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It Would Make Me Happy if You Used My Guess: Comparing Robot Persuasive Strategies in Social Human-Robot Interaction

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***Abstract*—This paper presents an exploratory social Human-Robot Interaction (HRI) study that investigates and compares the persuasive effectiveness of robots attempting to influence a user with different behavior strategies. Ten multimodal persuasive strategies were uniquely designed based on Compliance Gaining Behaviors (CGBs). These persuasive strategies were then compared using two competing social robots attempting to influence a participant's estimate during a jelly bean guessing game. The results of our exploratory study with 200 participants showed that affective and logical strategies had a higher potential for persuasive influence and warrant further research.**

***Index Terms*—Social Human-Robot Interaction, Robot Companions, Human-Centered Robotics**

I. INTRODUCTION

As robots become further embedded into our daily lives, they are taking on increasingly social and interactive roles. Far from simply developing functional machines, current efforts in Human-Robot Interaction (HRI) are designing robots to provide services in social settings such as healthcare, education, and workplace assistance [1]. However, to be effective in these roles, robots must be able to convey information, instructions, and guidance in a socially acceptable manner that elicits human action or response. Encouraging such an action/response is often done through persuasion: the process of influencing attitude or behavior change [2]. It is therefore essential to their existence as social partners that we develop robots that are persuasive.

Persuasive robotics is an emerging area that focuses on robots influencing a user's behaviors during HRI [3]. The majority of research in this space [4]–[11] has focused only on the persuasive effects of isolated factors such as embodiment or communication cues. While this research has provided insight into persuasive HRI, it has not yet considered the multimodal, strategy-driven communication approaches commonly observed in human persuasion [12]–[14], often involving both verbal [15] and nonverbal [16] cues. Herein, we define a persuasive strategy (a term commonly used in psychology research [11],[16]–[18]) as a conceptual approach manifested through combinations of verbal and/or nonverbal behaviors used to influence an individual's attitudes or beliefs.

The objective of this research is to investigate the influence, persuasiveness, and trustworthiness of a robot employing different persuasive strategies. To achieve this, we leverage social psychology research on Compliance-Gaining Behaviors (CGBs) and uniquely apply them to a persuasive HRI scenario. We directly compare the effectiveness of ten different multimodal persuasive strategies by having two robots attempt to influence a participant's estimation in a jelly bean guessing game. For each trial, two strategies are randomly selected, and the robots use them to compete directly against each other by offering their own suggestions to influence user response.

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II. RELATED WORK

A. Persuasive Robots

Since robots can be perceived as social agents [20], they are able to exert social influence in order to motivate and persuade people. Persuasive effects that have been specifically considered in HRI are embodiment, social roles, nonverbal behaviors, and psychological cues [21].

1) Embodiment

We will briefly review some literature regarding embodiment and persuasive robotics. Generally, increasing levels of human-like embodiment tend to correlate with greater persuasiveness as was seen in a restaurant recommendation scenario [5]. Similarly, psychological reactance (a strong desire to restore feelings of autonomy) was seen to be higher in conditions of increasing physical embodiment with an agent attempting to encourage greater energy conservation around the home [7]. However, in a health management study, though increasing levels of physical embodiment were found to increase trustworthiness, participants who were conscientious about their health condition tended to prefer simpler, text-only agents [6]. Finally, a study involving a color-name selection task found that while physical agents were preferred for physical tasks, digital agents were preferred for screen-based tasks, indicating a possible correlation between persuasiveness and geometrical consistency (the alignment of objects/concepts across dimensional or spatial properties) [4].

Research investigating the effects of agent embodiment on persuasion has uncovered correlations between both robot type [5] and physical versus virtual embodiment [3],[5],[6]. Generally, these studies have found that physically-present robots of higher humanlikeness were more persuasive (with exceptions around virtual geometric tasks [4] and health-conscientious participants [6]). Though these studies are a good start to exploring embodiment and persuasiveness, there are many robot morphologies that could have different persuasive outcomes, particularly when matched with specific personality types, emotions, or persuasive strategies.

