Implicit Communication Through Social Distancing: Can Social Navigation Communicate Social Norms?

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ABSTRACT

Socially-aware navigation seeks to codify the rules of human-human and human-robot proxemics using formal planning algorithms. However, the rules that define these proxemic systems are highly sensitive to a variety of contextual factors. Recently, human proxemic norms have been heavily influenced by the COVID-19 pandemic, and the guidelines put forth by the CDC and WHO encouraging people to maintain six feet of social distance. In this paper, we present a study of observer perceptions of a robot that not only follows this social distancing norm, but also leverages it to implicitly communicate disapproval of norm-violating behavior. Our results show that people can relate a robot's social navigation behavior to COVID safety protocols, and view robots that navigate in this way as more socially intelligent and safe.

KEYWORDS

Social Navigation, Social Norms, Proxemics, COVID-19

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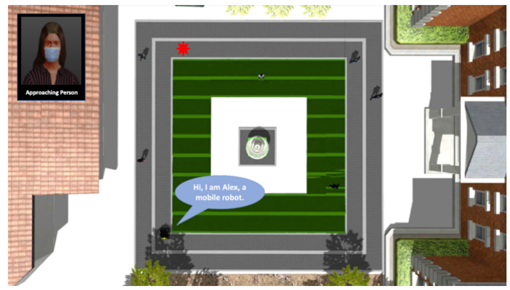

Figure 1: Top-down view of a pandemic scenario simulated in Gazebo. Top-left is a dedicated area where a headshot of the person is shown. The red star is the robot's destination.

Figure 2: Headshots of the simulated humans.

1 INTRODUCTION

Human behavior and interaction are both governed by a host of mutually agreed upon social and moral norms, which dictate what actions are viewed as appropriate in different contexts, including what to say, how to act, what to wear, and how to move within and interact with the world around us generally. The COVID-19 pandemic has, for example, led to a host of new social and moral norms, such as mask-wearing and social-distancing, which are at once social, dictating what is polite and appropriate, and moral, dictating what is right and wrong. However, large segments of the population seem to have recognized these norms as more social than moral, viewing these new requirements as social impositions rather than guidelines for engaging with a world under plague morally. To help limit this pandemic's further impact, it is thus everyone's moral duty to try to increase compliance with these new norms as quickly as possible.

Recent evidence has suggested that robots wield significant social and moral influence. Not only can robots socially influence, persuade, and coerce humans in a variety of ways [5, 9, 12, 13, 21, 26, 39, 43, 48], but recent evidence suggests that robots are capable of exerting moral influence over humans as well, even through highly indirect means, such as through tacit agreement with immoral dispositions [23, 24]. Moreover, research has shown that robots' influence can have "ripple effects" in which robots not only influence others, but influence the underlying dispositions of others so that others in turn influence wider populations [29, 44].

However, calling people out too directly can be viewed as overly harsh [25], with the potential to backfire and reinforce the negative behavior the robot (or human) was trying to call out [see also 27]. And in fact, researchers have observed just this phenomenon with moral communication surrounding COVID-19 [47]. Moreover, in our own recent work, we have shown that there may be safety concerns with social robots using purely verbal strategies to encourage COVID-19 norm adherence, which may backfire due to the ability of such robots to increase engagement among groups [31]. Accordingly, in addition to tuning the phrasing of moral language (when used) to embody an appropriate level of tact [25], we suggest that robots also seek to employ less direct *nonverbal* approaches to persuasion, just as humans do. Instead of calling others out directly and verbally for not wearing masks, many people currently opt instead to simply take overly exaggerated and *legibly displeased* paths around the maskless.

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But while robots can exert moral influence through nonverbal behaviors [22, 36, 46], it is unclear whether people will *consciously infer* robots' nonverbal behaviors to be generated as a result of norm-following. Moreover, while people can infer intent from robots' trajectories [15] it is unclear whether people will infer robots' nonverbal behaviors to be intended to communicate dispositions regarding norms. In this paper, we seek to examine whether robots can also use their proxemic and navigation behaviors to communicate moral and social dispositions related to social distancing and mask-wearing norms. If so, robots could use such behavior to exert social and moral influence to encourage pro-social ripples of compliance with those norms.

