic behavior	-.19	-3.20*	.68	.03
	Gaze	.06	1.04		
Close	Proxemic behavior	1.83	10.02*	.53	.01
	Gaze	.21	1.25		
Anticipate	Proxemic behavior	-.30	-1.88	.50	
	Gaze	.07	.41		
In The Way	Proxemic behavior	2.75	12.95*	.45	.45
	Gaze	.04	.26		

Note: * p < .001

DISCUSSION

In this study, we utilized an ecologically valid hallway navigation scenario to examine the influence of social cues expressed by a robot on human perceptions of the robot. We sought to examine the effects that social cues a robot displays, however minimally expressive, have on the types of social signals participants report perceiving after the interaction.

Consistent with our prior research, we found that, in such a scenario, gaze was not a significant predictor of human perceptions of the robot, although the proxemic behavior was (e.g., Fiore et al., 2013). The Assertive proxemic behavior setting resulted in higher perceptions of the robot as antagonistic and controlling, while the Passive proxemic behavior setting resulted in higher perceptions of the robot as cooperative and docile. Likewise, the Passive proxemic behavior setting was associated with higher perceptions of the robot moving in a safe and more natural way, and participants were more comfortable around the robot when it was behaving according to the Passive setting. By contrast, when the robot acted according to the Assertive setting, participants perceived it as being more physically close and more likely to get in their way. These findings have several implications for the design of future robots for use in spaces shared with humans. Note that in our Discussion we have included interpretations of both the Assertive and Passive proxemic behaviors; whereas, in our results we primarily referred only to the effects of the Assertive behavior. Our interpretations here are consistent with traditional regression logic using dichotomous predictors (Cohen, Cohen, West, & Aiken, 2003).

For practical implications, we suggest that if robots are to be deployed in environments where a higher degree of perceived safety and human comfort when moving with or around the robot is desired, the robot should be programmed to move similarly to our Passive proxemic behavior settings. That is, a navigational setting that prioritizes the human's proxemic space and navigational trajectory, resulting in the robot moving more slowly as the physical distance with humans decreases to give the human the "right of way" during any potential navigational conflicts, would be preferred. This would also result in the robot being perceived as more cooperative with its human interactors, potentially as a result of this behavior simulating a form of "social mindfulness", allowing co-present humans more choices with regards to their possible behavior (Van Doesum et al., 2013).

Limitations and Future Research

Generalizability of our results across situations is limited, however, as the present study only investigated a shared navigation scenario, located in a relatively narrow hallway. Future research will need to consider shared navigation scenarios in more diverse settings, perhaps even those with fewer physical constraints on movement (e.g., open areas in parks). However, given the increasing presence for social robots in environments where similar physical constraints to navigation are present (e.g., office buildings), these findings can still be leveraged by roboticists for the design, programming, and implementation of future robots.

Similarly, although the present experiment only examined the influence of two specific social cues, gaze and proxemic behavior, these are cues that are more easily instantiated in various robot forms, from more human-like to very mechanical in appearance. Other robot platforms may be able to express additional social cues, such as gesture-like behavior for robots with limbs, which would allow for examining the influence of those cues in combination with the currently studied cues of gaze and proxemic behavior. Future research is needed to assess the degree to which similar participant responses regarding the robot perceptions maintain when robots of different morphologies display these same social cues and further, how these are related to the cues that humans would display (e.g., Wiltshire & Fiore, 2014).

An additional limitation is the interrelationship between other measures that we included in this study (See Fiore et al., 2013; Wiltshire et al., 2013). These included a circumplex model of affect and a social presence inventory. Future work could examine whether there is any moderating relationships between those measures and the ones presented here.

CONCLUSION

In an ecologically valid setting, examining real interactions with an autonomously behaving robot, the findings reported in this article reveal the importance of understanding how social cue expressions by a robot influence the interpersonal attributes towards a robot (see also, Fiore et al., 2013) and other perceptions of the interaction. As such, this paper contributes to theory on HRI by studying how social cues are related to social signals (i.e., mental state attributions) in a situated social setting. Further, through our multidisciplinary approach, utilizing methods from Psychology and Computer Science, we reveal the relationships associated with assertive and passive behaviors on the part of a robot. These results can be leveraged in the design of robots deployed in areas where interactions with humans are expected to facilitate natural and seamless integration of social robots into the environment.

ACKWNOWLEDGEMENTS

This work was partially supported by the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-10-2-0016. Views contained here are of the authors and should not be interpreted as representing official policies, either expressed or implied, of the Army Research Laboratory, the U.S. Government or the University of Central Florida. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation.

REFERENCES

Bates, D.M., Maechler, M., & Bolker, B. (2012). lme4: Linear mixed-effects models using S4 classes. R package version 1.1-7.

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language, 59*(4), 390-412.

Castiello, U. (2003). Understanding other people's actions: intention and attention. *Journal of Experimental Psychology: Human Perception and Performance, 29*(2), 416.

Chang, W. L., Sabanovic, S., & Huber, L. (2014, August). Observational study of naturalistic interactions with the socially assistive robot PARO in a nursing home. In *Robot and Human Interactive Communication, 2014 RO-MAN: The 23rd IEEE International Symposium* on (pp. 294-299). IEEE.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). Applied multiple correlation/regression analysis for the behavioral sciences. Hillsdale, NJ: Lawrence Erlbaum.