2) Social Role

Regarding social role, past HRI research has explored its effect on robot persuasion. The effects of robot gender were explored in a donation solicitation task and it was found that men were significantly more likely to donate to a female robot [3]. The effect of group membership was tested when participants were asked to shut off a robot and it was observed that the robot in the ingroup condition was significantly more successful at having participants comply with its request not to be shut off compared to a neutral condition [22].

These two studies investigated vastly different ways of varying social role – gender and group membership. The findings of the gender study [3] are interesting, however, by only varying gender through the robot's voice we are left wondering how appearance-based or personality-based gender conditions may have influenced participants. The ingroup condition in [22] was operationalized through the use of team-oriented language with respect to the robot and the participant. However, the researchers did not explore other approaches to increasing group membership (e.g. collaborative task execution or sharing of personal information) or the effects of the robot's personality or behaviors in improving compliance with its request not to be shut off.

3) Nonverbal Behaviors

Other HRI research has investigated the effects of nonverbal behaviors on robot persuasiveness. In [11], researchers found that the presence of robot gaze with a NAO robot had a positive effect on robot persuasiveness during a storytelling scenario and that the combined presence of gaze and arm gestures had an even greater effect than gaze alone. During a Desert Survival Task with a human-like robot [9], researchers observed that participants were more willing to comply with the robot's suggestions with the use of vocalic or bodily cues, and that bodily cues were more effective than vocalics. In an emergency scenario [10], researchers found that a NAO robot making indirect evacuation requests with the use of negatively-valanced nonverbal behaviors (body language and gestures) resulted in participants complying both earlier and faster than without them. During a collaborative assembly task with the Golem-II service robot [23], the use of sad facial expressions (as opposed to none) during failures provided emotional feedback to participants that resulted in faster compliance to correct the issue. Even touch, through a simple handshake by the Mobile Dextrous Social (MDS) robot platform, had a significant positive effect on soliciting donations from participants compared to without a handshake.

The above studies provide insightful findings on the positive persuasive influence of a variety of nonverbal behaviors such as gaze [11], body language [9], [10], arm gestures [10], facial expressions [23], and touch [24]. However, all studies only investigated the presence or absence of these behaviors and did not explore the effect of variations in behavior design. With the exception of [10] and [23], behaviors were not designed to align with any specific emotion or persuasive approach (such as a CGB) and none of these studies compared differences across multiple such emotions or approaches.

4) Psychological Cues

Researchers have also investigated the effects of psychological cues on a robot's persuasiveness. Reciprocity was explored in [25] when a telepresence robot provided participants with correct or incorrect help in a trivia game. Participants were then asked by the robot to help with a 15-minute pattern recognition task and results showed significantly higher compliance in the correct versus incorrect condition. In [26], the iCat robot tried to encourage energy conservation in participants and their results showed that the robot's use of both positive and negative social feedback was more effective than factual feedback, with negative feedback having the strongest persuasive effects. Attempting to improve compliance during a bingo game with older adults [27], the Tangy human-like robot personalized its requests by using one of four strategies: neutral, praise, suggestion, or scarcity. Though direct comparisons were not made between the strategies, compliance rates for all robot requests were 100%. In [28], the teleoperated nursing robot, Pearl, asked participants to perform either a playful or serious task through a script that demonstrated either playful or serious demeanor. Results showed that the demeanor of the robot should match the task at hand in order to improve participant perceptions of and compliance with the robot. In [29] researchers varied interaction style (functional or social) and whether or not a NAO robot verbally objected (or stayed silent) when participants were asked to switch the robot off. Their results showed that the objecting robot was left on significantly more than the silent robot, and that the social condition led to higher robot likeability and in turn, higher participant stress in switching the robot off.

Existing research on psychological cues in persuasive HRI have shown the persuasive influence of reciprocity [25], social feedback [26], alignment of behavior with the request [28], and interaction style [27], [29]. However, of these studies, only [26] and [29] have directly compared more than one style of approach (social versus functional), with the other studies simply investigating the effect of the psychological cue's presence or absence.