2 RELATED WORK

Social Norm Following and Moral Norm Influence: Prior work in social navigation suggests that robots can be programmed either to perform or learn social norms such as *not going between two conversing people* [38], social hallway maneuvers like *passing, meeting, walking together* [2, 40], and *avoiding activity zones* [35]. Zhu *et al.* [49] suggest that a morally competent social robot must be willing to communicate its objection to a violation of shared norms by a human, even if such communication is not polite. Prior empirical studies in HRI suggest that robots are capable of directly influencing a human's behavior and moral norms [9, 13, 37].

Implicit Robot Communication: In our day-to-day interactions, knowingly or unknowingly, humans rely heavily on nonverbal implicit communication. For example, while walking in a narrow hallway, we communicate our intent of passing on the right side by slightly veering towards the right (or gazing in the direction). Such communication helps in avoiding hallway conflicts. Prior work utilized such implicit non-verbal communication to improve human-robot teams' task efficiency in collaborative environments [15, 30]. In similar implicit robot communication research, the use of the robot's hesitant hand motions was explored to communicate uncertainty for safe and ethical human-robot interaction [32]. Another work studied implicit communication in indoor navigation tasks where the robot actively communicated its navigational intentions and avoided collisions [11].

Persuasive Robotics: Recent work in HRI has demonstrated that a robot's ability to persuade humans can play an essential role in interaction quality. In a persuasive HRI study, participants could better recall a story when the storytelling robot used persuasive cues [33]. Baroni *et al.* [4] studied the application of persuasive HRI as diet coach for children. Ghazali *et al.* [18] found that there could be an increase in likability and decrease in reactance when the robot exhibits persuasive behavior. Siegal *et al.* [41] study focused on a robot's behavior and appearance (gender) on its ability to persuade an interacting partner; Concerning trustworthiness, and credibility.

The literature above broadly suggests that (1) humans can infer the *intent* behind robots' trajectories; (2) humans infer *norms* from robots' trajectories; (3) robots have the potential to impact humans' systems of social and moral norms. However, it is not yet clear whether humans infer not only intentions and norms, but also norm-relevant communicative acts, such as blame and sanction, from such simple signals as robot trajectories. In this work, we seek to examine whether this might be the case, as, if so, it would present a powerful modality for robots to use to exert subtle prosocial influence on their moral ecosystems. Specifically, we investigate the following four hypotheses:

- **H1** Participants will relate robots' proxemic deviation behaviors to social distancing norms and observed mask violations.
- **H2** Participants will view robots that follow exaggerated social distancing norms in response to mask violations as more likable.
- **H3** Participants will view robots that follow exaggerated social distancing norms in response to mask violations as safer.
- **H4** Participants will view robots that follow exaggerated social distancing norms as more socially intelligent.

3 METHOD

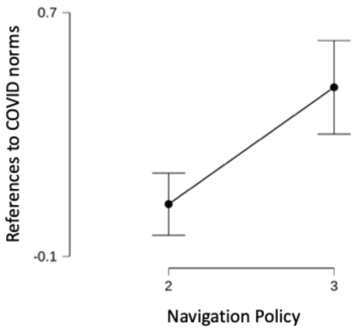
To evaluate our hypotheses, we conducted an online human subjects experiment in which participants observed robots either (a) navigating normally, (b) exaggeratedly avoiding all pedestrians, or (c) exaggeratedly avoiding only maskless pedestrians. This experiment was conducted using Amazon's Mechanical Turk platform [10], through the psiTurk framework [20]. While Mechanical Turk is not entirely free of population bias [42], it has been more successful at reaching a broader demographic sample of the US population [14].