Delaherche, E., Chetouani, M., Mahdhaoui, A., Saint-Georges, C., Viaux, S., & Cohen, D. (2012). Interpersonal synchrony: A survey of evaluation methods across disciplines. *Affective Computing, IEEE Transactions on*, 3(3), 349-365.

Fiore, S. M., Wiltshire, T. J., Lobato, E. J. C., Jentsch, F. G., Huang, W. H. , & Axelrod, B. (2013). Towards understanding social cues and signals in human-robot interaction: Effects of robot gaze and proxemics behavior. *Frontiers in Psychology: Cognitive Science, 4*(859), 1-15. DOI: 10.3389/fpsyg.2013.00859

Franklin, S., Strain, S., McCall, R., & Baars, B. (2013). Conceptual Commitments of the LIDA Model of Cognition. *Journal of Artificial General Intelligence, 4*(2), 1-22.

Gangopadhyay, N., & Schilbach, L. (2012). Seeing minds: a neurophilosophical investigation of the role of perception-action coupling in social perception. *Social Neuroscience, 7*(4), 410-423.

Hall, E. T. (1963). A system for the notation of proxemic behavior. *American Anthropologist, 65*(5), 1003-1026.

Hegel, F., Gieselmann, S., Peters, A., Holthaus, P., & Wrede, B. (2011, July). Towards a typology of meaningful signals and cues in social robotics. In *RO-MAN, 2011 IEEE* (pp. 72-78). IEEE.

Kleinke, C. L. (1986). Gaze and eye contact: a research review. *Psychological Bulletin, 100*(1), 78.

Mumm, J., & Mutlu, B. (2011, March). Human-robot proxemics: physical and psychological distancing in human-robot interaction. *Proceedings of the 6th international conference on Human-robot interaction* (pp. 331-338).

Mutlu, B., Yamaoka, F., Kanda, T., Ishiguro, H., & Hagita, N. (2009, March). Nonverbal leakage in robots: communication of intentions through seemingly unintentional behavior. In Proceedings of the 4th ACM/IEEE international conference on Human robot interaction (pp. 69-76). ACM.

Pitsch, K., Vollmer, A. L., & Muhlig, M. (2013). Robot feedback shapes the tutor's presentation: How a robot's online gaze strategies lead to micro-adaptation of the human's conduct. *Interaction Studies*, *14*(2).

Rios-Martinez, J., Spalanzani, A., & Laugier, C. (2014). From Proxemics Theory to Socially-Aware Navigation: A Survey. *International Journal of Social Robotics, 7*(2), 137-153.

Rozgic, V., Xiao, B., Katsamanis, A., Baucom, B., Georgiou, P. G., & Narayanan, S. (2011, May). Estimation of ordinal approach-avoidance labels in dyadic interactions: Ordinal logistic regression approach. In *Acoustics, Speech and Signal Processing (ICASSP)*, 2011 IEEE International Conference on (pp. 2368-2371). IEEE.

Saulnier, P., Sharlin, E., & Greenberg, S. (2011, July). Exploring minimal nonverbal interruption in HRI. In *RO-MAN, 2011 IEEE* (pp. 79-86).

Srinivasan, V., Bethel, C. L., Murphy, R., & Nass, C. (2012). Validation of a behavioral robotics framework for social head gaze. In *Proceedings of the "Gaze in Human-Robot Interaction" Workshop held at the 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI 2012)* March 5, 2012, Boston, MA.

Takayama, L., & Pantofaru, C. (2009, October). Influences on proxemic behaviors in human-robot interaction. In Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on (pp. 5495-5502). IEEE.

Van Doesum, N. J., Van Lange, D. A. W., & Van Lange, P. A. M. (2013). Social mindfulness: Skills and will to navigate the social world. *Journal of Personality and Social Psychology, 105*(1), 86-103.

Vinciarelli, A., Pantic, M., & Bourlard, H. (2009). Social signal processing: Survey of an emerging domain. Image and Vision Computing, 27(12), 1743-1759.

Wiltshire, T. J. & Fiore, S. M. (2014). Social, cognitive, and affective neuroscience in human-machine systems: A roadmap for improving training, human-robot interaction, and team performance. *IEEE Transactions on Human-Machine Systems, 44*(6), 779-787.DOI: 10.1109/THMS.2014.2343996

Wiltshire, T. J., Lobato, E. J. C., McConnell. D., & Fiore, S. M. (2015). Prospects for direct social perception: A multi-theoretical integration to further the science of social cognition. *Frontiers in Human Neuroscience*, *8*(1007). DOI: 10.3389/fnhum.2014.01007.

Wiltshire, T. J., Snow, S. L., Lobato, E. J. C., & Fiore, S. M. (2014). Leveraging social judgment theory to examine the relationship between social cues and signals in human-robot interactions. In *Proceedings of the Human Factors and Ergonomics Society 58th Annual Meeting*, 1336-1340.

Wiltshire, T. J., Lobato, E. J. C., Wedell, A., Huang, W., Axelrod, B, & Fiore, S. M. (2013). Effects of robot gaze and proxemic behavior on perceived social presence during a hallway navigation scenario. In *Proceedings of the Human Factors and Ergonomics Society 57th Annual Meeting*, 1273-1277.

Winter, B. (2013). Linear models and linear mixed effects models in R with linguistic applications. arXiv:1308.5499. [http://arxiv.org/pdf/1308.5499.pdf]