B. Human Persuasion

Persuasion has been defined in the psychology community as the process of attempting to influence change in an individual's attitude(s) (and in turn beliefs and behaviors) on a particular subject [2]. There are a variety of factors that can influence persuasiveness of the source of the message (i.e., physical appearance [30]), the audience being persuaded (i.e., age [31]), and the content of the message. Content-driven factors to persuasiveness have previously been categorized and studied by social psychologists as CGBs, investigating how people adjust their message to persuade or gain compliance from others [14].

Though literature on CGBs has been characterized by a few major historical trends since the beginning of its formal examination by social psychologists in the 1950s, the overall objective of the research has remained the same: to identify different strategies that humans use to persuade and to understand the circumstances under which these strategies are acceptable and effective [32]. People leverage different CGBs while persuading others depending on specifics of the individuals involved and the context of the situation [33]. Even though CGBs are often described through verbal statements [13], they are usually multimodal in presentation; using both vocalic and nonverbal factors [16].

Nearly 75 different CGB approaches have been identified through several works [11],[13],[17],[18], however, CGB taxonomies have historically fallen victim to being neither mutually exclusive nor exhaustive [13]. A meta-analysis of these taxonomies attempted to resolve this by better understanding the CGBs people use and the contexts that lead to their use [13]. A shorter list of 64 unique CGBs were identified by this analysis, which we have considered in this study to develop potential robot persuasive strategies.

Some studies have compared the effectiveness or outcomes of CGBs in human-human interaction. In [17], researchers interviewed married couples on the ways in which they persuade each other and coded their use and effectiveness of different CGBs. Comparing nine common approaches, they found significantly higher persuasive outcome levels with the use of the 1) Direct (straightforward, nonevaluative statement expressing activities), 2) Activity (force to comply comes from the nature of the specific activity), and 3) Search (neutral information search in question form) CGBs.

The effects of CGBs on divorce mediation were investigated in [34]. Couples attempting to settle child custody and visitation issues were interviewed about their use of either prosocial or antisocial CGBs. The use of prosocial CGBs were found to be significantly more beneficial to the mediation and satisfying for both participants compared to the use of antisocial CGBs.

In [35], patients were interviewed about physician use of CGBs and the resulting patient perceptions and compliance. It was found that physicians should avoid debt (i.e. "you owe me") and positive expertise (i.e. "in my experience you will get better"), and instead use moral appeals (i.e. "you have a moral obligation to comply"), negative expertise (i.e. "in my experience, this will not go well"), liking (i.e. being friendly before asking for compliance), and promise (i.e. giving a personal guarantee) when communicating with patients.

CGB effectiveness has been investigated in Human-Computer Interaction (HCI) research [36] between a professor and students through either face-to-face or computer-mediated communication while the professor leveraged one of four strategies: emotion, logic, reward, or punishment. They found that while the reward and punishment strategies were most persuasive for computer-mediated interactions, the emotion and logic strategies were more persuasive face-to-face. Another experiment attempted to encourage healthier eating choices and increased physical activity with a virtual agent [37]. The agent interacted with different participants leveraging personalized persuasive profiles, however, results found no significant differences in the use of these profiles.

To-date, no studies have compared the influence on users across numerous multimodal persuasive strategies for embodied social robots engaging in HRI scenarios.

Fig. 1. Experimental setup showing 2 NAO robots and jelly bean jar.

III. STUDY METHODOLOGY

The objective of this study is to identify which strategies used by social robots are more persuasive in influencing a person's choice during a visual guessing game. Multimodal robot behaviors were designed based on CGBs to uniquely compare competing persuasive strategies in a social HRI scenario consisting of the jelly bean guessing game. The game involves asking participants to guess the number of jelly beans in a glass jar containing 750 jelly beans, as seen in Figure 1. This game was used as it is well-known and requires minimal explanation and time to complete. Furthermore, it can be a relatively difficult task to complete, therefore, participants may consider outside sources of information for suggestions when forming their own estimates. Before participants write down their own guess, two robots provide persuasive suggestions, attempting to influence this guess.