Experimental Design: To study human perceptions of robot social distancing behavior, we designed a simulated environment mimicking the ongoing COVID-19 pandemic situation, using Gazebo [28]. As shown in Figure 1, the setup is a quad-like environment consisting of pathways leading to a set of quad-adjoining buildings. The area inscribed between the pathways is colored green to represent a lawn, making robot trajectory deviations clearly identifiable. Within this environment, we simulated a navigation scenario in which people were observed traversing the environment's paths, some of whom were depicted as wearing masks, and some were not. The humans in this simulated environment, designed using MakeHuman software [7, 8], included four mid-aged human characters: a masked male and an unmasked male, and a masked female and an unmasked female. As shown in Figure 2, these characters were designed to avoid easy categorization into stereotypical categories to mitigate potential effects of racial bias.

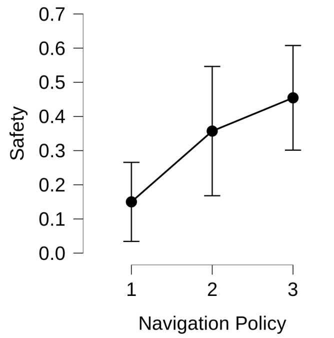
Each participant was assigned to one of three experimental conditions (**P1**, **P2**, **P3**). For each of these categories, we created a video filmed within our simulation environment in which a Husky robot was shown performing a navigation task between two points (these points were the same in all videos). The robot begins by introducing itself as Alex (a gender-neutral name) and then proceeds along the path before passing the two pedestrians, one masked and one unmasked. The navigation policies followed in each video depend on the experimental condition associated with that video:

- **P1** **No Deviation** - The robot takes the shortest path possible without any social distancing protocol.
- **P2** **Deviation** - The robot deviates from the shortest path when it encounters a human (distancing itself from pedestrians regardless of whether or not they are wearing masks).
- **P3** **Social Deviation** - The robot deviates from the shortest path only when encountering an unmasked pedestrian.

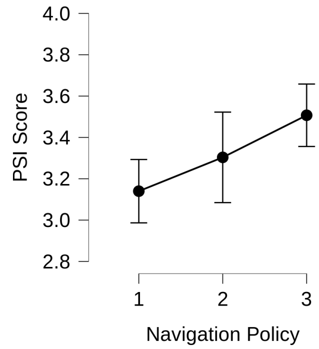
In all cases, the robot was teleoperated. When the experimental condition required the robot to deviate from its path, the robot was



(a) Percentage of participants who referenced COVID norms in Q4 across navigation policies 2 and 3.



(b) Frequency of references to safety in Q3 across all three navigation policies.



(c) Perceived social intelligence scores across all three navigation policies. (1. *No Deviation*, 2. *Deviation*, and 3. *Social Deviation*). 95% credible intervals.

teleoperated to follow a socially-aware navigation trajectory [1, 17] parameterized to avoid the pedestrian's proxemic zone using an exaggerated social distancing threshold of 10 feet. Within each experimental condition, we systematically varied the order in which the pedestrians were encountered (masked first or unmasked first) and the gender presented by the pedestrians encountered (both male or both female), resulting in a total of 12 videos.

Procedure: After providing informed consent, participants completed a demographic questionnaire, including experience with robotics and AI (scale of 1-7). Participants then watched a test video to verify their video and audio were working correctly, followed by a Negative Attitude Towards Robots (NARS) questionnaire [34]. The participants then watched the one-minute video associated with their experimental condition. After watching this video, participants completed the measures described in the following section.

Measures: Our quantitative measures of interest are negative attitude towards robots [34], perceived likeability [6], perceived safety [6], and perceived social intelligence [3]. Our qualitative measures consisted of four open-ended questions.

- **Q1** In a sentence, describe the people that the robot encountered.
- **Q2** In a sentence, explain what was the robot doing?
- **Q3** Would you be comfortable with a robot like this in your workplace or a public place? Answer with YES/NO, followed by an explanation of your choice.
- **Q4** When the robot deviated from a straight-line path, why do you think the robot deviated? (This question was only given to participants in the **P2** and **P3** conditions, for whom the robot's path deviated.)