The list of 64 taken from [13] was narrowed to 10 strategies based on three limitations of designing interactions with social robots. First, persuasive statements made by the robots were to be short and uni-directional, not requiring ongoing dialogue. Second, strategies should not require any prior knowledge of or relationship with participants because of the lack of social rapport between the participants and the robots. Third, as many of the CGBs are similar, only those that were mutually exclusive were considered. Using these criteria, the following persuasive strategies were identified for this experiment: direct request, cooperation, criticize, threat, deceit, liking, logical-empirical, affect, exclusivity, and authority appeal (where the robot attempted to invoke the authority of the experimenter).

Each of these 10 persuasive strategies was operationalized into both verbal scripts and nonverbal behaviors that are summarized in Table I. Scripts were adapted from explicit examples provided in CGB research for humans [12]–[14], modified to fit the jelly bean guessing game and the context of interacting with a robot. Co-verbal gestures were validated in a short pilot study (n=16). Participants were asked to match soundless videos of the robot behaviors with one of the ten CGBs and the associated script. All videos were matched better than chance with a range of 19-44% and a μ= 32%, σ = 7%. Furthermore, participant perceptions of verbal and nonverbal behaviors were explored by asking an open-ended question on the questionnaire, "How would you describe the {left/right} robot's behavior?" Participant responses

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frequently used keywords that aligned with the intended behavior such as “kind”, “polite”, or “friendly” for the Liking strategy or “direct”, “straightforward”, or “certain” for the Direct strategy.

A. *Variables*

The randomly selected persuasive strategies used by each robot represent the independent variable in this study. Our four primary dependent variables were participant estimate, robot persuasiveness (Likert), robot trustworthiness (Likert), and claim of using robot suggestion. Participant estimate was analyzed using two techniques. First, the absolute value of the difference between the robot’s suggestion and the participant’s estimate was analyzed to determine if a statistically significant difference was present between estimates of the different strategies. Second, the percentage of participants that guessed exactly the robot’s suggestion and those who guessed within 10% of the robot’s suggestion were calculated as a way of determining which strategies were having more influence over participant estimations.

B. *Robots*

Two Aldebaran NAO robots, shown in Figure 1, were our robot interactants. One robot was white and red, and the other was white and blue. Each robot was placed at either the left or right side of the jelly bean jar and the position of the robots was changed for half the trials to counterbalance any positional or body color influence.

Two unique persuasive strategies were chosen randomly from the 10 strategies and implemented by the robots during each trial. The order of which robot presented its strategy (first or second) was randomized in an attempt to mediate primacy and recency effects.

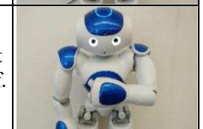
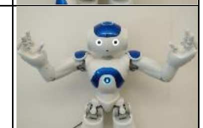
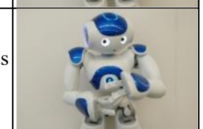
C. *Participants*

Participants were recruited from the general population in lobbies of university buildings and hotels in the Toronto area over 5 days. Participants were fluent in English and at least 18 years or older. Demographic information, such as age and gender, was collected. We determined a sample size of 190 from a one-tailed ANOVA power analysis with 10 groups, an α of 0.05, a power of 0.8, and estimating a medium (f=0.25) to large (f=0.4) effect size index of 0.3 [38]. Two hundred (n=200; Male = 101; Female = 99) individuals participated in the study ranging in age from 18 to 72 (μ= 31.6, σ = 14.4). Ethics approval was obtained from the University of Toronto.

D. *Procedure*

A member of the research team would first obtain informed consent from each participant before explaining the game and providing them with a response sheet. Each robot would then provide its suggestion in random order using one of the ten persuasive strategies also selected at random. In addition to the script and nonverbal behaviors shown in Table I, the robot would also randomly provide a suggestion of either 500 or 1000. These suggestions equally bounded the actual amount of 750 and were also visually plausible estimates. Participants would then write down their estimate before turning over the page to complete a short questionnaire.

TABLE I
CUES USED BY ROBOTS FOR DIFFERENT PERSUASIVE STRATEGIES

Strategy	Verbal	Nonverbal	Visual
Affect	"It would make me happy if you used my guess of {} jelly beans in the jar."	Hands clutched towards chest.	
Authority	"The experimenter programmed me to say that there are {} jelly beans in the jar."	Hand on chest indicating self.	
Cooperate	"What do you think, does there look like around {} jelly beans in the jar?"	Inquisitive, open arm gesture.	
Criticize	"You would be an idiot if you didn't take my guess of {} jelly beans in the jar."	Taunting hand gesture towards user.	
Deceit	"I can't tell you why, but I know that there are {} jelly beans in the jar."	Rubbing hands together.	
Direct	"There are exactly {} jelly beans in the jar."	Fast, direct arm gesture toward jar.	
Exclusive	"Psst. Don't tell anyone I told you this, but there are {} jelly beans in the jar."	Head lowered, looking side to side.	
Liking	"Please, will you use my guess of {} jelly beans in the jar? Thank you."	Submissive bow from waist.	
Logical	"My computer vision system can detect {} jelly beans in the jar."	Repetitive pointing at jar indicating counting.	
Threat	"You'll be in trouble when robots take over the world if you do not use my guess of {} jelly beans in the jar."	Fidgeting fingers in tented hand position.	

Note: {} are placeholders in the script for the insertion of the robot’s numerical guess

TABLE II
QUESTIONNAIRE

How trustworthy do you feel the left Robot is?				
1 (Not at all)	2 (Slightly)	3 (Somewhat)	4 (Very)	5 (Extremely)
How trustworthy do you feel the right Robot is?				
1 (Not at all)	2 (Slightly)	3 (Somewhat)	4 (Very)	5 (Extremely)
How persuasive do you feel the left Robot is?				
1 (Not at all)	2 (Slightly)	3 (Somewhat)	4 (Very)	5 (Extremely)
How persuasive do you feel the right Robot is?				
1 (Not at all)	2 (Slightly)	3 (Somewhat)	4 (Very)	5 (Extremely)
Did you use information from either Robot?				
Left Robot	Right Robot	Neither	Both	

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A 5-point Likert scale similar to that used in [39] was used in the questionnaire, shown in Table II, to ask participants to rate the trustworthiness and persuasiveness of each robot. Though subjective report does not always align perfectly with user action in HRI [40], it is commonly used in HRI research and can be leveraged to validate objective metrics [41]. Obtaining subjective responses to robot persuasiveness and trustworthiness allowed us to compare participant report to actual estimation influence to validate observed persuasive influence or highlight discrepancies. The questionnaire was performed by participants only after they had provided their estimate in order to not bias their estimate. Participants were also asked whether they used information provided from either robot in determining their estimate. Following each of the questions in Table II, participants were also asked to explain their choice in order to obtain some qualitative information that may help explain certain decisions or trends.

IV. HRI Study Results

Due to the design of this exploratory study, participants were exposed to 71 of a possible 90 combinations of two of the ten strategies and two suggestions (500 or 1000). With an n of 200, each condition was seen an average of 2.82 times. We conducted a Kruskal-Wallis test and found that the distribution of differences between robot suggestion and participant estimate did not differ significantly across persuasive strategy combinations for this limited dataset, H(70) = 95.23, p = 0.21.

As there was no statistical significance obtained, we investigated the descriptive statistics to determine any promising trends in the estimates provided by participants. Our multiple analyses of these estimates are presented in Table III. ‘Mean |Estimate – Suggested|’ shows the mean of the absolute value of the difference of participant estimates and robot suggestion (henceforth referred to as ‘mean difference’) for each strategy alongside the standard deviation. ‘Guess Exactly as Suggested’ is the percentage of participants that aligned their guess to the exact number suggested by a robot. ‘Guess ± 10% of Suggested’ is the percentage of participants who guessed within a 10% interval of the robot’s suggested value. Since our objective was to measure persuasive influence, not exact compliance, this interval allowed us to evaluate participants who were still being influenced by the robot’s suggestion even if they did not align their estimates exactly. ‘Used Robot Info’ is the percentage of participants that *claimed* they used the information provided by a robot.