Participants: We recruited 112 subjects[1] (38 female, 73 male, and 1 did not report) from Amazon's Mechanical Turk. Participants ranged from 22 to 70 years (M=38.56, SD=9.92). Participants received compensation of $2.01 for their time. No participants were excluded on the basis of negative attitudes towards robots as no difference between conditions was observed.

Data Analysis: Free-text responses to Q3 and Q4 were coded TRUE/FALSE based on whether they contained any references to safety and COVID, respectively. For example, the text "*Yes, the robot is moving away from people so that it does not run into people*" would be coded as TRUE for safety. We used a Bayesian statistical framework to analyze our results for likeability, quantitative safety ratings, and social intelligence, using JASP [45].

4 RESULTS

Connection with COVID Norms: Bayesian Contingency Table Analysis of the coded results of our thematic analysis provided extreme evidence in favor of an effect of Navigation Policy on References to COVID-related norms in Q4 (BF=150.524), as shown in Figure **??** [a], with 2/28 participants reference COVID-related norms in the Deviation condition, and 20/44 participants referencing COVID-related norms in the Social Deviation condition.

Likeability: A Bayesian ANOVA of likeability from the Godspeed questionnaire [6] indicated substantial evidence that the robot's navigation behavior did *not* influence perceived likeability (Bayes Factor = 0.215).

Safety: A Bayesian ANOVA of safety from the Godspeed questionnaire [6] indicated substantial evidence against an effect of Navigation Policy on perceived safety (BF=0.115). Bayesian Contingency Table Analysis of the coded results of our thematic analysis provided moderate evidence in favor of an effect of Navigation Policy on References to Safety in Q3 (BF=6.702), as shown in Figure **??** [b]. Post-Hoc pairwise Bayesian Contingency Table Analysis provided strong evidence in favor of a difference between the No Deviation navigation policy (for which 6/40 participants referenced safety) and the Social Deviation navigation policy (for which 20/44 participants referenced safety). Inconclusive evidence was found between the Deviation condition (for which 18/28 participants referenced safety) and both the No Deviation (BF=1.693) and Social Deviation (Bf=0.398) conditions, suggesting that more data is needed before these pairwise effects can be confirmed or ruled out.

Social Intelligence: A Bayesian ANOVA provided substantial evidence in favor of an effect of Navigation Policy on Perceived Social Intelligence (BF=7.770), as shown in Figure **??** [c]. Post-hoc analyses revealed strong evidence (BF=32.621) in favor of a difference between the *No Deviation* navigation policy (M=3.140, SD = 0.479) and

[1]Participants who provided clearly unrelated data on free-response questions, especially Q1 and Q2, were identified as inauthentic participants and discarded.

the *Social Deviation* navigation policy (M=3.507, SD=0.497), with inconclusive evidence neither conclusively for or against a difference between the *Deviation* navigation policy (M=3.303, SD=0.565) and the No Deviation (BF=0.509) and Social Deviation (BF=0.743) navigation policies.

5 DISCUSSION

We hypothesized that participants will relate robots' proxemic deviation behaviors to social distancing and mask norms (**H1**) and that participants would rate the robot following exaggerated social distancing norms in response to mask violations as more likable, safe, attentive to safety, and socially intelligent (**H2-4**). Our results partially support hypotheses **H1**, **H3**, and **H4** but refute hypothesis **H2**. Specifically, our results suggest three major findings: (1) Participants were able to infer norm adherence from robots' proxemic behaviors but did not appear to infer norm-oriented dispositions or communicative intent from those behaviors. (2) Participants more frequently referenced safety in assessments of their comfort with robots that followed exaggerated proxemic behaviors but did not rate the robots as overall safer on numerical scales. (3) Participants inferred greater social intelligence from robots that exhibited proxemic behaviors sensitive to social norms.