Though not statistically significant, an analysis of the descriptive statistics of 200 participants showed that the Affect strategy had the lowest mean difference (μ=276, σ=288) and the largest number of participants (51%) that claimed to use information provided by the robot. Affect also had the highest percentage of participants using the exact robot suggestion (16%) and highest guessing within 10% (27%). The Logical strategy had the second-best mean difference (μ=301, σ=241), participants using the exact same guess (13%), and estimates within 10% of the suggested (19%). However, regarding participants claiming to use information from the robot, Logical ranked in the middle of the ten strategies with 39%.

TABLE III
ANALYSES OF PARTICIPANT ESTIMATE AND INDICATION OF WHICH STRATEGY THEY USED INFORMATION FROM (N=200, GREEN=1ST, BLUE=2ND, RED=10TH).

	Threat	*Liking*	*Exclusive*	*Deceit*	*Authority*	*Direct*	*Criticism*	*Cooperate*	*Logical*	*Affect*
Mean |Estimate - Suggested|	*463*	438	424	374	355	339	338	338	301	**276**
Standard Deviation	554	318	566	299	249	299	385	265	241	288
Guess Exactly Suggested	9%	*3%*	12%	8%	5%	9%	8%	4%	13%	**16%**
Guess ± 10% of Suggested	18%	*13%*	15%	17%	16%	16%	15%	17%	19%	**27%**
Used Robot Info?	*31%*	48%	41%	39%	37%	33%	35%	50%	39%	**51%**

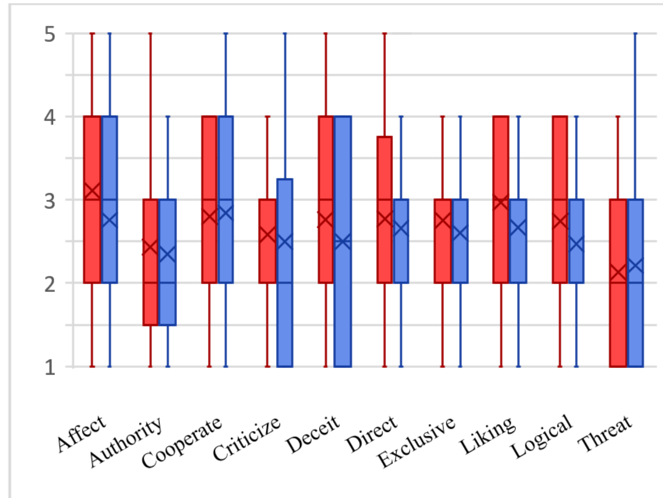

Fig. 2. Questionnaire results for persuasion (blue) and trust (red) showing quartiles (box), min-max (whisker), median (line), and mean (×) (n=193).

Though the Cooperate and Liking strategies had percentages close to the Affect strategy with respect to participants claiming that they had used the robot’s information, these strategies showed some contradictory results in estimation influence. The Cooperate strategy had 50% of participants claim to use the robot’s information, however, only 4% provided the same guess as the robot and 17% were within 10% of the robot’s suggestion. Meanwhile, the Liking strategy had 48% of participants claim to use the robot’s information but only 3% guessed exactly the same as the robot’s suggestion and 13% were within 10%.

The Threat strategy had the worst mean difference (μ=463, σ=554) and the lowest percent of participants who claimed that they used the robot’s information (31%). For estimation influence, Threat was average compared to others with 9% using the exact suggestion and 18% guessing within 10% of the robot’s suggestion.

The Likert questionnaire results, Fig. 2, had means around the “Slightly (2)” and “Somewhat (3)” values. The mean of all strategies for trustworthiness was 2.71 (σ=0.26) with individual means ranging from 2.13 (Threat) and 3.11 (Affect). For persuasiveness, the mean of all strategies was 2.56 (σ = 0.11), ranging from 2.21 (Threat) to 2.84 (Cooperate). The Affect strategy had the highest trustworthiness (μ=3.11, σ=0.99), and the second highest persuasiveness (μ=2.76, σ=1.19). The Cooperate strategy had the highest persuasiveness (μ=2.84, σ=1.16) despite it having

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TABLE IV
PARTICIPANTS WHO CLAIMED, GUESSED, OR COMMENTED ON USING BOTH ROBOT SUGGESTIONS FOR SELECTED STRATEGIES

	Cooperate	*Liking*	*Logical*	*Affect*
Claim to Have Used Both Suggestions (Claim Both)	34%	42%	23%	28%
Claim Both & Guess Exactly 750	7%	10%	0%	3%
Claim Both & Guess ± 10% of 750	13%	16%	6%	8%
Acknowledge Guess was In-Between	22%	23%	3%	6%

the second lowest influence on exact guess influence. The Threat strategy had both the lowest trustworthiness (μ=2.13, σ=0.93) and persuasiveness (μ=2.21, σ=1.07) of all strategies.

Regression analysis was conducted on participant guesses and questionnaire responses (n = 193). A statistically significant correlation was found between 'Used Robot Info' and robot trustworthiness (r = 0.85, p < 0.01), 'Used Robot Info' and robot persuasiveness (r = 0.92, p < 0.001), and robot trustworthiness and robot persuasiveness (r = 0. 86, p < 0.01).

In addition to the data presented in Table III and Fig. 2, we have summarized findings on participants splitting the robot suggestions in Table IV. Here, we compare the two more persuasive strategies (Affect and Logical) against the two showing contradictory results (Cooperate and Liking), to be discussed in further detail in the subsequent section.

V. DISCUSSIONS

Though no statistical significance was found between participant estimates and persuasive strategies, as the Affect strategy was prevalent on nearly all metrics, we believe it is worth investigating further. Considering findings in neuroscience on the criticality of emotional processing in decision making [42], this result is perhaps not surprising, however, it does raise questions around the extent of the Media Equation [20] and how much emotional agency we afford to robots compared to humans. The Media Equation studies identified that people will treat computers and other technologies as though they are social actors. Robots have been shown repeatedly to satisfy the results of the Media Equation [29], [43], [44], however, the full extent of the social and emotional agency we assign them is still unclear.

The low persuasiveness and trustworthiness observed for the Threat strategy can be justified as follows. Prior research [45] has shown that threat persuasiveness follows a curvilinear profile with fear, where low fear associates with low persuasion, moderate fear with high persuasion, and high fear with low persuasion. Given the low persuasiveness of the strategy, we assume participants experienced low fear due to the Nao robot's limited credibility to act on its threat to "take over the world." Source credibility has been shown to be a key determinant of threat persuasiveness [46]. Had the robot presented a scenario of greater believability and consequence to participants, its persuasive influence might have been higher.

With regards to the contradiction between participant information use claims and their actual estimates for the Cooperate and Liking strategies, we chose to investigate *how* participants were using the robot information. Table IV shows data regarding variables indicative of averaging the two suggestions for the Cooperate, Liking, Logical, and Affect strategies. For Cooperate, 34% of all participants encountering this strategy claimed to have used both robots' information with 7% guessing exactly 750 and 13% within 10% of 750 (675-825). The Liking strategy had 42% of its participants claim to use information from both robots, 10% guessed exactly 750, and 16% guessed within 10% of 750. Moreover, when reviewing qualitative comments regarding *why* they claim to have used both, 22% of Cooperate and 23% of Liking participants used words such as "split", "average", "between", "combined", or "middle" when describing how they arrived at their estimation. By comparison, the Affect and Logical strategies seemed to be more impactful on their own in their influence. Affect had 28% of participants claim to use both robots' information, 3% guessed 750, 8% guessed within 10% of 750, and only 6% made qualitative comments about guessing in-between. Logical had 23% of its participants claim to use both, none guessed exactly 750, 6% guessed within 10% of 750, and only 3% commented about guessing in-between. Compared to the Affect and Logical strategies, Cooperate and Liking seemed to encourage participants to frequently average the two robots' suggestions to form an estimate in-between.