What norm-related inferences do observers draw from robots' proxemic deviations? Our results provided extreme evidence suggesting that participants were uniquely likely to infer dispositions related to masks and social distancing from the behavior of robots that followed the *Social Deviation* navigation policy, as evidenced through responses such as those shown below (from navigation policy P3): (1) "*They avoided the person who was not wearing a mask because that person was not being responsible.*" (2) "*To move around the man without a mask (due to COVID or something similar).*" These observer responses clearly indicate that the participants were able to correlate the robot's exaggerated social distancing with the observed violation of mask-wearing norms.

For designers of HRI and social robots who are explicitly seeking to increase their robotic platforms' perceived (social) intelligence, implementing a *Social Deviation* navigation policy may be a straightforward way to achieve this benefit without the need for any verbal capabilities. Moreover, while we did not find widespread evidence of participants inferring norm-related dispositions or intended moral communication from the robot's motion, a few isolated cases were observed in which participants did make such inferences. For example, consider the following participant from P3, who stated: "*No. Since for me a workplace is not applicable, in public I suppose I'd rather not experience a robot like this, as it would be weird, along with rude / shaming to unmasked people.*"

One possible explanation for this is recent evidence suggesting that blame is more intense and differentiated from praise [19]. It is possible that participants who noticed the behavior and condoned it did not feel the need to mention it, whereas participants who noticed the behavior and were displeased by it felt the need to speak up about it. Future research will be needed to re-examine this topic using a paradigm that explicitly asks participants about specific inferences to overcome this asymmetry.

How do robots' proxemic deviations impact perceptions of robot safety? Our results provide partial support for **H3**. While participants were no more likely to rate the robot as safe when it followed the *Social Deviation* or *Deviation policy*, participants in the *Social Deviation* condition were more likely to refer to the robot's safety when assessing their comfort in it, compared to participants in the No Deviation condition, as evidenced by responses such as those shown below (from navigation policy P3): (1) "*Yes, because he/she seems pretty safe and looks like they mean no harm.*" (2) "*YES, it seems to avoid people to make sure it doesn't run into people. So, I would be very comfortable*" (3) "*YES, qualified. Avoiding people is only one way to keep them safe.*" It is unclear whether the importance of safety in these responses is entirely related to the robot deviating to avoid running into people - (2) or following the new social distancing norm - (3) or general safety - (1).

How are robots social deviations viewed? Finally, our results suggest that observers viewed robots in the Social Deviation condition as more socially intelligent than those in the No Deviation condition, partially supporting hypothesis **H4**. However, this finding was tempered by substantial evidence *against* an effect of navigation policy on robot likability (thus refuting **H2**). However, this result may suggest that robots may be able to enact socially aware navigation policies that adhere to pandemic-relevant social norms without experiencing backlash from observers.

One potential concern might be if the robot was perceived as more socially intelligent in the *Social Deviation* condition simply because it followed a more complex trajectory. However, we do not believe this to be the case since an attenuated effect was found in the *Deviation* condition. That being said, the differences between the *Deviation* condition and both the *No Deviation* and *Social Deviation* conditions was inconclusive; further study will be needed to identify whether the *Deviation* navigation policy truly sits between the *No Deviation* and *Social Deviation* navigation policies, or if it is functionally equivalent to one but not the other in terms of Perceived Social Intelligence.

6 CONCLUSION

In this work, we explore the roles of spatial communication in communicating social norms. We experimented with three navigation policies (*No deviation*, *Deviation*, and *Social Deviation*), and the results show that observers rated the robot with *Social Deviation* as socially intelligent than the other navigation policies, i.e., participants were able to relate social awareness in navigation policy to perceived social intelligence of the robot. Furthermore, there is significant evidence that people could relate the robot's deviation from a straight-line path to COVID safety protocols, demonstrating the importance of non-verbal spatial communication to communicate social norms through social trajectories. In the future, once the current pandemic subsides [cf. 16], we want to explore further the importance of non-verbal communication by utilizing social navigation on real-robots with an in-person experiment.

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