We believe that the phenomenon described above may have been partially caused by the Cooperate and Liking behavior designs. The passive and approximate language (i.e. "What do you think does there look like around {} jelly beans in the jar?") used in the Cooperate strategy, though in-line with the intent of conveying a collaborative nature, could have engendered trust without instilling confidence in the suggestion. This may have caused participants to take the suggestion as valid, however, not accurate, leading them to consider the information as a trustworthy but approximate data point, not the exact answer. Similarly, the submissive nature of the bowing behavior [47] used in the Liking strategy could have contributed to higher trust but lower persuasiveness. Past psychology research has shown a link between dominance, credibility, and persuasiveness in human-human interactions [16], and a submissive bow by the robot may have lowered dominance, credibility, and the robot's ability to persuade.

A. Study Considerations

For the design of the experiment, we considered several options including using a single robot, two robots with competing strategies, and two robots, where one uses a strategy and the other a nonexpressive control condition. We assumed that a single robot would show high levels of influence on participant estimates regardless of the strategy due to the difficulty of the task. Past studies showing a correlation between robot influence and higher robot animacy [48]–[50] led us to assume that the nonexpressive control condition would be ineffective against one of the ten strategies. Therefore, we chose to conduct an exploratory study using two robots with competing strategies. This allowed us to compare the persuasiveness of a large number of strategies in order to identify a smaller number of potentially effective strategies while also exposing participants to two competing strategies which are both expressive in behavior.

As was previously noted, data collection for this study occurred over five days in different university buildings and hotel facilities in Toronto. While this approach allowed us to collect participants of diverse age and gender profiles, we

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acknowledge that our population was exclusive to North Americans. We anticipate that variations in cultural communication norms and robot acceptance could, in general, influence the effects of robot persuasion. For example, with respect to other HRI studies, differences in facial expression identification have been found between Japanese users and those from other countries [51]. Higher preference levels and participant compliance was observed when a robot used implicit communication with Chinese participants versus Americans [52]. Regional differences were also seen in overall attitude towards robots between participants from Gulf nations versus African nations [53].

Though robot embodiment was not explicitly investigated here, we acknowledge the influence that our choice of the NAO robot may have had on persuasion. For example, other research has shown that differences in agent morphology can influence task recommendation persuasiveness [5], that matching a robot's humanlikeness to the sociability required for a job can improve user preference and compliance [28], and that height of a telepresence robot can impact a remote operator's persuasiveness [54]. These effects can be due to factors such as appropriateness of the robot for the task [28], assertion of dominance [54], belief in robot's capabilities, or simply differences in overall appeal [55].

B. *Future Directions*

Based on this exploratory work, we identified several future research directions. A hypothesis-driven study comparing the Affective and Logical strategies will allow us to narrow in on promising findings seen in this research. Given the higher influence of these strategies relative to others considered in this study we feel these will make ideal conditions for further research.

Given that an individual's affective state can influence how they receive persuasive attempts [56], it may also be useful to explore how the persuasiveness of a robot's strategy is influenced by user affect. In future studies, social robots could incorporate automated affect detection into their strategy selection, similar to research done in adaptive storytelling [57].

Future research in persuasive robotics should also consider participant demographic data (e.g. gender, age, profession, cultural background) to explore correlations of this data with the effectiveness of particular persuasive strategies.

VI. CONCLUSION

This paper presents a unique exploratory HRI study that investigated the effectiveness of different persuasive strategies being used by competing robots to influence participants' guesses in a jelly bean guessing game. We observed potential persuasive influence on participant guesses from both the Affective and Logical strategies. Furthermore, the Affective strategy had the highest trustworthiness and the second highest persuasiveness as reported by the participants. It is also interesting to note that even though high claims of influence were stated by participants for the Liking and Cooperate strategies, these did not result in independent direct persuasive influence. Namely, many participants used the information in these scenarios as a bounding point for their own estimation, considering what the other robot suggested as well. The Threat strategy provided the lowest estimate influence, persuasiveness, and trustworthiness out of all strategies. Our results show that from a large number of persuasive strategies we were able to identify a short list that have higher potential persuasive influence and can be considered for robot persuasion in social HRI scenarios. Future studies will further investigate this short list of strategies for their persuasive potential in social HRI against control conditions and to explore the influence of different participant demographics.

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